Firm-Level Strategic Analysis: Product Quality, Production in the Value Chain, and IT Expenditure

Ying Dai

PhD Dissertation

Aarhus University
Aarhus BSS
Department of Economics and Business Economics

2024



This version: December 2024 © Ying Dai

PREFACE

As the sun sets and the moon rises, time slips away with the passing days and months. This dissertation marks the culmination of my PhD journey in the Department of Economics and Business Economics at Aarhus University, spanning from September 2021 to September 2024. As I set down my pen at the end of this writing, thoughts and emotions flood my mind. I am profoundly grateful to the Department and the FIND Research Center for providing an exceptional academic environment and invaluable research resources. I extend my heartfelt thanks to the Department, the FIND Research Center, and the Carlsberg Foundation for their financial support.

First and foremost, I would like to express my sincere gratitude to my supervisors, Ina Jäkel and Allan Sørensen, for their invaluable guidance, unwavering support, and patience throughout my PhD journey. Their extensive knowledge and experience have been a constant source of encouragement in both my academic pursuits and daily life. While my PhD journey may come to an end, my gratitude knows no bounds. I am also grateful to Philipp Schröder, Tor Eriksson, Luca Macedoni, Michael Koch, Valerie Smeets, Sarah Schroeder, Jackie Chan, Daisuke Adachi, and every member at the FIND Center, as well as scholars from conferences (seminars, workshops, and meetings) for their helpful comments on my research. Additionally, I appreciate Carsten Eckel and Claudia Steinwender from LMU for their support and care during my research stay in Munich, Germany.

Thanks to my officemate Frederik for sharing insights about Danish culture and fostering a cheerful and productive office environment. I feel very fortunate to have met and worked with both former and current PhD students inside and outside the Department. In particular, I want to thank Mark, Søren, Ilya, Jiwen, Ye, Martin, Lina, Christian, Javier, Rasmus, as well as Jonas, Ida, Tim, and Gabriele from LMU. Your kind company made my time in Denmark and Munich truly wonderful. Furthermore, I wish to express my gratitude to the department secretaries and administrative coordinators Susanne Christensen, Malene Vindfeldt Skals, and Christel Brajkovic Mortensen, with special thanks to Betina Sørensen for her kindness and positive energy when I was unwell.

My gratitude to my family and friends is beyond measure. They are like a vine that allows me to climb the tree freely from the sheltered side. Their tremendous understanding and encouragement have been invaluable not only during my PhD journey but throughout my entire growth. My final tribute goes to those who know my imperfections but still love me, as well as to the people we have met and those we will meet. May we never be limited by the past, nor confined to this moment, but ride on dreams, chase the wind, and pursue the moon without hesitation, for beyond the tranquil plains await the mountains of spring.

Ying Dai
Aarhus, December 2024

UPDATED PREFACE

The pre-defence took place on November 7th, 2024. The assessment committee consists of Professor Tor Eriksson (Aarhus University), Professor Natalie Chen (University of Warwick), and Associate Professor Inga Heiland (Norwegian University of Science and Technology). I am deeply grateful for their time and efforts in assessing my dissertation and for providing valuable feedback and constructive suggestions. Their comments have helped refine several aspects of this work, enhancing its clarity and rigor. I have already implemented some of their suggestions in the current version of the dissertation, while others have inspired ideas for potential future research directions. I sincerely appreciate their guidance throughout this process, which has been instrumental in improving the quality of this work.

Ying Dai
Aarhus, December 2024

CONTENTS

Summaries **vii**

1 Quality Complementarity of Imported Inputs and Output Quality **1**
1.1 Introduction . . . 2
1.2 Theoretical Framework . . . 4
1.3 Data and Measurement . . . 13
1.4 Empirical Analysis . . . 20
1.5 Conclusion . . . 32
1.6 References . . . 34
1.A Appendix . . . 37

2 The Span of In-house Production: Insights from Chinese and Danish Firms **47**
2.1 Introduction . . . 48
2.2 GVC Structure . . . 52
2.3 Data and Stylized Facts . . . 57
2.4 Empirical Analysis . . . 68
2.5 Conclusion . . . 77
2.6 References . . . 80
2.A Appendix . . . 82

3 Firms' Trading Activities and IT Expenditures **101**
3.1 Introduction . . . 102
3.2 Theoretical Considerations . . . 105
3.3 Data . . . 107
3.4 Empirical Approach . . . 114
3.5 Exports, Foreign Sourcing, and IT Expenditures . . . 117
3.6 Extensions and Robustness . . . 124
3.7 Conclusion . . . 128
3.8 References . . . 131
3.A Appendix . . . 134

Co-author Statement **141**

SUMMARY

Firms are central to the global economy, and their strategic choices regarding product quality, production position in the value chain, and IT expenditure have profound implications for economic outcomes. High-quality inputs are essential for producing superior products and enhancing firm competitiveness. Analyzing how firms position themselves within global value chains (GVCs) is crucial for navigating geopolitical and supply chain challenges, also with significant implications for domestic labor markets. Additionally, expenditure on IT is important for boosting operational efficiency and fostering innovation, enabling firms to maintain a competitive edge in a technology-driven environment. These interconnected strategies drive firm growth and contribute to the broader adaptability of the global economic system. This PhD dissertation explores these themes through three interrelated chapters, each addressing a key dimension of firm strategy: product quality, in-house production span, and IT expenditure.

The first chapter, *Quality Complementarity of Imported Inputs and Output Quality*, examines how the dispersion of input qualities affects the final product's quality, emphasizing the role of complementarity among input qualities in the production process. While previous research has primarily focused on average input quality, this paper introduces a new perspective by exploring the dispersion of input qualities. Building on the *O-ring* theory, the chapter develops a theoretical framework where the output quality exhibits varying sensitivity to the qualities of different inputs. I show that the optimal quality of the final good depends on the dispersion of input quality—conditional on average input quality—and on the elasticity of substitution across input qualities. The model suggests that when input qualities are complementary, greater dispersion among them reduces the overall output quality, whereas if input qualities are sufficiently substitutable, increased dispersion in input qualities may enhance product quality. Empirical evidence is provided using data from Danish manufacturing firms between 2000 and 2018. By matching firm-product level import data with firms' production data, using input prices as a proxy for input quality, and measuring output both by price and as a demand residual, the analysis reveals that

greater dispersion in input quality negatively affects output quality, even after controlling for average input quality. These findings align with the model's prediction regarding complementarity, indicating the presence of interdependence between input qualities in production processes. This study highlights the importance of not only focusing on high-average-quality inputs but also managing the variation in input qualities to ensure optimal product outcomes. The results have practical implications for firms, suggesting that strategic input selection and quality management are critical to maintaining product quality and fostering firm growth.

The second paper, *The Span of In-house Production: Insights from Chinese and Danish Firms*, explores an important factor determining firms' "in-house production span", which is defined as the gap between a firm's upstream input sourcing position and downstream output production position in the value chain. Building on findings from prior studies, this paper posits that a firm's optimal in-house production span is related to the relative size of demand elasticity and the elasticity of substitution across the inputs firms use. This prediction is tested using data from China and Denmark, two countries selected not only for their data accessibility but also for their distinct roles in Global Value Chains (GVCs). China, as a global manufacturing hub, and Denmark, with its high-tech industry focus, provide contrasting economic structures that allow for a more robust and generalizable understanding of how firms across varying economic contexts position themselves in GVCs. By combining input-output data with firm-product level trade data and firms' accounting data in China and Denmark, the paper first presents stylized facts on position patterns in both countries. Although the positions of specific manufacturing industries differ between the two countries, the overall trade patterns for manufacturing share some similarities. The subsequent empirical analysis provides strong evidence that, in both countries, firms tend to integrate more production stages when their inputs are highly substitutable and demand for their products is less elastic. Conversely, when demand for their outputs is more elastic and inputs are less substitutable, firms prefer to specialize in fewer stages. These results highlight a competition-driven mechanism in firms' production scope decisions (captured by the difference between the two elasticities): in highly competitive markets, firms are more likely to specialize their production, while greater market power—associated with the firm's gains from purchasing and selling—encourages firms to internalize more production steps. Understanding firms' production decisions has become increasingly critical amid rising geopolitical tensions, supply chain disruptions, and discussions on reshoring and friend-shoring. The findings carry particularly important policy implications for domestic economic growth and employment.

The third paper, *Firms' Trading Activities and IT Expenditures*, is co-authored

with Ina C. Jäkel and Allan Sørensen. We investigate how firms' trading activities, specifically imports and exports, play roles in their information technology (IT) expenditures. Using a firm-level IT expenditure dataset containing information on a continuous measure of firms' IT expenses from Denmark covering the period 2002-2015, we merge it with firms' detailed trade and firm-register data to explore these relationships. The analysis begins by documenting positive correlations between both imports and exports and firms' IT expenditures. To determine causal effects, we employ well-established measures of exogenous firm-level export demand shocks and import supply shocks. Our findings reveal a robust causal effect of imports on firms' overall IT expenditures, particularly driven by expenses on software. However, interestingly, we do not provide any evidence that firms' export demand shocks affect their IT expenditures or their IT intensity (expenditures per employee). This non-existence of a causal link from exports is initially surprising, but further analysis reveals that while export demand shocks do increase firms' IT investments, they simultaneously reduce their IT operating expenses, resulting in a net-zero impact when the two categories are combined. The significant role of imports in driving firms' IT expenditure may be attributed to the increasing complexity and communication needs of managing global supply chains. Indeed, the rise of global value chains (GVCs) has oftentimes been linked to the 'I(C)T revolution'. While exports increase certain IT investments, they also lead to a reallocation of resources away from IT operations. This study contributes to a deeper understanding of how firms' imports and exports separately affect their technological expenses, with implications for both firm strategy and policy aimed at fostering innovation and productivity through technology adoption.

Each of the three chapters provides novel insights into specific aspects of firm strategy within global production, contributing to a deeper understanding of firms' behaviors and decisions in this context. By integrating the analysis of product quality, positioning in global value chains, and digitalization, the dissertation develops a comprehensive framework for examining the dynamics of firms in an increasingly interconnected global economy. It carries important implications for businesses intending to enhance competitiveness and for policymakers aiming to promote economic growth.

BRIEF SUMMARY

Firms are key components of the global economy, with their strategies around product quality, positioning in value chains, and digitalization driving both their competitiveness and economic growth. This PhD dissertation explores these themes across three independent chapters, focusing on product quality, in-house production span, and IT expenditure.

The first chapter, *Quality Complementarity of Imported Inputs and Output Quality*, investigates how the dispersion of input qualities affect a firm's final product quality, focusing on the complementarity among input qualities. Unlike previous studies that emphasize average input quality, this chapter explores the role of input quality dispersion in shaping output quality. Drawing on *O-ring* theory, I develop a framework showing that when input qualities are complementary, an increase in the dispersion among them reduces output quality, while if the input qualities are sufficiently substitutable, an increase in dispersion may enhance product quality. Empirical evidence from Danish manufacturing firms aligns with the complementarity scenario in the model, revealing the interdependence between input qualities. The findings offer insights for firms on strategic input selection to optimize product quality and drive growth.

In Chapter 2, *The Span of In-house Production: Insights from Chinese and Danish Firms*, I explore one important factor associated with firms' decisions on their "in-house production span", which is defined as the gap between a firm's input sourcing position and output production position in the value chain. Building on prior studies, this paper posits that firms' production span is related to the relative size of the demand elasticity of their products and the elasticity of substitution across the inputs they use. This prediction implies a competition-driven mechanism in firms' production scope decisions, which is empirically tested using data from China and Denmark. The results from these two distinct country contexts robustly indicate that firms tend to integrate more production stages when the demand elasticity of their products is low and the elasticity of substitution across inputs they use is relatively higher. Conversely, greater demand elasticity of their products and lower substitutability of

inputs lead firms to specialize in fewer production stages. The study has important policy implications for addressing challenges like supply chain disruptions, reshoring, and boosting domestic growth.

Chapter 3, *Firms' Trading Activities and IT Expenditures*, co-authored with Ina C. Jäkel and Allan Sørensen, examines how firms' trading activities—specifically imports and exports—impact their IT expenditures. Exploiting the Danish firms' IT expenditure dataset from 2002-2015, we first document positive correlations between both imports and exports and firms' IT expenditures. To identify causal effects, we employ well-established measures of exogenous firm-level export demand shocks and import supply shocks. Our analysis reveals a robust causal effect of imports on firms' IT expenditures, but no direct effect of export demand shocks on overall IT expenditures. This absence of a causal link from exports is explained by a simultaneous increase in IT investments and a reduction in IT operating expenses, resulting in a net-zero effect. Our findings shed light on how imports and exports separately shape firms' technological expenditures, with important implications for both firm strategies and policies promoting digitalization.

BRIEF SUMMARY IN DANISH

Virksomheder er centrale i den globale økonomi, og deres strategier vedrørende produktkvalitet, placering i værdikæder og digitalisering driver både deres konkurrenceevne og økonomisk vækst. Denne ph.d.-afhandling udforsker disse temaer i tre uafhængige kapitler med fokus på virksomheders produktkvalitet, omfanget af intern produktion og IT-udgifter.

Det første kapitel, *Quality Complementarity of Imported Inputs and Output Quality*, undersøger, hvordan spredningen i inputkvaliteter påvirker en virksomheds endelige produktkvalitet med fokus på komplementariteten mellem inputkvaliteter. I modsætning til tidligere studier, der har lagt vægt på gennemsnitlig inputkvalitet, udforsker dette kapitel, hvordan spredningen i inputkvaliteter former produktkvaliteten. Baseret på *O-ring* teorien udvikles et framework, der viser, at når inputkvaliteterne er komplementære, da medfører en større spredning i inputkvaliteten en reduktion i produktkvaliteten, hvorimod en stigende spredning kan forbedre produktkvaliteten, hvis inputkvaliteterne i tilstrækkelig grad er substituerbare. Empirisk evidens fra danske produktionsvirksomheder stemmer overens med modellens komplementaritetsscenarie og viser, at der er indbyrdes afhængighed mellem inputkvaliteter. Resultaterne giver virksomheder indsigt i de strategiske aspekter vedrørende valget af inputs, som kan optimere produktkvaliteten og fremme væksten.

I Kapitel 2, *The Span of In-house Production: Insights from Chinese and Danish Firms*, undersøger jeg en vigtig faktor, der er forbundet med virksomheders beslutninger om deres "in-house production span", der er defineret som afstanden mellem virksomhedens position i værdikæden angående anskaffelse af inputs og produktion af outputs. Baseret på tidligere studier argumenterer denne artikel for, at virksomheders "in-house production span" er relateret til den relative forskel mellem efterspørgselselasticitet på deres produkter og substitutionselasticiteten mellem deres anvendte inputs. Denne forudsigelse indebærer en konkurrence-drevet mekanisme i virksomheders beslutninger om produktionsomfang, hvilket testes empirisk ved hjælp af data fra Kina og Danmark. Resultaterne fra disse to forskellige lande giver robuste indikationer af, at virksomheder har en tendens til at integrere flere produk-

tionsled, når inputs har højere substitutionselasticitet og efterspørgselselasticiteten på deres produkter er lav, hvorimod virksomheder specialiserer sig i færre produktionsled, når inputs har lavere substitutionselasticitet og efterspørgselselasticiteten på deres produkter er høj. Resultaterne giver vigtige politiske indsigter til håndtering af udfordringer som forstyrrelser i forsyningskæden, reshoring og fremme den indenlandske vækst.

Det sidste kapitel, *Virksomheders Handelsaktiviteter og IT-Udgifter*, skrevet sammen med Ina C. Jäkel og Allan Sørensen, undersøger, hvordan virksomheders handelsaktiviteter – specifikt import og eksport – påvirker virksomhedernes IT-udgifter. Ved at udnytte data om danske virksomheders IT-udgifter fra 2002-2015 dokumenterer vi først en positiv korrelation mellem virksomhedernes import og eksport og deres IT-udgifter. For at identificere årsagssammenhænge anvender vi veletablerede mål for eksogene eksport-efterspørgselschok og import-udbudschok på virksomhedsniveau. Vores analyse afslører en robust kausal effekt af import- udbudschok på virksomhedernes IT-udgifter, men ingen direkte effekt af eksport-efterspørgselschok på de samlede IT-udgifter. Denne mangel på en kausal forbindelse fra eksport forklares ved en samtidig stigning i IT-investeringer og fald i IT-driftsomkostningerne, hvilket resulterer i en nettoeffekt på nul. Vores resultater kaster lys over, hvordan import og eksport hver især former virksomhedernes teknologiske udgifter, med vigtige implikationer for både virksomhedsstrategier og politikker, der fremmer digitalisering.

CHAPTER 1

QUALITY COMPLEMENTARITY OF IMPORTED INPUTS AND OUTPUT QUALITY

Ying Dai
Aarhus University

Abstract

This paper investigates the interconnection between input qualities by examining the relationship between input quality dispersion and the firm's output quality. I outline a theoretical framework in which firms' optimal output quality depends on the complementarity of input quality, leading them to allocate intermediates based on their importance for final product quality. The model suggests that, for the same product, for the same average input quality, firms may achieve different output quality if the qualities of inputs are not perfectly substitutable. Apart from the average input quality, output quality depends on the dispersion of intermediates' quality, with a stronger negative effect observed in cases of higher input quality complementarity. To empirically test this mechanism, I match data on firm-product level imports of intermediates with data on firm-product level production for a sample of Danish manufacturing firms over the 2000-2018 period. I focus on the quality (price) dispersion of inputs and investigate its impact on output quality, conditional on the average level of input quality. My results indicate that the dispersion of intermediates' quality negatively impacts output quality. Interpreted through the lens of the theoretical model, this finding implies that the quality of imported inputs exhibits a high degree of complementarity.

Keywords: Quality Complementarity · Product Quality · Input · *O-ring* Theory.
JEL classification: L15, L20, D21, D22, F10, C67.

1.1 Introduction

Differences across firms in the quality of products account for a significant portion of the firm heterogeneity in size, sales, and revenue productivity (Hottman, Redding, and Weinstein, 2016). Enhanced input quality has the potential to optimize production efficiency and increase product quality. One reason is that superior input quality effectively reduces defects in the production process, thereby resulting in higher-quality output (see Kugler and Verhoogen (2012) and Manova and Zhang (2012)). Despite the increasing focus on the effect of average input quality on product outcomes, there remains a gap in understanding the complementarity among intermediate qualities and its role in shaping the final goods' quality.

Extensive evidence on product quality at the firm level has typically assumed that qualities of inputs for a specific product are substitutable. Therefore, the majority of previous studies empirically measure a firm's input quality as the average quality of all relevant inputs (see Mayer, Melitz, and Ottaviano (2014), Manova and Yu (2017), Bastos, Silva, and Verhoogen (2018), Demir, Fieler, Xu, and Yang (2021)). However, if the qualities of different inputs are complementary rather than substitutable, the quality of final goods can be determined by the quality of certain inputs rather than the simple average quality of all inputs. Kremer's *O-ring* theory (Kremer, 1993) provides theoretical foundations for this concept, highlighting the importance of complementarities in production processes: a failure of even one input could jeopardize the entire production.

This paper aims to fill this gap in the literature by examining the degree of complementarity between the qualities of different inputs used for production. To shed light on this question, I develop a theoretical framework where the quality of the output exhibits varying sensitivity to the qualities of different inputs. I show that the optimal quality of the final good depends on the dispersion of input quality—conditional on average input quality—and on the elasticity of substitution across input qualities. The model indicates that when input qualities are complementary or weakly substitutable, an increase in the dispersion of input quality tends to decrease output quality. In contrast, if input qualities are sufficiently substitutable, a higher dispersion can increase output quality. Leveraging these two contrasting outcomes, the interconnection between input qualities—whether complementary or substitutable—can be empirically determined by analyzing the effect of input quality dispersion on output quality.

To empirically investigate how the dispersion of input qualities affects the output quality, I match data on firm-product level imports of intermediates with data on firm-product level production for a sample of Danish manufacturing firms over the

2000-2018 period. Following prior studies, I exploit input price as a proxy for input quality, and output quality is measured in two ways: calculated as unit value (price) and estimated as demand residuals. The empirical results show that the dispersion of the imported input qualities negatively affects the quality of the final product, even after controlling for average input quality. Referring to the predictions of the model, the results are in line with a situation where the elasticity of substitution across input qualities is small, i.e. input qualities are complementary or weakly substitutable. The heterogeneity analysis reveals that the elasticity of quality substitution varies across industries.

This study contributes to the broad literature on input complementarity, product quality, and firms' quality choices in the context of international trade. Complementarities between different production stages have been explored by Grossman and Maggi (2000) and Acemoglu, Antràs, and Helpman (2007). Several studies specifically examine the complementarity between various types of inputs, such as capital versus energy (Berndt and Wood, 1979; Zha and Ding, 2014; Thompson, 2006; Koetse, De Groot, and Florax, 2008), capital versus labor skills (Berlingieri, Lashkari, Boeri, and Vogel, 2022), and low-skill versus high-skill labor (Kremer, 1993; Amiti and Cameron, 2012; Voigtlaender, Saravia, et al., 2015). While these papers explicitly address the complementarity between different inputs or tasks, they overlook the role of input quality and its dispersion.

Another strand of related literature focuses on the measurement of product quality. Several studies such as Kugler and Verhoogen (2012) and Manova and Zhang (2012) have employed prices as a proxy for the quality of products. However, prices also capture other factors like markups. For instance, Chen and Juvenal (2022) show that variations in export prices are also driven by markup variation, conditional on quality. Moreover, for multi-product firms, Manova and Yu (2017) highlight that the relationship between prices and product quality is even more complex.

Given these issues associated with price, Khandelwal, Schott, and Wei (2013) construct quality measures by calibrating price-elasticity with estimates from Broda and Weinstein (2006). Based on this approach, Piveteau and Smagghue (2019) improve it by using exchange rates as instruments for prices and identify firm-level quality from demand residual after controlling for prices. Other studies, including Jover, Montes, and Fuentes (2004) and Chen and Juvenal (2016) measure the quality of red wine using the ratings or scales. This paper primarily employs the first two methodologies—price proxy and demand residual approaches—to measure a firm's product quality.

In analyzing firms' quality choices within the context of international trade, several studies have explored various determinants. Bastos and Silva (2010), Manova and

Zhang (2012), and Bastos et al. (2018) examine firms' product quality decisions based on the income levels of destination countries. Antoniades (2015) investigates firms' scope for quality differentiation in response to competitive pressures. Additionally, Amiti and Khandelwal (2013) provide insights into how trade barriers influence firms' approaches to product quality improvements. Chen and Juvenal (2016) uncover the effects of exchange rate changes on firms heterogeneous in product quality.

Due to data availability, the empirical analysis focuses solely on imported inputs, making it relevant to studies on foreign intermediates. They have found that trade liberalization reduces the cost of imported inputs, thereby improving export quality and encouraging product creation (Goldberg, Khandelwal, Pavcnik, and Topalova, 2010; Colantone and Crinò, 2014; Bas and Strauss-Kahn, 2015; Fan, Li, and Yeaple, 2015). Additionally, research has explored the benefits of foreign intermediate inputs for economic growth (Amiti and Konings, 2007; Bernard, Jensen, Redding, and Schott, 2007; Crinò, 2009), firm productivity (Yu and Li, 2014; Halpern, Koren, and Szeidl, 2015) and firms' export performance (Feng, Li, and Swenson, 2016). Existing studies have highlighted two main channels that contribute to the gains from outsourcing: (a) reduction of production costs due to low-priced imported inputs; (b) access to new or tailored and higher-quality intermediates.

The paper is organized as follows: Section 1.2 constructs a theoretical framework, elaborates on the mechanism, and proposes predictions; Section 1.3 presents the data; Section 1.4 exhibits the empirical results; and Section 1.5 concludes.

1.2 Theoretical Framework

The theoretical framework is inspired by Kremer (1993)'s *O-ring* theory: The space shuttle *"Challenger"* failed the entire mission due to the malfunction of a small O-ring, despite the thousands of other components functioning properly. Kremer (1993) extended this insight to firms, arguing that a company can fail because of poor marketing, even if product design, manufacturing, and accounting are excellent, and applied this logic to different labor inputs. This study builds on this work but makes several important contributions. First, it remains agnostic about the relationship between input qualities, allowing for both substitutability and complementarity, thus providing a broader framework. Second, the focus shifts from labor skills to the qualities of intermediate goods. Lastly, this paper introduces a parameter for each input quality, capturing the varying sensitivity of the final product's quality to the quality of each input, aligning more closely with real-world production processes.

1.2.1 Production

This model focuses on a specific industry where a continuum of firms produce outputs with differentiated quality within a framework of monopolistic competition. To examine the relationship between the quality of intermediate inputs and output quality while maintaining tractability, I assume a simple production technology—a Leontief-type technology with unit coefficients. This is expressed as $Y_{(f\omega)} = min(y_{(f\omega 1)}, y_{(f\omega 2)}, .., y_{(f\omega i)})$, where $Y_{(f\omega)}$ is the quantity of final goods ω in firm f, and $y_{(f\omega i)}$ is the quantity of intermediate good i used in the production of the final good ω in firm f. This setup implies that the quantities of intermediate goods are not substitutable and are used in fixed proportions, similar to the assumptions made in Kremer (1993).

N_ω represents the portfolio of all inputs, and the inputs in this portfolio used to produce output ω are identical across firms. This implies that product innovation by firms is not considered in the model, instead, it is assumed that all firms share the same general input components for the production of product ω. The quality of the final product, $Q_{(f\omega)}$, is assumed to be described by the following CES aggregator:

$$Q_{(f\omega)} = \left[\sum_{i=1}^{N_\omega} \left(\alpha_{f\omega i} q_{f\omega i} \right)^{\frac{\rho-1}{\rho}} \right]^{\frac{\rho}{\rho-1}}, \tag{1.1}$$

where $q_{f\omega i}$ is the quality of input i used for product ω by firm f, and ρ denotes the elasticity of substitution between the qualities of different inputs. When $\rho \in (0,1)$, the qualities of inputs are complements, whereas when $\rho > 1$, they behave as substitutes. A lower value of ρ (approaching 0) suggests that the qualities of the inputs are approaching perfect complementarity.

The parameter $\alpha_{f\omega i} \in [0,1]$ represents the sensitivity of output quality to the quality of input i for firm f, with the assumption that $\sum_{i=1}^{N_\omega} \alpha_{f\omega i} = 1$. A larger value of $\alpha_{f\omega i}$ indicates that the quality of input i ($q_{f\omega i}$) contributes more significantly to the overall quality of the final good $Q_{f\omega}$. The parameters, $\alpha_{f\omega i}$, are exogenously assigned and vary across firm-product-input combinations. For example, in mobile phone production, the quality of the phone may be more inherently sensitive to the quality of its processor compared to other components, given the processor's originally critical role in determining the overall performance of the phone. Therefore, the value of α for the processor will be higher than that for other parts in mobile phone production. Furthermore, even for the same intermediate input i, $\alpha_{f\omega i}$ can differ across firms. For instance, the quality sensitivity of the screen in Samsung phones may differ from that in Apple phones, with this variation being exogenously determined as well.

1.2.2 Consumption

The general setup of the model considers a closed economy within the framework of monopolistic competition, where firms make optimal decisions in the partial equilibrium of the production market. To provide a more comprehensive understanding of product quality, this subsection explores the consumption side as well. From the demand perspective, the quality of product ω produced by firm f, denoted as $Q_{(f\omega)}$, is integrated into the consumer utility (U) function under a CES framework:

$$\mathrm{U} = \left[\int_{\omega \in \Psi} (Q_{(f\omega)} Y_{(f\omega)})^{\frac{\sigma-1}{\sigma}} d\omega \right]^{\frac{\sigma}{\sigma-1}}, \tag{1.2}$$

where $Y_{(f\omega)}$ denotes the quantity consumed, Ψ represents the set of differentiated varieties available within a given industry, and σ is the elasticity of substitution between varieties. Assuming that varieties within the industry are substitutable, so $\sigma > 1$. Following Kugler and Verhoogen (2012) and Voigtlaender et al. (2015), the quality of a product is interpreted as any product attribute valued by the consumers, thus the equation implies that consumers' utility is amplified by the quality of the goods they consume. The demand for product ω in a market with an aggregate expenditure X yields:

$$Y_{(f\omega)} = \frac{Q_{(f\omega)}^{\sigma-1}}{P_{(f\omega)}^{\sigma}} \cdot P^{\sigma} \mathrm{X}. \tag{1.3}$$

In this equation, $P_{(f\omega)}$ represents the price of product ω, and P denotes the industry-level price index, which is exogenous to individual firms in a monopolistic competition framework. This equation illustrates that the demand for product ω is positively correlated with its quality but inversely related to its price.

1.2.3 Optimization of the Firm

Again, firms make optimal decisions in the partial equilibrium of the production market, assuming consumers prefer higher-quality products, and firms aim to maximize output quality while taking into account the costs of inputs. Given the Leontief-type technology, the firm's optimization problem can be expressed as follows:

$$\max_{\{q_{f\omega i}\}} Q_{(f\omega)} = \left[\sum_{i=1}^{N_\omega} \left(\alpha_{f\omega i} q_{f\omega i} \right)^{\frac{\rho-1}{\rho}} \right]^{\frac{\rho}{\rho-1}}, \quad S.t. \sum_{i=1}^{N_\omega} q_{f\omega i} \leq \overline{C}_{f\omega}. \tag{1.4}$$

I use input prices as a proxy for input quality, given their positive correlation, such that $q_{f\omega i} = p_{f\omega i}$. Consequently, $\bar{C}$ represents the firm's unit cost of inputs and

also reflects the aggregate quality of inputs[1]. Therefore, $\bar{C}$, to some extent, aligns with the focus of previous studies on the sum (or average) quality of inputs. According to Equation (1.4), the optimal input quality is given by:

$$q^*_{f\omega j} = \bar{C}\frac{\left(\alpha_{f\omega j}\right)^{\rho-1}}{\sum_{i=1}^{N_\omega}\left(\alpha_{f\omega i}\right)^{\rho-1}}. \tag{1.5}$$

Subsequently, by substituting the optimal qualities for all inputs j back into the output production function, the optimal output quality yields correspondingly:

$$Q^*_{(f\omega)} = \bar{C}\left[\sum_{j=1}^{N_{f\omega}}\left(\alpha_{f\omega j}\right)^{\rho-1}\right]^{\frac{1}{\rho-1}}. \tag{1.6}$$

Equation (1.5) illustrates that the relation between input quality (q^*) and quality sensitivity (α) depends on the internal connection among input qualities, as indicated by the value of ρ. When inputs are substitutable, i.e., $\rho > 1$, the input quality at the optimum q^* increases with α, thus generating an asymmetric pattern between α and q: inputs with higher quality sensitivity are associated with higher quality, while those with lower sensitivity correspond to lower quality. In contrast, when inputs are complements, i.e., $\rho \in (0,1)$, the optimal input quality q^* decreases with α, leading to a symmetric pattern between α and q: inputs with lower quality sensitivity are associated with higher quality, while inputs with higher quality sensitivity are matched with lower quality.

The intuition behind it is that when input qualities are substitutable, for instance, in mobile phone production, the higher quality of the processor can make up for the defects from the low-quality screen. If the phone's performance is especially sensitive to the processor's quality, the producer will increase the processor's quality further to fully leverage this compensatory effect. On the contrary, if the qualities of the inputs are complementary, for example, if the performance of a high-quality processor is constrained by a low-quality battery regardless of how superior the processor is, then the optimization will be achieved by balancing the combinations of $\alpha_{f\omega i}^{1-\rho}$ and $q_{f\omega i}$, i.e., $\alpha_{f\omega i}^{1-\rho} * q_{f\omega i}$ are identical for all inputs i. Consequently, in this complementary scenario, the allocation of input quality and sensitivity exhibits a symmetric pattern.

The two patterns observed when $\rho \in (0,1)$ and $\rho > 1$ are not completely novel, especially the complementarity case (when $\rho \in (0,1)$) which can be traced back to Kremer (1993). However, Kremer's study does not explore the role of intermediate quality nor introduce different sensitivities of input qualities. Furthermore, it does

[1] Since $q_{f\omega i} = p_{f\omega i}$ and the quantity of input is fixed at 1 unit, the sum of the input qualities (which corresponds to their prices) is equivalent to the firm's unit cost of inputs.

not apply the model to data for empirical testing. This study seeks to fill these gaps. Next, I aim to examine how dispersion plays a role in shaping firms' product quality.

1.2.4 Input Quality Dispersion and Output Quality

According to Equation (1.5), the relative quality of inputs is given by Equation (1.7). This suggests that, for $\rho > 1$, the relative quality of inputs increases with α, while for $\rho < 1$, the relative quality decreases with α.

$$\frac{q^*_{f\omega i}}{q^*_{f\omega j}} = \frac{{\alpha_{f\omega i}}^{\rho-1}}{{\alpha_{f\omega j}}^{\rho-1}}. \tag{1.7}$$

I first consider how product quality $Q_{(f\omega)}$ responds to changes in the quality sensitivities α:

$$dQ_{f\omega} = \bar{C}\left[\sum_{j=1}^{N_{f\omega}}\left(\alpha_{f\omega j}\right)^{\rho-1}\right]^{\frac{1}{\rho-1}-1}\sum_{j=1}^{N_{f\omega}}\left(\alpha_{f\omega j}\right)^{\rho-2}d\alpha_{f\omega j}. \tag{1.8}$$

Since $\sum_{i=1}^{N_{f\omega}}\alpha_{f\omega i}$=1, it follows that $\sum_{i=1}^{N_{f\omega}}d\alpha_{f\omega i}$=0. Considering when $d\alpha_{f\omega i} > 0$, as $d\alpha_{f\omega i} = -d\alpha_{f\omega j}$, $d\alpha_{f\omega j} < 0$, and $d\alpha_{f\omega k} = 0$ for $k \neq i, j$. This ensures that $\sum_{i=1}^{N_{f\omega}}d\alpha_{f\omega i}$=0. Equation (1.8) simplifies to:

$$\begin{aligned} dQ_{f\omega} &= \bar{C}\left[\sum_{j=1}^{N_{f\omega}}\left(\alpha_{f\omega j}\right)^{\rho-1}\right]^{\frac{1}{\rho-1}-1}\left[\left(\alpha_{f\omega i}\right)^{\rho-2}d\alpha_{f\omega i}+\left(\alpha_{f\omega j}\right)^{\rho-2}d\alpha_{f\omega j}\right] \\ &= \bar{C}\left[\sum_{j=1}^{N_{f\omega}}\left(\alpha_{f\omega j}\right)^{\rho-1}\right]^{\frac{1}{\rho-1}-1}\left[\left(\alpha_{f\omega i}\right)^{\rho-2}-\left(\alpha_{f\omega j}\right)^{\rho-2}\right]d\alpha_{f\omega i}. \end{aligned} \tag{1.9}$$

From Equation (1.9), it is not difficult to see that the role of the quality sensitivity $\alpha_{f\omega i}$ in shaping firm's product quality $Q_{f\omega}$ relies on the value of ρ and relative size of $\alpha_{f\omega i}$ and $\alpha_{f\omega j}$: $\frac{dQ_{f\omega}}{d\alpha_{f\omega i}} > 0$ for $(\alpha_{f\omega i})^{\rho-2} - (\alpha_{f\omega j})^{\rho-2} > 0$. This implies that an increase in sensitivity will enhance output quality when $\rho > 2$, and conversely, will reduce it when $\rho < 2$.

Next, I turn to input quality and define the dispersion of input qualities as the ratio of the higher input quality to the lower input quality, assuming that input i is any input with higher quality, and input j be any input with lower quality than

input i.[2] The dispersion is denoted as: $\delta^*_{f\omega} = \frac{q^*_{f\omega i}}{q^*_{f\omega j}}$, given that $q^*_{f\omega i} > q^*_{f\omega j}$, thereby ensuring that the dispersion is always greater than 1. Therefore, the expression for the optimal dispersion, $\delta^*_{f\omega}$, is similar to Equation (1.7), but with the value greater than 1: $\delta^*_{f\omega} = \frac{q^*_{f\omega i}}{q^*_{f\omega j}} = \frac{\alpha_{f\omega i}{}^{\rho-1}}{\alpha_{f\omega j}{}^{\rho-1}} > 1$. As discussed above, the firm's product quality $Q_{f\omega}$ is determined by the quality sensitivity of input $\alpha_{f\omega i}$. This effect specifically depends on whether ρ is greater than or less than 2, as well as the relative sizes of the αs. Furthermore, the dispersion of input quality is determined by α and ρ. Hence, I will next explore the relationship between input quality dispersion and the quality of the final good in the two cases when $\rho > 2$ and $\rho < 2$:

- When $\rho > 2$, it follows that $\frac{dQ_{f\omega}}{d\alpha_{f\omega i}} > 0$. It is also the case where input qualities are substitutable. Given that $\delta^*_{f\omega} = \frac{q_{f\omega i}}{q_{f\omega j}} = \frac{\alpha_{f\omega i}{}^{\rho-1}}{\alpha_{f\omega j}{}^{\rho-1}} > 1$, $\alpha_{f\omega i} > \alpha_{f\omega j}$, and $\frac{d\delta_{f\omega}}{d\alpha_{f\omega i}} > 0$. Therefore, $\frac{dQ_{f\omega}}{d\delta_{f\omega}} > 0$.

- When $\rho < 2$, the sign of $\frac{dQ_{f\omega}}{d\delta_{f\omega}}$ requires further examination by discussing two specific cases: when $\rho > 1$ and when $\rho < 1$:

  - When $1 < \rho < 2$, the input qualities are substitutable. Given that $\delta^*_{f\omega} = \frac{q^*_{f\omega i}}{q^*_{f\omega j}} = \frac{\alpha_{f\omega i}{}^{\rho-1}}{\alpha_{f\omega j}{}^{\rho-1}} > 1$, $\alpha_{f\omega i} > \alpha_{f\omega j}$. Therefore, $\frac{dQ_{f\omega}}{d\alpha_{f\omega i}} < 0$, $\frac{d\delta_{f\omega}}{d\alpha_{f\omega i}} > 0$, and $\frac{dQ_{f\omega}}{d\delta_{f\omega}} < 0$.
  - When $0 < \rho < 1$, the input qualities are complementary. Given that $\delta^*_{f\omega} = \frac{q^*_{f\omega i}}{q^*_{f\omega j}} = \frac{\alpha_{f\omega i}{}^{\rho-1}}{\alpha_{f\omega j}{}^{\rho-1}} > 1$, $\alpha_{f\omega i} < \alpha_{f\omega j}$. Therefore, $\frac{dQ_{f\omega}}{d\alpha_{f\omega i}} > 0$, $\frac{d\delta_{f\omega}}{d\alpha_{f\omega i}} < 0$, and $\frac{dQ_{f\omega}}{d\delta_{f\omega}} < 0$.

Based on the preceding discussion, it can be concluded that the critical value of ρ for determining the effect of input quality dispersion on output quality is 2: when $\rho > 2$, an increase in the dispersion of input qualities leads to an improvement in product quality. Conversely, when $\rho < 2$, an increase in input quality dispersion results in a decrease in product quality. In other words, the change in input quality dispersion $\delta_{f\omega}$ will affect output quality in the same direction only when input qualities are sufficiently substitutable. These two corresponding propositions are summarized as follows:

[2] The dispersion can take the form of any ratio of input qualities, provided it is greater than 1. In the empirical analysis, two specific ratios are used: the 90th to 10th percentile and the 75th to 25th percentile of input quality. Moreover, while this framework primarily focuses on a single random measure of input quality dispersion, changes in the relative qualities of other inputs also matter. To account for this, the Appendix includes empirical results using the standard deviation (SD) as an additional measure to capture the dispersion across all input qualities.

Proposition 1. *An increase in the dispersion of input qualities decreases output quality when the input qualities exhibit complementarity.*

Proposition 2. *An increase in the dispersion of input qualities enhances output quality when the input qualities are sufficiently substitutable.*

As discussed earlier, $\bar{C}$ reflects the information on the sum of input quality. The output quality is a function determined solely by the dispersion of input quality $\delta_{f\omega}$ and the aggregate level of the $\bar{C}$. Regardless of the value of ρ, we have $\frac{dQ_{f\omega}}{d\bar{C}_{f\omega}} > 0$, which consistently holds, indicating that an increase in average input quality always enhances the final product's quality. This finding aligns with previous research that has explored the positive relationship between average input quality and output quality.

Several key values of ρ warrant further explanation. When the qualities of inputs are perfect substitutes, i.e., when ρ is approaching $+\infty$, the product quality depends solely on the input with the highest sensitivity, and in this case, the quality of that input equals $\bar{C}$. When $\rho = 2$, it implies that $Q_{f\omega} = \bar{C}\sum_{j=1}^{N_{f\omega}} \alpha_{f\omega j} = \bar{C}$, making the output quality invariant to the distribution of $\alpha_{f\omega i}$ and $\alpha_{f\omega j}$. However, this does not indicate perfect substitutability of inputs (which occurs only as ρ approaches $+\infty$). Last, when $\rho = 1$, it implies that $q_{f\omega i} = \bar{q} = \frac{\bar{C}}{N_{f\omega}}$ for all inputs i, leading to no variation in input quality. Figure 1.1 explicates the connection between input quality dispersion and output quality as it relates to the value of ρ.

An important question is why the critical point for the role of input quality dispersion in shaping output quality occurs at $\rho = 2$ rather than $\rho = 1$, the point distinguishing substitutability and complementarity. The potential answer can be found when revisiting equation (1.9): although $\rho \in (1,2)$ ensures that $q_{f\omega i} > q_{f\omega j}$ when $\alpha_{f\omega i} > \alpha_{f\omega j}$, the degree of substitutability is not sufficient to generate a positive effect on output quality. A positive change occurs only when the substitution effect is strong enough to compensate the constraints posed by both the lower input quality and the lower sensitivity. This compensation effect explains why the turning point lies at $\rho = 2$.

1.2.5 Distinguish Inputs from Domestic and Foreign Markets

Expanding the model to inputs sourced from both domestic and foreign markets introduces additional complexity. However, the theoretical framework developed here remains applicable in explaining the general effect of input quality dispersion on firms' product quality, regardless of whether the inputs are sourced domestically

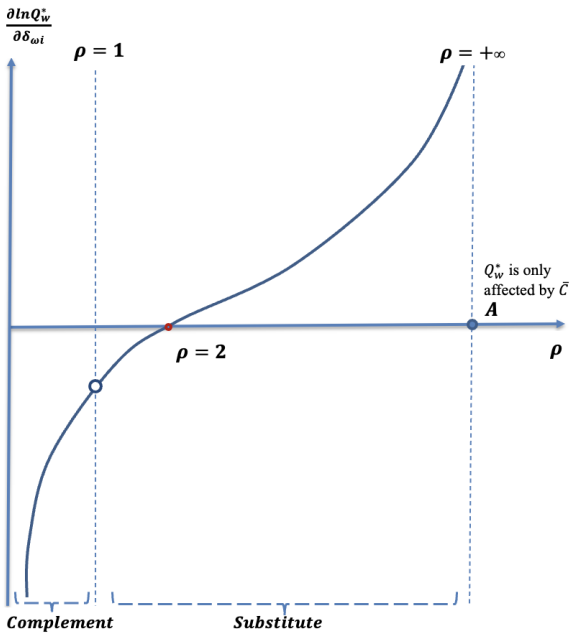


Figure 1.1: Effect of Input Quality Dispersion on Output Quality

Note: This figure exhibits how the effect of dispersion $\delta_{f\omega}$ on the output quality $Q_{f\omega}$ (vertical axis) depends on the elasticity of substitution between input qualities ρ (horizontal axis).

or internationally.

The previous subsection suggests that the allocation of input quality (q) and quality sensitivity (α) depends on the value of ρ, the elasticity of substitution between input qualities. When the qualities of intermediates are complementary, the combination of inputs tends to be symmetric, while in the case of substitution, it becomes asymmetric. The key distinction in the current scenario is that the intermediates are now differentiated by their domestic and foreign origins. For small open economies like Denmark, firms typically source intermediates from both foreign and domestic markets. As a result, the intermediates include a mix of imported and domestic components, introducing additional dimensions of input quality dispersion within the firm: dispersion among domestic input qualities, dispersion among imported input qualities, and dispersion between domestic and imported input qualities.

Rewriting Equation (1.6) by separating input qualities into components from

domestic and foreign markets yields:

$$
\begin{aligned}
Q^{*}_{(f\omega)} &= \bar{C}_{f\omega} \cdot \left[\sum_{i=1}^{N_{f\omega D}} (\alpha_{\tilde{f}\omega i})^{\frac{\rho-1}{\rho}} + \sum_{i=1}^{N_{f\omega M}} (\alpha_{\tilde{f}\omega i})^{\frac{\rho-1}{\rho}} \right]^{\frac{\rho}{\rho-1}} \\
&= \left\{ \left[\bar{C}_{f\omega} \cdot \left(\sum_{i=1}^{N_{f\omega D}} (\alpha_{\tilde{f}\omega i})^{\frac{\rho-1}{\rho}} \right)^{\frac{\rho}{\rho-1}} \right]^{\frac{\rho-1}{\rho}} + \left[\bar{C}_{f\omega} \cdot \left(\sum_{i=1}^{N_{f\omega M}} (\alpha_{\tilde{f}\omega i})^{\frac{\rho-1}{\rho}} \right)^{\frac{\rho}{\rho-1}} \right]^{\frac{\rho-1}{\rho}} \right\}^{\frac{\rho}{\rho-1}} \\
&= \left\{ Q_{(f\omega D)}^{\frac{\rho-1}{\rho}} + Q_{(f\omega M)}^{\frac{\rho-1}{\rho}} \right\}^{\frac{\rho}{\rho-1}},
\end{aligned}
\tag{1.10}
$$

where $\alpha_{\tilde{f}\omega i}$ in Equation (1.10) represents the allocation of $\alpha_{f\omega i}$ adjusted by ρ, that is, $\alpha_{\tilde{f}\omega i} = \alpha^{\rho}_{f\omega i}$, one attributable to imported inputs and the other to domestically sourced inputs. Importantly, output quality increases with each component, and each behaves in the same manner as described for output quality in Subsection 1.2.4. Therefore, conditional on domestically sourced inputs, the findings regarding quality dispersion among imported inputs and its impact on output quality, as derived in Subsection 1.2.4, remain applicable.

1.2.6 Labor and Intermediate Inputs

This model can be applied to labor in a manner analogous to intermediates by treating input i in a general sense that includes both intermediates and labor. However, when distinguishing between labor and intermediate inputs, the relationship between a worker's skill and the quality of intermediates becomes important. Suppose producing one unit of output requires one unit of $N_{f\omega K}$ types of inputs and one unit of $N_{f\omega L}$ types of labor. In this context, the quality of intermediate inputs and the skill level of workers may either be substitutes or complements. Nonetheless, the qualities of all inputs, whether they are intermediates or labor, are characterized by the same quality substitutability parameter ρ. This parallels the same logic discussed regarding domestic versus outsourced inputs. Therefore, following the structure of Equation

(1.10), the equation including labor can be similarly formulated as follows:

$$Q^*_{(f\omega)} = \bar{C}_{f\omega} \cdot \left[\sum_{i=1}^{N_{f\omega K}} (\alpha \tilde{f}_{\omega i})^{\frac{\rho-1}{\rho}} + \sum_{i=1}^{N_{f\omega L}} (\alpha \tilde{f}_{\omega i})^{\frac{\rho-1}{\rho}} \right]^{\frac{\rho}{\rho-1}} \tag{1.11}$$

$$= \left\{ Q^{\frac{\rho-1}{\rho}}_{(f\omega K)} + Q^{\frac{\rho-1}{\rho}}_{(f\omega L)} \right\}^{\frac{\rho}{\rho-1}}.$$

From Equation (1.11), it is noticeable that the elasticities of substitution between different workers' skills, between the qualities of intermediates, and between worker skill and intermediate quality are assumed to be the same ρ that we discussed in the general setup[3]. Consequently, the impact of quality dispersion—whether in intermediate inputs or labor—on the quality of final goods remains analogous. Specifically, if the varying labor skills within the firm are complementary, increased dispersion in labor skills will degrade the quality of the final product. Conversely, if labor skills are substitutable, higher dispersion in labor skills may enhance the final product's quality. This finding highlights the importance of considering both labor and intermediate input quality when evaluating production processes and their outcomes.

Therefore, this model is applicable not only to domestic sourcing, international sourcing, and complex production scenarios that involve a mix of both, but also to variations in both intermediates and labor. However, due to data availability and research focus, the empirical analysis in this paper primarily concentrates on imported intermediate inputs (Section 1.4). It is important to clarify that while the empirical study emphasizes foreign intermediate inputs, this does not imply that domestic sourcing or labor is insignificant. Rather, the study aims to provide insights into the impact of imports on a firm's product quality.

1.3 Data and Measurement

1.3.1 Data

The comprehensive production database (VARS) from Statistics Denmark provides detailed information on the sales of own-produced products manufactured by Danish firms, recorded in both physical quantities and values, and categorized by the international classification of Combined Nomenclature (CN) at the eight-digit level. The survey includes all firms with at least 10 employees, covering over 90% percent of

[3] Nevertheless, this could be a strong assumption, as in principle, the substitutability between different types of labor, between varying intermediate inputs, and between labor and intermediates could each have different values.

the Danish manufacturing turnover. Sales are reported in current prices in Danish kroner, excluding VAT. In the following, I refer to each product sold by a firm as a "variety" of that product. This dataset contains information on both domestic and export sales; however, it does not distinguish between products sold in domestic versus international markets. Despite this limitation, the dataset still allows for the effective measuring of the firm's product quality.

The production dataset is paired with trade data from Danish customs in terms of firm and product. The trade data provides comprehensive coverage of each firm's imports and exports at the detailed CN-8-digit product level, including information on both the value and quantity (in units) of the products involved. To distinguish intermediate inputs from goods intended for final consumption, I adhere to the Broad Economic Categories (BEC) classification system and exclude imported products in the machinery and transportation sectors that are classified as "capital goods" or "final consumption goods". [4] The baseline sample is restricted to varieties where the firm imports at least two intermediate products in order to measure the dispersion. The final merged dataset includes 3,072 manufacturing goods, 3,607 firms and 78,880 observations at the firm-product-year level from the year 2000 to 2018.

1.3.2 Measurement

1.3.2.1 Input Quality and Dispersion

Following most existing studies, the price (unit value) of the input is used as a proxy for measuring its quality. To make the input qualities comparable across different product categories, in the spirit of Kugler and Verhoogen (2012), I start with the market price $\bar{P}$ for each input, computed by considering all firms in the market that import the input i. In the equations below, i represents the imported inputs of the firm f, and the price (unit value) of the input is calculated using the value of imports V and the quantity of i.

$$\bar{P}_{it} = \frac{\sum_f V_{fit}}{\sum_f quantity_{fit}} = \sum_f P_{fit} \frac{quantity_{fit}}{quantity_{it}}. \tag{1.12}$$

Subsequently, I compare the firm's imported price of i relative to the market price of the same product, obtaining the ratio (θ_{fit}). If θ_{fit} is greater than 1, it indicates that the firm imports the input at a quality higher than the market level. The same

[4] The machinery and transportation sectors refer to product codes starting with '8.' In these industries, "capital goods" and "final consumption goods" typically consist of large machines that are hardly used in the production of other goods. However, in other industries, some products, such as fruits and vegetables, may be classified as "final consumption goods" under BEC but still possibly serve as intermediates in subsequent stages of production, e.g., peaches used for peach juice.

logic applies when θ_{fit} equals 1 or is less than 1. The advantage of constructing this ratio is that it allows for the comparison of input unit values across different varieties. For instance, it enables the comparison of the quality of a processor with the quality of cotton.

$$\theta_{fit} = \frac{P_{fit}}{\bar{P}_{it}}. \tag{1.13}$$

Although I avoid using the price of the input directly and comparing it with the market price, potential issues may still arise from the prices originally. For instance, there may be price outliers and unreasonable values. Therefore, to mitigate the impact of these anomalies, for each product, I trim prices by 1% on both tails of the distribution. Moreover, because measurement error might be significant for imported inputs with small volumes, I also drop observations where the import value is less than 500 DKK and observations with an import share of the firm's total imports below the 1st percentile of the distribution, as these inputs are likely to have minimal impact on production and, from the import side, may be prone to potential measurement bias.

Due to the lack of information matching the actual adopted intermediate inputs with their corresponding final goods, I address this matching issue by following prior studies in two ways: 1). exploiting the industry connection in the input-output table; 2). assuming that potential inputs are those within the same broad industry classification as the output product (captured by the same HS-2 digit)[5]. $Ave_{f\omega t}$ represents the average quality of all imported inputs for producing final goods ω, weighted by import share. The dispersion of input qualities is defined as the relative value of higher input quality to lower input quality within each sector group. To align with the theory, I use the 90-10 ratio and 75-25 ratio of input qualities[6] to proxy the quality dispersion of inputs ($\delta_{f\omega t}$).

$$Ave_{f\omega t} = \sum_i \frac{V_{fit}}{V_{f\omega t}} \theta_{fit}. \tag{1.14}$$

1.3.2.2 Output Quality

The quality of final goods $Q_{f\omega t}$ is measured using two methods: product price (unit value) and the demand residual. The product price approach utilizes price as a proxy for product quality, employing a method similar to that described earlier for measuring input quality. It involves computing the market price for each product by considering all firms that sell this product and then calculating the ratio of the

[5] In the next subsection, robustness checks include HS4 and firm-level.

[6] The Appendix also includes empirical results using the standard deviation (SD) as an additional measure to capture the dispersion across all input qualities.

firm's sale price to the market price of each product to make their product qualities comparable. Similarly, to mitigate the influence of outliers, prices are trimmed by 1% on both tails of the distribution for each product.

For the second method, I apply the demand residual approach proposed by Khandelwal et al. (2013), which captures variations in product quality through an analysis of demand dynamics. This approach is based on a theoretical framework incorporating Constant Elasticity of Substitution (CES) preferences and constant mark-ups, as outlined in Khandelwal (2010). The intuition is that, for a given price, higher-quality products are able to capture larger market shares. This methodology has also been applied in a large number of prior studies such as Fan et al. (2015), Manova and Yu (2017), and Jäkel and Sørensen (2020).

Specifically, product quality is inferred from the residual of Equation (1.3), which serves as a proxy for the quality of each product variety. As shown in Equation (1.15), the perceived product quality ($Q_{f\omega t}$) is embedded in the regression residual ($\hat{\varepsilon}_{f\omega t}$), based on domestic demand ($Y^D_{f\omega t}$) and domestic price ($p^D_{f\omega t}$). Product quality is then calculated as: $Q_{f\omega t} = \hat{\varepsilon}_{f\omega t} \cdot (\sigma_\omega - 1)^{-1}$. The expenditure and industry-level price index from Equation (1.3) are absorbed in the product-year fixed effects $X_{\omega t}$, allowing product quality to be measured relative to the average quality of all varieties within the same product category for each year.

$$\log Y^D_{f\omega t} + \sigma_\omega \log p^D_{f\omega t} = \varepsilon_{f\omega t} + X_{\omega t},$$
$$\varepsilon_{f\omega t} = (\sigma_\omega - 1) \log Q_{f\omega t}. \tag{1.15}$$

When measuring product quality as the demand residual, previous studies, such as Antràs and Chor (2013) and Alfaro, Chor, Antras, and Conconi (2019), rely on the elasticity of substitution estimates from Broda and Weinstein (2006). In this study, however, the estimates from Soderbery (2015) are used as the baseline, given that the estimates in Soderbery (2015) are more recent and employ a hybrid methodology combining the approaches of Feenstra (1994) and Broda and Weinstein (2006), which addresses the significant biases and idiosyncrasies shown in standard estimator. Therefore, the hybrid estimator performs favorably in Monte Carlo analysis and in relation to first principles. Nonetheless, the estimates from Broda and Weinstein (2006) are also used as alternative measures for robustness checks.

1.3.3 Summary Statistics

Table 1.1 summarizes key characteristics of varieties and firms in the sample. Panel A exhibits the average number of products and imported inputs of the firms before

matching the inputs and outputs with Input-Output table. On average, to produce 4 products, a firm uses 22 imported inputs. The average number of imported products only slightly reduced to 20 when restricting the sample to firms that import at least two intermediate products after matching them with IO table and excluding singletons in the output variety (see Panel B). In other words, the slight difference between Panel A and Panel B implies that, almost all imported inputs are included in the production of final goods, the IO table only excludes few unrelated inputs for production. Due to the restrictions on inputs and outputs, as well as the number of firms decreased from 29,251 to 22,756.

Panel C displays information on key variables at the firm-product level after matching intermediate inputs to outputs: for each final good with a quality almost equal to the market level (ratio equals 0.92), the firm imports 47 inputs with an average quality slightly lower than the market level (ratio equals 0.82). The dispersion of input quality is 1.55 for the 75th to 25th percentile, 2.93 for the 90th to 10th percentile, and 1.70 for the standard deviation.

Table 1.1: Summary Statistics

	MEAN	SD	N
Panel A: Firm level (without restriction)			
Number of products	3.86	7.93	29,251
Number of imported inputs	21.73	34.05	29,251
Panel B: Firm level (matched with IO table)			
Number of products	3.46	6.12	22,756
Number of imported inputs	19.91	28.62	22,756
Panel C: Firm-product level (matched with IO table)			
Price index for output (compared to market level)	0.92	0.74	78,880
Average input price (compared to market level)	0.82	2.94	78,880
Log dispersion ($\delta^{IO}_{f\omega t}$) of input price (75/25)	1.55	0.78	78,880
Log dispersion ($\delta^{IO}_{f\omega t}$) of input price (90/10)	2.93	1.25	78,880
SD of input price	1.70	3.87	78,880
Number of imported inputs	46.72	64.18	78,880

Notes: Panel A presents the number of all imported inputs and outputs at the firm level for all firms. Panel B follows a similar pattern but restricts the sample to firms that import at least two intermediate products after matching inputs and outputs by IO table, and also excluding singletons in the output variety. Panel C provides input and output information at the firm-product level, similarly matching inputs and outputs with IO table and retaining only firms that import at least two intermediate products, while also excluding singletons in the output variety.

Table 1.2 and Table 1.3 illustrate the correlations between key variables in this study. Specifically, from the input side, the two dispersion ratios (75th to 25th percentile and 90th to 10th percentile) are highly correlated with each other (with a

Table 1.2: Correlations Between Average Input Quality and Dispersion

	Dispersion 75/25	Dispersion 90/10	SD of input quality	Average input quality	Input number
Dispersion 75/25	1				
Dispersion 90/10	0.6974	1			
SD of input quality	0.2325	0.3188	1		
Average input quality	-0.0349	0.0217	0.3736	1	
Input number	-0.0823	0.1244	0.0958	0.1022	1

Notes: All variables except SD of input quality are logarithmic. Observation is 78,880.

Table 1.3: Correlations between Output Price and Output Quality

	Output Price	Demand Residual (B&W)	Demand Residual (Soderberry)
Output Price	1		
Demand Residual (B&W)	0.3504	1	
Demand Residual (Soderberry)	0.4383	0.8693	1

Notes: Observation of output price is 78,880, and observation of output quality is 26,648.

correlation coefficient of 0.70) and weakly correlated (with correlation coefficients of around 0.30) with the standard deviation of input quality. However, unlike the standard deviation, the two dispersion ratios are not correlated with the average input quality, which is measured as the average ratio of the firm's input price to the market price of the input. The number of inputs shows a slight positive correlation with the 90th to 10th percentile ratio, with a correlation coefficient of 0.12. However, it exhibits no correlations with the 75th to 25th percentile ratio and the standard deviation of input quality. To align with the dispersion defined in the theoretical framework, I will use the 75th-to-25th percentile ratio and the 90th-to-10th percentile ratio in the baseline analysis. Results based on the standard deviation are provided in the Appendix.

When it comes to the output side, recall that the output price is calculated as the ratio of the firm's sale price to the market price across all markets, output quality is estimated as the demand residual which only focuses on the domestic market and includes product-year fixed effects. Hence, the number of observations for product quality that is measured as the demand residual has been reduced to 26,648.[7] The table shows that the output quality estimated as the price ratio is positively correlated with output quality, with correlation coefficients of around 0.4, suggesting that higher-

[7] Detailed information on data cleaning is provided in the Appendix.

quality varieties generally have higher prices. The demand residuals calculated using the two estimates from Broda and Weinstein (2006) and Soderbery (2015) are highly correlated, with a correlation coefficient of 0.87.

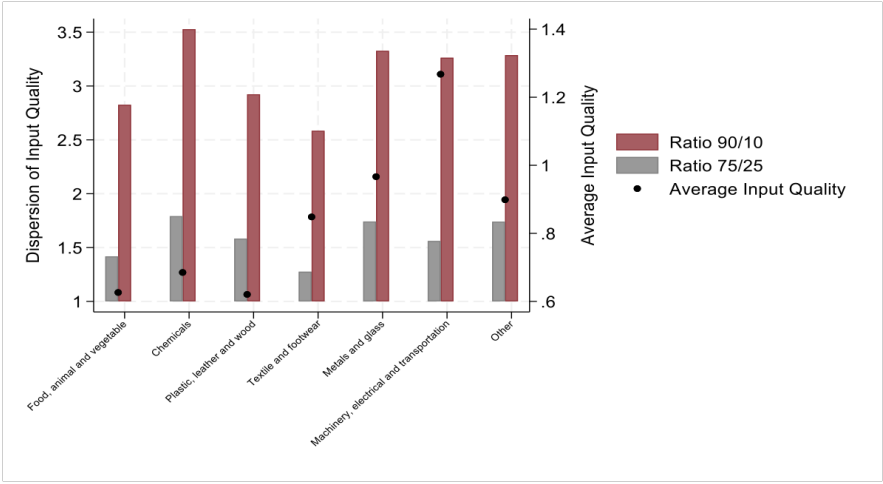


Figure 1.2: Mean of Dispersion and Average Input Quality - Variations across Industries, 2018

Note: This figure displays the average dispersion of input quality (the left vertical axis) and the mean of average input quality (the right vertical axis) across all firms within each industry. Both dispersion and average input quality are in logarithmic form.

Figure 1.2 illustrates the heterogeneity of input quality dispersion across different industries in 2018. Specifically, the bars represent the mean input quality dispersion of all firms in each industry, while the scatter points indicate the mean of average input qualities of firms within industries. It can be concluded that industries vary in both the dispersion and average of input qualities. In particular, industries with complex production processes, such as chemicals, metals, machinery, electrical, and transportation, exhibit relatively larger dispersion in intermediate qualities compared to simpler industries like textiles and footwear. The average input quality is also higher for industries like metals, machinery, electronics, and transportation. This may be attributed to the more complicated processes and longer production chains in these sophisticated sectors. The number of imported inputs for each industry is shown in the Appendix, in Figure A.1.

Figure 1.3 demonstrates the variations in the dispersion and average of input qualities across firms in each industry. Specifically, the bars highlight the standard deviation of the dispersion across firms within each industry in 2018, while the scatter points represent the standard deviation of the average quality of inputs across

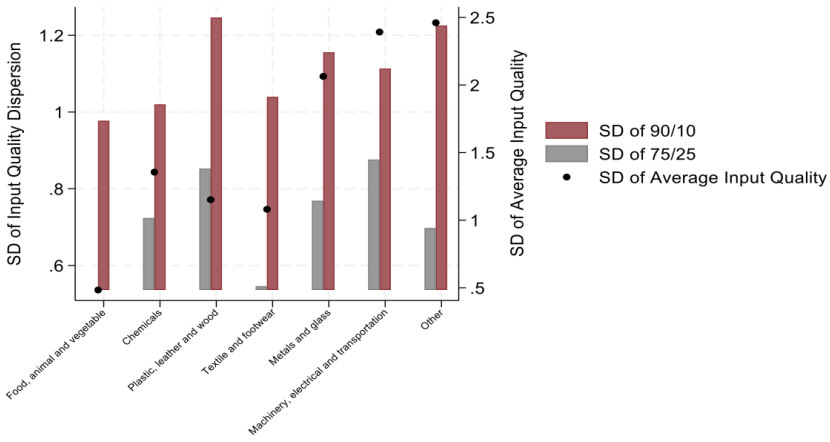


Figure 1.3: SD of Dispersion and Average Input Quality - Variations across Firms, 2018

Note: This figure depicts the standard deviation of the input quality dispersion (the left vertical axis) and the standard deviation of average input quality (the right vertical axis) across firms in each industry. Both dispersion and average input quality are in logarithmic form.

firms. It is evident that firms vary significantly in both dispersion and average input qualities, with firm heterogeneity present in every industry. Moreover, there is a trend indicating that the variation across firms in high-tech and R&D-intensive industries (such as chemicals, metals, machinery, electrical, and transportation) is greater than that in industries like food and textiles. This trend can be explained by the possibility that firms in these high-tech sectors are more productive and competitive, enabling them to source various intermediates from suppliers worldwide. In contrast, less productive firms in other sectors may have limited options for offshoring. Figure A.2 in the Appendix displays the variation in the number of import inputs across firms in each industry, as captured by the standard deviation.

1.4 Empirical Analysis

This section investigates the role of quality dispersion of imported intermediates in shaping firms' product quality. According to the framework in section 1.2, dispersion will reduce the output quality when input qualities display a degree of complementarity ($2 > \rho$), whereas it will increase the quality of final goods when they are sufficiently substitutable ($2 < \rho$). By leveraging these two different impacts, this analysis can deduce which case the interconnection between the qualities of imported inputs in the sample belongs to. In other words, it is possible to roughly determine whether a

degree of complementarity exists between input qualities.

1.4.1 Empirical Approach

Based on the theoretical framework, the role of input quality dispersion in shaping the firm's output quality is tested using the following baseline equation:

$$\log Q_{f\omega t} = \beta_1 \log \delta_{f\omega t} + \beta_2 \log Ave_{f\omega t} + \beta_3 \log N_{f\omega t} + \beta_4 \chi_{ft} + \alpha_{\omega t} + \alpha_{f\omega} + \varepsilon_{f\omega t}. \quad (1.16)$$

As mentioned earlier, the imported intermediates are connected with output using Input-Output table, or alternatively, at the same HS-2-digit level. There is indeed a trade-off between relevance and inclusivity when matching inputs to outputs. Exploiting IO table allows for capturing the diversity in production requirements across industries but could overlook the relevance of specific input-output relationships (Compare Panel A and Panel B in Table 1.1, the IO table only excludes few unrelated inputs for production.). On the other hand, restricting inputs that are within the same industry to output by HS-2 digit category, though captures close relevance between inputs and outputs, yet may omit potential inputs from other industries. To balance these factors, I follow the approach of Manova and Yu (2017) by using both methodologies in the main analysis. I first display the results of using IO table in baseline and results of matching by HS2 are shown in the following subsection.

$\delta_{f\omega t}$ indicates the dispersion of input quality within firm (if the inputs are matched with outputs using IO table) or within the HS-2 level (if the inputs are matched with outputs by the same HS-2 digit, same below), measured by the 75th to 25th ratio and the 90th to 10th ratio of input qualities. $Ave_{f\omega t}$ is the average input quality of the firm or of each HS-2 group, computed through Equation (1.14). As displayed in Table A.5, the number of intermediates is slightly correlated with the dispersion (ratios) of input quality. Therefore, the regression additionally controls for the number of inputs (variable $N_{f\omega t}$ in the baseline equation) within the firm (when inputs and outputs are matched based on IO table) or within each HS-2 category. χ_{ft} is a time-varying firm-level control variable, such as firm productivity, proxied here by total factor productivity (TFP)[8]. Since input quality dispersion is specific to each firm or each HS-2 industry group, I cluster standard errors at the firm level (when inputs are matched with outputs using the IO table) or at the firm-HS2 level (when inputs are matched with outputs by the same HS2-digit).

$\alpha_{\omega t}$ and $\alpha_{f\omega}$ are product-year and firm-product fixed effects. $\alpha_{\omega t}$ controls for both time-variant and time-invariant differences in products, meaning that the varia-

[8] I also replace it with other time-varying firm-level control variables, such as employment or labor productivity, and the results remain consistently robust.

tion comes from the firms. Meanwhile, product-firm fixed effects control for time-invariant differences in firm-products (e.g., a firm's production technology and product design of products), capturing variation within firms across years. The theoretical model is more aligned with variations across different firms, thus it primarily corresponds to product-year fixed effects. However, I also present results that additionally incorporate firm-product fixed effects in the empirical studies for robustness.

1.4.1.1 Baseline Results-Matched with IO Table

Table 1.4 displays the results of the baseline Equation (1.16), where Inputs and outputs are matched based on Input-Output table.

An IO table models the structure of an economy, detailing how industries acquire their inputs (either intermediate inputs or value added) and what they do with their output (producing either intermediate inputs for other industries or for final consumption). In this subsection, I use the Danish IO table in 2007, which comprehensively covers 117 manufacturing goods and services sectors. These detailed datasets enable me to match inputs with outputs effectively: retaining specifically inputs and outputs with direct requirement coefficients larger than 0.01[9]. Compared to the restricting inputs and outputs within the same industry, the linkage information between inputs and outputs obtained from the IO table allows for cross-sector inputs and is closer to reality .

The quality of final goods in Table 1.4 is proxied by output price (unit value), and all variables are logarithmic. In columns (1) to (3), the dispersion of input quality is measured by the ratio of the 75th and 25th percentiles. In columns (4) to (6), the dispersion of input quality is measured by the ratio of the 90th and 10th percentiles. Different combinations of fixed effects are considered in each column to observe variations from distinct aspects: columns (1) and (4) capture the variations of input dispersion across firms, whereas the remaining columns reflect the effects within firms over time.

From the table, the following trends can be observed: There is an economically significant positive correlation between input price and output price for one product across firms and within the firm across years. Columns (1) and (4) show that a 1% increase in average input quality (proxied by price) contributes to approximately an 0.17% increase in output quality (proxied by price), which aligns with previous studies (Voigtlaender et al., 2015; Manova and Yu, 2017). However, the quality of products also depends negatively on the dispersion of input quality, though these

[9]The direct demand coefficient represents the share of industry i's output used in the production of industry j. A larger value indicates a stronger relatedness between the two industries. This threshold can help exclude insignificant inputs for each output.

Table 1.4: Dispersion of Input Quality and Output Quality (Matched with IO Table)

	(1) Output Price	(2) Output Price	(3) Output Price	(4) Output Price	(5) Output Price	(6) Output Price
75/25 ratio	-0.0463***	-0.0109	-0.0079			
	(0.0117)	(0.0068)	(0.0048)			
90/10 ratio				-0.042***	-0.011**	-0.007**
				(0.0086)	(0.0047)	(0.0031)
Average	0.168***	0.0157*	0.00733	0.172***	0.0168*	0.00804
	(0.0162)	(0.0093)	(0.0060)	(0.0162)	(0.0093)	(0.0060)
Con Vars	YES	YES	YES	YES	YES	YES
Product-Year FE	YES	YES	YES	YES	YES	YES
Firm FE		YES			YES	
Firm-Product FE			YES			YES
Observation	78880	78294	71848	78880	78294	71848
R2	0.394	0.674	0.892	0.394	0.674	0.892

Notes: All variables are logarithmic. Output quality is measured by price. Inputs and outputs are matched based on Input-Output table. The control variable contains the number of inputs and firm productivity. Standard errors are clustered at the firm level and are shown in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

effects are observed primarily across firms rather than within firms. The negative effect is significant for both the 75th-to-25th percentile ratio (a 1% increase in this ratio decreases output quality by 0.046%) and the 90th-to-10th ratio (a 1% increase in this ratio decreases output quality by 0.042%). Referring to the theoretical framework in Section 1.2, this finding implies that the quality of intermediates exhibits a degree of complementarity, consistent with the classical *O-ring* theory, which suggests that the qualities of inputs are interdependent.

Table 1.5 presents baseline results structured similarly to Table 1.4. Inputs and outputs are still matched based on Input-Output table, but product qualities are estimated as demand residuals. Recall that the quality estimates reflect consumers' demand for firms' products that are independent of prices, considering different elasticities of substitution as provided by Soderbery (2015). The number of observations decreases since the estimation of product quality is based solely on the domestic market and contains product-year fixed effects. The results of using elasticity of substitution estimates from Broda and Weinstein (2006) are demonstrated in Table A.2 in the Appendix.

Notably, the role of average input quality (proxied by price) in shaping output quality (estimated as demand residual) is still statistically significant in columns

Table 1.5: Dispersion of Input Quality and Output Quality (Matched with IO Table)

	(1) Quality SB	(2) Quality SB	(3) Quality SB	(4) Quality SB	(5) Quality SB	(6) Quality SB
75/25 ratio	-0.190*	-0.0370	-0.0498			
	(0.1068)	(0.0732)	(0.0635)			
90/10 ratio				-0.148*	-0.0282	-0.0059
				(0.0792)	(0.0528)	(0.0454)
Average	0.414***	-0.126	-0.0640	0.429***	-0.123	-0.0670
	(0.1538)	(0.1058)	(0.0872)	(0.1546)	(0.1063)	(0.0884)
Con Vars	YES	YES	YES	YES	YES	YES
Product-Year FE	YES	YES	YES	YES	YES	YES
Firm FE		YES			YES	
Firm-Product FE			YES			YES
Observation	26648	26184	23299	26648	26184	23299
R2	0.0447	0.472	0.740	0.0449	0.472	0.740

Notes: All variables are logarithmic. Output quality is estimated as demand residual, using estimates of Soderbery (2015). Inputs and outputs are matched based on Input-Output table. The control variable contains the number of inputs and firm productivity. Standard errors are clustered at the firm level and are shown in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

(1) and (4) of Table 1.5, but not in other columns that include firm fixed effects. Furthermore, the negative effects of dispersion increase in magnitude across firms for the same product. This implies that input quality dispersion has a greater effect on output quality when the output quality is estimated after excluding the effect of price. Specifically, a 1% increase in dispersion, measured by the 75th to 25th percentile ratio, decreases output quality by 0.19% across firms and by 0.15% for dispersion measured by the 90th to 10th percentile ratio when using estimates from Soderbery (2015). The robust negative finding regarding the dispersion of input quality suggests complementarity between the qualities of intermediates.

1.4.1.2 Baseline Results-Matched by HS2

As discussed earlier, there is a trade-off between relevance and inclusivity when matching inputs to outputs. In practice, the production of final goods often involves inputs from diverse sectors rather than exclusively from the same sector as the outputs. Therefore, exploiting IO table allows for capturing the input diversity across industries. However, a comparison of Panel A and Panel B in Table 1.1 shows that this matching methodology excludes only 2 unrelated imported inputs out of a total of 22 used in the production of 4 outputs. This approach, however, may overlook the

relevance of certain specific input-output relationships. To ensure that only truly relevant inputs are considered in production, this study employs an alternative matching method based on the same HS2 code of inputs and outputs. The HS2 level is broad enough to capture inputs across multiple sub-sectors while maintaining their key relationships with the outputs.

Table 1.6: Dispersion of Input Quality and Output Quality (Matched by HS2)

	(1) Output Price	(2) Output Price	(3) Output Price	(4) Output Price	(5) Output Price	(6) Output Price
75/25 ratio	-0.030***	-0.0021	-0.0004			
	(0.0104)	(0.0061)	(0.0046)			
90/10 ratio				-0.016*	0.00027	-0.00045
				(0.0084)	(0.0044)	(0.0033)
Average	0.182***	0.0249***	0.00929	0.181***	0.0245***	0.00933
	(0.0144)	(0.0090)	(0.0061)	(0.0145)	(0.0091)	(0.0060)
Con Vars	YES	YES	YES	YES	YES	YES
Product-Year FE	YES	YES	YES	YES	YES	YES
Firm FE		YES			YES	
Firm-Product FE			YES			YES
Observation	55109	54596	49621	55109	54596	49621
R2	0.424	0.685	0.893	0.424	0.685	0.893

Notes: All variables are logarithmic. Output quality is measured by output price. Inputs and outputs are matched if they are within the same HS-2 industry category. The control variable contains the number of inputs and firm productivity. Standard errors are clustered at the firm-HS2 level and are shown in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

The two tables in this subsection exhibit the results of matching the inputs and outputs by HS-2 digit category: the output quality is proxied by price in Table 1.6, while Table 1.6 presents the results where output quality is estimated as the demand residual. The negative effects of input quality dispersion on output quality remain robustly significant, as reflected in both tables. A 1% increase in dispersion, measured by the 75th-to-25th reduces output quality (measured by price) by 0.030%, and 0.016% when the dispersion is measured by 90th-to-10th percentile ratio. A 1% increase in input quality dispersion decreases output quality by around 0.1% when output quality is estimated as demand residual.

Overall, regardless of the methodology used to measure output quality or the method of matching inputs and outputs, the negative impact of input quality dispersion on the quality of final goods remains consistent. This robust finding highlights the interdependence of input qualities. Given that the effects of both average input

Table 1.7: Dispersion of Input Quality and Output Quality (Matched by HS2)

	(1) Quality SB	(2) Quality SB	(3) Quality SB	(4) Quality SB	(5) Quality SB	(6) Quality SB
75/25 ratio	-0.163*	-0.0206	-0.0319			
	(0.1004)	(0.0708)	(0.0664)			
90/10 ratio				-0.0906	-0.0473	-0.0258
				(0.0700)	(0.0474)	(0.0428)
Average	0.478***	0.132	0.0397	0.471***	0.142	0.0405
	(0.1401)	(0.0981)	(0.0986)	(0.1421)	(0.0985)	(0.0983)
Con Vars	YES	YES	YES	YES	YES	YES
Product-Year FE	YES	YES	YES	YES	YES	YES
Firm FE		YES			YES	
Firm-Product FE			YES			YES
Observation	20871	20486	17990	20871	20486	17990
R2	0.0648	0.453	0.716	0.0646	0.453	0.716

Notes: All variables are logarithmic. Output quality is estimated as demand residual, using estimates of Soderbery (2015). Inputs and outputs are matched if they are within the same HS-2 industry category. The control variable contains the number of inputs and firm productivity. Standard errors are clustered at the firm-HS2 level and are shown in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

quality and dispersion of input quality mainly arise from variation across firms, the results presented in the remainder of this paper will include only product-year fixed effects.

1.4.1.3 Robustness Check: Alternative Criteria for Matching Inputs and Outputs

In the main analysis, one of the matching strategies relies on the HS-2 digit level, assuming that intermediates are used in production if the final goods and intermediates share the same industry classification (HS-2 code). To observe how the effects of input quality dispersion vary with different matching approaches, I extend the matching criteria for potential inputs and final goods to HS-4 and firm-level classifications[10]. It is important to note that this robustness analysis does not imply that other matching dimensions are more reliable or more accurate than HS-2 or Input-Output (IO) table-based matching methods, but rather emphasizes the importance of selecting appropriate matching criteria as effects can differ across cases. The results for the different matching approaches are presented in Table 1.8.

[10]The firm level matching approach assumes that all inputs imported by the firm are adopted in the production of each of the firm's products.

Table 1.8: Robustness Check: Other Matching Dimensions

	(1) Output Price	(2) Quality SB	(3) Output Price	(4) Quality SB
75/25 ratio	-0.0110	-0.162	-0.0502***	-0.144
	(0.0118)	(0.1218)	(0.0117)	(0.1292)
Average	0.204***	0.715***	0.174***	0.460***
	(0.0182)	(0.1836)	(0.0161)	(0.1467)
Con Vars	YES	YES	YES	YES
Product-Year FE	YES	YES	YES	YES
Matched by	HS-4	HS-4	Firm	Firm
Observation	31745	12945	80952	27055
R2	0.432	0.114	0.392	0.0449

Notes: All variables are logarithmic. Output quality is measured by price or estimated as demand residual, using estimates of Soderbery (2015). Inputs and outputs are matched if they are within the same HS-4 industry category or assuming all inputs imported by the firm are used for the production of their products. The control variable contains the number of inputs and firm productivity. Standard errors are clustered at the firm-HS4 level or firm level, and they are shown in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Similarly, the quality of final goods is measured in two ways: measured by product price or estimated as demand residuals utilizing elasticity of substitution estimates from Soderbery (2015) due to their recent calculation using a comprehensive methodology. Given the space constraints and for clarity in presentation, only the results measuring dispersion as the 75th to 25th percentile ratio are displayed in the tables throughout the rest of the paper. However, the negative effects of the 90th to 10th percentile ratio are robust to those of the 75th to 25th percentile ratio. When comparing the results across these two matching dimensions, it is noticeable that as the matching criteria broaden from the HS-4 digit level to the firm level, the effect of average input quality diminishes (from 0.20% to 0.17% when product quality is proxied by price, and from 0.72% to 0.46% when product quality is estimated as a demand residual).

At the same time, the increase in input quality dispersion results in a more pronounced reduction in output quality when broadening the matching criteria, particular when product quality is proxied by price, the effect of input quality dispersion on final product quality changes from -0.01% (column (1)) to -0.05% (column (3)), but insignificant statistically when product quality is measured as a demand residual. The different effects yielded by matching at the HS-4 digit level and by the firm underscore the importance of the matching approach between inputs and outputs. Accurately capturing the relationship between input qualities and output quality also depends

on how appropriately the input-output matching is assumed based on the available data.

1.4.2 Heterogeneity Analysis

1.4.2.1 Industry Heterogeneity

The analysis so far has focused on the average interconnection of input qualities across all sectors rather than on specific industries or products. However, referring to Figure 1.2, the observed variation in input quality dispersion across industries suggests that there may be different elasticities of quality substitution within each industry. To explore this, I categorize industries into high-tech and low-tech sectors based on the technology intensity definitions provided by the OECD[11]. The classification standard is originally in ISIC format; to match the data used in this study, I converted it into HS format. In this study, I define industries categorized as "High-technology" and "Medium-high-technology" in the OECD report as "High-tech industries", and those categorized as "Low-technology" and "Medium-low-technology" as "Low-tech industries". In the regression analysis, the dispersion variable is interacted with the dummy variable representing this technology classification. It helps determine whether the effects of input quality dispersion on output quality differ between high-tech and low-tech industries. Following the main analysis, I also match the inputs and outputs based on the IO table and by HS-2 digit level, respectively.

The interaction of 75th to 25th ratio[12] with technology dummy only exhibits positive and statistically significant results in column (2) of Table 1.9, which slightly suggests that for low-tech products, the interdependence between intermediates' qualities is relatively stronger. In contrast, the quality of intermediates for high-tech products leans more toward substitution. On average, a 1% increase in the 75th to 25th percentile ratio of input quality for low-tech products results in a 0.46% greater reduction in the quality of the firm's outputs compared to high-tech products when inputs are matched with IO table and output quality is estimated as a demand residual.

A possible explanation for this is that high-tech products, due to the complexity of their production processes, rely on a more diverse range of intermediates with varying levels of importance. As a result, the likelihood of including less important inputs is higher than in low-tech products, leading to a more pronounced compensation effect. For example, automobile production involves crucial inputs like engines and tires,

[11] The classification can be found in the Appendix.

[12] The results for 90th to 10th ratio are still robust, thus for clarity in presentation, only results of 75th to 25th percentile ratio are displayed in the table, same for tables throughout the rest of the paper.

Table 1.9: Industry Heterogeneity - Technology

	(1) Output Price	(2) Quality SB	(3) Output Price	(4) Quality SB
75/25 ratio	-0.0620***	-0.398**	-0.0446***	-0.293*
	(0.0165)	(0.1549)	(0.0152)	(0.1511)
75/25 ∗ Hightech	0.0264	0.457**	0.0258	0.204
	(0.0220)	(0.2070)	(0.0206)	(0.1960)
Con Vars	YES	YES	YES	YES
Product-Year FE	YES	YES	YES	YES
Matched by	IO table	IO table	HS-2	HS-2
Observation	78880	26648	55109	20871
R2	0.394	0.0460	0.424	0.0679

Notes: All variables are logarithmic. Output quality is measured by price or estimated as demand residual using estimates of Soderbery (2015). Input and output are matched based on IO table or by HS-2 industry category. The control variables contain average input quality, technology dummy variable, interaction of technology with average input quality, the number of inputs and firm productivity. Standard errors are clustered at the firm level or firm-HS2 level, and they are shown in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

alongside less critical ones such as textiles. In this case, the high quality of the engine can easily compensate for the lower quality of the textile. On the other hand, for low-tech products like T-shirts, the qualities of cotton and sewing thread are equally important, making the quality interdependence between them more straightforward.

1.4.2.2 Firm Heterogeneity

Another potential reason for results in Table 1.9 could stem from firm heterogeneity. In Table 1.10, I further interact input quality dispersion with the firm's productivity (measured using revenue-based TFP estimates, following the Olley-Pakes method), and find that more productive firms exhibit a smaller negative effect of input quality dispersion on output quality. This finding implies that productive firms may be better equipped to manage or mitigate quality inconsistencies among inputs. For example, more productive firms may have the capacity to implement advanced production technologies, or flexible substitution strategies, or refined processes, or higher-skilled labor, which enable these firms to develop ways to maintain output quality despite variation in input quality. In contrast, less productive firms, which may lack such resources or technologies, are more likely to suffer from variations in input quality, leading to their output quality more vulnerable to the dispersion of input quality.

The firms in high-tech industries, as shown in Table 1.9, are primarily more productive compared to those in low-tech industries. Therefore, high-tech firms may have a greater capacity to manage input quality variations and are potentially

less affected by the same level of input quality dispersion. As a result, comparing to high-tech industries, the results of dispersion observed for low-tech industries in Table 1.9 are relatively stronger.

Table 1.10: Firm Heterogeneity

	(1) Output Price	(2) Quality SB	(3) Output Price	(4) Quality SB
75/25 ratio	-0.297***	-1.028**	-0.153***	-0.531
	(0.0585)	(0.4963)	(0.0568)	(0.6204)
75/25 ∗ Productivity	0.0215***	0.0751*	0.0106**	0.0326
	(0.0051)	(0.0450)	(0.0049)	(0.0533)
Productivity	0.0201	-0.152	0.0152	-0.181*
	(0.0148)	(0.1077)	(0.0118)	(0.1009)
Con Vars	YES	YES	YES	YES
Product-Year FE	YES	YES	YES	YES
Matched by	IO table	IO table	HS-2	HS-2
Observation	78880	26648	55109	20871
R2	0.394	0.0450	0.424	0.0649

Notes: All variables are logarithmic. Firm productivity is measured using revenue-based TFP estimates, following the Olley-Pakes method. Output quality is measured by price or estimated as demand residual using estimates of Soderbery (2015). Input and output are matched based on IO table or by HS-2 industry category. The control variables contain average input quality and the number of inputs. Standard errors are clustered at the firm level or firm-HS2 level, and they are shown in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

1.4.2.3 Interaction with Average Input Quality

Table 1.11 further explores how the average quality of inputs influences the effect of dispersion. To explore it, I interact the input quality dispersion with average input quality and estimate how the quality of output responds to this interaction variable. In a similar format as displayed in other tables, inputs and outputs are matched based on the IO table in Denmark or by the same HS2-digit category. The negative sign of the interaction variable highlights the importance of paying particular attention to the dispersion of intermediate input quality, especially when the average quality of inputs is high. In other words, when most inputs are of high quality, firms should be more cautious about variations in input quality, as dispersion could more seriously deteriorate output quality and potentially impede the firm's growth. This finding suggests that maintaining consistent quality across all inputs is critical for firms already adopting high-average-quality intermediates.

Table 1.11: Interaction with Average Input Quality

	(1) Output Price	(2) Quality SB	(3) Output Price	(4) Quality SB
75/25 ratio	-0.0657***	-0.383***	-0.0601***	-0.299***
	(0.0133)	(0.1333)	(0.0125)	(0.1098)
75/25 ∗ Average	-0.0239***	-0.219***	-0.0365***	-0.180***
	(0.0071)	(0.0692)	(0.0071)	(0.0554)
Average	0.217***	0.842***	0.252***	0.823***
	(0.0229)	(0.2378)	(0.0205)	(0.1733)
Con Vars	YES	YES	YES	YES
Product-Year FE	YES	YES	YES	YES
Matched by	IO table	IO table	HS-2	HS-2
Observation	78880	26648	55109	20871
R2	0.394	0.0458	0.425	0.0664

Notes: All variables are logarithmic. Output quality is measured by price or estimated as demand residual using estimates of Soderbery (2015). Input and output are matched based on IO table or by HS-2 industry category. The control variables contain the number of inputs and firm productivity. Standard errors are clustered at the firm level or firm-HS2 level, and they are shown in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

1.4.3 Include Labor

In this extended study, I include labor and expand the conceptual framework to a broader context that includes both intermediates and labor. Following a similar logic to the baseline analysis, three analogous variables related to labor quality (skill) are included in the regression: average wage, wage dispersion, and the number of employees within the firm. Aligned with the baseline table, inputs and outputs are matched either based on connections in the IO table or by the same HS-2 digit industry category, while labor is measured at the firm level. It is obvious from Table 1.12 that the complementarity of intermediates' qualities remains robust even when labor is included.

However, product quality does not respond in the same manner to the dispersion of labor skills. Several potential explanations for this observation include: First, not all employees within the firm are involved in the production of every product, and matching specific workers to particular products is challenging with the available data. Second, the complementarity among intermediate inputs may differ inherently from that among labor skills. Additionally, beyond the quality interconnections within each input type, the substitutability between labor and intermediate inputs also needs to be considered.

Table 1.12: Dispersion of Input Quality and Output Quality - Including Labor

	(1) Output Price	(2) Quality SB	(3) Output Price	(4) Quality SB
75/25 ratio	-0.0490***	-0.194*	-0.0309***	-0.142
	(0.0113)	(0.1052)	(0.0104)	(0.1004)
Average input quality	0.168***	0.424***	0.181***	0.476***
	(0.0162)	(0.1530)	(0.0145)	(0.1340)
75/25 labor	-0.00704	-0.985	0.0380	-0.730
	(0.1089)	(1.0461)	(0.1232)	(1.1674)
Average wage	0.371***	0.168	0.0998	-1.842
	(0.1184)	(1.1233)	(0.1387)	(1.1475)
Con Vars	YES	YES	YES	YES
Product-Year FE	YES	YES	YES	YES
Matched by	IO table	IO table	HS-2	HS-2
Observation	78821	26626	55068	20853
R2	0.395	0.0451	0.424	0.0672

Notes: All variables are logarithmic. Output quality is measured by price or estimated as demand residual using estimates of Soderbery (2015). Input and output are matched based on IO table or by HS-2 industry category. The control variables contain the number of inputs, the numbers of employees and firm productivity. Standard errors are clustered at the firm level or firm-HS2 level, and they are shown in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

1.5 Conclusion

This paper contributes to the *O-ring* theory by shedding light on the interconnection of input qualities. The theoretical framework demonstrates how the dispersion of intermediate input quality affects a firm's product quality, conditional on the average input quality. In this framework, product quality exhibits varying degrees of sensitivity to each intermediate. In equilibrium, the optimal allocation of input quality depends on the elasticity of substitution between input qualities, which determines output quality.

The model's predictions highlight that quality dispersion impacts product quality differently in two scenarios: it reduces output quality when input qualities exhibit a degree of complementarity and increases output quality when they are sufficiently substitutable. By leveraging these distinct effects, the framework can be empirically tested using data to deduce the interconnections between input qualities. Specifically, it enables me to determine whether the input qualities fall under the complementarity or substitutability scenario.

Using Danish data, the empirical results demonstrate that changes in input quality

dispersion are negatively correlated with changes in product quality. This finding aligns with the model's complementarity scenario among input qualities. Moreover, the heterogeneity analysis reveals that the elasticity of quality substitution varies across industries. These results have significant implications for firm production: apart from focusing on average input quality, firms should also pay attention to the dispersion of input qualities as it can spoil product quality and potentially hinder firm growth. It highlights the importance of quality management and strategic input selection in optimizing production processes.

One limitation of this paper is that the empirical analysis only considers imported inputs, overlooking intermediates from the domestic market due to data availability. This omission may restrict the comprehensive understanding of input quality dynamics. Moreover, using price as a proxy for input quality may not be optimal as price also reflects markups, trade costs, supplier efficiency, and the firm's outsourcing technology. Estimating quality based on demand residuals relies on the same market for comparability, which may result in the loss of some observations. Additionally, there is the potential issue of endogeneity where reverse causality might affect the observed relationships between input qualities in this analysis. Future research could address these issues and explore the mechanisms underlying firm heterogeneity in input quality choices. Specifically, what factors determine why some firms use intermediates with varying quality while others show little variation, even when the average quality of inputs is similar.

1.6 References

Acemoglu, D., Antràs, P., Helpman, E., 2007. Contracts and technology adoption. American Economic Review 97 (3), 916–943.

Alfaro, L., Chor, D., Antras, P., Conconi, P., 2019. Internalizing global value chains: A firm-level analysis. Journal of Political Economy 127 (2), 508–559.

Amiti, M., Cameron, L., 2012. Trade liberalization and the wage skill premium: Evidence from indonesia. Journal of International Economics 87 (2), 277–287.

Amiti, M., Khandelwal, A. K., 2013. Import competition and quality upgrading. Review of Economics and Statistics 95 (2), 476–490.

Amiti, M., Konings, J., 2007. Trade liberalization, intermediate inputs, and productivity: Evidence from indonesia. American Economic Review 97 (5), 1611–1638.

Antoniades, A., 2015. Heterogeneous firms, quality, and trade. Journal of International Economics 95 (2), 263–273.

Antràs, P., Chor, D., 2013. Organizing the global value chain. Econometrica 81 (6), 2127–2204.

Bas, M., Strauss-Kahn, V., 2015. Input-trade liberalization, export prices and quality upgrading. Journal of International Economics 95 (2), 250–262.

Bastos, P., Silva, J., 2010. The quality of a firm's exports: Where you export to matters. Journal of International Economics 82 (2), 99–111.

Bastos, P., Silva, J., Verhoogen, E., 2018. Export destinations and input prices. American Economic Review 108 (2), 353–392.

Berlingieri, G., Lashkari, D., Boeri, F., Vogel, J., 2022. Capital-skill complementarity in firms and in the aggregate economy. Tech. rep., Working paper.

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.

Berndt, E. R., Wood, D. O., 1979. Engineering and econometric interpretations of energy-capital complementarity. The American Economic Review 69 (3), 342–354.

Broda, C., Weinstein, D. E., 2006. Globalization and the gains from variety. The Quarterly journal of economics 121 (2), 541–585.

Chen, N., Juvenal, L., 2016. Quality, trade, and exchange rate pass-through. Journal of International Economics 100, 61–80.

Chen, N., Juvenal, L., 2022. Markups, quality, and trade costs. Journal of International Economics 137, 103627.

Colantone, I., Crinò, R., 2014. New imported inputs, new domestic products. Journal of International Economics 92 (1), 147–165.

Crinò, R., 2009. Offshoring, multinationals and labour market: a review of the empirical literature. Journal of Economic Surveys 23 (2), 197–249.

Demir, B., Fieler, A. C., Xu, D., Yang, K. K., 2021. O-ring production networks. Tech. rep., National Bureau of Economic Research.

Fan, H., Li, Y. A., Yeaple, S. R., 2015. Trade liberalization, quality, and export prices. Review of Economics and Statistics 97 (5), 1033–1051.

Feenstra, R. C., 1994. New product varieties and the measurement of international prices. The American Economic Review, 157–177.

Feng, L., Li, Z., Swenson, D. L., 2016. The connection between imported intermediate inputs and exports: Evidence from chinese firms. Journal of International Economics 101, 86–101.

Goldberg, P. K., Khandelwal, A. K., Pavcnik, N., Topalova, P., 2010. Imported intermediate inputs and domestic product growth: Evidence from india. The Quarterly journal of economics 125 (4), 1727–1767.

Grossman, G. M., Maggi, G., 2000. Diversity and trade. American Economic Review 90 (5), 1255–1275.

Halpern, L., Koren, M., Szeidl, A., 2015. Imported inputs and productivity. American Economic Review 105 (12), 3660–3703.

Hottman, C. J., Redding, S. J., Weinstein, D. E., 2016. Quantifying the sources of firm heterogeneity. The Quarterly Journal of Economics 131 (3), 1291–1364.

Jäkel, I. C., Sørensen, A., 2020. Quality-cum-price sorting. The World Economy 43 (5), 1346–1370.

Jover, A. J. V., Montes, F. J. L., Fuentes, M. d. M. F., 2004. Measuring perceptions of quality in food products: the case of red wine. Food Quality and preference 15 (5), 453–469.

Khandelwal, A., 2010. The long and short (of) quality ladders. The Review of Economic Studies 77 (4), 1450–1476.

Khandelwal, A. K., Schott, P. K., Wei, S.-J., 2013. Trade liberalization and embedded institutional reform: Evidence from chinese exporters. American Economic Review 103 (6), 2169–2195.

Koetse, M. J., De Groot, H. L., Florax, R. J., 2008. Capital-energy substitution and shifts in factor demand: A meta-analysis. Energy Economics 30 (5), 2236–2251.

Kremer, M., 1993. The o-ring theory of economic development. The quarterly journal of economics 108 (3), 551–575.

Kugler, M., Verhoogen, E., 2012. Prices, plant size, and product quality. The Review of Economic Studies 79 (1), 307–339.

Manova, K., Yu, Z., 2017. Multi-product firms and product quality. Journal of International Economics 109, 116–137.

Manova, K., Zhang, Z., 2012. Export prices across firms and destinations. The Quarterly Journal of Economics 127 (1), 379–436.

Mayer, T., Melitz, M. J., Ottaviano, G. I., 2014. Market size, competition, and the product mix of exporters. American Economic Review 104 (2), 495–536.

Piveteau, P., Smagghue, G., 2019. Estimating firm product quality using trade data. Journal of International Economics 118, 217–232.

Soderbery, A., 2015. Estimating import supply and demand elasticities: Analysis and implications. Journal of International Economics 96 (1), 1–17.

Thompson, H., 2006. The applied theory of energy substitution in production. Energy Economics 28 (4), 410–425.

Voigtlaender, N., Saravia, D., et al., 2015. Imported inputs, quality complementarity, and skill demand. In: 2015 Meeting Papers. No. 1538. Society for Economic Dynamics.

Yu, M., Li, J., 2014. Imported intermediate inputs, firm productivity and product complexity. The Japanese Economic Review 65 (2), 178–192.

Zha, D., Ding, N., 2014. Elasticities of substitution between energy and non-energy inputs in china power sector. Economic Modelling 38, 564–571.

1.A Appendix

1.A.1 Theory Appendix

1.A.1.1 Two Inputs

To enhance understanding of the model, this subsection of the Appendix presents a simplified case involving only two inputs. This straightforward scenario illustrates the different allocations of input quality—symmetric and asymmetric—in complementarity and substitutability contexts more clearly. Additionally, the derivative of output quality with respect to input quality dispersion in this simple case better explains why the turning point occurs when the elasticity of substitution between input qualities equals 2.

Complement - Symmetric Allocation

If these inputs are complements ($\rho \in (0,1)$), as concluded above, the allocation of input quality at the optimum is to ensure the effective qualities of the inputs (combinations of $\alpha_{\omega i} q_{\omega i}$) are balanced, thus displaying a symmetric pattern. Dispersion of input quality $\delta^*_{f\omega} = \frac{q^*_{f\omega Max}}{q^*_{f\omega Min}} = \frac{\alpha_{f\omega Max}{}^{1-\rho}}{\alpha_{f\omega Min}{}^{1-\rho}} \geq 1$. By substituting the dispersion equation into the output quality equation, we can reformulate the optimal quality function to express it solely in terms of dispersion $\delta_{f\omega}$ and input costs $\bar{C}_{f\omega} = q_{f\omega Max} + q_{f\omega Min}$. The resulting expressions are as follows:

$$Q^*_{(f\omega)} = \left[\left(\alpha_{\text{Min}}\, q_{Max}\right)^{\frac{\rho-1}{\rho}} + \left(\alpha_{\text{Max}}\, q_{\text{Min}}\right)^{\frac{\rho-1}{\rho}} \right]^{\frac{\rho}{\rho-1}}, \tag{A.1}$$

$$Q^*_{(f\omega)} = \left[1 + \frac{1}{\delta_{f\omega}}\right]^{\frac{\rho}{\rho-1}} \cdot \left[\frac{\bar{C}_{f\omega}\delta_{f\omega}}{\left(1+\delta_{f\omega}\right)\left[1+\left(\delta_{f\omega}\right)^{\frac{1}{1-\rho}}\right]} \right]. \tag{A.2}$$

Again, as discussed before, $\bar{C}$ can reflect information about average input quality. The output quality from Equation (A.2) is a function determined solely by dispersion and average input costs. Taking the logarithm on both sides simultaneously and differentiating with respect to dispersion $\delta_{f\omega}$, it yields as:

$$\frac{\partial \ln Q^*_{(f\omega)}}{\partial \delta_{f\omega}} = \frac{\left(1+\left(\delta_{f\omega}\right)^{\frac{1}{1-\rho}}\right) - \left(1+\delta_{f\omega}\right)\cdot\left(\delta_{f\omega}\right)^{\frac{1}{1-\rho}}}{\delta_{f\omega}\cdot\left(1+\delta_{f\omega}\right)(1-\rho)\left[1+\left(\delta_{f\omega}\right)^{\frac{1}{1-\rho}}\right]}, \text{ which is } < 0. \tag{A.3}$$

The derived equation is negative since the denominator is positive, but the numerator is negative for all $\delta_{f\omega} \geq 1$ when $\rho \in (0,1)$, which implies that a change in input quality dispersion $\delta_{f\omega}$ is negatively correlated with a change in output quality. Increases in the dispersion of input quality lead to a decrease in product quality.

$$\frac{\partial^2 \ln Q^*_{(f\omega)}}{\partial \delta_{f\omega} \partial \rho} = \frac{\rho \left[1+\left(\delta_{f\omega}\right)^{\frac{1}{\rho-1}}\right]\left[\left(\delta_{f\omega}\right)^{\frac{\rho-2}{\rho-1}}-1\right]-\left(\delta_{f\omega}\right)^{\frac{\rho-2}{\rho-1}}+\left(\delta_{f\omega}\right)^{\frac{1}{\rho-1}}-\delta_{f\omega}\left(\ln\delta_{f\omega}+1\right)-\ln\delta_{f\omega}+1}{\left(\delta_{f\omega}\right)^{\frac{\rho-2}{\rho-1}}\cdot\left(1+\delta_{f\omega}\right)\left[1+\left(\delta_{f\omega}\right)^{\frac{1}{\rho-1}}\right]^2(1-\rho)^3} < 0. \tag{A.4}$$

Furthermore, if further taking the derivative of Equation (A.3) with respect to ρ, the result remains negative, which implies that a smaller ρ deepens this negativity. In other words, if inputs are more complementary, the quality dispersion among them will more severely damage the quality of the final good[13].

Substitute - Asymmetric Allocation

If these intermediates are substitutes, the strategy of allocating input quality will be asymmetric: firms choose higher quality for more important (or more quality-sensitive) inputs, as it can compensate for the lower quality of the less important (or less quality-sensitive) intermediates. Following the same logic, we can rearrange the optimal function of variety quality as an expression that includes only dispersion $\delta_{f\omega}$ and the sum of input quality (overall input costs) $\bar{C}$:

$$Q^*_{(f\omega)} = \left[\left(\alpha_{\text{Max}}\, q_{Max}\right)^{\frac{\rho-1}{\rho}} + \left(\alpha_{\text{Min}}\, q_{\text{Min}}\right)^{\frac{\rho-1}{\rho}}\right]^{\frac{\rho}{\rho-1}}, \tag{A.5}$$

$$Q^*_{(f\omega)} = \left[1+\delta_{f\omega}\right]^{\frac{\rho}{\rho-1}} \cdot \left[\frac{\bar{C}_{f\omega}}{\left(1+\delta_{f\omega}\right)\left[1+\left(\delta_{f\omega}\right)^{\frac{1}{\rho-1}}\right]}\right]. \tag{A.6}$$

Similarly, taking the logarithm of both sides and differentiating with respect to dispersion $\delta_{\omega i}$:

$$\frac{\partial \ln Q^*_{(f\omega)}}{\partial \delta_{f\omega}} = \frac{\delta_{f\omega} - \left(\delta_{f\omega}\right)^{\frac{1}{\rho-1}}}{\delta_{f\omega}(\rho-1)\left(1+\delta_{f\omega}\right)\left[1+\left(\delta_{f\omega}\right)^{\frac{1}{\rho-1}}\right]}. \tag{A.7}$$

[13] Here, when taking the further derivative with respect to ρ, ρ is not considered as a function of dispersion δ, meaning that $\frac{d\delta}{d\rho}$ is ignored. This approach focuses more on how the value of ρ affects the static effect observed in Equation (A.3)

The sign of Equation (A.7) is not as straightforward: a turning point at $\rho = 2$ is observed here:

$$\frac{\partial \ln Q^*_{(f\omega)}}{\partial \delta_{f\omega}} < 0, \text{ when } \rho < 2 \text{ for all } \delta_{f\omega} > 1;$$

$$\frac{\partial \ln Q^*_{(f\omega)}}{\partial \delta_{f\omega}} > 0, \text{ when } \rho > 2 \text{ for all } \delta_{f\omega i} > 1.$$

Furthermore, by taking the derivative of Equation (A.7) with respect to ρ, it can examine how the degree of substitution plays a role in this effect, exhibiting distinct patterns on either side of $\rho = 2$:

$$\frac{\partial^2 \ln Q^*_{(f\omega)}}{\partial \delta_{f\omega} \partial \rho} = \frac{\rho \left[1 + \left(\delta_{f\omega i}\right)^{\frac{1}{\rho-1}}\right] \left[\left(\delta_{f\omega}\right)^{\frac{1}{\rho-1}} - \delta_{f\omega}\right] - \left(\delta_{f\omega}\right)^{\frac{2}{\rho-1}} + \left(\delta_{f\omega}\right)^{\frac{1}{\rho-1}} \cdot \left(\left(\delta_{f\omega}+1\right)\ln \delta_{f\omega} + \delta_{f\omega} - 1\right) + \delta_{f\omega}}{\delta_{f\omega} \cdot \left(1+\delta_{f\omega}\right)\left[1 + \left(\delta_{f\omega}\right)^{\frac{1}{\rho-1}}\right]^2 (\rho-1)^3}. \tag{A.8}$$

$$\frac{\partial^2 \ln Q^*_{(f\omega)}}{\partial \delta_{f\omega} \partial \rho} < 0, \text{ when } \rho < 2;$$

$$\frac{\partial^2 \ln Q^*_{(f\omega)}}{\partial \delta_{f\omega} \partial \rho} > 0, \text{ when } \rho > 2.$$

In the case of substitution, the effect of dispersion on product quality is more subtle: dispersion still reduces the quality of final goods when $1 < \rho < 2$ and a positive effect appears when $\rho > 2$. In other words, changes in input quality dispersion $\delta_{f\omega i}$ only lead to the same movement in output quality when the inputs are sufficiently substitutable. Equation (A.8) implies that this effect amplifies with a greater degree of substitution. When the qualities of inputs are perfect substitutes, i.e., as ρ approaches $+\infty$, product quality depends on the input with the highest sensitivity, and the quality of that input equals ($\bar{C}_{f\omega}$).

When revisiting the denominators of both Equation (A.2) and Equation (A.6), it can be noticed that there is always the same term $(1 + \delta_{f\omega})$, which remains independent of ρ, denoting the negative effect of dispersion. This highlights the importance of paying attention to low-quality inputs, irrespective of whether the input qualities are substitutes or complements. The positive effect in the substitution context occurs only when the compensation effect is sufficiently large to offset the negative effects arising from both the lowest input quality and the lowest sensitivity. This is why the turning point in the substitution context is at $\rho = 2$.

1.A.1.2 Limitation

One limitation of the framework is that Equation (1.10) in Section 1.2 fails to capture a specific scenario involving internal adjustments between domestic and foreign outsourcing. For instance, if a firm reallocates goods A and B between the domestic

and foreign markets, this alters the dispersion ($\delta_{f\omega M}$) of imported intermediates, as well as the foreign output quality $Q_{f\omega M}$ and domestic output quality $Q_{f\omega D}$ in the equation. However, the overall dispersion for production ($\delta_{f\omega}$) remains unchanged. In this case of internal adjustments within firms, $\Delta Q_{f\omega M} = -\Delta Q_{f\omega D}$, meaning the change in $Q_{f\omega M}$ offsets the change in $Q_{f\omega D}$. Hence, examining $\delta_{f\omega M}$ alone may not explain the movements in product quality.

1.A.2 Data Appendix

1.A.2.1 Data Cleaning

Production data are collected through a survey of all manufacturing firms (including mining and quarrying) with at least 10 employees. In the survey, firms are asked to report the sales volume of their own-produced goods in terms of quantities and values for each product they produce. Products are defined at the eight-digit level of the Combined Nomenclature (CN). Sales of own-produced goods include both domestic and export sales. I drop observations without information on revenue or quantity. Quantities are recorded in different units (e.g., kg, pieces, liters) depending on the product code. Product prices are estimated as the ratio of revenue to quantity. To mitigate the influence of outliers, I trim the prices of each product by 1% at both tails of the distribution.

The trade statistics also provide information on imports by firm, product, and country of origin. I aggregate this import information to the firm-product level, weighted by the value of imports. Firm-product-level observations with an import value of less than 500 DKK or a low import share (below the 1st percentile of the distribution) are excluded. Furthermore, to classify imported products as intermediate inputs rather than goods for final consumption, I adhere to the classification system of the Broad Economic Categories (BEC) for machinery and transportation[14]. Apart from mitigating measurement errors in import prices, these data constraints also help identify the actual and effective inputs used in a firm's production. Input prices are estimated as the ratio of revenue to quantity. Similar to output prices, I trim input prices by 1% at both tails of the distribution to avoid the influence of outliers.

Estimating output quality as a demand residual requires information on domestic products. Therefore, I combine production statistics with external trade statistics to infer domestic sales and prices. Domestic sales and quantities are calculated as the difference between production and exports. Observations with negative domestic

[14]The products classified as final-consumption goods in the BEC are primarily food, machinery, and transportation. However, in practice, food items such as vegetables and fruits can also be used as intermediate inputs by firms. Therefore, I exclude only machinery and transportation items classified as final goods or capital goods according to the BEC.

sales or quantities are excluded. A small portion of the observations are recorded in different units of measurement in the two statistics (e.g., kg vs. pieces). Consequently, domestic sales and prices cannot be inferred for these products, resulting in a smaller sample for domestic prices compared to overall output prices. Moreover, due to the presence of product-year fixed effects in the demand equation, a variety's quality is measured relative to the average quality across all varieties for each product and year. Products with only one observation on domestic prices and quantities in a specific year are dropped from the sample because the fixed effects would predict the dependent variable perfectly. After all data restrictions and matching with inputs (at least two) based on IO table, as well as excluding singletons in output (product-year fixed effect in the baseline), the observations for the baseline equation reduce to 26,648.

1.A.2.2 Summary Statistics

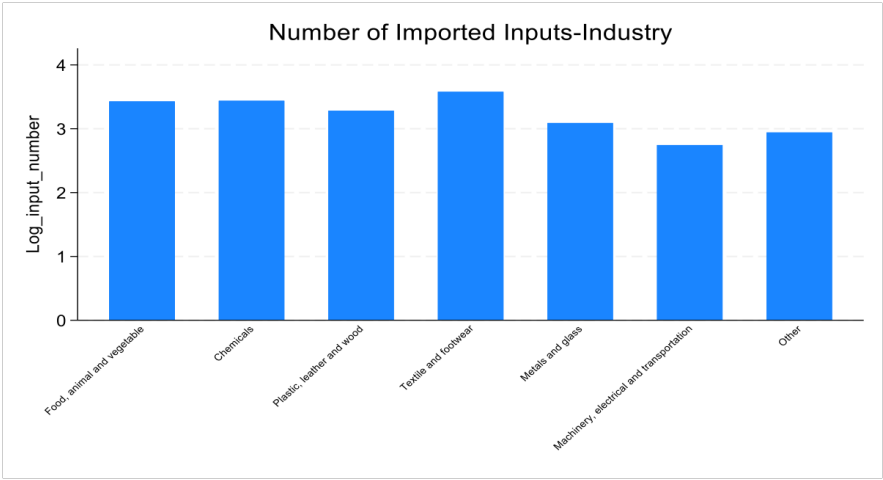


Figure A.1: Number of Inputs - Variations across Industries, 2018

Note: This figure displays the average number of imported inputs across all firms within each industry. The number of inputs is in logarithmic form.

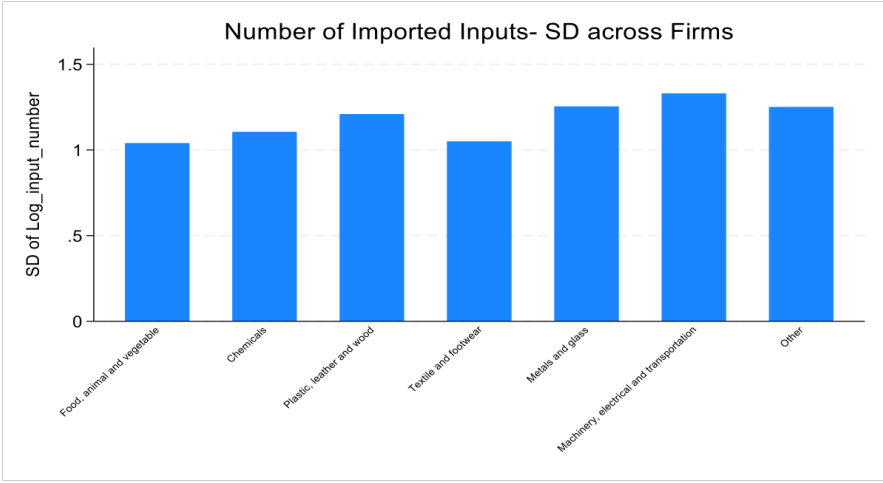


Figure A.2: SD of Input Quality Number - Variations across Firms, 2018

Note: This figure displays the standard deviation of the number of imported inputs across firms in each industry. The number of inputs is in logarithmic form.

1.A.2.3 OECD Technology Classification

In Section 1.4, I segment firms' outputs into high-tech and low-tech products for the heterogeneity analysis based on the technology intensity definitions provided by the OECD (see Table A.1). Specifically, industries categorized as "High-technology" and "Medium-high-technology" in the OECD report are considered "High-tech industries" in this study, while those categorized as "Low-technology" and "Medium-low-technology" are considered "Low-tech industries" in this study.

Table A.1: Industry Classification - OECD

High-technology Industries	**Medium-high-technology Industries**
Aircraft and spacecraft	Electrical machinery and apparatus, n.e.c.
Pharmaceuticals	Motor vehicles, trailers and semi-trailers
Office, accounting and computing machinery	Chemicals excluding pharmaceuticals
Radio, TV and communications equipment	Railroad equipment,and transport equipment
Medical, precision and optical instruments	Machinery and equipment, n.e.c.
Medium-low-technology Industries	**Low-technology Industries**
Building and repairing of ships and boats	Manufacturing, n.e.c.; Recycling
Rubber and plastics products	Wood, pulp, paper, paper products, printing
Coke, petroleum products and nuclear fuel	Food products, beverages and tobacco
Other non-metallic mineral products	Textiles, textile products, leather and footwear
Basic metals and fabricated metal products	

Notes: Data source: OECD report.

1.A.3 Empirical Appendix

This section of the Appendix presents two additional robustness checks to the baseline equation: (1) the results of measuring output quality as demand residuals using estimates from Broda and Weinstein (2006), and (2) replacing the dispersion of percentile ratios with standard deviation. These robustness checks are essential for validating the consistency and reliability of our findings, ensuring that the interconnection of input qualities in the sample is not sensitive to alternative specifications or estimation approaches.

1.A.3.1 Robustness Checks: Quality Estimation with B&W (2006)

Similar to the baseline regression in Section 1.4, the inputs and outputs in Table A.2 are matched based on IO table. The key difference here is that output quality is estimated as demand residuals based on estimates from Broda and Weinstein (2006), rather than being measured by price or estimated using the methodology from Soderbery (2015) as described in Section 1.4.

Table A.2: Dispersion of Input Quality and Output Quality (Matched with IO table)

	(1) Quality BW	(2) Quality BW	(3) Quality BW	(4) Quality BW	(5) Quality BW	(6) Quality BW
75/25 ratio	-0.0690	-0.0021	-0.0288			
	(0.0790)	(0.0471)	(0.0435)			
90/10 ratio				-0.0444	-0.0208	-0.0135
				(0.0596)	(0.0355)	(0.0329)
Average	0.0423	-0.0866	-0.0338	0.0462	-0.0823	-0.0334
	(0.0957)	(0.0617)	(0.0491)	(0.0965)	(0.0623)	(0.0502)
Con Vars	YES	YES	YES	YES	YES	YES
Product-Year FE	YES	YES	YES	YES	YES	YES
Firm FE		YES			YES	
Firm-Product FE			YES			YES
Observation	26648	26184	23299	26648	26184	23299
R2	0.0348	0.449	0.742	0.0348	0.449	0.742

Notes: All variables are logarithmic. Output quality is estimated as demand residual, using estimates of Broda and Weinstein (2006). Inputs and outputs are matched based on Input-Output table. The control variable contains the number of inputs and firm productivity. Standard errors are clustered at the firm level and are shown in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

It is noticeable that when using different elasticity estimates to measure output quality, the impact of input quality dispersion on output quality remains consistently negative. Specifically, a 1% increase in the 75th to 25th percentile ratio of input quality leads to an approximate 0.07% decrease in product quality (measured as demand residuals using elasticity estimates from Broda and Weinstein (2006)), though the results are not statistically significant. However, this lack of statistic significance does not necessarily imply the economic absence of findings so far. As discussed in Soderbery (2015), the elasticity estimates from Broda and Weinstein (2006) exhibit significant biases and idiosyncrasies due to the over-weighting of outlier observations. The standard estimator used in their work suffers from small-sample biases and erratic results due to constrained grid search deficiencies, which can introduce

systematic bias, skewing the measuring of output quality and diminishing statistical significance in the analysis. Future work could strive to estimate these elasticities directly from Danish data, which may provide more accurate, contextually relevant elasticity estimates, enhancing the robustness and significance of the results.

1.A.3.2 Robustness Checks: Standard Deviation

The theoretical framework primarily focuses on a single random ratio of input qualities (the dispersion $\delta_{f\omega}$), provided it is greater than 1. In the empirical analysis, to align with this framework, two specific ratios are employed: the 90th to 10th percentile and the 75th to 25th percentile of input quality. However, changes in the relative quality of the rest of inputs are also important. To account for this, the Appendix provides additional empirical results using the standard deviation (SD) as an alternative measure to capture the dispersion across all input qualities.

Table A.3: SD of Input Quality and Output Quality (Matched with IO Table)

	(1) Output Price	(2) Output Price	(3) Output Price	(4) Quality SB	(5) Quality SB	(6) Quality SB
SD	-0.006**	-0.0014	-0.0010	-0.013	-0.0018	-0.0046
	(0.0024)	(0.0012)	(0.0008)	(0.0229)	(0.0131)	(0.0111)
Average	0.176***	0.0177*	0.00879	0.435***	-0.123	-0.0545
	(0.0169)	(0.0099)	(0.0063)	(0.1536)	(0.1140)	(0.0917)
Con Vars	YES	YES	YES	YES	YES	YES
Product-Year FE	YES	YES	YES	YES	YES	YES
Firm FE		YES			YES	
Firm-Product FE			YES			YES
Observation	78880	78294	71848	26648	26184	23299
R2	0.393	0.674	0.892	0.0444	0.472	0.740

Notes: All variables except SD are logarithmic. Dispersion of input quality is captured by the standard deviation (SD) of all input qualities. Output quality is measured by price or estimated as demand residual using estimates of Soderbery (2015). Input and output are matched based on IO table. The control variables contain the number of inputs and firm productivity. Standard errors are clustered at the firm level and are shown in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.3 presents the results of using the standard deviation (SD) of all input qualities to capture the dispersion of them. This approach is more stringent compared to the baseline analysis as it takes into account the quality variation of all inputs rather than the relative quality of specific pairs. The negative effects of input quality dispersion, as measured by the standard deviation, are consistent with the baseline findings, particularly when comparing results across firms and when output quality is measured by price. Specifically, a 1-unit increase in the standard deviation of input

quality leads to a 0.006% reduction in product quality.

1.A.3.3 Discussion on Domestic Input Quality

As mentioned in the paper, the omission of domestic input quality in empirical analysis is indeed a limitation that warrants further discussion. If domestic inputs are assumed to be complements to imported inputs, the analysis may underestimate the dispersion of input quality and its impact on output quality, as it fails to capture the full spectrum of input quality. On the other hand, if domestic inputs are substitutes to imported inputs, excluding them could lead to an overestimation of the effect of imported input quality dispersion on output quality, as the firm would not account for the potential substitution between domestic and imported inputs.

Regarding the firm-level purchase data (VARK) available for Chapter 2, I regret that it lacks product quantity information, which prevents the calculation of unit values (proxy for input quality) for each input. However, I have considered the firm's import intensity—defined as the share of import value to total purchase value—and interacted this variable with the dispersion measure. Unfortunately, the interaction term was not statistically significant, suggesting that import intensity does not appear to have a strong differential effect on the relationship between input quality dispersion and output quality in this specification. Nevertheless, I acknowledge the importance of this issue and aim to explore the potential methods for including domestic inputs into the analysis in future work.

CHAPTER 2

THE SPAN OF IN-HOUSE PRODUCTION: INSIGHTS FROM CHINESE AND DANISH FIRMS

Ying Dai
Aarhus University

Abstract

Production entails a continuum of sequential stages, forming a complete production chain through various specialized suppliers. When these stages are distributed across borders via international trade, the concept of Global Value Chains (GVCs) emerges. This paper investigates how firms strategically position themselves and organize their production spans along the GVC (e.g., taking over more production steps within the firm domestically or specializing in only a few stages). In this study, the domestic production span, or the scope of in-house production, is defined as the gap between a firm's upstream purchasing position and downstream selling position. Based on prior research, this paper predicts that the difference between two elasticities—the elasticity of substitution between a firm's outputs and the elasticity of substitution between inputs—is a key factor determining the span of a firm's in-house production. This prediction could imply a competition-driven mechanism in firms' production scope decisions, which is empirically tested using Input-Output data, firm-level accounting data, and trade data from China and Denmark. Findings from both countries robustly suggest that when the demand for a firm's products is more elastic and inputs are relatively less substitutable, firms focus on fewer domestic production stages. Conversely, when inputs are more substitutable and demand is less elastic, firms tend to integrate more production stages.

Keywords: Production Span · Production Position · GVC · Firm-level Analysis.

JEL classification: D22, D23, F61, F02, L22, L23.

2.1 Introduction

The manufacturing process often contains a series of naturally sequenced stages: raw materials are initially processed into basic components, which are then combined with other parts in subsequent stages until they are assembled into final goods in the last step (Baldwin and Venables, 2013). At the same time, international trade in parts and components allows production stages within the supply chain to be allocated across different countries in the most efficient way, distributing value added along the supply chain and evolving the concept of Global Value Chains (GVCs).

This paper focuses on firms' in-house production span, which refers to the range of production stages they choose to undertake within firm in the domestic market. For example, a pizza shop that makes pizza starting production from flour has a broader production span than one that uses pre-made dough. Unlike previous research that has examined participation and positioning at the country level in the GVC context (Hummels, Ishii, and Yi, 2001; Yi, 2003; Johnson and Noguera, 2012; Koopman, Wang, and Wei, 2014), this study aims to explore the factors behind firms' heterogeneous choices regarding their production spans. Understanding how firms position themselves along the GVC has become increasingly critical amid rising geopolitical tensions, supply chain disruptions, and discussions on reshoring and friend-shoring. For policymakers, these questions are closely linked to domestic economic growth and employment.

To investigate this, I assume that the production process is sequential, with each intermediate input corresponding to a specific stage. The gap between a firm's production position (relatively downstream) and its purchasing position (relatively upstream) defines its in-house production span. Notably, a firm's expansion may occur downstream (selling more refined products closer to final goods), upstream (purchasing inputs closer to primary inputs), or in both directions. Intuitively, expanding the scope of production involves a trade-off between the costs of expansion and the potential benefits derived from expansion. On the cost side, expansion entails fixed costs, variable costs such as hiring additional labor and acquiring machinery for the new tasks, and possible inefficiencies arising from producing beyond the firm's core competencies[1]. On the other hand, by undertaking a broader range of production stages, the firm can avoid markups imposed by external suppliers, gain greater control over its supply chain, and, most importantly, capture additional revenue associated with potential market power.

Specifically, a firm's production revenue depends on both the prices of the final

[1]Alternatively, a firm could achieve an expanded production scope through mergers and acquisitions. However, the feasible expansion also follows a similar logic: the total surplus generated by the integrated relationship should exceed the combined surpluses of the arms-length relationship.

products it sells and the intermediate inputs it purchases. Along the value chain, the prices of products generally increase toward downstream stages due to higher value-added. By expanding both upstream and downstream, the firm benefits from selling higher-priced outputs and obtaining intermediate inputs at lower costs. Furthermore, if market competition enables the firm to widen the difference between its selling price and purchasing price, the additional revenue from expansion could possibly outweigh the associated costs, and the two prices are decided by the elasticity of substitution between the firm's outputs and the elasticity of substitution between its inputs. This competition-driven mechanism behind these two elasticities is associated with the concept of *double-marginalization* proposed by Tirole (1988). In sum, the expansion is viable as long as the additional revenue from internal production exceeds the expansion costs, and this incremental revenue is linked to the demand elasticities of both outputs and inputs.

This study builds on the existing literature on firms' vertical integration, particularly drawing from the works of Antràs and Chor (2013) and Alfaro et al. (2019). These studies also emphasize the role of elasticity of substitution between products and find that when the demand elasticity for final goods exceeds the elasticity of substitution across a firm's inputs, the incentive to integrate suppliers increases as the firm moves downstream along the value chain. While this paper draws on this insight, it differs from their studies in several key ways. First, in their models, firms are assumed to be final good producers that determine which input stages to outsource, without altering the final output. In contrast, this study allows firms to expand their scope both upstream (towards suppliers) and downstream (towards customers), with downstream expansion influencing the firm's output mix. Second, previous studies typically analyze firm boundary decisions through the lens of property-rights theory, emphasizing strategic control in vertical integration. This paper, however, shifts focus to competition-driven mechanisms, arguing that the expansion of a firm's production span may be motivated by profitability considerations rather than solely by strategic control. Last, the measurement of the elasticity of substitution between inputs is slightly different from the earlier work: this paper focuses on the elasticity of substitution between different varieties of the same input, and calculates the average elasticity of all inputs, while earlier work measures the elasticity of substitution between different types of inputs.

Inspired by previous work, this study posits that a firm's optimal production span is related to the relative size of the two elasticities it faces: the elasticity of demand for its product and the elasticity of substitution between the inputs the firm purchases. When demand is elastic and inputs are not highly substitutable, the firm tends to specialize in specific stages. However, it expands its span when inputs are sufficiently

substitutable and demand is relatively inelastic. This intuition is tied to market power: in a highly competitive market reflected by both sides of purchasing and selling, a firm is more inclined to specialize in its core production stage. Only when the firm privileges rents from market power will it expand into other activities.

This prediction is empirically tested using Input-Output tables, firm accounting data, and firm-product-level trade data from China and Denmark. The Input-Output (IO) tables allow me to track the position of each industry within the respective countries. To capture the firm's position in the value chain and its span of in-house production along the value chain, I follow the methodology of Chor, Manova, and Yu (2021), merging industry positions with firms' products in the trade data, weighted by trade values. Firm productivity (TFPR) is estimated from the accounting data, and following Alfaro et al. (2019), the two elasticities are measured using estimates from Broda and Weinstein (2006)[2].

The concept of position along the value chain is a cornerstone in international trade and industrial organization research. Its importance is equally recognized in business cycle literature, particularly in studies examining the transmission of shocks through value chains (e.g., Burstein, Kurz, and Tesar (2008); Di Giovanni and Levchenko (2010); Zavacka et al. (2012); Carvalho (2014)). The modified *position* index in this work is derived from the upstreamness measure introduced by Fally (2012) and Antràs, Chor, Fally, and Hillberry (2012), and the downstreamness concept developed by Miller and Temurshoev (2017). Furthermore, these two well-established indicators from existing studies are the basis of the newly introduced *length* index of the value chain, providing a novel perspective for analyzing value chain structures.

I first present some stylized facts concerning production patterns in China and Denmark at the aggregate level. Although the positions of specific manufacturing industries differ between the two countries, the overall trade patterns for manufacturing share some similarities: in both countries, exports are positioned relatively downstream compared to imports. The subsequent empirical analysis reveals firm behavior regarding production scope, showing that a larger difference between the elasticity of demand and the elasticity of substitution across inputs (stages) reduces the firm's incentive to internalize more tasks domestically. As a result, firms tend to specialize in specific tasks, exhibiting a shorter production span. Additionally, Denmark's comprehensive datasets on firms' total sales and purchases[3] provide a more complete view of their overall production decisions, offering stronger evidence by including all economic activities, not just trade.

[2] I also use the elasticity of substitution estimates from Soderbery (2015) for robustness checks, and the results are shown in the Appendix. The results remain robust and barely change for both countries.

[3] The data includes both domestic and foreign markets but does not distinguish between domestic and foreign products.

Apart from the two studies already mentioned (Antràs and Chor, 2013; Alfaro et al., 2019), related research on the property-rights approach to vertical integration includes Grossman and Hart (1986), which emphasizes the costs arising from misaligned incentives under vertical integration. Similarly, the transaction-cost approach to vertical integration has been explored by Klein, Crawford, and Alchian (1978) and Williamson (1981), highlighting the trade-offs associated with contracting versus internalizing production stages. Another closely related study by Fally and Hillberry (2018) investigates how firm-level behavior within supply chains influences a country's overall production dynamics. Their theoretical model examines how transaction and coordination costs determine the scope of a firm's activities and, consequently, a country's comparative advantage along and across these chains.

This research also contributes to research on vertical fragmentation and global value chains (e.g., Hummels et al. (2001); Yi (2003); Wang, Wei, Yu, and Zhu (2017a); Wang, Wei, Yu, and Zhu (2017b)). It builds on the assumptions of Baldwin and Venables (2013), Antràs and Chor (2013), and Tyazhelnikov (2022), who highlight the importance of sequential technology in production. These studies have developed methodologies to estimate industry positions along the value chain, enhancing our understanding of GVC structure and identifying which industries are more upstream, providing primary inputs, and which are more downstream, closer to final goods production. Collectively, all these foundational works have laid the groundwork for this paper.

One of the closely related studies on a firm's span of in-house production along the value chain is by Chor et al. (2021), who use Chinese data and find that as firms become more productive over their lifecycle, they tend to internalize more stages of production within the firm. In other words, more productive firms expand from a few specialized stages to a more integrated approach in China. However, my replication study using Danish data reveals a different trend: Danish firms do not exhibit the same tendency to expand their in-house production stages as they become more productive. This discrepancy suggests that there are factors unique to the two countries that determine firms' choices. However, this paper aims to explore the potential existence of a universal factor influencing decisions regarding the production span.

Apart from data accessibility, choosing China and Denmark as the sample countries in this study is motivated by their significant but distinct roles in GVCs: China's prominence as a manufacturing hub and Denmark's focus on high-tech sectors reflect differing economic structures. China, as a competitive emerging economy, offers insights into industrializing contexts, while Denmark's status as a developed, open economy provides a contrasting perspective. Consequently, examining a factor that explains firms' in-house production spans across these diverse economic

environments highlights its robustness and generalizability.

The remainder of the paper is organized as follows: Section 2.2 outlines the methodology for measuring the production position along the GVC. Section 2.3 presents the data and stylized facts for China and Denmark. Section 2.4 proposes predictions based on prior research and provides the empirical analysis. Lastly, Section 2.5 concludes.

2.2 GVC Structure

This section outlines the indicators that measure a firm's position and production span within the Global Value Chain (GVC). To obtain firm-level results, I first calculate the positions of industries in the GVC using Input-Output tables. Based on the positions of industries and the allocation of products to industries, I calculate the positions of firms by aggregating the positions of their product mix from both purchases and sales (or imports and exports). The position index considers both upstreamness (constructed by Antràs et al. (2012) and Fally (2012)) and downstreamness (proposed by Miller and Temurshoev (2017) and Antràs and Chor (2018)). Specifically, I define the position index as the logarithm of the ratio of downstreamness to upstreamness.

2.2.1 Industry Upstreamness

From the perspective of use, the total output of a sector can be classified into two categories: intermediate outputs, which are used as inputs in other industries, and final goods, which are directly consumed by consumers. Therefore, the total use of sector i (Y_i) is the sum of all intermediate outputs (Z_{ij}) from sector i to each sector j (including sector i itself), plus the output consumed as final goods (F_i). The relationship between industries is captured by the direct requirements coefficient d_{ij} from the Input-Output table, which expands the total output equation as shown in Equation (2.2.1).

$$\begin{aligned} Y_i = F_i + Z_{ij} = F_i + \sum_{j=1}^{N} d_{ij} Y_j \\ = F_i + \sum_{j=1}^{N} d_{ij} F_j + \sum_{j=1}^{N}\sum_{k=1}^{N} d_{ik} d_{kj} F_j + \sum_{j=1}^{N}\sum_{k=1}^{N}\sum_{l=1}^{N} d_{il} d_{lk} d_{kj} F_j + \ldots \end{aligned} \tag{2.2.1}$$

The interconnections between sectors can be leveraged to calculate the number of production steps required for a sector's output to become a final good, thereby

deriving the concept of upstreamness. The weighted average upstreamness of an industry's output can be computed by multiplying each term by its distance from final use plus one and dividing by Y_i. For instance, if sector i's output is directly consumed as final goods, it is assigned a weight of 1, and if it is used as intermediates for industry j's final consumption, it is weighted as 2, and so on.

$$Up_i = 1 \cdot \frac{F_i}{Y_i} + 2 \cdot \frac{\sum_{j=1}^{N} d_{ij} F_j}{Y_i} + 3 \cdot \frac{\sum_{j=1}^{N} \sum_{k=1}^{N} d_{ik} d_{kj} F_j}{Y_i} + 4 \cdot \frac{\sum_{j=1}^{N} \sum_{k=1}^{N} \sum_{l=1}^{N} d_{il} d_{lk} d_{kj} F_j}{Y_i} + \ldots \tag{2.2.2}$$

The numerator described above corresponds exactly to the i-th entry of $[I-D]^{-2}F$, where D is an N × N matrix with the (i, j)-th element as d_{ij}, and F is a column matrix with F_i in row i. The denominator, $Y_i = [I-D]^{-1}F$, and $[I-D]^{-1}$ is the so-called Leontief inverse matrix. The upstreamness in the equation reflects the total number of forward linkages in a given industry, measuring the distance of an industry's output to final demand. A higher value of upstreamness indicates that the industry is closer to raw material production and more likely to serve as an input in the production processes of other industries.

2.2.2 Industry Downstreamness

An alternative method for measuring an industry's position in the value chain is to examine the inputs used by the industry. The total inputs (Y_i) of industry i also contain two components: intermediate inputs (Z_{ji}) purchased from other industries j (including i itself), and the value added (VA_i) in sector i. By exploiting the output coefficient b_{ij}, which represents the share of industry j's output used in the production of industry i, Equation (2.2.3) can be expanded:

$$\begin{aligned} Y_i &= VA_i + Z_{ji} = VA_i + \sum_{j=1}^{N} b_{ij} Y_j \\ &= VA_i + \sum_{j=1}^{N} b_{ij} VA_j + \sum_{j=1}^{N} \sum_{k=1}^{N} b_{ik} b_{kj} VA_j + \sum_{j=1}^{N} \sum_{k=1}^{N} \sum_{l=1}^{N} b_{il} b_{lk} b_{kj} VA_j + \ldots \end{aligned} \tag{2.2.3}$$

Comparing Equation (2.2.3) with Equation (2.2.1), downstreamness can be viewed as the flipped side upstreamness. Using a similar approach to the construction of upstreamness, Miller and Temurshoev (2017) propose that the weighted average

downstreamness of an industry's inputs can be calculated by multiplying each term by its distance from primary inputs, plus one, and then dividing by the total inputs of the industry.

$$Down_i = 1 \cdot \frac{VA_i}{Y_i} + 2 \cdot \frac{\sum_{j=1}^{N} b_{ij} VA_j}{Y_i} + 3 \cdot \frac{\sum_{j=1}^{N} \sum_{k=1}^{N} b_{ik} b_{kj} VA_j}{Y_i} + 4 \cdot \frac{\sum_{j=1}^{N} \sum_{k=1}^{N} \sum_{l=1}^{N} b_{il} b_{lk} b_{kj} VA_j}{Y_i} + \ldots \tag{2.2.4}$$

The main difference between Equation (2.2.4) and Equation (2.2.2) is that each term in Equation (2.2.4) represents how far inputs are from being primary factors, rather than their distance from final goods. The total input shares are multiplied by $[I-B]^{-2}VA$. The denominator, $Y_i = [I-B]^{-1}VA_i$, and $[I-B]^{-1}$ is the Ghosh inverse matrix, which serves as the input counterpart to the Leontief inverse. In this context, downstreamness can be interpreted as the number of backward linkages, and a high downstreamness value indicates that the industry is far from primary inputs (or close to final goods) and is rarely used as an intermediate input in other industries.

In summary, upstreamness and downstreamness measure an industry's "average distance from final output users" and "average distance from primary input suppliers", respectively. In other words, upstreamness focuses on the output supply chain, while downstreamness considers the input demand chain. Both perspectives are essential to understanding the entire production process. Miller and Temurshoev (2017) highlight that the gross-output weighted average upstream value across all industries within a country is exactly equal to the corresponding gross-output weighted average downstream value. To account for open-economy dynamics and net inventories, I follow the methodology of Antràs et al. (2012), adjusting d_{ij} by $\frac{Y_i}{Y_i - X_i + M_i - NI_i}$, where X_i and M_i are total exports and imports of industry i respectively, and NI_i is the net change in inventories. This adjustment ensures that the measure reflects the share of domestic output from industry i used by industry j as an input, regardless of whether industry j is domestic or foreign. Additionally, this adjustment accounts for inputs derived from past inventories.

2.2.3 Industry Position and Length of Value Chain

As previously discussed, upstreamness and downstreamness quantify an industry's position in the value chain from different perspectives. Output upstreamness refers to the distance an industry's outputs are from becoming final goods, while input downstreamness captures how far an industry's inputs are from being value-added inputs. For example, if an industry, such as construction, relies on inputs that have

passed through many production stages before entering the construction industry, it is considered a relatively downstream industry. On the other hand, if it is a sector, such as oil and coal mining, where its outputs are primarily used as intermediate inputs in other industries, then it is classified as occupying a relatively upstream position in the value chain.

Based on this concept, measuring an industry's position in the value chain by relying on only one of these two indicators can be problematic as supply chains vary in length. Two industries with identical upstreamness may differ significantly in downstreamness, and vice versa. For example, in Figure 2.1, industry A and industry B are involved in two different value chains, and both of them have an upstreamness of 2, indicating they are two steps away from the final goods. However, industry A has a downstreamness of 4, meaning it is four steps away from the value-added input, whereas industry B has a downstreamness of only 1 step. Clearly, industry A is relatively downstream in the value chain it is involved in, while industry B is relatively upstream in the chain it is engaged in. Considering only upstreamness could lead to the mistaken conclusion that these two industries have the same position in the value chains. Hence, comparing the positions of different industries requires taking both upstreamness and downstreamness into account to provide an accurate assessment.

To address this issue, I define a position index, $GVC_{position}$, and calculate the position of industry i as the logarithm of the ratio of downstreamness to upstreamness. This GVC position index compares the relative strength of these two dimensions, with a larger value indicating a relatively downstream industry. By taking the logarithm, a positive index signifies that the backward linkage (downstreamness) exceeds the forward linkage (upstreamness), positioning the industry downstream in the value chain. Conversely, a negative value indicates the industry is located upstream. Compared to previous studies that consider only upstreamness or downstreamness, including both measures provides a more precise assessment of an industry's position.

$$GVC_{position,i} = log(\frac{Down_i}{Up_i}). \tag{2.2.5}$$

Another example of value chain length differences is the contrast between service industries and certain manufacturing sectors. Services typically involve few stages, with consumption occurring immediately after production, resulting in low upstreamness, low downstreamness, and a short overall value chain. In contrast, the production of some intermediate manufacturing inputs—such as paper, automobile tires, bricks, and cotton—exhibits higher upstreamness and downstreamness, reflecting longer value chains with more extensive forward and backward linkages. To capture this variation, I define an industry's value chain length as the sum of its upstreamness and downstreamness, emphasizing the importance of evaluating both

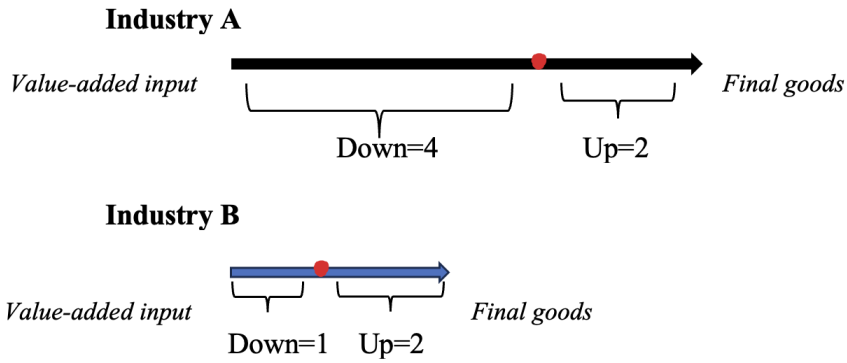


Figure 2.1: Definition of Position Index

Note: The arrow indicates the production process, moving from value-added inputs to final goods. The red dot represents the industry's position. The distance from the industry to the value-added input reflects its downstreamness, while the distance from the industry to the final goods reflects its upstreamness.

to better understand an industry's role in the value chain.

$$GVC_{length,i} = Up_i + Down_i. \tag{2.2.6}$$

2.2.4 Span of Firm's In-house Production

Next, following the approach of Chor et al. (2021), I link firms' products in trade data with industry positions calculated from Input-Output (IO) tables. The highly detailed and disaggregated classifications in the IO tables for both countries allow the industry's position to closely reflect the position of the product. Consequently, the weighted-average position of a firm's imports and exports in the value chain, along with its span of in-house production in the chain within the domestic market, are computed as follows.

$$Pos^M_{ft} = \sum_{i=1}^{N} \frac{M_{fit}}{M_{ft}} GVC_{position,i} \qquad Pos^X_{ft} = \sum_{i=1}^{N} \frac{X_{fit}}{X_{ft}} GVC_{position,i},$$
$$Span_{ft} = Pos^X_{ft} - Pos^M_{ft}. \tag{2.2.7}$$

In Equation (2.2.7), M_{fit} represents the import value of product i for firm f, while $GVC_{position,i}$ indicates the industry position of product i, calculated using Equation (2.2.5). Similarly, X_{fit} represents the export value of product i for firm f. These variables in Equation (2.2.7) aim to capture the extent of a firm's participation in domestic production processes, despite lacking detailed information on the firm's

structure—such as whether it has affiliates in other countries or is an establishment of a foreign headquarters.

By aggregating the calculations to the firm level, we can estimate the firm's import and export positions in the value chain. Specifically, Pos^M_{ft} represents the average position of intermediate inputs imported by the firm, while Pos^X_{ft} can be seen as the average position of finished goods exported by the firm. For firms that engage in both importing and exporting, the difference between these two positions, $Pos^X_{ft} - Pos^M_{ft}$, captures the range of the firm's position from global sourcing to global sales, reflecting the firm's span of in-house production within the GVC context.

In Chor et al. (2021)'s study, they focus solely on Chinese firms' trade data rather than overall purchases and sales. However, complete purchase and sale data for Danish companies are available. I also estimate the firm's span using this more comprehensive dataset, with results presented in Section 2.4. As explained by Chor et al. (2021), although this approach does not account for the possibility of outsourcing to domestic suppliers for firms in both countries, it still provides valuable insights into the firm's internal production activities within the domestic market.

2.3 Data and Stylized Facts

In this section, I document the data sources for both countries and present stylized facts about production patterns in China and Denmark at both the macro level (industry and country) and the micro level (firm). In particular, this study focuses solely on the production choices of manufacturing firms, excluding wholesalers and retailers, and firms in other industries for both countries. Apart from the availability and quality of data, there are several reasons for analyzing and comparing manufacturing firms' production behaviors in Denmark and China.

First, it offers valuable insights into GVCs due to their distinct institutional contexts and levels of economic development. Denmark, as a high-income, market-oriented economy, exemplifies advanced, open economies with a focus on innovation and high-tech industries, often leading to specialized manufacturing processes within GVCs. In contrast, China, a rapidly industrializing economy and major manufacturing hub, provides insights into how emerging economies scale up production and integrate into global networks, resulting in more extensive and diverse value chains.

Furthermore, different macroeconomic environments between Denmark and China also contribute to distinct patterns in firm positioning within the GVC. Danish firms typically focus on high-value-added activities and maintain a shorter, more specialized production scope within Denmark. Conversely, Chinese firms, given the

country's expansive industrial base and focus on competitive manufacturing, may engage in broader, more integrated production processes within the country. All these differences highlight the importance of examining firms' production strategies and GVC positioning in different countries.

2.3.1 Data

2.3.1.1 Firm and Trade Data

For Chinese firms, the accounting dataset is sourced from the Annual Survey of Industrial Firms (ASIF) conducted by China's National Bureau of Statistics, covering the period from 2000 to 2007. This survey includes all state-owned enterprises, regardless of size, and private firms with annual sales exceeding 5 million Chinese Yuan[4], providing detailed information typically found in firm balance sheets. Chinese trade dataset is obtained from the Chinese Customs Trade Statistics (CCTS), including all international trade transactions from 2000. This dataset records firm-level export and import values in US dollars, disaggregated by HS 6-digit product, firm ownership type, and trade regime. To address the seasonality and lumpiness of monthly trade flows, the data are aggregated to an annual level. Firm accounting data and trade data can be linked using a unique firm identifier in China. The final merged dataset covers the period from 2000 to 2007.

Danish firm-level data come from Statistics Denmark, which includes information on firms' economic activities, such as size, total sales, revenue, and typical balance sheet items, all recorded in Danish kroner. This dataset is matched with detailed trade data from Danish customs by the unique firm identifier (CVRNR). The trade dataset provides comprehensive coverage of each firm's imports and exports at a detailed HS-8 product level starting from 2000[5]. It captures product values, units, and quantities. The final merged dataset for regression in Denmark covers the period from 2000 to 2016. Again, as this study focuses on the production patterns of manufacturing firms, firms in other sectors are excluded in both Denmark and China.

2.3.1.2 Sale and Purchase Data

Moreover, comprehensive purchase and sales data are available for Danish firms, which I use to provide supplementary evidence supporting the conjectures in this paper. The purchases dataset (VARK) contains detailed information on Danish manufacturing firms' purchases of raw materials, semi-manufactured products, interme-

[4]This is equivalent to 0.5 million EUR, based on the bilateral exchange rate in 2007.

[5]Although the original trade data begin in 1993, this study only includes samples from 2000 onward due to data quality concerns before 2000 and to maintain consistency in comparison with China.

diary goods, packaging, and services at the HS-4 digit level, for firms with more than 50 employees, regardless of whether the inputs are domestic or imported.

The sales dataset (VARS) records manufacturers' sales of goods by volume and value, classified by the international classification of Combined Nomenclature (CN) at the eight-digit level. This dataset includes all manufacturing firms with at least 10 employees and covers over 90% of Danish manufacturing turnover, accounting for both domestic and export sales. All values are recorded in current prices, excluding VAT, in Danish kroner. However, it is not possible to distinguish between domestic and foreign markets for products in the sales and purchase datasets. The datasets are matched using unique firm identifiers, and after merging with other data sources, the final sample includes manufacturing firms with more than 50 employees from 2000 to 2016.

2.3.1.3 Input-Output Table

The Chinese Input-Output (IO) table for 2007 is provided by the Chinese National Bureau of Statistics (NBS), while the Danish IO table for 2007 comes from Statistics Denmark. An IO table models the structure of an economy by detailing how industries acquire their inputs (either intermediate inputs or value-added) and utilize their output (either as inputs to other industries or for final consumption). The Chinese IO table covers 135 goods and services industries, and the Danish IO table includes 117 industries. These detailed datasets form the basis for computing the position of each industry, which serves as the foundation for measuring firms' production spans in this paper. To derive firm-level measures and investigate firms' strategic decisions, the industry position results are merged with firm-level accounting and trade (purchase and sales) data.

2.3.2 Industry-level Facts

In this subsection, I first use the IO tables for Denmark and China to calculate each industry's GVC position index according to Equation (2.2.5). As discussed earlier, this paper particularly focuses on the production patterns of manufacturing firms, thus, this section limits the analysis to the manufacturing sector to maintain consistency with the subsequent empirical analysis. However, results for all sectors are also presented in the Appendix.

2.3.2.1 Industry Facts - China

Table 2.1 lists the top 10 manufacturing industries in China with the smallest and largest position values. To recall the definition of the position index in Section 2.2: it

Table 2.1: Position of Manufacturing in China

Top 10 upstream industries	**Top 10 downstream industries**
Scrap waste	Convenience food manufacturing
Coking	Communications equipment manufacturing
Basic chemical raw materials manufacturing	Liquid milk and dairy products manufacturing
Steel making	Other food manufacturing
Petroleum and nuclear fuel processing	Other special equipment manufacturing
Iron	Home audio-visual equipment manufacturing
Ferroalloy smelting	Lifting and transport equipment
Nonferrous metal smelting and alloy manufacturing	Household electrical and non-electrical appliance
Chemical fiber manufacturing	Special machinery for agriculture, forestry, animal husbandry and fishery
Paper and paper products	Radar and broadcasting equipment

Notes: This table only contains manufacturing industries in China. The position of an industry is calculated using the position index from Equation (2.2.5), which is defined as the logarithm of the ratio of downstreamness (calculated from Equation (2.2.4)) to upstreamness (calculated from Equation (2.2.2)). The left column lists the top 10 industries with the smallest position index (in ascending order), indicating that these industries are the most upstream in the value chain. Similarly, the right column presents the top 10 industries with the largest position index (in descending order), identifying them as the most downstream in the value chain.

is the logarithm of the ratio of downstreamness (calculated from Equation (2.2.4)) to upstreamness (calculated from Equation (2.2.2)), so a greater value of this index indicates that the industry is relatively closer to the downstream end of the value chain. Therefore, the left column of Table 2.1 refers to the top 10 relatively upstream sectors, while the right column lists the top 10 relatively downstream industries. Consistent with common intuition, the most upstream industries are raw materials and primarily serve as intermediate inputs for production in other industries (e.g., chemical raw materials, metal, petroleum, etc.), while the most downstream industries consist of final outputs and are rarely used as intermediate inputs for other industries (e.g., sophisticated machinery and transport equipment).

In Section 2.2, I define the length of a value chain as the overall linkages (both forward and backward) of the industry within that chain. Based on Equation (2.2.6), Table 2.2 calculates and reports the top 10 shortest and longest production chains in which manufacturing industries are involved. Notably, industries associated with shorter chains in China are primarily concentrated in food production, suggesting that their inputs are higher value-added activities or their outputs are consumed as final goods, resulting in low rankings for both upstreamness and downstreamness.

Table 2.2: Length of Value Chains in China - Manufacturing

Shortest 10 industries (ascending)	**Longest 10 industries (descending)**
Tobacco products	Chemical fiber manufacturing
Convenient food manufacturing	Basic chemical raw material manufacturing
Other food manufacturing	Special chemical product manufacturing
Liquid milk and dairy products	Nonferrous metal smelting and alloy manufacturing
Other food processing	Knitwear, knitted goods and products manufacturing
Condiments and fermented products	Cotton, chemical fiber textile and printing and dyeing finishing
Slaughterhouse and meat processing	Coatings, inks, pigments and similar products
Alcohol and wine	Iron making
Grain milling	Synthetic materials manufacturing
Aquatic product processing	Coking

Notes: This table only contains manufacturing industries in China. The length of the value chain is calculated based on Equation (2.2.6), as the sum of upstreamness (calculated from Equation (2.2.2)) and downstreamness (calculated from Equation (2.2.4)).

In contrast, industries involved in the longest chains are mainly high-value-added intermediate inputs, such as metal production and chemical manufacturing, typically receive inputs that have already been through multiple stages of production, and their outputs pass through numerous stages before reaching final consumption. These industries are characterized by both high upstreamness and downstreamness and are generally positioned in the middle of complex GVCs.

2.3.2.2 Industry Facts - Denmark

Table 2.3 and Table 2.4 exhibit the corresponding results for industry position and value chain length in Denmark. The most upstream manufacturing industries in Denmark primarily involve the production of raw materials and basic intermediates, such as wood, concrete, and metal, which serve as inputs for other industries. In contrast, the downstream industries are concentrated in consumer goods and transport equipment, such as footwear, furniture, food and beverages, and shipbuilding. Although the specific upstream and downstream manufacturing industries vary between the two countries due to differences in industrial structure and economic environment, the overall trend aligns with the GVC structure: upstream sectors are mainly inputs used in other industries, while downstream sectors typically produce final goods for consumption.

Table 2.3: Position of Manufacturing in Denmark

Top 10 upstream industries	Top 10 downstream industries
Printing etc.	Manufacture of leather and footwear
Repair and installation of machinery and equipment	Manufacture of ships and other transport equipment
Manufacture of paper and paper products	Production of meat and meat products
Manufacture of rubber and plastic products	Manufacture of dairy products
Manufacture of fabricated metal products	Manufacture of wearing apparel
Manufacture of concrete and bricks	Manufacture of furniture
Manufacture of basic metals	Manufacture of beverages
Manufacture of wood and wood products	Manufacture of grain mill and bakery products
Manufacture of wires and cables	Pharmaceuticals
Manufacture of computers and communication equipment etc.	Manufacture of toys and other manufacturing

Notes: This table only contains manufacturing industries in Denmark. The position of an industry is calculated using the position index from Equation (2.2.5), which is defined as the logarithm of the ratio of downstreamness (calculated from Equation (2.2.4)) to upstreamness (calculated from Equation (2.2.2)). The left column lists the top 10 industries with the smallest position index (in ascending order), indicating that these industries are the most upstream in the value chain. Similarly, the right column presents the top 10 industries with the largest position index (in descending order), identifying them as the most downstream in the value chain.

Compared to China, the top 10 industries associated with the shortest production chains in Denmark include a mix of consumer-focused manufacturing (e.g., apparel, furniture, and footwear) and capital goods (e.g., ships and transport equipment). This suggests that these industries involve fewer production steps, resulting in shorter value chains. Similar to China, although the specific industries differ, the top 10 industries involved in the longest value chains in Denmark are also intermediate inputs typically located in the middle of complex global value chains—such as paper, meat, dairy products, concrete, and bricks— characterized by both large upstreamness and downstreamness.

2.3.3 Country-level Facts

Next, I link the industry positions to firms' trade data using Equation (2.2.7), obtaining firm-level positions for both export and import activities. To aggregate these results at the country level, Equation (2.3.1) calculates the positions of all manufacturing firms engaged in exporting or importing, weighted by each firm's share of the total exports or imports within the country for each year. This method enables the calculation of the weighted average position of manufacturing exports and imports at the country level.

Table 2.4: Length of Value Chains in Denmark - Manufacturing

Shortest 10 industries (ascending)	**Longest 10 industries (descending)**
Manufacture of medical instruments, etc.	Printing etc.
Manufacture of leather and footwear	Manufacture of dairy products
Manufacture of toys and other manufacturing	Production of meat and meat products
Manufacture of wearing apparel	Repair and installation of machinery and equipment
Manufacture of furniture	Manufacture of paper and paper products
Manufacture of other electronic products	Manufacture of fabricated metal products
Manufacture of tobacco products	Manufacture of concrete and bricks
Manufacture of ships and other transport equipment	Other manufacture of food products
Pharmaceuticals	Manufacture of wood and wood products
Manufacture of other machinery	Oil refinery etc.

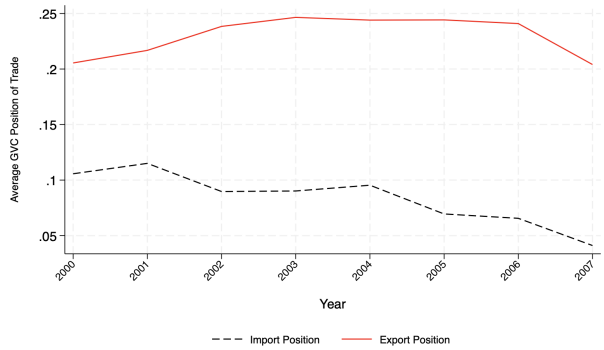
Notes: This table only contains manufacturing industries in Denmark. The length of the value chain is calculated based on Equation (2.2.6), as the sum of upstreamness (calculated from Equation (2.2.2)) and downstreamness (calculated from Equation (2.2.4)).

$$Pos^{M}_{\text{Country},t} = \sum_{f} \frac{M_{ft}}{M_t} Pos^{M}_{ft}, \text{ and } \quad Pos^{X}_{\text{Country},t} = \sum_{f} \frac{X_{ft}}{X_t} Pos^{X}_{ft}. \tag{2.3.1}$$

2.3.3.1 Position of Trade

Figure 2.2 illustrates the results computed from Equation (2.3.1), exhibiting the average positions of exports and imports in China and Denmark over time. As mentioned when constructing Equation (2.3.1), the import and export indexes are calculated for, respectively, all manufacturing firms that import and all manufacturing companies that export. Both panels demonstrate that exports in China and Denmark have consistently been positioned further downstream than imports, reflecting that manufacturing firms in both countries generally import products closer to raw materials and export products closer to final goods to meet global consumption demands. Additionally, the position of imports in both countries has moved upstream over time. While the position of Danish exports remains stable throughout the sample period, Chinese exports show a slight downstream shift beginning in 2001.

When comparing the magnitude of trade positions between the two countries (as shown by the values on the vertical axis), China's positions (positive) are generally higher than Denmark's (negative). According to the definition of the position index, which is the logarithm of the ratio of downstreamness to upstreamness, this indi-



(a) Trade Position in China



(b) Trade Position in Denmark

Figure 2.2: Import and Export Position along the Value Chain in China and Denmark

Note: This table only contains manufacturing industries in both China and Denmark. The trade position at the country level is calculated based on Equation (2.3.1), and aggregates the position of industries associated with all manufacturing firms' exports and imports in China and Denmark, respectively. The position of an industry is calculated using the position index from Equation (2.2.5).

cates that the average trade position of China is relatively downstream based on the Chinese IO table, while Denmark's trade position is relatively upstream based on the Danish IO table. This difference could be due to firms in the two countries specializing in different types of industries and products. For instance, the data shows that Denmark's export-intensive industries focus on meat, leather, footwear, and dairy, while its import-intensive industries are centered on food and mineral products. In contrast, China's export-intensive products include transport equipment, machinery, and textiles, while it primarily imports footwear, wood, and leather.

However, directly comparing the values on the vertical axis between the two countries is not rigorous for two reasons. First, the industry classifications in the IO tables differ between the two countries. The Chinese IO table includes 135 industries,

while Denmark's includes 117, and the classifications are not identical. Second, the production structures in the two countries may vary significantly. Even for the same product, differences in production steps[6], sectoral interconnections, and the use of intermediate inputs can lead to variations between the two countries. Therefore, for the sake of rigor, I refrain from directly comparing the exact values between the countries. However, it is possible to compare the general trends within each country, such as the relative positions of their exports and imports.

2.3.3.2 Length of Trade

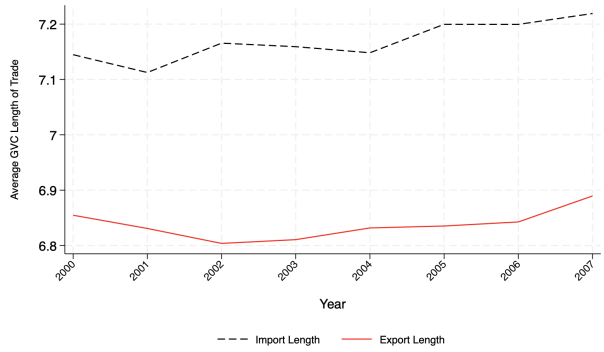
In a similar analysis, by substituting the position index in Equation (2.2.7) and Equation (2.3.1) with the length of the value chain, we can depict the export and import lengths at the country level. Figure 2.3(a) indicates that, throughout the sample period, China's import length (around 7.15 steps) has consistently exceeded its export length (around 6.85 steps). This suggests that China tends to export products associated with relatively shorter supply chains while importing those involved in longer ones. A similar pattern is observed for Denmark in Figure 2.3(b), where Denmark's import length is also greater than its export length, with the gap widening significantly over time.

Similar to Figure 2.2, the magnitude of the vertical axis in Figure 2.3 differs between the two countries. China's average value chain length is approximately 7 production steps, whereas Denmark's is about 3.4 steps. Moreover, in the data, both upstreamness and downstreamness of industries in China are generally higher compared to those in Denmark. Apart from the different industry classifications in the IO tables, the difference in production steps also highlights distinct production modes in the two countries. Therefore, comparing the exact values on the vertical axis between China and Denmark may lack precision. However, it is feasible to compare lengths within each country and analyze trade trends, such as the relative sizes of export and import lengths in both China and Denmark.

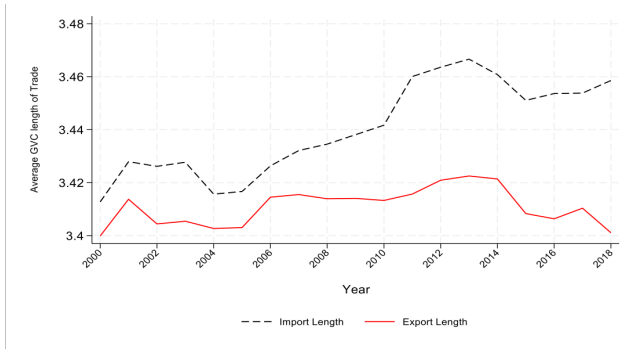
2.3.4 Two-way Trade Firms

In the previous subsection, the import and export indexes consider all manufacturing firms that import and all manufacturing companies that export. In this subsection, I limit the sample to two-way traders, that is, firms that both export and import. The span of a two-way firm's in-house production is calculated using Equation (2.2.7) as

[6]This is also reflected in the data. For example, the average length of value chains in China is approximately 7, while in Denmark it is around 3.4 (see Figure (2.3)). Both upstreamness and downstreamness of industries are generally higher in China compared to Denmark.



(a) Length of Trade in China



(b) Length of Trade in Denmark

Figure 2.3: Import and Export Length along the Value Chain in China and Denmark

Note: This table only contains manufacturing industries in both China and Denmark. The trade length at the country level is calculated based on Equation (2.3.1), but substituting the position index with the length of the value chain. The length of the value chain is computed from Equation (2.2.6).

the difference between its export position and import position in each year. Figure 2.4 depicts the average production span of two-way traders in China. Positive values of the span indicate that firms generally add value to products before exporting, consistent with the typical manufacturing process, different from wholesalers and retailers who operate without production. There is a steady decline before a sharp drop in 2004, reflecting the peak of offshoring from developed countries to China[7]. After this sharp drop, the span surges the following year and then experiences another decline until 2006.

Figure 2.5 displays the in-house production span for two-way trade firms in Denmark. Similar to Chinese firms, a positive span indicates that Danish manufacturing

[7]Which is also observed by IMF (2016), Frankel (2016), and Chor et al. (2021).

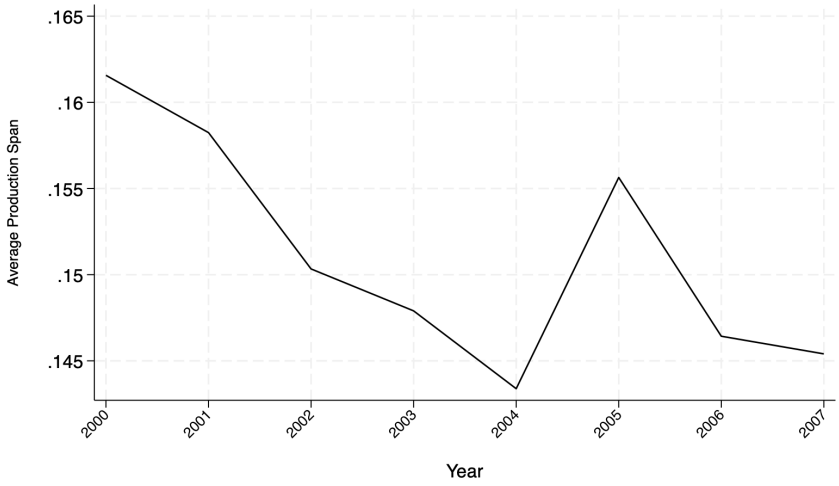


Figure 2.4: In-house Production Span of Two-way Firms in China

Note: The firm's in-house production span is computed based on Equation (2.2.7). The figure displays the average span of all two-way trade firms in China.

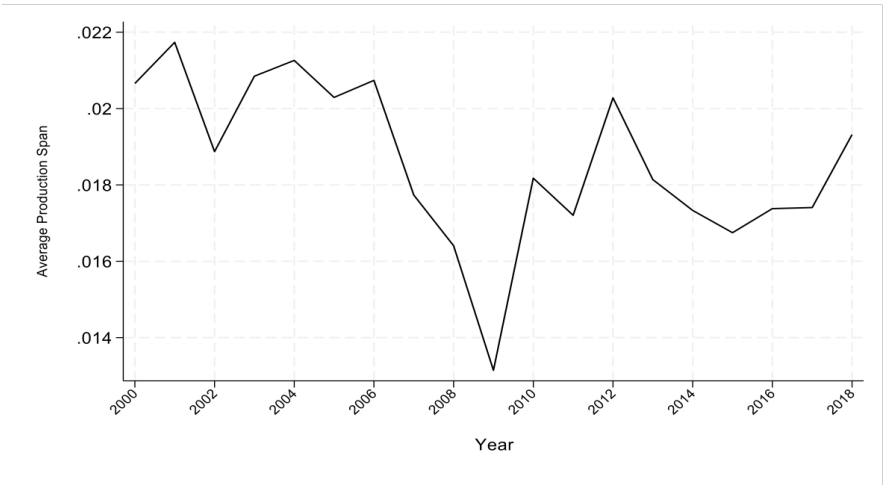


Figure 2.5: In-house Production Span of Two-way Firms in Denmark

Note: The firm's in-house production span is computed based on Equation (2.2.7). The figure displays the average span of all two-way trade firms in Denmark.

firms typically import upstream materials, add value, and export products positioned further downstream in the value chain. Notably, there is a significant drop occurring in 2009, which can be attributed to firms' adjustments during the global financial

crisis: reduced demand and financial constraints forced them to cut in-house production steps, outsource more, or scale back operations to save costs.

In the Appendix, I provide additional graphs showing the position, length, and span of trade for Denmark based on the comprehensive purchases and sales datasets. To align with existing studies (Antràs and Chor, 2013; Alfaro et al., 2019; Chor et al., 2021) that use only upstreamness as the position measure, I also include results for China and Denmark using upstreamness exclusively. This approach ensures comparability and consistency with earlier findings.

2.4 Empirical Analysis

This section proposes a projection based on prior related studies and empirically tests the prediction using data from both China and Denmark. Specifically, inspired by Klein et al. (1978), Williamson (1981), Tirole (1988), Antràs and Chor (2013), Fally and Hillberry (2018), and Alfaro et al. (2019), this paper posits that the difference in elasticities of substitution between a firm's products and the inputs it uses ($\rho - \alpha$) reflects firm's potential rents from market power, thereby is associated with its production span within the firm. As discussed earlier, both China and Denmark play important roles in GVC, yet their institutional contexts and levels of economic development differ significantly, which could contribute to distinct patterns in industry specialization and firms' production in GVC, as displayed in some graphs in Section 2.3. This section examines firms' decisions regarding their in-house production span in these two diverse economies and highlights the robustness and generalizability of the prediction.

2.4.1 Prediction Based on Prior Studies

2.4.1.1 The Elasticity of Substitution

Previous studies (Antràs and Chor, 2013; Alfaro et al., 2019) that also focuses on the role of elasticity of substitution between products have demonstrated that a supplier's marginal return on investment at the current stage is shaped by all investment decisions in prior stages. When the elasticity of substitution between a firm's products is larger than the elasticity of substitution between the inputs it uses ($\rho > \alpha_{AC}$), investment choices are sequential complements. This means that higher investment levels by upstream suppliers increase the marginal return on the supplier's own investment at the current stage. In this case, the firm's incentive to integrate suppliers increases as it moves downstream along the value chain because it generates positive spillovers on the investment of downstream suppliers. Conversely, when $\rho < \alpha_{AC}$, investment

choices are sequential substitutes, and high levels of upstream investment reduce the marginal return on investing at the current stage. In this scenario, the firm is more likely to integrate upstream to capture the rents. Additionally, Antràs and Chor (2013) also find that higher market power, reflected by a decrease of low ρ, will necessarily expand the range of stages that are vertically integrated.

Inspired by these findings, this paper similarly emphasizes the importance of the relative size of these two elasticities, while departing from the existing literature in several key aspects: (1) Elasticity Measurement: while prior studies examine the elasticity of substitution between different types of inputs (α_{AC}), this study focuses on the elasticity of substitution between different varieties of the same input (α). (2) Scope of Expansion: in earlier models, firms are assumed to be final good producers deciding which input stages to outsource without altering their final output. In contrast, this study allows firms to expand their scope both upstream (toward suppliers) and downstream (toward customers), with downstream expansion affecting the firm's output mix. (3) Analytical Lens: most importantly, earlier work approaches firm boundary decisions through the property-rights theory, emphasizing strategic control in vertical integration. This paper shifts the focus to competition-driven mechanisms, arguing that the expansion of a firm's production span may be driven by profitability considerations rather than solely by strategic control.

Although prior studies primarily focus on a firm's integration position, the potential production span can be deduced using similar logic: When a firm's integration moves downstream—when the elasticity of substitution between the firm's products exceeds that between its inputs ($\rho > \alpha_{AC}$)—the maximum possible production scope narrows compared to upstream integration. Conversely, when the firm's integration moves upstream—where the elasticity of substitution between the firm's products is smaller than that of its inputs ($\rho < \alpha_{AC}$)—the largest potential production span expands. This mechanism suggests, to some degree, that the relationship between a firm's in-house production span and these two elasticities aligns with the findings of earlier studies. Additionally, the relationship between ρ and the range of vertically integrated stages identified by Antràs and Chor (2013) aligns with this prediction, albeit primarily from the downstream perspective.

2.4.1.2 Trade-offs and Competition-driven Mechanism

In research that provide theoretical foundation for understanding vertical integration decisions have discussed the trade-offs behind it. For instance, in Klein et al. (1978), vertical integration is optimal when the benefits of mitigating opportunism and ensuring coordination outweigh the bureaucratic and managerial inefficiencies. Similarly, Williamson (1981) formalizes this trade-off in the context of transaction

cost economics. The decision to vertically integrate depends on the magnitude of transaction costs in market exchanges versus the internal organization costs of integration. This analytical approach has also been applied by Fally and Hillberry (2018) and Chor et al. (2021): the firm's production scope is determined by the trade-off between internalizing costs and the gains (or revenue) associated with expanding its production span.

Therefore, another perspective on the relationship between a firm's in-house production span and the two elasticities is informed by the trade-offs highlighted in previous research: A firm will have the incentive to expand its production scope as long as the additional revenue from expansion exceeds the associated costs. Expansion typically involves fixed costs, such as those related to transactions and organizational complexities; variable costs, including hiring additional labor and acquiring machinery for new tasks; and potential inefficiencies arising from operating beyond the firm's core competencies. [8] On the other hand, by internalizing a broader range of production stages, the firm can avoid markups imposed by external suppliers, gain greater control over its supply chain, and, most importantly, capture additional revenue derived from potential market power. This paper specifically emphasizes the latter point—the revenue gains from market power.

Recalling that the production span is defined as the difference between a firm's purchase position and sale position along the value chain. The price of products in the chain generally increases towards downstream stages as value-added accumulates. Consequently, by expanding both upstream and downstream, for instance, a firm benefits from increased revenue by selling higher-priced outputs and acquiring intermediate inputs at lower costs. Moreover, if market power enables the firm further widen the gap between its selling price and purchasing price, the additional revenue from expansion could potentially outweigh the associated costs. These prices, in turn, are determined by the elasticity of substitution between the firm's outputs (ρ) and the elasticity of substitution between its inputs (α).

The market competition captured by these two elasticities is closely related to the concept of *double-marginalization* proposed by Tirole (1988). Double-marginalization occurs in a vertically integrated supply chain where both the upstream supplier and the downstream retailer impose their own markups on the price of a product. This leads to an inefficiently high final price sold than what would be socially optimal. Since each firm maximizes its profit independently, the cumulative effect is a "double" markup. Building on this concept, this study argues that a firm would expand its

[8] Alternatively, instead of producing the additional scope itself, the firm may expand through mergers and acquisitions. However, this approach also entails similar fixed and variable costs associated with such transactions.

production span if it can avoid the upstream supplier's markup by targeting markets with a higher elasticity of substitution for inputs (α), at the same time, apply its own downstream markup to consumers by producing goods with a lower elasticity of substitution (ρ). This combination allows the firm to extract greater monopoly rents from both its purchasing and selling activities. These rents, in turn, offset the high costs of expansion, thereby enabling the firm to achieve a broader in-house production span.

In summary, both strands of prior research support the prediction that the difference between the two elasticities—on the firm's demand side and input side—is linked to the firm's in-house production span. In the next subsection, I will measure the two elasticities and test this prediction using the data.

2.4.2 Estimation Methodology

According to the proposed projection, when the elasticity of substitution across inputs the firm uses (α) is greater than the elasticity of demand for final goods (ρ), the firm has an incentive to internalize more production stages, leading to a wider production span. Conversely, when ρ exceeds α, the firm tends to focus on specific stages of production within the firm. I explore this mechanism using the following regression model:

$$Span_{ft} = \beta_1(\rho_{ft} - \alpha_{ft}) + \beta_2\varphi_{ft} + \beta_3\chi_{ft} + \alpha_{jt} + \alpha_f + \varepsilon_{ft}. \tag{2.4.1}$$

The outcome variable in the regression, $Span_{ft}$, represents the firm's in-house production span within the domestic country, calculated as the difference between the firm's export position and its import position along the value chain (see Equation (2.2.7)). The main explanatory variable is $\rho_{ft} - \alpha_{ft}$, denoting the difference between the elasticity of substitution for the products the firm sells and the elasticity of substitution for the inputs it uses. Drawing on Alfaro et al. (2019), ρ_{ft} and α_{ft} are calculated using the estimated U.S. import demand elasticities from Broda and Weinstein (2006)[9]. Specifically, ρ_{ft} is calculated as the weighted average demand elasticity across all exported products ω within the firm, with weights based on the export share of ω relative to the firm's total exports. α_{ft}, meanwhile, is closely related to the elasticity of demand for intermediate inputs imported by the firm, with weights determined by each input's import share within the firm[10].

[9] I also use estimates from Soderbery (2015) for robustness checks, and the results remain robust, as shown in the Appendix.

[10] As discussed earlier, the the elasticity of substitution between inputs in this study is slightly different from existing papers: in their study measures between different types of inputs (α_{AC}), this study focuses on the elasticity of substitution between different varieties of the same input (α)

φ_{ft} represents the productivity of the firm, estimated as value-added per worker and total factor productivity (TFPR) residuals derived from the Olley-Pakes (OP) and Levinsohn-Petrin (LP) methodologies for each industry. Due to space constraints, I present the results using TFPR-LP in the baseline tables, with the results from the other two methods reported in the Appendix. The control variables χ_{ft} include measures of labor intensity (proxied by average wage) and capital intensity (proxied by fixed assets per employee) to account for differences in the firm's reliance on these factors. Additionally, α_{jt} and α_f represent industry-year fixed effects and firm fixed effects, respectively. These fixed effects control for sector-specific fluctuations and capture both observed and unobserved characteristics unique to each firm. ε_{ft} is the error term in the regression model. Since the variation in explanatory variables is firm-specific, I cluster the standard errors by firm to account for potential correlations in shocks within firms over time.

It should be noted that the calculations for both ρ_{ft} and α_{ft} are derived from the constant elasticity of substitution estimates provided by Broda and Weinstein (2006), which are then linked to the firm's exported and imported products. Consequently, variations in these two elasticities within a firm over time (accounted for by firm fixed effects)[11] reflect changes in its product mix related to export and import activities. Hence, the baseline regression investigates how shifts in the firm's product choices—reflected by changes in $\rho_{ft} - \alpha_{ft}$—affect its in-house production span. For example, if a firm imports only flour to produce pizza dough in one year, but in the following year, it imports flour, beef, and cheese to produce a complete pizza, these changes in inputs and products might be associated with the firm's gains from exporting and importing, as captured by changes in $\rho_{ft} - \alpha_{ft}$. This study explores whether these changes are correlated with the firm's production scope, and if so, in which direction (narrow or expand).

2.4.3 Production Span and Elasticity Difference

Before presenting the regression results, I examine how the average in-house production span and the average difference in elasticities ($\rho_{ft} - \alpha_{ft}$) evolve over time for all two-way trade firms in both China and Denmark. The analysis suggests a negative relationship between these two factors. Specifically, the figures show that as the difference in elasticities ($\rho_{ft} - \alpha_{ft}$) changes, the production span of firms moves in the opposite direction. This pattern is observed in both Chinese firms (Figure 2.6) and Danish firms (Figure 2.7). However, these figures only represent the average trends

[11] To align with Chor et al. (2021) and account for time-invariant firm-level factors, the model includes fixed effects. Additionally, I investigate the effect across firms (without firm fixed effects), and the results regarding the elasticity difference remain robust for both countries.

across all firms. For more robust conclusions, a detailed analysis using the empirical model is required.

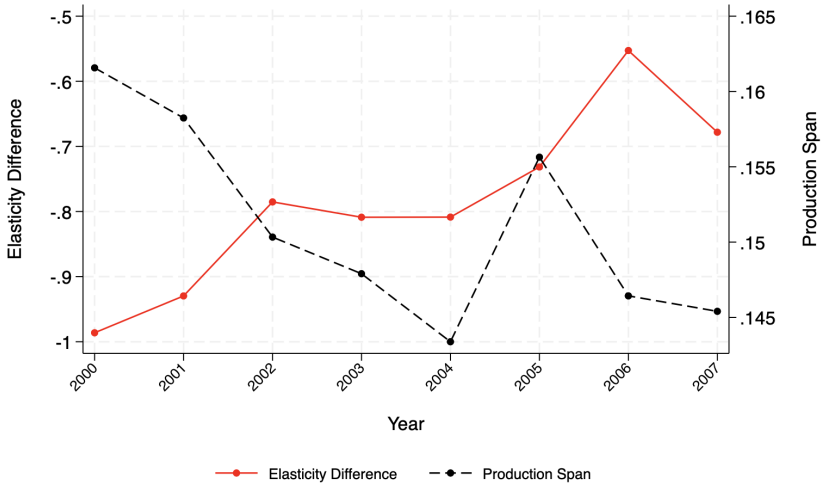


Figure 2.6: Link between In-house Production Span and Elasticity Difference in China

Note: This figure illustrates the average trends over time in the in-house production span (right axis) and the difference between the two elasticities $\rho_{ft} - \alpha_{ft}$ (left axis) for all two-way trade firms in China.

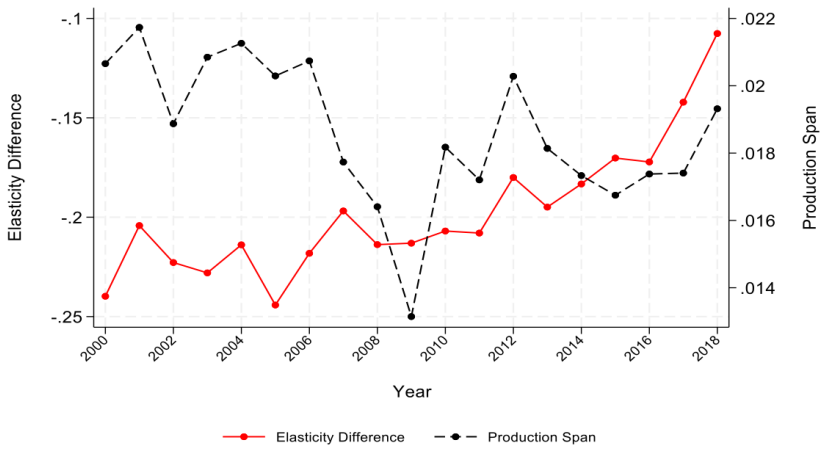


Figure 2.7: Link between In-house Production Span and Elasticity Difference in Denmark

Note: This figure illustrates the average trends over time in the in-house production span (right axis) and the difference between the two elasticities $\rho_{ft} - \alpha_{ft}$ (left axis) for all two-way trade firms in Denmark.

2.4.4 Baseline Results for China and Denmark

Table 2.5 presents the baseline regression results for Chinese firms. The change in the elasticity difference, $\rho_{ft} - \alpha_{ft}$, driven by shifts in the firm's export and import product mix over time, shows a negative correlation with the firm's in-house production span, even after accounting for firm productivity. This finding supports the prediction that when a firm faces high competition for its final products relative to the substitutability of its inputs—that is, when the firm fails to generate rents from market power—it will contract its in-house production span and specialize in fewer stages of production. Column (2), which separates the effects of ρ_{ft} and α_{ft}, further confirms that both elasticities individually influence the firm's production scope.

Table 2.5: In-house Production Span and Elasticity Difference - China

	(1) Span	(2) Span	(3) Import Position	(4) Import Position	(5) Export Position	(6) Export Position
E Difference ($\rho - \alpha$)	-0.0021***		0.0018***		-0.00023	
	(0.0003)		(0.0002)		(0.0002)	
TFPR-LP	0.0043**	0.0043**	-0.0037**	-0.0037**	0.0006	0.00058
	(0.0018)	(0.0018)	(0.0015)	(0.0015)	(0.0010)	(0.0010)
Intermediates Substitution (α)		0.0027***		-0.0028***		-0.00014
		(0.0003)		(0.0003)		(0.0001)
Demand E (ρ)		-0.0011**		0.00022		-0.00084*
		(0.0005)		(0.0002)		(0.0005)
Con Vars	YES	YES	YES	YES	YES	YES
Industry-Year FE	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Observation	125120	125120	125120	125120	125120	125120
R2	0.846	0.846	0.831	0.831	0.952	0.952

Notes: Control variables contain measures of labor intensity (proxied by average wage) and capital intensity (proxied by fixed assets per employee) of the firm. Standard errors are clustered by firm and are shown in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

The effects of the two elasticities on import position (Column (3)) and export position (Column (5)) vary for Chinese firms. The main impact of $\rho_{ft} - \alpha_{ft}$ is observed on the import side, where firms narrow their production span by outsourcing inputs that are further downstream, while their export position remains primarily unchanged. It is important to interpret the results in columns (4) and (6) with caution due to potential mechanical issues. For instance, the findings in column (4) may suggest that more upstream products have higher substitution elasticities, but this could be unrelated

to the firm's production decision. Similarly, the interpretation of ρ on export position in column (6) may also reflect such mechanical effects. However, the other elasticity in these two columns offers informative evidence for testing the prediction, that is, the impact of α on the export position and ρ on the import position. That said, in Table 2.5, neither the effect of ρ on the import side in column (4) nor the effect of α on the export position in column (6) is statistically significant. Additionally, consistent with the findings of Chor et al. (2021), increased productivity over a firm's lifecycle in China leads to an expanded in-house production span, particularly with a significant shift in imports further upstream. These results remain robust and consistent even when alternative estimates of firm productivity are used (see Appendix).

The correlation between the elasticity difference and a firm's in-house production span remains consistent and robust for Danish firms, as shown in Table 2.6, though several differences emerge compared to Chinese firms. First, while the elasticity difference in China primarily influences the import side, in Denmark it affects both export and import positions. Specifically, Danish firms adjust both their outsourcing and export activities in response to changes in the elasticity difference (Columns (3) and (5)). Moreover, a correlation between a firm's import position and its demand elasticity for outputs in Denmark is observed in column (4), yet, no such relationship is found between the export position and the elasticity for inputs in column (6)[12].

Second, in Denmark, increased productivity of the firm is associated with a reduction in in-house production tasks, contrasting with Chinese firms. This opposite result of productivity could be explained by the distinct institutional contexts and levels of economic development between the two countries. Chinese firms benefit from a vast industrial base and lower production costs, leading them to expand their tasks within China as they become more productive. In contrast, Danish firms, which typically specialize in high-value-added activities, are more likely to transfer low-value production tasks that were previously performed domestically to developing countries (i.e., through vertical FDI) to exploit cheaper production costs as they grow.

However, data on firms' establishments and FDI activities are unavailable. To test this prediction for Denmark, I exploit the fact that large firms are typically the ones engaged in vertical FDI. After excluding firms with more than 500 employees, Table 2.7 shows that the effect of firm productivity on its production span disappears, suggesting that firms potentially involved in vertical FDI are the primary drivers of this mechanism. Additionally, Table A.10 in the Appendix provides results for all sample firms in Denmark but calculates their in-house production span based on upstreamness—the measure employed in prior studies. The effect of productivity is

[12] As explained earlier, due to potential mechanical issues, only the impact of α on the export position and ρ on the import position in columns (4) and (6) are considered informative.

Table 2.6: In-house Production Span and Elasticity Difference - Denmark

	(1) Span	(2) Span	(3) Import Position	(4) Import Position	(5) Export Position	(6) Export Position
E Difference ($\rho-\alpha$)	-0.0095***		0.0055***		-0.0040***	
	(0.0019)		(0.0015)		(0.0011)	
TFPR-LP	-0.0035*	-0.0035*	0.0029**	0.0028*	-0.0006	-0.0007
	(0.0021)	(0.0021)	(0.0014)	(0.0015)	(0.0014)	(0.0014)
Intermediates Substitution (α)		0.0072***		-0.0068***		0.00043
		(0.0021)		(0.0021)		(0.0008)
Demand E (ρ)		-0.0138***		0.0032**		-0.0106***
		(0.0030)		(0.0015)		(0.0029)
Con Vars	YES	YES	YES	YES	YES	YES
Industry-Year FE	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Observation	40294	40294	40294	40294	40294	40294
R2	0.624	0.624	0.828	0.828	0.915	0.915

Notes: Control variables contain measures of labor intensity (proxied by average wage) and capital intensity (proxied by fixed assets per employee) of the firm. Standard errors are clustered by firm and are shown in parentheses, * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

no longer significant economically, indicating that the methodology of measuring a firm's position in GVC plays a substantial role in shaping the findings. Moreover, recognizing the endogeneity of productivity, I adopt the same methodology as Chor et al. (2021) to construct the instrumental variable for firm productivity. However, no causal effects are observed. Regardless of whether the correlation relationship or causal effects, the impact of firm productivity on in-house production scope in Denmark does not exhibit the same positive effects observed in China.

2.4.5 Purchase and Sale - Denmark

So far, the analysis has focused on two-way trade firms in China and Denmark—those actively engaged in GVC. However, the mechanism and prediction are not limited to firms' trade behavior and should extend to a broader context of overall production. To test this, I expand the analysis to include firms' overall purchases and sales by leveraging comprehensive datasets from Denmark. Although the data do not differentiate between domestic and foreign products in purchases and sales, it provides a more holistic view—beyond just trade—of firms' in-house production spans within the country. This broader analysis offers more robust evidence to validate the projections

Table 2.7: In-house Production Span and Elasticity Difference - Danish SMEs

	(1) Span	(2) Span	(3) Import Position	(4) Import Position	(5) Export Position	(6) Export Position
E Difference ($\rho-\alpha$)	-0.0101***		0.00612***		-0.004***	
	(0.0020)		(0.0015)		(0.0011)	
TFPR-LP	-0.00297	-0.00301	0.00240	0.00237	-0.00058	-0.00064
	(0.0021)	(0.0021)	(0.0015)	(0.0015)	(0.0015)	(0.0015)
Intermediates Substitution (α)		0.00793***		-0.0075***		0.00041
		(0.0022)		(0.0021)		(0.0009)
Demand E (ρ)		-0.0143***		0.0035**		-0.0108***
		(0.0030)		(0.0015)		(0.0029)
Con Vars	YES	YES	YES	YES	YES	YES
Industry-Year FE	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Observation	39048	39048	39048	39048	39048	39048
R2	0.623	0.623	0.826	0.826	0.914	0.914

Notes: The table excludes large firms potentially involved in vertical FDI by dropping those with more than 500 employees. Control variables contain measures of labor intensity (proxied by average wage) and capital intensity (proxied by fixed assets per employee) of the firm. Standard errors are clustered by firm and are shown in parentheses, * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

regarding the difference in the two elasticities.

Table 2.8 displays the results of the extended analysis. Despite changes in the dataset and the recalculation of the firm's production span based on overall purchases and sales, the effects of the elasticity difference remain consistent with those observed using trade data. An increase in $\rho_{ft}-\alpha_{ft}$ is still associated with a reduction in the firm's in-house production span. Notably, firm productivity no longer affects the decision regarding in-house production span (calculated as the difference between purchase and sale positions). Additionally, the change in production span in response to the elasticity difference is primarily driven by shifts in the purchase position.

2.5 Conclusion

This paper explores one potential factor that influences firms' decisions regarding their in-house production spans along the value chain. The production span is defined as the difference between a firm's export position and import position in the value chain. The analysis begins by calculating the positions of industries in China and Denmark using input-output tables from each country, revealing several stylized

Table 2.8: In-house Production Span and Elasticity Difference - Denmark (Purchase and Sale)

	(1) Span	(2) Span	(3) Purchase Position	(4) Purchase Position	(5) Sale Position	(6) Sale Position
E Difference ($\rho - \alpha$)	-0.0067***		0.0068***		0.00010	
	(0.0019)		(0.0020)		(0.0011)	
TFPR-LP	-0.00099	-0.00100	0.00135	0.00174	0.00037	0.00074
	(0.0028)	(0.0028)	(0.0026)	(0.0026)	(0.0023)	(0.0023)
Intermediates Substitution (α)		0.0067***		-0.0070***		-0.0003
		(0.0019)		(0.0020)		(0.0010)
Demand E (ρ)		-0.00656		0.00214		-0.00442
		(0.0072)		(0.0043)		(0.0074)
Con Vars	YES	YES	YES	YES	YES	YES
Industry-Year FE	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Observation	12806	12806	12806	12806	12806	12806
R2	0.941	0.941	0.942	0.942	0.988	0.988

Notes: The table utilizes the firms' purchases and sales, which include firms' overall buying and selling activities from both domestic and foreign markets. Control variables contain measures of labor intensity (proxied by average wage) and capital intensity (proxied by fixed assets per employee) of the firm. Standard errors are clustered by firm and are shown in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

facts for both countries. Subsequently, building on prior research, the study hypothesizes that a firm's in-house production span may be associated with the elasticities it faces from both demand and input perspectives. Specifically, when the inputs used by the firm are more substitutable than the products it sells—allowing the firm to gain rents from market power—it has a greater incentive to integrate additional production stages internally.

To empirically evaluate this prediction, I combine input-output tables with firm-level accounting data, as well as trade data at the firm-product level for both Denmark and China. The empirical results, which are consistent across both countries, support the proposed prediction: changes in a firm's production span are correlated with the relative sizes of the two elasticities of substitution—between the products produced by the firm and the inputs it uses. This study not only enhances the understanding of firms' production behavior but also carries important policy implications, particularly for shaping strategies that optimize production processes within the global value chain and promote domestic economic development.

Future research could broaden this analysis by considering firms' in-house production across international affiliates, if such data become available. This expanded

approach would yield deeper insights into firms' global production strategies and could have significant implications for regional economic development. Additionally, examining how international trade shocks—such as variations in trade costs—affect firms' production scope would further advance the literature on GVCs and trade policy. A key limitation of this study is the lack of a formal theoretical model to support the proposed mechanism, as existing models tend to overlook the role of elasticity differences in shaping a firm's production span and often rely on restrictive assumptions. Furthermore, while this study demonstrates a correlation between production span and elasticity differences, it does not establish causality. Future work should focus on addressing endogeneity issues and developing a theoretical framework that better aligns with the empirical findings.

2.6 References

Alfaro, L., Chor, D., Antras, P., Conconi, P., 2019. Internalizing global value chains: A firm-level analysis. Journal of Political Economy 127 (2), 508–559.

Antràs, P., Chor, D., 2013. Organizing the global value chain. Econometrica 81 (6), 2127–2204.

Antràs, P., Chor, D., 2018. On the measurement of upstreamness and downstreamness in global value chains. World Trade Evolution: Growth, Productivity and Employment 5, 126–194.

Antràs, P., Chor, D., Fally, T., Hillberry, R., 2012. Measuring the upstreamness of production and trade flows. American Economic Review 102 (3), 412–416.

Baldwin, R., Venables, A. J., 2013. Spiders and snakes: Offshoring and agglomeration in the global economy. Journal of International Economics 90 (2), 245–254.

Broda, C., Weinstein, D. E., 2006. Globalization and the gains from variety. The Quarterly journal of economics 121 (2), 541–585.

Burstein, A., Kurz, C., Tesar, L., 2008. Trade, production sharing, and the international transmission of business cycles. Journal of Monetary Economics 55 (4), 775–795.

Carvalho, V. M., 2014. From micro to macro via production networks. Journal of Economic Perspectives 28 (4), 23–48.

Chor, D., Manova, K., Yu, Z., 2021. Growing like china: Firm performance and global production line position. Journal of International Economics 130, 103445.

Di Giovanni, J., Levchenko, A. A., 2010. Putting the parts together: trade, vertical linkages, and business cycle comovement. American Economic Journal: Macroeconomics 2 (2), 95–124.

Fally, T., 2012. Production staging: measurement and facts. Boulder, Colorado, University of Colorado Boulder, May, 155–168.

Fally, T., Hillberry, R., 2018. A coasian model of international production chains. Journal of International Economics 114, 299–315.

Feenstra, R. C., 1994. New product varieties and the measurement of international prices. The American Economic Review, 157–177.

Frankel, J. A., 2016. Globalization and chinese growth: Ends of trends?

Grossman, S. J., Hart, O. D., 1986. The costs and benefits of ownership: A theory of vertical and lateral integration. Journal of political economy 94 (4), 691–719.

Hummels, D., Ishii, J., Yi, K.-M., 2001. The nature and growth of vertical specialization in world trade. Journal of international Economics 54 (1), 75–96.

IMF, 2016. Global trade: what's behind the slowdown?

Johnson, R. C., Noguera, G., 2012. Accounting for intermediates: Production sharing and trade in value added. Journal of international Economics 86 (2), 224–236.

Klein, B., Crawford, R. G., Alchian, A. A., 1978. Vertical integration, appropriable rents, and the competitive contracting process. The journal of Law and Economics 21 (2), 297–326.

Koopman, R., Wang, Z., Wei, S.-J., 2014. Tracing value-added and double counting in gross exports. American economic review 104 (2), 459–494.

Miller, R. E., Temurshoev, U., 2017. Output upstreamness and input downstreamness of industries/countries in world production. International regional science review 40 (5), 443–475.

Soderbery, A., 2015. Estimating import supply and demand elasticities: Analysis and implications. Journal of International Economics 96 (1), 1–17.

Tirole, J., 1988. The theory of industrial organization. MIT press.

Tyazhelnikov, V., 2022. Production clustering and offshoring. American Economic Journal: Microeconomics 14 (3), 700–732.

Wang, Z., Wei, S.-J., Yu, X., Zhu, K., 2017a. Characterizing global value chains: production length and upstreamness. Tech. rep., National Bureau of Economic Research.

Wang, Z., Wei, S.-J., Yu, X., Zhu, K., 2017b. Measures of participation in global value chains and global business cycles. Tech. rep., National Bureau of Economic Research.

Williamson, O. E., 1981. The economics of organization: The transaction cost approach. American journal of sociology 87 (3), 548–577.

Yi, K.-M., 2003. Can vertical specialization explain the growth of world trade? Journal of political Economy 111 (1), 52–102.

Zavacka, V., et al., 2012. The bullwhip effect and the Great Trade Collapse. European Bank for Reconstruction and Development.

2.A Appendix

2.A.1 Appendix - Stylized Facts

2.A.1.1 Position and Length of the Value Chain - All Industries

This subsection presents the positions and lengths of value chains across all industries in China and Denmark. In other words, in addition to manufacturing, as outlined in Section 2.3, it also covers other sectors, including services.

Table A.1 lists the top 10 industries in China with the smallest (most upstream) and largest (most downstream) values of the position index. As defined in Equation (2.2.5), the left column refers to the top 10 relatively upstream sectors, while the right column lists the top 10 relatively downstream industries. Consistent with common intuition, the most upstream industries are primarily raw materials, which serve as value-added inputs for production in other sectors (e.g., Oil, Mining, Forestry). In contrast, the most downstream industries produce final outputs and are rarely used as intermediate inputs (e.g., Construction, Advanced Manufacturing, Public Services).

Table A.1: Position of Industries in China

Top 10 upstream industries	**Top 10 downstream industries**
Scrap waste	Construction
Forestry	Physical education
Oil and gas extraction	Convenience food manufacturing
Banking, securities and other financial activities	Public facilities management
Coal mining and washing	Health
Oil and gas Pipeline transportation	Public administration and social organizations
Non-ferrous metal mining and processing	Software
Railway transportation	Communication equipment manufacturing
Coking	Liquid milk and dairy products
Ferrous metal mining and processing	Other food manufacturing

Notes: This table contains all sectors in the Chinese IO table. The position of an industry is calculated using the position index from Equation (2.2.5), defined as the logarithm of the ratio of downstreamness to upstreamness. The left column lists the top 10 industries with the smallest position index (in ascending order), indicating that these industries are located the most upstream in the value chain. Similarly, the right column presents the top 10 industries with the largest position index (in descending order), identifying them as the most downstream industries in the value chain.

Table A.2 demonstrates the top 10 industries associated with the shortest and longest value chains, respectively. The length of the value chain is calculated based on Equation (2.2.6). industries involved in shorter production chains in China are

predominantly services, reflecting that their inputs consist largely of value-added activities and/or their outputs are usually consumed as final goods. This leads to their low rankings in both upstreamness and downstreamness. In contrast, industries engaged in the longest production chains are typically found in sectors producing intermediate inputs, such as non-ferrous metal production and chemical manufacturing. These industries use inputs that have already passed through several production stages, and their outputs will also undergo numerous additional stages before becoming final goods. As a result, they tend to be located in the middle of complex GVCs, with high levels of both upstreamness and downstreamness.

Table A.2: Length of Value Chains in China

Shortest 10 industries (ascending)	**Longest 10 industries (descending)**
Social welfare industry	Chemical fiber manufacturing
Real estate industry	Non-ferrous metal mining and dressing
Public administration and social organizations	Basic chemical raw material manufacturing
Education	Specialty Chemical Products Manufacturing
Public facilities management industry	Non-ferrous metal smelting and alloy manufacturing
Residential services	Knitwear, knitted goods and products manufacturing
Physical education	Cotton, chemical fiber textile and printing and dyeing finishing
Software industry	Electricity and heat production and supply
Social security industry	Paint, ink, pigment and similar product manufacturing
Urban public transportation industry	Ferrous metal mining and processing

Notes: This table contains all industries in the Chinese IO table. The length of the value chain is calculated based on Equation (2.2.6), as the sum of upstreamness and downstreamness.

Table A.3 and Table A.4 exhibit the corresponding results regarding industry position and lengths of value chains for all industries in Denmark. Despite differences between countries, upstream and downstream industries show some similarities. As in China, Denmark's most upstream sectors focus on raw material extraction and processing, while the most downstream sectors are dominated by construction and complex manufacturing. This alignment reflects the tendency for industry positions to be consistent across countries, as highlighted in studies like Antràs et al. (2012) and Chor et al. (2021). Additionally, the industries associated with the shortest value chains in Denmark follow a similar pattern to those in China, with services such as

Table A.3: Position of Industries in Denmark

Top 10 upstream industries	**Top 10 downstream industries**
Extraction of oil and gas	Construction of new buildings
Water transport	Gambling and betting activities
Mining support service activities	Sports activities(non-market)
Accounting and bookkeeping activities	Buying and selling real estate
Employment activities	Manufacture of leather and footwear
Security and investigation activities	Manufacture of ships and other transport equipment
Renting of non-residential buildings	Production of meat and meat products
Support activities for transportation	Scientific research and development(market)
Printing tec.	Manufacture of dairy products
Legal Activities	Residual care activities

Notes: This table contains all sectors in the Danish IO table. The position of an industry is calculated using the position index from Equation (2.2.5), defined as the logarithm of the ratio of downstreamness to upstreamness. The left column lists the top 10 industries with the smallest position index (in ascending order), indicating that these industries are located the most upstream in the value chain. Similarly, the right column presents the top 10 industries with the largest position index (in descending order), identifying them as the most downstream industries in the value chain.

education and public investments leading the list. However, Denmark's industries engaged in the longest value chains differ somewhat from those in China, with most being business and financial-related services.

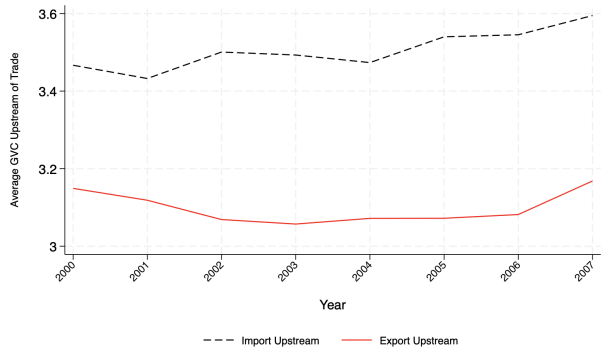
Table A.4: Length of Chains in Denmark

Shortest 10 industries (ascending)	**Longest 10 industries (descending)**
Activities of households as employers of domestic personnel	Advertising and market research
Primary education	Mining support service activities
Social work activities without accommodation	Business consultancy activities
Scientific research and development(non-market)	Other technical business services
Defense, public order, security and justice activities(non-market)	Forestry
Library, museums and other cultural activities(non-market)	Printing etc.
Renting of residential buildings	Agriculture and horticulture
Travel agent activities	Publishing
Higher education	Other financial activities
Medical and dental practice activities	Other business service activities

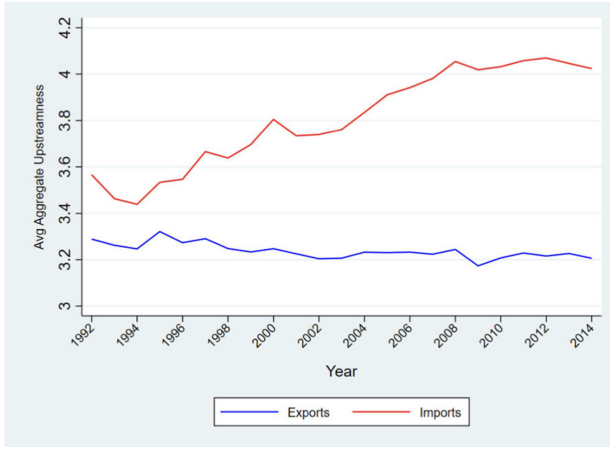
Notes: This table contains all industries in the Danish IO table. The length of the value chain is calculated based on Equation (2.2.6), as the sum of upstreamness and downstreamness.

2.A.1.2 Macro Trend - Upstreamness

In this subsection of the appendix, I present the trade positions for China and Denmark at the country level using only the upstreamness measure, rather than the position index developed in this paper (see Section 2.3.3). The aim is to compare the differences between these two methodologies and to validate that the upstreamness measurement aligns with previous studies, particularly by comparing the results with those in Chor et al. (2021).



(a) Upstreamness of Chinese Trade - This Study



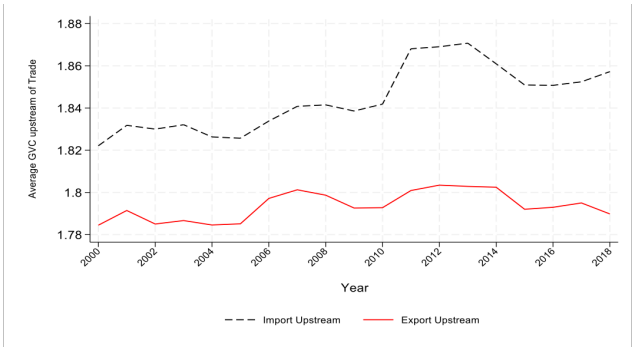
(b) Upstreamness of Chinese Trade - Chor et al. (2021)

Figure A.1: Average Upstreamness of Chinese Trade - Comparison

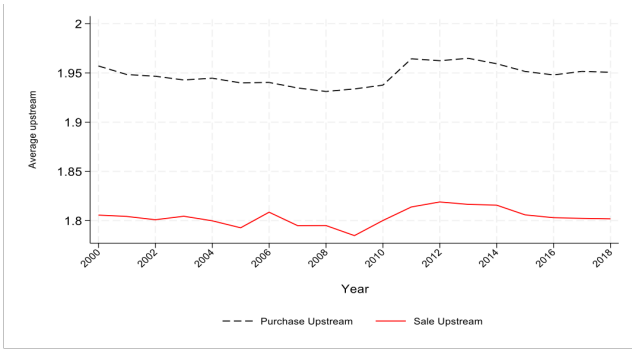
Note: The two figures demonstrate the position of Chinese trade of manufacturing using upstreamness. The left graph is calculated in this study, while the right graph is sourced from the prior study by Chor et al. (2021).

Figure A.1 compares the upstreamness of Chinese trade as calculated in this study with the results from Chor et al. (2021). Again, calculations here solely include the

manufacturing sector. The two graphs align closely over the same period (2000–2007), showing strong similarities in both the patterns and values of import and export upstreamness. This alignment provides robust evidence that the methodology used in this study for measuring upstreamness is consistent with that employed in previous research. Furthermore, whether the position is measured using upstreamness or the position index constructed in this study (see Figure 2.2(a)) in Section 2.3), the average import position of Chinese manufacturing firms remains robustly more upstream than their export position.



(a) Upstreamness of Danish Trade



(b) Upstreamness of Danish Purchase and Sale

Figure A.2: Average Upstreamness in Denmark

Note: The two figures reveal Denmark's manufacturing position along the value chain, both are calculated using upstreamness. The left graph displays the position of Danish trade, while the right graph depicts the positions of Denmark's purchases and sales.

Following the same logic, Figure A.2 displays the upstreamness of Danish trade alongside the upstreamness of overall purchases and sales for Danish manufacturing. The results are consistent with those based on the position index (see Figure 2.2(b) in Section 2.3), showing that Danish manufacturing firms tend to import and purchase inputs that are located upstream in the value chain, while exporting and selling

outputs that are positioned further downstream. However, a notable distinction emerges when comparing the two graphs: the gap between the purchase and sale positions is significantly larger than the gap between the import and export positions. This suggests that the overall purchase and sale data capture more pronounced value-adding activities of Danish firms compared to only considering their trade activities.

2.A.1.3 Macro Trend - Purchase and Sale

Given the availability of purchase and sale data for Danish firms, this subsection presents the calculation results incorporating both trade and domestic activities of Danish manufacturing firms. By utilizing this broader dataset, the analysis moves beyond trade data alone, offering a more complete view of firms' production activities. This approach enables a deeper understanding of how Danish manufacturing firms strategically position themselves along the value chain through their procurement and sales practices, capturing a more holistic picture of their operations.

Figure A.3 exhibits the purchase and sale positions of Danish manufacturing firms, with positions estimated using the position index from Equation (2.2.5). In comparison to Figure A.2, the position pattern holds: firms sell (export) products that are located downstream and purchase (import) products upstream. Comparing with Figure 2.2(b), again, the gap between purchase and sale positions is larger than the gap between export and import positions. This difference primarily arises from the positions of imports versus purchases, as the export and sale positions are nearly identical, with the value of the position index at around -0.08. This suggests that firms are sourcing products further upstream domestically compared to their imports.

Next, Figure A.4 illustrates that the purchase length of Danish manufacturing firms exceeds their sale length significantly. This trend is more pronounced than their trade patterns, as shown in Figure 2.3(b). Similar to the position analysis, the length gap between purchase and sale, as well as between export and import, is primarily driven by the differences in the length of imports and purchase.

When comparing the in-house production span of two-way purchase and sale firms (Figure A.5) with that of two-way trade firms (Figure 2.5), the production scope calculated using purchase and sale data is notably larger—approximately 0.65 compared to 0.25 when using trade data. This suggests that firms typically have a more extensive production scope when accounting for their domestic activities, compared to considering solely their international trade activities. As a result, the broader production scope captured by purchase and sale data offers a more comprehensive understanding of a firm's operations, providing a different perspective on firms' production span.

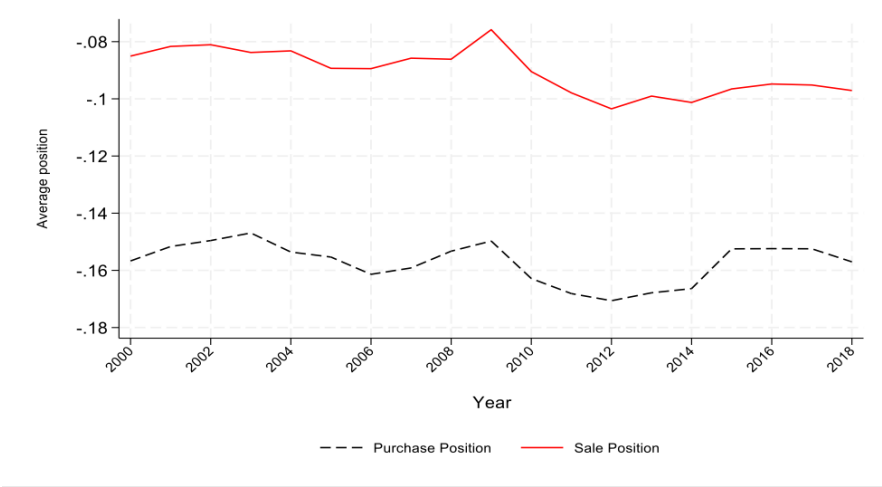


Figure A.3: Purchase and Sale Position along the Value Chain in Denmark

Note: This table only contains manufacturing industries. The positions of purchase and sale at the country level are calculated based on Equation (2.3.1), and aggregate the position of industries associated with all manufacturing firms' purchases and sales in Denmark. The position of an industry is calculated using the position index from Equation (2.2.5).

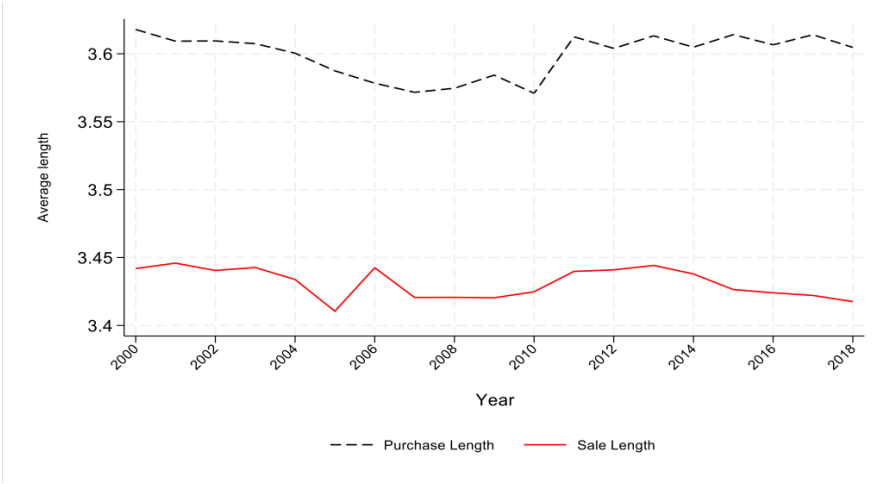


Figure A.4: Purchase and Sale Lengths along the Value Chain in Denmark

Note: This table only contains manufacturing industries. The lengths of purchase and sale at the country level are calculated based on Equation (2.3.1), but substituting the position index with the length of the value chain, aggregates all industries associated with firms' purchases and sales. The length of the value chain is computed from Equation (2.2.6).

In general, the patterns observed in the purchase and sale data are consistent with those identified through firms' trade activities. However, certain values, such as the production scope, tend to be larger when calculated using purchase and sale data. This is because the purchase and sale data contain a wider range of transactions,

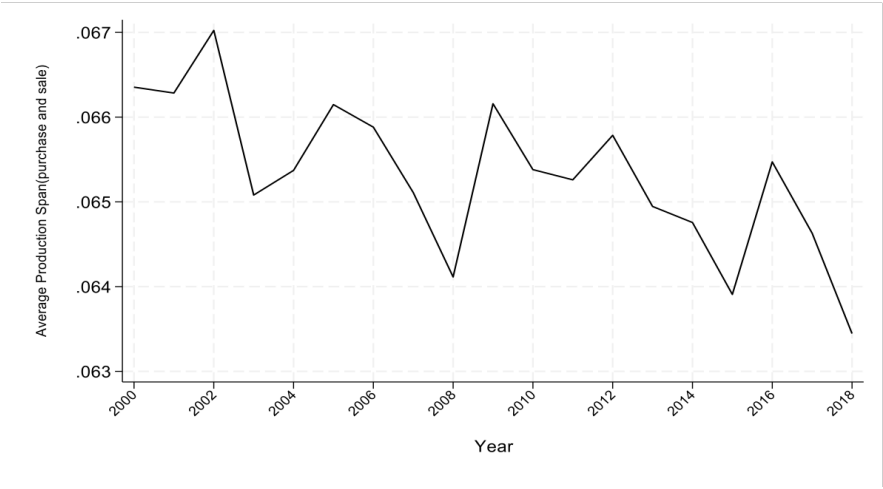


Figure A.5: In-house Production Span in Denmark

Note: The firm's in-house production span is computed based on Equation (2.2.7), as the difference of sale position and purchase position. The figure displays the average span of all two-way purchase and sale firms in Denmark.

including domestic activities not captured by trade data alone. Consequently, this dataset offers a more comprehensive view of how firms position themselves within the value chain.

2.A.2 Empirical Appendix

To more accurately replicate the study by Chor et al. (2021), I substitute the position index in the regressions with the upstreamness measure, consistent with the approach used in their analysis. The regression results using upstreamness are displayed in this section.

2.A.2.1 Correlations between Measures from Different Methods

Before presenting the results of the regressions using upstreamness, Table A.5 and Table A.6 show the correlations between the position variables measured by upstreamness and the position index (defined as the logarithm of the ratio of downstreamness to upstreamness) in China and Denmark, respectively. The tables highlight a strong correlation between the firm's in-house production span as computed by the position index and that calculated using upstreamness, with coefficients greater than 0.88 in both tables. Additionally, the positions of exports (imports), as measured by both upstreamness and the position index, are also correlated, though the correlation

coefficients differ between China and Denmark.[13]

Table A.5: Correlations between Position Measures - China

	Span	Upstream Span	Export Position	Import Position	Export Upstream	Import Upstream
Span	1					
Upstreamness Span	0.9603	1				
Export Position	0.6234	0.6025	1			
Import Position	-0.5158	-0.4911	0.3484	1		
Export Upstream	-0.6162	-0.6359	-0.9683	-0.3222	1	
Import Upstream	0.9526	0.9805	0.7477	-0.3227	-0.7677	1

Notes: The variable Span in the table represents the firm's in-house production span calculated using the position index from Equation (2.2.5), while Upstream Span denotes the production span computed based solely on upstreamness. The same calculations are applied to the firm's export and import positions. The observation for the Chinese sample is 125,120.

Table A.6: Correlations between Position Measures - Denmark

	Span	Upstream Span	Export Position	Import Position	Export Upstream	Import Upstream
Span	1					
Upstreamness Span	0.8807	1				
Export Position	0.5430	0.4899	1			
Import Position	-0.2196	-0.1797	0.7000	1		
Export Upstream	-0.4657	-0.5359	-0.8490	-0.5903	1	
Import Upstream	0.2694	0.2979	-0.5171	-0.8298	0.6463	1

Notes: The variable Span in the table represents the firm's in-house production span calculated using the position index from Equation (2.2.5), while Upstream Span denotes the production span computed based solely on upstreamness. The same calculations are applied to the firm's export and import positions. The observation for the Danish sample is 40,294.

2.A.2.2 Upstreamness Results - Chinese and Danish Trade

Table A.7 and Table A.8 replicate the analysis by Chor et al. (2021) for China and Denmark, respectively, focusing solely on productivity without introducing elasticity differences—the primary variable in the baseline of this paper. The findings for Chinese firms align closely with those of the original paper, showing that higher firm productivity correlates with an expanded production span (measured by upstreamness). However, for Danish firms, productivity does not significantly affect their in-house production spans, highlighting a distinct contrast between the two countries' manufacturing sectors.

The in-house production spans for Chinese and Danish manufacturing firms in Table A.9 and Table A.10 are still measured using upstreamness, but the regressions

[13] The negative coefficients result from the position index being defined as the logarithm of the ratio of downstreamness to upstreamness.

Table A.7: Upstreamness Results - China

	(1) Upstream Span	(2) Upstream Span	(3) Import Upstream	(4) Export Upstream
TFPR-LP	0.0131**	0.0115**	0.0137**	-0.00165
	(0.0054)	(0.0047)	(0.0060)	(0.0030)
Export Upstream		-0.957***		
		(0.0079)		
Con Vars	YES	YES	YES	YES
Industry-Year FE	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Observations	125120	125120	125120	125120
R^2	0.847	0.882	0.876	0.956

Notes: The table replicates Chor et al. (2021)'s study by measuring the position of industry along the value chain solely using upstreamness, with a focus exclusively on productivity without considering elasticity differences. Control variables contain measures of labor intensity (proxied by average wage) and capital intensity (proxied by fixed assets per employee) of the firm. Standard errors are clustered by firm and are shown in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.8: Upstreamness Results - Denmark

	(1) Upstream Span	(2) Upstream Span	(3) Import Upstream	(4) Export Upstream
TFPR-LP	-0.00286	-0.00277	-0.00276	0.0000977
	(0.0036)	(0.0025)	(0.0025)	(0.0025)
Export Upstream		-0.942***		
		(0.0137)		
Con Vars	YES	YES	YES	YES
Industry-Year FE	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Observations	40294	40294	40294	40294
R^2	0.601	0.748	0.794	0.894

Notes: The table replicates Chor et al. (2021)'s study by measuring the position of industry along the value chain solely using upstreamness, with a focus exclusively on productivity without considering elasticity differences. Control variables contain measures of labor intensity (proxied by average wage) and capital intensity (proxied by fixed assets per employee) of the firm. Standard errors are clustered by firm and are shown in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

now include the elasticity difference. For Chinese firms, the impact of productivity on their in-house production span remains robust, consistent with the baseline results in Table 2.5. However, for Danish firms, the previously observed negative effect of productivity in Table 2.6 disappears when using upstreamness to calculate the production span, as shown in Table A.10. his suggests that different methods

of calculating production span may capture distinct aspects of the production process, potentially overlooking the accurate productivity-driven effects in Danish firms. Furthermore, the elasticity difference variable shows a significant and consistent effect on firms' production scope in both China and Denmark, aligning with the baseline results where the production span is calculated using the position index. This consistency strongly highlights the robustness of the prediction.

Table A.9: Upstreamness Results - China

	(1) Upstream Span	(2) Upstream Span	(3) Import Upstream	(4) Import Upstream	(5) Export Upstream	(6) Export Upstream
E Difference ($\rho-\alpha$)	-0.0038***		-0.004***		-0.00017	
	(0.0006)		(0.0007)		(0.0004)	
TFPR-LP	0.0132**	0.0133**	0.0138**	0.0139**	-0.0016	-0.0016
	(0.0054)	(0.0054)	(0.0060)	(0.0060)	(0.0030)	(0.0030)
Intermediates Substitution (α)		0.0053***		0.0052***		0.0006**
		(0.0007)		(0.0007)		(0.0003)
Demand E (ρ)		-0.0012		-0.002		0.0005
		(0.0010)		(0.0014)		(0.0010)
Con Vars	YES	YES	YES	YES	YES	YES
Industry-Year FE	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Observations	125120	125120	125120	125120	125120	125120
R^2	0.848	0.848	0.876	0.876	0.956	0.956

Notes: This table is analogous to the baseline regression but measures the position of industries using upstreamness instead of the position index constructed in this paper. Control variables contain measures of labor intensity (proxied by average wage) and capital intensity (proxied by fixed assets per employee) of the firm. Standard errors are clustered by firm and are shown in parentheses, * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

Table A.10: Upstreamness Results - Denmark

	(1) Upstream Span	(2) Upstream Span	(3) Import Upstream	(4) Import Upstream	(5) Export Upstream	(6) Export Upstream
E Difference ($\rho - \alpha$)	-0.0370***		-0.022***		0.0151***	
	(0.0029)		(0.0022)		(0.0018)	
TFPR-LP	-0.00243	-0.0026	-0.0025	-0.0023	-0.00008	0.00025
	(0.0035)	(0.0035)	(0.0025)	(0.0025)	(0.0025)	(0.0024)
Intermediates Substitution (α)		0.0321***		0.0310***		-0.00113
		(0.0032)		(0.0031)		(0.0014)
Demand E (ρ)		-0.046***		-0.0047*		0.0413***
		(0.0049)		(0.0025)		(0.0047)
Con Vars	YES	YES	YES	YES	YES	YES
Industry-Year FE	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Observations	40294	40294	40294	40294	40294	40294
R^2	0.612	0.613	0.797	0.798	0.896	0.898

Notes: This table is analogous to the baseline regression but measures the position of industries using upstreamness instead of the position index constructed in this paper. Control variables contain measures of labor intensity (proxied by average wage) and capital intensity (proxied by fixed assets per employee) of the firm. Standard errors are clustered by firm and are shown in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

2.A.2.3 Upstreamness Results - Danish Purchase and Sale

Similarly, this subsection in the Appendix presents the results of measuring a firm's in-house production span using upstreamness but based on the purchase and sale data for Denmark. Table A.11 provides results without accounting for elasticity differences, while Table A.12 includes the elasticity difference variable. Consistent with the baseline findings, both tables show that the difference between demand elasticity and the elasticity of substitution across a firm's inputs significantly reduces its production scope. However, as in previous analyses, productivity remains insignificant in determining a firm's production span in Denmark.

Table A.11: Upstreamness Results - Danish Purchase and Sale

	(1) Upstream Span	(2) Upstream Span	(3) Purchase Upstream	(4) Sale Upstream
TFPR-LP	0.000451	0.000192	0.000168	-0.000284
	(0.0048)	(0.0042)	(0.0042)	(0.0034)
Sale Upstream		-0.916***		
		(0.0451)		
Con Vars	YES	YES	YES	YES
Industry-Year FE	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Observations	12806	12806	12806	12806
R^2	0.927	0.943	0.902	0.986

Notes: This table replicates the study by Chor et al. (2021), measuring the position of industries along the value chain using upstreamness, but utilizes purchase and sale data for Danish firms instead of trade data. Control variables contain measures of labor intensity (proxied by average wage) and capital intensity (proxied by fixed assets per employee) of the firm. Standard errors are clustered by firm and are shown in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.12: Upstreamness Results - Danish Purchase and Sale

	(1) Upstream Span	(2) Upstream Span	(3) Purchase Upstream	(4) Purchase Upstream	(5) Sale Upstream	(6) Sale Upstream
E Difference						
$(\rho - \alpha)$	-0.0138**		-0.0136**		0.00021	
	(0.0058)		(0.0058)		(0.0014)	
TFPR-LP	-0.00198	-0.00150	-0.00222	-0.00309	-0.00025	-0.00158
	(0.0049)	(0.0049)	(0.0044)	(0.0044)	(0.0034)	(0.0033)
Intermediates						
Substitution (α)		0.0135**		0.0141**		0.000567
		(0.0059)		(0.0059)		(0.0014)
Demand E						
(ρ)		-0.0195*		-0.00315		0.0164
		(0.0114)		(0.0079)		(0.0103)
Con Vars	YES	YES	YES	YES	YES	YES
Industry-Year FE	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Observations	12806	12806	12806	12806	12806	12806
R^2	0.928	0.928	0.903	0.903	0.986	0.986

Notes: This table measures the position of industries using upstreamness and utilizes purchase and sale data for Danish firms. Control variables contain measures of labor intensity (proxied by average wage) and capital intensity (proxied by fixed assets per employee) of the firm. Standard errors are clustered by firm and are shown in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

2.A.2.4 Robustness Check: Other Productivity Measures

Table A.13 presents robustness checks using two alternative productivity measures: total factor productivity (TFPR) residuals derived from the Olley-Pakes (OP) method and value added per employee. The results for both China and Denmark show that the effects of firm productivity remain largely unchanged compared to the baseline findings. For Chinese firms, productivity continues to be positively correlated with the in-house production span, while for Danish firms, productivity has a slightly negative effect or no significant impact on their in-house production scope.

Table A.13: Robustness Check: Other Productivity Measures

	(1) Span	(2) Span	(3) Span	(4) Span	(5) Span	(6) Span
E Difference ($\rho - \alpha$)	-0.0021***	-0.0021***	-0.0095***	-0.0095***	-0.0067***	-0.0067***
	(0.0003)	(0.0003)	(0.0019)	(0.0019)	(0.0019)	(0.0019)
TFPR-OP	0.0043***		-0.0042**		-0.0015	
	(0.0014)		(0.0018)		(0.0026)	
Log VA per worker		0.0024***		-0.0012		0.0005
		(0.0007)		(0.0014)		(0.0016)
Con Vars	YES	YES	YES	YES	YES	YES
Industry-Year FE	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Country	China	China	Denmark	Denmark	Denmark (P&S)	Denmark (P&S)
Observations	125120	125120	40294	40294	12806	12806
R^2	0.846	0.846	0.624	0.624	0.941	0.941

Notes: This table presents robustness checks using two alternative productivity measures: TFPR-OP and value added per employee. The first two columns analyze Chinese trade data, the middle two columns apply Danish trade data, and the final two columns use Danish purchase and sale data. Control variables include measures for labor intensity (proxied by average wage) and capital intensity (proxied by fixed assets per employee). Standard errors are clustered at the firm level and are shown in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

2.A.2.5 Robustness Checks: Alternative Estimates of Elasticity

In the baseline analysis, following Alfaro et al. (2019), I measure ρ_{ft} and α_{ft} using the U.S. import demand elasticities estimated by Broda and Weinstein (2006). For robustness, I utilize the more recent import demand elasticity estimates from Soderbery (2015), which employs a hybrid methodology combining the approaches of Feenstra (1994) and Broda and Weinstein (2006). Despite using these alternative estimates, the relationship between the firm's in-house production span and the elasticity difference remains consistent with the baseline results, as shown in Table A.14 for China and Table A.15 for Denmark.

Table A.14: Robustness Check (Soderbery (2015)) - China

	(1) Span	(2) Span	(3) Import Position	(4) Import Position	(5) Export Position	(6) Export Position
E Difference ($\rho-\alpha$)	-0.0018***		0.0017***		-0.00008	
	(0.0001)		(0.0001)		(0.0001)	
TFPR-LP	0.00394**	0.00391**	-0.00238	-0.00234	0.00156	0.00157
	(0.0019)	(0.0019)	(0.0016)	(0.0016)	(0.0012)	(0.0012)
Intermediates Substitution (α)		0.0022***		-0.0022***		-0.000003
		(0.0001)		(0.0001)		(0.0000)
Demand E (ρ)		-0.00058**		0.00021*		-0.00037*
		(0.0002)		(0.0001)		(0.0002)
Con Vars	YES	YES	YES	YES	YES	YES
Industry-Year FE	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Observation	113056	113056	113056	113056	113056	113056
R2	0.845	0.846	0.826	0.827	0.941	0.941

Notes: This table presents a robustness check using import demand elasticity estimates from Soderbery (2015) to measure the two elasticities. Control variables include labor intensity (proxied by average wage) and capital intensity (proxied by fixed assets per employee). Standard errors are clustered at the firm level and are shown in parentheses, * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

Table A.15: Robustness Check (Soderbery (2015)) - Denmark

	(1) Span	(2) Span	(3) Import Position	(4) Import Position	(5) Export Position	(6) Export Position
E Difference						
$(\rho-\alpha)$	-0.0047***		0.0051***		0.00043	
	(0.0005)		(0.0003)		(0.0003)	
TFPR-LP	-0.00228	-0.00238	0.00128	0.00135	-0.00100	-0.00103
	(0.0021)	(0.0021)	(0.0015)	(0.0015)	(0.0015)	(0.0015)
Intermediates						
Substitution (α)		0.00719***		-0.0069***		0.00028
		(0.0005)		(0.0005)		(0.0002)
Demand E						
(ρ)		0.000605		0.00129***		0.00189**
		(0.0009)		(0.0004)		(0.0009)
Con Vars	YES	YES	YES	YES	YES	YES
Industry-Year FE	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
	38264	38264	38264	38264	38264	38264
R2	0.638	0.642	0.832	0.833	0.907	0.907

Notes: This table presents a robustness check using import demand elasticity estimates from Soderbery (2015) to measure the two elasticities. Control variables include labor intensity (proxied by average wage) and capital intensity (proxied by fixed assets per employee). Standard errors are clustered at the firm level and are shown in parentheses, * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

CHAPTER 3

FIRMS' TRADING ACTIVITIES AND IT EXPENDITURES

Ina C. Jäkel
Aarhus University

Allan Sørensen
Aarhus University

Ying Dai
Aarhus University

Abstract

This paper investigates the role of firms' trading activities, including both exports and imports, for their IT expenditures. We exploit information from a firm-level survey on IT expenditures for Danish firms for the years 2002-2015, which we combine with detailed trade and firm-register data. First, we document positive within-firm conditional correlations between imports (exports) and IT expenditures. Second, we apply well-established measures of exogenous firm-level export demand shocks and import supply shocks to ask if these positive correlations capture causal effects. For imports, we find causal and sizeable effects on IT expenditures. These effects seem primarily driven by firms' expenditures on software. Instead, surprisingly, no overall effect on IT expenditures is found for exports. To shed light on this puzzle, we show that export demand shocks positively and strongly affect firms' investments into IT. Instead, effects are negative and significant when considering operating expenses.

Keywords: IT · Export · Imports · Firm heterogeneity.
JEL classification : F1, F14, F61, D22.

3.1 Introduction

New technologies – such as information technology (IT), robots, or artificial intelligence (AI) – hold the promise of productivity enhancements, organizational improvements, and competitive advantages for firms, and, ultimately, the potential to transform a country's economy. For the case of IT, a number of firm-level studies do indeed find positive productivity effects (cf. Cardona, Kretschmer, and Strobel (2013) for a review, and Dhyne, Konings, Van den bosch, and Vanormelingen (2021) for recent evidence). Moreover, IT has been shown to affect firm organization (e.g. Bloom, Garicano, Sadun, and Van Reenen, 2014), and it has also been linked to increases in market concentration and the emergence of 'superstar firms' (Brynjolfsson, Jin, and Wang, 2023). Given its potential consequences at the micro and macro levels, an important question is why we observe large differences across firms in IT adoption (Gierten, Viete, Andres, and Niebel, 2021). In this paper, we investigate the role of firms' trading activities for explaining the observed heterogeneity in firms' IT expenditures.

In a recent survey, Chen and Martincus (2022) classify new technologies depending on the channels through which these technologies generate productivity gains. Interpreted through the lens of their classification, we can think of IT as offering benefits to firms by either (i) lowering search, communication, and transaction costs, and/or (ii) lowering production costs. Accordingly, there are several channels through which firms' trading activities might affect IT expenditures. First, if IT lowers the costs of international transactions (e.g., by overcoming information frictions), then the returns from IT are increasing as the firm internationalizes. Thus, firms may find it optimal to increase their IT expenditures as they expand on export or import markets. Second, if IT lowers production costs, firms' export activities may affect IT expenditures through a standard market size (scale) effect.[1]

Importantly, this last market size argument for a link from trade to IT is mostly relevant for exports. However, other links from trade to IT are more likely to be particularly relevant for imports. Indeed, the rise of global value chains (GVCs) has oftentimes been linked to the 'I(C)T revolution'. While the chain of causality most often discussed is from I(C)T to the fragmentation of production, firms may internalize such linkages, and optimally expand their IT expenditures in reaction to changes in import (possibilities). In addition, access to better/cheaper intermediates may make a firm more competitive (Aghion, Bergeaud, Lequien, Melitz, and Zuber, 2024b), thereby spurring IT expenditures via a scale effect. Finally, firms' expansion on import

[1] This argument is akin to the effects uncovered by Aghion, Bergeaud, Lequien, and Melitz (2024a) for firm patenting driven by increasing foreign demand (exports).

markets is related to offshoring activities, inducing changes in the composition of tasks within the firm. Such changes may make the firm more IT intensive, e.g., if the remaining tasks are more communication intensive.

To investigate the effects of trade on IT, we exploit a survey on Danish firms' IT expenditures for the period 2002-2015. We can link these data to other firm-level register data, including trade data. Importantly, our data contain information on a continuous measure of firms' IT *expenditures* rather than the adoption of specific IT technologies. While IT expenditures capture a firm's ongoing investments in IT infrastructure and activities, it is necessary to acknowledge the limitations of this measure. Specifically, this measure includes not only capital investments in IT but also recurring operational expenses, such as maintenance, licensing, and support, which may not directly contribute to the firm's stock of IT capital. Furthermore, IT expenditures at a given point in time do not account for past investments in IT, which can have a cumulative and enduring impact on a firm's technological capabilities. Third, capital investments in IT are often lumpy in nature, meaning they are made infrequently and in large amounts, which further complicates the interpretation of expenditures over a specific period. Despite these challenges, the use of overall IT expenditures remains meaningful as it reflects the firm's current allocation of resources toward IT and serve as a practical and informative proxy for understanding the role of IT in firm behavior and performance.

In order to investigate the causal link from trade to IT, we construct shift-share-type instruments for firms' trading behaviour along the lines of Hummels, Jørgensen, Munch, and Xiang (2014) and Aghion et al. (2024a). In particular, we exploit export-demand and import-supply shocks in firms' pre-sample export and import markets in both reduced form and instrumental variable regressions. The reduced-form regressions capture how IT expenditures respond to trade potential irrespective of whether the potential is realized or not. Even unrealized potential may change IT expenditures if firms prepare for a potential/expected increase in trade (intend-to-treat effect). The IV regressions restrict the focus and capture only the effect of realized trade changes (driven by changes in trade potential) on IT expenditures.

We start our empirical analysis by documenting a positive within-firm correlation between exports and imports, and firms' IT expenditures. Do these (conditional) correlations reflect causal effects? To answer this question, we exploit information on exogenous, firm-specific export demand and import supply shocks. We first verify that export demand shocks do indeed affect measures of firm scale (exports, revenue, and employment). However, no such scale effect is detected for import supply shocks. Thus, any potential scale-related effects of trade (shocks) on IT expenditures are relevant for exports only. Both our reduced form as well as the instrumental variable

regressions do, however, not provide any evidence that firm-level exports affect firms' IT expenditures or their IT intensity (expenditures per employee). Instead, we find large effects of import (supply shocks) on IT expenditures.

Our findings on the positive effects of import supply shocks (as well as actual imports) are in line with the hypothesis that firms' importing opportunities (and activities) induce firms to invest in IT. In regressions where we exploit detailed information on different types of IT expenditures, we find that these positive effects mainly operate via an increase in expenditures on software. This finding is in line with the intuition that certain types of software (e.g., e-commerce applications) might be crucial for firms to increase their international sourcing because they allow for faster and more reliable communication along the supply chain. Moreover, we find that import supply shocks affect both investments into IT, as well as IT operating expenses.

The non-existence of a causal link from export demand shocks (as well as actual exports) to firms' IT expenditures may, instead, seem puzzling. Again, our results exploiting detailed information on disaggregate types of IT expenditures shed light on this puzzle. In particular, we find that export demand shocks positively and strongly affect firms' investments into IT. Instead, effects are negative and significant when considering operating expenses. These contrasting effects explain why we do not find any significant effects if we lump these two very different activities together.

Our paper speaks to three strands of literature. First, it speaks to a broad literature on the effects of globalization and trade on firms' investment activities. Bustos (2011) shows how trade liberalization in Brazil has fostered firms' investment in technology. Other authors have considered the effects of trade and trade liberalization on firms' innovation activities, for instance, process innovation or introduction of new products (Lileeva and Trefler, 2010) and R&D expenditures (Aw, Roberts, and Xu 2011; Coelli, Moxnes, and Ulltveit-Moe 2022); see e.g., Akcigit and Melitz (2022) for a review of the literature on the link from export to innovation.[2] Chen, Zhang, and Zheng (2017) document positive effects of export and *import* intensity on R&D intensity using Chinese firm-level data. We contribute to this strand of literature by considering firms' IT expenditures as a distinct source of firms' technology/investment.

Second, our paper builds on and complements the literature on the effects of IT or ICT technologies on trade across borders. An early strand of studies has analyzed the effects of the internet on bilateral trade exploiting country-level data; see, e.g., Freund and Weinhold (2004), Clarke and Wallsten (2006) and Choi (2010). More recent papers have exploited firm-level data. Ricci and Trionfetti (2012) use firm-level data to

[2] Other studies, such as Wakelin (1998) and Cassiman, Golovko, and Martínez-Ros (2010), have highlighted the reverse link from innovation to exports.

reveal the close association between communication networks and corporate export capabilities. Akerman, Leuven, and Mogstad (2022) exploit exogenous variation in the availability and adoption of broadband by firms to explore how ICTs affect bilateral trade flows. For imports, Malgouyres, Mayer, and Mazet-Sonilhac (2021) show that broadband access raises firm-level imports by 25%, while Abramovsky and Griffith (2006) find that ICT makes firms more likely to purchase offshore. We complement this strand of literature by considering the reverse link, namely the effects of imports and exports on IT expenditures.

Third, but not least, our paper obviously speaks to the literature on determinants of IT adoption/expenditures. Giotopoulos, Kontolaimou, Korra, and Tsakanikas (2017) shows the importance of innovation and R&D activities and collaborations, well-educated and skilled workers, decentralized decision-making and visionary leadership for various IT adoption measures for SMEs (the bulk of firms), while Haller and Siedschlag (2011) show the effects of size, age, export-intensity and location.[3] Lashkari, Bauer, and Boussard (2024) show that even IT intensity (IT expenditures per employee) increases with scale using French firm-level data. The present paper contributes to this literature by exploring the role of (potential) export and import for IT expenditures. While many papers in the literature consider specific measures of IT adoption (e.g., electronic invoicing, online sales, PCs per employee) we consider overall or sub-categories of firm-level IT expenditures.

This paper proceeds as follows. In Section 3.2, we discuss potential mechanisms for a link from firms' trading behaviour in general to firms' IT expenditures, as well as effects that may be specific to firm-level exports or imports. Section 3.3 discusses data sources and presents summary statistics. Our empirical approach is outlined in Section 3.4. In Section 3.5, we present our main empirical findings on the effects of trade on firms' IT expenditures. Section 3.6 discusses further results where we distinguish IT investments from operating expenses, as well as results where IT expenditures are split into different types of IT (software, IT equipment, and IT services). Finally, Section 3.7 concludes.

3.2 Theoretical Considerations

Information technology is omnipresent in modern business and serves a myriad of purposes. The multiple purposes and natures of IT expenditures suggest multiple mechanisms through which engagement with the global economy – via imports and exports – may affect IT expenditures. Any single mechanism or model cannot capture

[3] See also the two OECD publications Andrews, Nicoletti, and Timiliotis (2018) and DeStefano, De Backer, and Moussiegt (2017) exploring other channels including managerial quality and being headquarter.

the full complexity. In the present section, we describe some basic mechanisms to structure thoughts.

Increasing trade may impact the scale of the firm – e.g., an output expansion to serve additional demand in the export markets or due to improved competitiveness driven by cheaper/better inputs via imports – as well as the composition of activities within the firm (domestic vs. global sales/purchases or via offshoring of certain activities). Changes in scale and composition of activities may warrant changes in IT expenditures.

An increase in scale – conditional on the composition of activities – is expected to increase IT expenditures. This certainly applies to the type of IT expenditures that vary directly with output (e.g., one device or one software license per worker). Other types of IT expenditures do not vary directly with output, but may still increase with scale as the return to such IT expenditures increases with scale. This applies to IT expenditures that improve production efficiency (e.g., enterprise service management or production monitoring software), reduce transaction and communication costs (e.g., web-shop or online meeting facilities) or improve quality (e.g., specialized software) – the underlying mechanisms correspond to those for general technology upgrading in (Lileeva and Trefler, 2010) and Bustos (2011) or innovation in Akcigit and Melitz (2022). Similarly, gains from better and thus data-driven decision making increase with scale, which again increases demand for IT. Yet, other IT expenditures may be part of costs that are truly fixed and thus invariant to scale, e.g. broadband access or web-hosting. While overall IT expenditures are thus expected to increase with scale, the effect of scale on IT intensity (IT expenditure per employee) is not clear.

A change in the composition of activities – conditional on scale – may also affect IT expenditures. Selling and purchasing internationally – compared to domestically – is complex and raises demand for IT (e.g., online meeting facilities and software) to handle those complexities. This is particularly so, if the shift towards international trading happens at the extensive margin, i.e., via adding destinations (origins), customers (suppliers) or products to the export (import) portfolio. An increase in importing may also reflect offshoring of previous in-house activities. Offshoring directly affects the composition of activities, which increases/decreases demand for IT (conditional on scale) if the offshored activities are less/more IT-intensive than the remaining in-house activities. Additionally, the complexity of handling an international value chain (the offshore activity) may require more coordination and communication, which again increases demand for IT.

Our empirical strategy to find causal effects of trade on IT expenditures at the firm level builds on the by now well-known firm-level instruments for exports and imports,

namely world-import-demand and world-export-supply at the country-product level, weighted by initial firm-level export (import) shares, see Section 3.4.2. We apply the instruments in reduced form as well as IV regressions, where the former captures how firms respond to changes in trade potential (realized or not), while the latter captures how firms respond to realized trade potential. Clearly, firms are expected to respond more to *realized* trade potential than to trade potential, but firms may respond to unrealized trade potential if they prepare to realize the potential.

Changes in these instruments – partly driven by business cycle fluctuations – and thus trade opportunities are less stable than changes in trade opportunities driven by changes in trade policies such as tariffs or free-trade agreements exploited in, e.g., Lileeva and Trefler (2010) and Bustos (2011). Accordingly, IT expenditures with a (partially) sunk/irreversible nature – e.g., purchase and installation of new/better/more servers, which would classify as IT investments – are expected to respond less to changes in trade opportunities in our empirical approach compared to a study relying on more permanent changes in trade opportunities as the option value of waiting is larger when it is less certain that a positive trade shock lasts.[4] Lumpiness (significant discrete upgrade) of these types of expenditures implies that whether or not a firm responds to a trade shock depends on whether the firm recently upgraded IT and therefore on previous trade shocks. Clearly, this issue is more pronounced in our approach with continuous trade shocks rather than clear pre- and post-treatment periods (and thus a single trade shock). Finally, we focus on firms that already engage in importing and exporting and therefore the large effect on technology upgrading found in e.g., Bustos (2011) for firms that start to export cannot be found for IT expenditures in our study where firms already trade. Despite the challenges of identifying effects using these instruments for incumbent two-way traders, it may be of great importance to obtain knowledge about this group of firms - including most larger firms and thus having substantial aggregate weight - and how they respond to changes in trade (potential) in normal times (and not only in times around the rare event of a major trade reform).

3.3 Data

In order to explore the causal effect of firms' trading activities on their IT expenditures, we combine several data sources that we can link through unique firm identifiers. All data are provided by Statistics Denmark, unless indicated otherwise.

[4] Notably, some IT expenditures that classify as operating expenses and not as investments may be prone to the same value of waiting argument. Consider e.g., the introduction of new software (license): reaping full benefits of such software typically takes time and costly efforts and may result in lower efficiency during an implementation/learning phase.

3.3.1 Data Sources

Our main data source is the IT expenditure survey (VITU). The survey, which was carried out on a yearly basis over the period 2003–2016, covers a stratified sample of private, non-financial firms with at least 10 full-time employees. In the sample, stratification is based on industry segments and company size.[5] Each year, the sample is selected independently of previous years, and therefore firms may drop in and out of the sample, resulting in an unbalanced panel. However, large companies with 250+ employees are always included. Since firms were asked to report their IT expenditures for the previous year, the sample period under consideration is 2002–2015.

In the survey, firms are asked to report their overall IT expenditures, and this is the outcome which we will focus on for most of our analysis. For the period 2007–2015, the data allow us to differentiate IT expenditures along two lines.[6] First, we have information on expenditures on three sub-categories of IT: (i) IT equipment (including hardware), (ii) software, and (iii) IT services. IT equipment includes hardware, telecommunication equipment, and other IT equipment. Software includes both standard software as well as specialized software. Finally, IT services comprise service contracts and IT consultancy, telecommunication services, rental of IT equipment, and other IT services. Particularly, software expenditures include both purchases of software as well as expenditures on software licenses. Notably, the data do not include IT costs associated with the firm's employees except for the Full-Time Equivalents (FTEs) specifically allocated to software development during the period. This distinction is crucial for understanding what the expenditure categories represent. For example, the dataset excludes general IT staff salaries, yet only captures labor expenses related to outsourcing or external software providers.

Second, overall IT expenditures can be divided into IT investments and operating expenses. Investment here refers to expenditures on IT which have been recorded as an asset in the financial year and will be gradually expensed over multiple years, typically through depreciation or amortization. This may include purchased IT equipment but also certain types of software, and even IT consultancy. For direct expenses, the entire cost has been recorded as an expense in the specified accounting year, rather than being spread out over multiple periods. While this information is only available for a sub-period of our sample, it allows us to gain some insights into the most important sources of IT expenditures.

[5] Stratification is along 12 industrial branches and 7 company size groups, resulting in a total of 84 strata. A "take-all" approach is applied for strata with over 250 employees and for strata with a maximum of 10 observations/companies.

[6] Due to a change in the survey questionnaire in 2007, the information on sub-categories of IT cannot be compared to information from the earlier years. (More precisely, the change in the survey questionnaire took place in the year 2008, with IT expenditures being recorded for 2007.)

We combine the information from the IT expenditure survey with data from several additional administrative registers. Data on individual firms, including information on variables such as employment and revenue, are obtained from the Firm Statistics (FIRM). Detailed information on firms' trading behaviour is collected from the Foreign Trade Statistics (UHDI). In the trade statistics, exports and imports are disaggregated, for each firm, by country of destination/origin and CN8-digit product. In a first step, we construct firm-year measures of exports and imports by aggregating these data, for each firm, across countries and products. In a second step, we use the disaggregated firm-product-country-level data to construct firm-specific measures of export demand shocks and import supply shocks. To this aim, we also exploit detailed data on bilateral trade flows at the HS6-level from CEPII's BACI database (Gaulier and Zignago, 2010). See Section 3.4.2 for a discussion of how these shocks are constructed.

3.3.2 Sample

Our starting point is the sample of firms reporting to the IT expenditure survey. Since our interest is in the effects of firm-level trading activities, we restrict our analysis to manufacturing firms. We further limit the sample as follows in order to study the issue at hand. First, we keep only firm-year observations with strictly positive exports and imports in the current and/or lagged year. Thus, we focus on the intensive – rather than the extensive – margin of firms' trading activities, and on two-way traders. Second, we also drop firm-year observations for which we cannot construct our export demand and import supply shocks (cf. below). Finally, we remove firm-year observations where IT expenditures are reported to be zero. This involves dropping only a small number (1.8%) of observations. After all these restrictions, we also drop observations for firms with a single observation, since these will not contribute to identification.[7]

The resulting sample is an unbalanced panel with 966 firms over the 2002–2015 period, containing 5,140 firm-year observations. 31% of firms in our sample only have two observations with information on trade and IT expenditure. Importantly, for the large majority of these (70%), observations are at most one year apart. The median number of observations per firm is 4 and the average is 5.3.

[7] Table A.1 in the Appendix documents how each of these sample restrictions affects the number of firms and observations in our final sample.

3.3.3 Summary Statistics

Figure 3.1(a) illustrates the growing importance of IT from the early 2000s until the end of our sample period: on average, firms' IT expenditures have more than doubled over the sample period, from 3 million DKK (roughly 400,000 EUR) in 2002 to more than 7 million DKK in 2015. Similarly, the average IT intensity (IT expenditures per employee) has also more than doubled, from roughly 11,000 DKK (1,600 EUR) per employee to almost 25,000 DKK per employee.[8,9] Apart from a decrease in 2008 due to the financial crisis, which is more pronounced for IT expenditures than for IT expenditures per employee, we see a consistent increase in both variables over the sample period.

IT expenditures in Figure 3.1(a) are measured in current prices. To put these numbers into perspective, Figure 3.1(b) shows the evolution of the consumer price index for two important components of IT expenditures – namely, Telecommunication Equipment and Services. We see a strong and persistent negative trend in prices of these IT components, implying that the numbers observed in Figure 3.1(a) significantly understate the actual increase in IT expenditures in real terms. In our empirical analysis, we will account for the evolution in IT prices by including (industry-)year fixed effects.

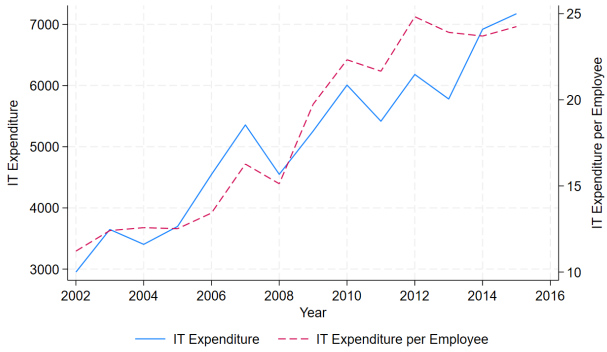
In Panel A of Table 3.1, we report summary statistics for all firm-year observations in our sample. In Panels B and C we report the same statistics, but restricting the sample to the top-20% of exporters and importers, respectively. On average, firms in our sample have roughly 420 employees. This number reflects the circumstance that large firms are over-sampled in the survey.[10] Not surprisingly, top-traders are much larger in terms of employment, with averages around 1,200 employees. Moreover, we note that top-importers tend to have larger exports (and top-exporters larger imports) than the average firm in our sample. Finally, top-traders have larger IT expenditures, not just when measured in levels, but also when measured relative to firm employment. These patterns highlight a potential link between firms' trading activities and their IT expenditures.

In Table A.2 in the Appendix, we report additional summary statistics for the subperiod 2007–2015, for which we can distinguish different types of IT expenditures. First, we divide total IT expenditures into operating expenses and investments into IT. Roughly 59% of firms in our sample report positive IT investments, while practically

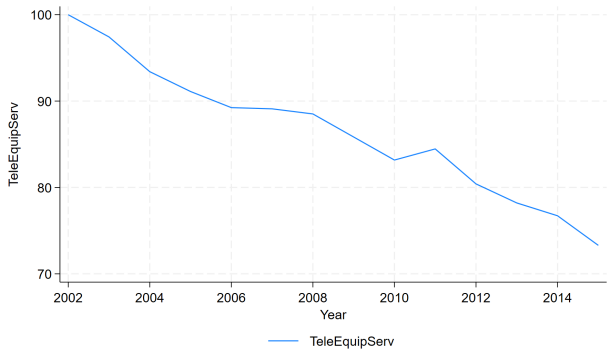
[8] To minimize the influence of outliers, in each year we exclude firms with IT expenditures (per employee) above the 95th percentile.

[9] For comparison, Brynjolfsson et al. (2023) report an average of IT expenditures per employee of 6,000 USD. Notably, however, the average firm in their sample is (with 3,800 employees) much larger.

[10] We discuss possible strategies to adjust for the sampling design in our empirical analysis in Section 3.6.



(a) Evolution of IT Expenditure



(b) Evolution of IT Prices

Figure 3.1: IT Expenditures and Prices

Note: The left-hand side figure shows how the average of IT expenditures across firms has evolved over our sample period. IT expenditures are measured in 1,000 DKK. To minimize the influence of outliers, in each year we exclude firms with IT expenditures (per employee) above the 95th percentile. The right-hand side figure shows how prices for Telecommunication Equipment and Services, as two important components of IT expenditures, have evolved over the period January 2004– January 2015, with prices normalized to 100 in January of 2014.

all firms report positive operating expenses. In fact, on average, IT investments only account for 14% of firms' total expenditures on IT. When considering only top-traders, these numbers increase somewhat: 73-74% of top-exporters and top-importers report positive investments into IT, and with 17% the share of investments in total expenditures is also somewhat larger than for the average firm. The large share of operating expenses in our measure of firms' total IT expenditures should be kept in mind when interpreting our subsequent empirical analysis.

Second, we divide total IT expenditures into three different types of IT expenditures – software, IT equipment, and IT services. We note that IT equipment only

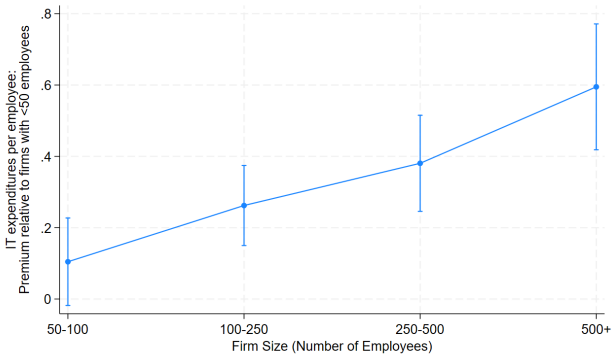
Table 3.1: Summary Statistics

	Mean	SD	Observations
Panel A: Full Sample			
Number of Employees	423.4	963.5	5,140
Exports (million DKK)	528.9	1,891	5,140
Imports (million DKK)	188.2	531.0	5,140
IT expenditure (1000 DKK)	17,618	116,910	5,140
IT expenditure per employee (1000 DKK)	20.77	26.85	5,140
Panel B: Top-Exporters			
Number of Employees	1,263	1,892	1,025
Exports (million DKK)	2,112	3,839	1,025
Imports (million DKK)	623.3	1,055	1,025
IT expenditure (1000 DKK)	72,231	253,719	1,025
IT expenditure per employee (1000 DKK)	34.90	41.00	1,025
Panel B: Top-Importers			
Number of Employees	1,212	1,835	1,025
Exports (million DKK)	1,885	3,745	1,025
Imports (million DKK)	702.4	1,034	1,025
IT expenditure (1000 DKK)	72,371	253,866	1,025
IT expenditure per employee (1000 DKK)	35.63	42.15	1,025

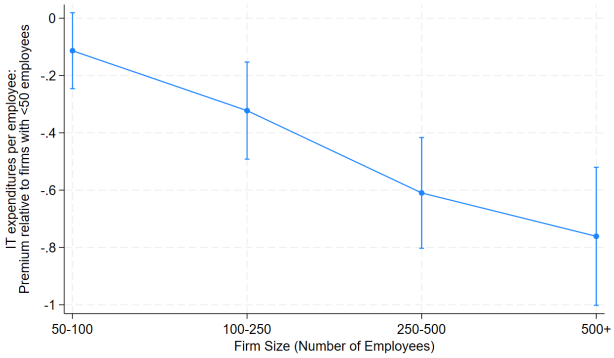
Notes: Panel A reports summary statistics for all firm-year observations in the sample; Panels B and C report summary statistics for top-exporters and top-importers, respectively. Top-traders are defined, for each year, as the top-quintile of the distribution of firm-level exports or imports. Notably, the set of top-importers and top-exporters is partly overlapping, but some firms belong to only one of the two categories.

accounts for a very small share of firms' overall IT expenditures (approximately 6%). The bulk of IT expenditures is accounted for by IT services (between 56-61%). Since IT services will typically be composed of operating expenses, this pattern can be linked back to the low share of IT expenditures that constitute investments. Around a third of all expenditures is on software, with this share being slightly higher for top-traders compared to the average firm.

Before we turn to our empirical approach and results, we investigate how firms' IT intensity co-varies with firm size. On the one hand, we might expect the IT intensity to increase with firm size, for example, if the benefits of IT increase with scale (cf. Section 3.2). On the other hand, IT (operating) expenditures may contain a large fixed-cost component. If so, we might expect firms' IT intensity to decrease with firm size, because this fixed cost can be spread over a larger employment base. Figure 3.2 provides evidence in this regard. Considering cross-sectional variation in firm size and IT intensity (panel (a)), we find that the IT intensity consistently increases across firm size brackets in terms of employment. Firms with 50–100 employees have a 10 percent higher IT intensity compared to firms with less than 50 employees. These differences further increase as we move to firms within the 100–250 employee bracket. Firms with 250–500 (more than 500) employees have, on average, an IT



(a) IT intensity, cross-sectional estimates



(b) IT intensity, within estimates

Figure 3.2: IT Intensity and Firm Size

Note: The figure shows how IT expenditures per employee vary with firm size. Estimated coefficients are based on a regression of IT per employee on a set of indicator variables for the different firm size categories, with firms with less than 50 employees constituting the base category. Regressions underlying Figure 3.2(a) include industry-year fixed effects to account for industry differences in firm size and IT expenditures. Regressions underlying Figure 3.2(b) additionally include firm fixed effects, thereby exploiting the within-firm variation in firm size and IT expenditures per employee.

intensity that is almost 40 (60) percent higher than the one for small companies. These patterns are consistent with those reported in Lashkari et al. (2024). However, when we instead consider only the within-firm variation (panel (b)), the pattern is reversed, with IT expenditures per employee *decreasing* in firm size.[11] While these patterns do not speak to any causal links between firm size and IT intensity, the within-firm co-variation observed in Figure 3.2 is consistent with the idea that IT expenditures contain a large fixed cost component.

[11] The patterns observed in Figure 3.2 are reinforced if we measure firm employment on a continuous scale, rather than by including indicators for firm size groups.

3.4 Empirical Approach

Our interest lies in estimating the causal effects of firms' trading activities on their IT expenditures. In the following, we first present the empirical model of interest. Next, we discuss how we exploit export demand shocks and import supply shocks for identification.

3.4.1 Empirical Model

We specify the empirical model of interest as follows:

$$\log y_{ft} = \alpha \log X_{f,t-\ell} + \beta \log M_{f,t-\ell} + \delta \mathbf{Z}_{f,t_0} \cdot \gamma_t + \gamma_f + \gamma_{st} + u_{ft}, \tag{3.4.1}$$

where f denotes firms and t denotes time. Our main dependent variables of interest relate to (the log of) firms' expenditures on IT. In our main empirical analysis of Section 3.5, we consider a firm's IT expenditure and its IT expenditure per employee (referred to as IT intensity in the following). To shed further light on the mechanisms underlying our estimates, in Section 3.6 we also exploit information on different types of IT expenditures, as discussed in Section 3.3.

The first explanatory variable of interest, $\log X_{f,t-\ell}$, is (the log of) firm-level exports at time $t-\ell$. The second variable of interest is $\log M_{f,t-\ell}$, which denotes (the log of) firm-level imports. We allow for dynamic responses of IT expenditures to exports and imports by varying the lag length ℓ. In our baseline model, we set $\ell = 1$, i.e., firms are assumed to observe their exports and imports in $t-1$ and adjust their IT expenditures in the following year. In addition, we also consider contemporaneous effects and provide results for $\ell = 0$. Moreover, in our robustness analysis in Section 3.6, we report estimates from a distributed lag model, where different lags of the trade variables are considered jointly.

By considering firm-level imports and exports, our empirical analysis will speak to how changes in firms' trading behaviour at the intensive margin affect IT expenditures. Indeed, given that our sample excludes small firms with fewer than 10 employees, changes at the intensive margin are more prevalent. Thus, our results will remain silent about any potential effects that could stem from changes at the extensive margin, i.e., starting or stopping to be an exporter/importer.

Our specification in Equation (3.4.1) controls for non-time-varying firm characteristics, which may be correlated with $\log X_{f,t-\ell}$ and $\log M_{f,t-\ell}$, by including firm fixed effects (denoted γ_f). Thus, α and β are identified based on within-firm changes in trade over time. Furthermore, we include a vector of firm-specific control variables, $\mathbf{Z}_{f,t_0}$, measured in the base year, interacted with year fixed effects. We thereby account for differences in trends across firms, which we allow to depend on initial conditions.

This part of our empirical specification flexibly controls for the circumstance that firms with favorable characteristics may both invest more in IT, as well as export to more attractive markets, which could experience different trends in export demand shocks.[12]

We include the following variables in $\mathbf{Z}_{f,t_0}$: first, we include log employment, and log total fixed assets, as measures of firm's size and capital stock. Note that controlling for both implies controlling for differences across firms in capital intensity as well. Next, we add the firm's total wage bill, which – in combination with firm employment – implies controlling for average wages at the firm as a measure of skill intensity. These control variables thus account for the circumstance that firms which are more capital and/or skill intensive are more likely to also record higher IT expenditures. In fact, previous literature has shown that skills are important for the adoption of IT (Bresnahan, Brynjolfsson, and Hitt, 2002; Bugamelli and Pagano, 2004; Akerman, Gaarder, and Mogstad, 2015). Finally, we add firms' initial level of labour productivity (value added per employee) to the vector $\mathbf{Z}_{f,t_0}$.

In addition, our empirical model controls for two-digit-industry-year fixed, γ_{st}. These fixed effects account for differences in the level and growth rate of IT expenditures across industries. Indeed, we find these differences across industries to be substantial.

3.4.2 Identification

Estimation of Equation (3.4.1) by OLS is unlikely to give causal estimates. First, we are faced with a classical endogeneity concern since causality may (also) run from IT expenditures to export sales and import purchases (rather than vice versa). Indeed, previous literature has provided ample evidence that the adoption of specific IT technologies (such as broadband internet) increases trade volumes; see, e.g., Freund and Weinhold (2004), Choi (2010), Malgouyres et al. (2021) and Akerman et al. (2022). Second, we may be concerned that firm-level trade and IT expenditures are correlated with omitted time-varying firm-specific factors in the empirical model of Equation (3.4.1). Notably, our model does not contain standard firm-level control variables such as employment or productivity. Such variables would indeed be bad control variables (Angrist and Pischke, 2009) because they are themselves affected by the explanatory variables of interest. In addition, certain omitted firm-level factors – such as management practices or workforce composition – might constitute mediators in the causal link from firms' trading behaviour to their IT expenditures.

[12] Recall that we observe firm's IT expenditures starting in 2002. We chose the year 2000 as the base year, such that firm characteristics are measured two years before the start of the sample period.

To circumvent the resulting endogeneity and reverse causality concerns, we exploit information on demand shocks in firms' export markets and supply shocks in firms' import markets. Export demand shocks are correlated with firms' (potential) export market size as well as actual exports, and they are plausibly exogenous to firms' IT expenditures. Similarly, supply shocks in firms' import markets are correlated with firms' importing opportunities, as well as actual imports.

Our empirical strategy follows Hummels et al. (2014) and Aghion et al. (2024a). Define world import demand for product p in country c, WID_{cpt}, as the country's total imports of product p from the world market (excluding Denmark). Specifically, we construct WID_{cpt} based on country-pair-product-level trade data from BACI. Next, define $s_{fcp}^{b_{f0}}$ as the share of country-product cell cp in firm f's total exports in the base year b_{f0}, i.e.:

$$s_{fcp}^{b_{f0}} = \frac{\text{X}_{fcp}^{b_{f0}}}{\sum_c \sum_p \text{X}_{fcp}^{b_{f0}}}. \tag{3.4.2}$$

The firm-specific base year, b_{f0}, is either the year 2000 or the first year thereafter for which we observe positive exports for firm f.[13] Using these definitions, we aggregate world import demand up to the firm level:

$$\text{Export demand}_{ft} = \sum_c \sum_p s_{fcp}^{b_{f0}} \text{WID}_{cpt}. \tag{3.4.3}$$

In our empirical results, we follow two alternative strategies. First, we use $\text{Export demand}_{ft}$ directly as a measure of the market size faced by firm f. These (reduced form) estimates will speak to the question of whether expansions in foreign market size spur IT expenditures, independent on whether the benefits of these expansions are actually reaped by firms in the form of increased export sales. In the econometrics jargon, these estimates will, thus, reflect intention-to-treat effects. Second, we use $\text{Export demand}_{ft}$ as an instrument for firms' actual export sales, $X_{f,t}$, and estimate Equation (3.4.1) by IV.[14]

Next, we leverage supply shocks in firms' import markets to address the endogeneity of firm-level imports. Based on country-pair-product-level trade data from BACI, we construct world export supply of product p for origin country c, WES_{cpt}, as

[13] Recall that our sample period starts in 2002, which is the first year for which we have data on IT expenditures. We here exploit the circumstance that we can observe trade data already for prior years. For firms which do not export (import) in 2000, we take the first year with positive exports (imports), and drop that year from the sample.

[14] In both the reduced form, intention-to trade, and the IV approach, the sum of shares $s_{fcp}^{b_{f0}}$ for a given firm f may be smaller than one (e.g., due to changes in the product classification which imply that product codes exported in the base year may no longer be observed in subsequent years). Borusyak, Hull, and Jaravel (2022) show that in such shift-share settings with incomplete shares, it is crucial to control for the sum of shares interacted with time fixed effects. We follow their recommendations.

the country's total exports of product p to the world market (excluding Denmark) at time t. Next, we define $\delta_{fcp}^{b_{f0}^{imp}}$ as the share of country-product cell cp in firm f's total imports in the base year b_{f0}^{imp}, i.e.:

$$\delta_{fcp}^{b_{f0}^{imp}} = \frac{\mathrm{M}_{fcp}^{b_{f0}^{imp}}}{\sum_c \sum_p \mathrm{M}_{fcp}^{b_{f0}^{imp}}}. \tag{3.4.4}$$

Again, the firm-specific base year, b_{f0}^{imp}, is either the year 2000 or the first year thereafter for which we observe positive imports for firm f. Using these definitions, we aggregate world export supply up to the firm level:

$$\text{Import supply}_{ft} = \sum_c \sum_p \delta_{fcp}^{b_{f0}^{imp}} \text{WES}_{cpt}. \tag{3.4.5}$$

3.5 Exports, Foreign Sourcing, and IT Expenditures

This section discusses the results of our empirical analysis. Given the strong correlation between firm-level exports and imports, we present empirical models considering each explanatory variable in isolation, as well as a model where both are included jointly. In the latter case, we also provide tests of joint significance of firm-level trade on the considered firm-level outcomes (reported at the bottom of each table).

3.5.1 OLS Estimates

We start our analysis by considering estimation of (3.4.1) by OLS. Coefficient estimates, reported in Table 3.2, should be interpreted as the conditional correlations between firm-level exports or imports, and IT expenditures. In the upper part of the table, firm-level exports and imports are included in lags; in the lower part, we consider contemporaneous effects.

In the first three columns of the table, we report results with IT expenditure as dependent variable. When we consider each trade measure in isolation, we find that within-firm changes in exports and imports are positively and significantly correlated with within-firm changes in IT expenditures; cf. columns (1) and (2). This result holds independently on whether we consider lagged effects (upper part of the table) or contemporaneous effects (lower part). For imports, both contemporaneous and lagged correlations are of similar magnitude, while for exports the contemporaneous correlation is much larger. Once we include both variables jointly, estimates decrease in size (as expected, given the positive correlation of firm-level exports and imports),

Table 3.2: Exports, Foreign Sourcing, and IT Expenditures: OLS Results

Dependent variable:	Log IT Expenditures			Log IT Expenditure per Employee		
	(1)	(2)	(3)	(4)	(5)	(6)
Log Export (t-1)	0.050**		0.029	-0.020		-0.024
	(2.055)		(1.268)	(-1.035)		(-1.279)
Log Import (t-1)		0.094***	0.084***		0.011	0.019
		(3.939)	(3.727)		(0.553)	(0.995)
Observations	5140	5140	5140	5140	5140	5140
R^2	0.907	0.908	0.908	0.755	0.755	0.755
p-value, joint significance[a]			0.000			0.313
Dependent variable:	Log IT Expenditures			Log IT Expenditure per Employee		
	(1)	(2)	(3)	(4)	(5)	(6)
Log Export (t)	0.091***		0.071***	-0.020		-0.022
	(3.579)		(3.029)	(-0.957)		(-1.080)
Log Import (t)		0.101***	0.083***		0.004	0.010
		(4.065)	(3.488)		(0.210)	(0.505)
Observations	5140	5140	5140	5140	5140	5140
R^2	0.908	0.908	0.909	0.755	0.755	0.755
p-value, joint significance[a]			0.000			0.506

Notes: OLS estimates from the empirical model in Equation (3.4.1). All regressions contain firm fixed effects, industry-year fixed effects, as well interactions of base-year firm controls with year fixed effects. Robust t-statistics, clustered by firm, in parentheses. *** p<0.01, ** p<0.05, * p<0.1. [a] p-value from a test of joint significance of firm-level exports and imports.

and the coefficient estimate for exports turns insignificant in the upper part of the table. When considering contemporaneous effects, instead, both coefficient estimates are positive, significant, and strikingly similar in magnitude.

Within-firm changes in imports and exports are positively correlated with changes in firm employment. Thus, we next ask whether the conditional correlations uncovered this far represent that IT expenditures increase in proportion with output and thus other inputs, or whether we find similarly positive correlations also when we consider the IT intensity (IT expenditures per employee). We report results in columns (4)–(6) of Table 3.2. Independent on whether we measure trade in year $t-1$ or t, we find that neither exports nor imports are correlated with the firm's IT intensity.

The insignificant conditional correlations of both exports and imports with firm IT intensity in columns (4)–(6) are striking. For comparison, in Table A.5 in the Appendix, we report results where we consider firms' fixed assets (as a measure of capital) and fixed assets per employee as alternative dependent variables. Reassuringly, all coefficient estimates – including those in regressions for the capital intensity as dependent variable – are positive and highly statistically significant, as expected. Thus, IT expenditures seem to behave differently from capital.

By their very nature, the OLS estimates of Table 3.2 do not tell us whether a firm's trading activities *causally* affect its IT expenditures. In the remainder of this paper, we will therefore exploit our world import demand and world export supply shocks in Equations (3.4.3) and (3.4.5) in reduced form (RF) and instrumental variable (IV) regressions.

3.5.2 First Stage Estimates

Before we turn to the RF and IV estimates, we briefly discuss results from the first stage regressions of the instrumental variable approach. Results can be found in Table A.3 in the Appendix.

For each of the two endogenous trade variables, we first report results exploiting only the relevant instrumental variable (e.g., export demand shocks in the case of firm-level exports). Next, we also report results from a specification including both instruments. Reassuringly, export demand shocks strongly predict firm-level exports, with a coefficient estimate that is both statistically significant as well as economically important. Similarly, import supply shocks strongly predict firm-level imports. We also note that export demand shocks have a large positive effect on firms' imports, while import supply shocks do not affect exports. Overall, these results confirm that the shocks considered will provide strong instruments in our IV regressions.

To further understand the workings of our instrumental variables, we ask *how* export demand shocks (import supply shocks) affect firm-level exports (imports). For simplicity, we focus on Import supply$_{ft}$ here, but note that our argumentation similarly extends to Export demand$_{ft}$. Import supply$_{ft}$ reflects the potential supply faced by a firm from those product-country markets from which it imported already in the pre-sample year b_{f0}^{imp}. By construction, we would thus expect the import supply shocks to mainly affect firm-level imports via a within-firm-product-country increase in imports (intensive margin of trade). However, product-country-specific import supply shocks may be correlated, for a given product, across countries, as well as for a given country across products. Indeed, we find that our instrument strongly predicts not just changes in total imports, but also changes in the number of import origins as well as the number of products imported; cf. Table A.4 in the Appendix. Thus, even though our trade shocks are constructed based on a fixed set of products and countries in the base year, both our reduced form as well as IV results will at least partly also capture changes in IT expenditures induced by changes in trade at various extensive margins. This circumstance is important, as we might expect that changes in firms' trading behaviour at the extensive margins (number of products imported/exported, or number of trade partner countries), could constitute an important channel via which trade might increase firms' demand

Table 3.3: Trade Shocks and Firm Scale

Dependent variable:	Log Revenue		Log Employment		Log Fixed Assets
	(t-1)	(t)	(t-1)	(t)	(t)
	(1)	(2)	(3)	(4)	(5)
Log Export Demand (t-1)	0.075***	0.038***	0.055***	0.028**	0.044*
	(4.701)	(2.600)	(3.980)	(2.295)	(1.740)
Log Import Supply (t-1)	0.015	-0.007	0.019	0.001	0.029
	(0.714)	(-0.380)	(1.069)	(0.083)	(1.527)
Observations	5140	5140	5140	5140	5140
R^2	0.971	0.972	0.970	0.971	0.958
p-value, joint significance[a]	0.000	0.034	0.000	0.071	0.048

Notes: OLS estimates from the empirical model in Equation (3.4.1). All regressions contain firm fixed effects, industry-year fixed effects, as well interactions of base-year firm controls with year fixed effects. Robust t-statistics, clustered by firm, in parentheses. *** p<0.01, ** p<0.05, * p<0.1. [a] Gives the p-value from a test of joint significance of export demand shocks and import supply shocks.

for IT (e.g. increasing complexity of handling more suppliers).

3.5.3 Trade Shocks and Firm Scale

Part of the theoretical arguments outlined in Section 3.2 postulate that export (shocks) may affect IT expenditures through a scale effect. Do trade shocks indeed affect firm scale? A positive export demand shock represents increasing demand in the (base-year) export markets of the firm, which typically raises marginal revenue of the firm in those export markets. The firm optimally responds to the increasing marginal revenue by raising output.[15] The increase in output demands more inputs and thus capital and labour. Revenue will increase due to the increase in demand (larger price conditional on output) as well as due to the implied increase in output. Hence, the scale of the firm measured in either input factors (capital and labour) or revenue is expected to increase with a positive export demand shock.

In Table 3.3, we test for and confirm such effects using the logs of revenue, employment, and fixed assets as dependent variables. As expected, the effects of export demand shocks are stronger for firm revenue than for employment and fixed assets. Moreover, contemporaneous effects (i.e., when export demand shocks and firm scale are both measured in $t-1$; cf. columns (1) and (3)) are stronger than lagged effects (columns (2) and (4)). Importantly, while we will use export demand shocks as instruments for firm-level exports in the following, these estimates suggest that firms do not merely react to positive shocks on export markets by reallocating their sales across markets: total sales increase as well.

[15] A firm with increasing marginal costs would reduce output in other markets, but the net-effect on total output would be positive.

For import supply shocks, instead, priors on scale effects are less clear-cut: for example, if we interpret import supply shocks as a positive shock to firms' offshoring opportunities, firm employment might increase or decrease depending on whether a replacement effect (foreign workers replacing domestic workers) or a productivity effect (firm's labour demand increasing as offshoring increases firm productivity) dominates. The same argument applies for fixed assets. Alternatively, the import supply shock may imply that the firm shifts supplier of an intermediate good either from a domestic to a foreign or from one foreign to another. In line with these contrasting predictions, Table 3.3 reports no effect of import supply shocks on either input-based size measure of firm scale. Similarly, we also do not find any effects of import supply shocks on firm revenue in either the current or the following year.[16]

3.5.4 Reduced Form and IV Estimates

In Tables 3.4 and 3.5, we report results from the reduced form and IV estimations, respectively. In each table, we report our main results with IT expenditures and the IT intensity as dependent variables in columns (1)–(3) and (4)–(6), respectively. Again, the upper part of the table includes the main explanatory variables in lags, while the lower part reports contemporaneous effects. In the IV regressions, we use only one or both instruments, depending on whether we include one or both of the endogenous variables. In particular, note that import demand shocks do *not* fulfill the exclusion restriction if firm-level imports are not included. Thus, our empirical set-up does not allow us to test for exclusion restrictions. For comparison, we also report results using firms' capital (intensity) as a dependent variable in Tables A.6 and A.7 of the Appendix.

The reduced form estimates in Table 3.4 can be interpreted as the intention-to-treat effects. For the purpose of this paper, these estimates are interesting in their own right. In particular, positive export demand shocks can be interpreted as increases in the *potential* market size for a firm's products, and firms might increase their IT expenditures in reaction to such increases in market size even if they haven't increased their actual exports (yet). Similarly, import supply shocks reflect opportunities for offshoring/importing, and firms may react to such shocks by increasing their IT expenditures in anticipation of future offshoring/importing activities.

We find positive and significant effects of import supply shocks on firms' IT expenditures, independent on whether we measure such shocks in year t or $t-1$ (cf. columns (2) and (3) of Table 3.4). Recall from Table 3.3 that import demand

[16] We have confirmed that the results in Table 3.3 uphold if we use export demand shocks and import supply shocks as instruments for firm-level exports and imports: we find positive scale effects of exports, but not imports.

Table 3.4: Exports, Foreign Sourcing, and IT Expenditures: Reduced Form Estimates

Dependent variable:	Log IT Expenditures			Log IT Expenditure per Employee		
	(1)	(2)	(3)	(4)	(5)	(6)
Log Export Demand (t-1)	0.019		0.012	-0.010		-0.016
	(0.746)		(0.493)	(-0.384)		(-0.622)
Log Import Supply (t-1)		0.048**	0.044*		0.041	0.043
		(2.148)	(1.944)		(1.602)	(1.626)
Observations	5140	5140	5140	5140	5140	5140
R^2	0.908	0.908	0.908	0.756	0.756	0.757
p-value, joint significance[a]			0.114			0.245
Dependent variable:	Log IT Expenditures			Log IT Expenditure per Employee		
	(1)	(2)	(3)	(4)	(5)	(6)
Log Export Demand (t)	0.008		-0.002	-0.016		-0.023
	(0.305)		(-0.067)	(-0.639)		(-0.882)
Log Import Supply (t)		0.065*	0.063*		0.036	0.040
		(1.958)	(1.798)		(0.970)	(1.025)
Observations	5140	5140	5140	5140	5140	5140
R^2	0.908	0.908	0.908	0.756	0.756	0.757
p-value, joint significance[a]			0.189			0.469

Notes: OLS estimates from the empirical model in Equation (3.4.1). All regressions contain firm fixed effects, industry-year fixed effects, as well interactions of base-year firm controls with year fixed effects. Robust t-statistics, clustered by firm, in parentheses. *** p<0.01, ** p<0.05, * p<0.1. [a] p-value from a test of joint significance of firm-level exports and imports.

shocks do not seem to affect firm employment. Thus, in theory, any positive effect on IT expenditures should also translate into a positive effect on firms' IT intensity. Indeed, for the IT intensity, in the upper part of Table 3.4 where we consider lagged effects of import shocks, estimates are also positive and similar in size to those for IT expenditures, but marginally insignificant (columns (5) and (6)). These results are reinforced in the IV regressions of Table 3.5. Effects are also economically large: for example, the IV estimates in column (3) of Table 3.5 imply that a 1% increase in imports in $t-1$ is predicted to increase IT expenditures in the subsequent year by roughly 0.3%.

In sum, we find that firms increase their spending on IT in response to off-shoring/importing possibilities (as well as actual increases in imports). Interestingly, these effects do not correspond to a scale effect: in fact, import supply shocks do not seem to affect firm scale (cf. Table 3.3). Instead, these effects must be driven by a change in the composition of activities within the firm, increasing the demand for IT. For example, these effects may be rationalized if purchasing internationally – compared to domestically – is complex and raises the demand for IT (cf. Section 3.2).

Next, we consider the effects of export (demand shocks). In the reduced form

Table 3.5: Exports, Foreign Sourcing, and IT Expenditures: IV Estimates

Dependent variable:	Log IT Expenditures			Log IT Expenditure per Employee		
	(1)	(2)	(3)	(4)	(5)	(6)
Log Export (t-1)	0.063		-0.095	-0.033		-0.207
	(0.752)		(-0.694)	(-0.383)		(-1.311)
Log Import (t-1)		0.247**	0.291*		0.211	0.322
		(2.033)	(1.651)		(1.403)	(1.456)
Observations	5140	5140	5140	5140	5140	5140
R^2	0.009	-0.012	-0.027	0.005	-0.037	-0.089
First stage *F*, exports	44.68		25.17	44.68		25.17
First stage *F*, imports		14.95	14.12		14.95	14.12
Kleibergen-Paap *rk* Wald	44.68	14.95	3.793	44.68	14.95	3.793
LM under-identification	35.83	15.07	7.774	35.83	15.07	7.774
– *p* value	0.000	0.000	0.005	0.000	0.000	0.005
p-value, joint significance[a]			0.155			0.338

Dependent variable:	Log IT Expenditures			Log IT Expenditure per Employee		
	(1)	(2)	(3)	(4)	(5)	(6)
Log Export (t)	0.048		-0.183	-0.099		-0.238
	(0.308)		(-0.867)	(-0.632)		(-1.118)
Log Import (t)		0.446*	0.471		0.249	0.284
		(1.669)	(1.538)		(0.882)	(0.877)
Observations	5140	5140	5140	5140	5140	5140
R^2	0.016	-0.109	-0.150	0.000	-0.060	-0.090
First stage *F*, exports	26.99		14.14	26.99		14.14
First stage *F*, imports		7.915	6.794		7.915	6.794
Kleibergen-Paap *rk* Wald	26.99	7.915	3.757	26.99	7.915	3.757
LM under-identification	22.15	8.151	7.783	22.15	8.151	7.783
– *p* value	0.000	0.004	0.005	0.000	0.004	0.005
p-value, joint significance[a]			0.300			0.530

Notes: OLS estimates from the empirical model in Equation (3.4.1). All regressions contain firm fixed effects, industry-year fixed effects, as well interactions of base-year firm controls with year fixed effects. Robust t-statistics, clustered by firm, in parentheses. *** p<0.01, ** p<0.05, * p<0.1. [a] *p*-value from a test of joint significance of firm-level exports and imports.

regressions, coefficient estimates on the export demand shock are small and statistically insignificant, independent of whether we consider IT expenditures (columns (1) and (3) of Table 3.4) or IT intensities (cf. columns (4) and (6)). Thus, increases in firms' potential market size do not seem to induce firms to increase their IT expenditures. Moreover, the IV estimates in Table 3.5 confirm that these findings uphold even if we consider only 'conformers', i.e., firms that actually increased their exports in response to positive demand shocks on export markets. Thus, any positive correlations of exports with IT expenditures uncovered in the OLS estimations of Table 3.2 do *not* reflect a causal effect.

Our findings on export (demand shocks) are puzzling because they would seem

at odds with the vast empirical literature on the positive effects of trade liberalization on firms' technology upgrading and innovation. However, IT expenditures differ from technology upgrading in several respects: first, the costs of technology upgrading can likely be thought of as being largely of a sunk-cost nature. Instead, in our dataset, IT expenditures are mainly composed of operating expenses, and therefore seem to largely capture costs that have to be incurred on a continuous basis. Second, IT expenditures may be thought of as having at least partly a fixed cost nature. Thus, IT expenditures may have a large component which plausibly might be invariant to firm scale. Finally, we differ from some of the previous papers in the literature in that we do not consider the effects of large-scale lasting reductions in trade barriers (tariff reductions or formation of free trade agreements), but rather short term changes in firms' potential export market size. In the following section, we try to shed some light on these alternative explanations for our findings by exploiting data on various types of IT expenditures for the 2007–2015 sub-period.

3.6 Extensions and Robustness

In the following two sections, we exploit data on IT expenditures at a more detailed level to further investigate the potential mechanisms through which trade may affect firms' IT expenditures. We start our analysis by asking whether IT investments and operating expenses might react differently to trade. Next, we consider the effects on different types of IT, namely, IT equipment, software, and IT services.

While practically all firms report positive IT expenditures (and we have excluded those firms which do not), IT expenditures can be zero for a significant fraction of firms once we disaggregate expenditures into different categories. With more than 40%, the fraction of firm-year observations with zero IT expenditures is particularly large if we consider investments in IT. Thus, in the following, we consider estimation of a model for IT expenditures (in levels) using Poisson pseudo maximum likelihood (PPML).[17] In addition, we focus on the reduced form estimates exploiting our export demand shocks and import supply shocks. We continue to find insignificant effects of trade on the IT intensity in the majority of our regressions[18], and therefore report only results for IT expenditures in the following.

[17] The PPML estimator will drop 'singletons', i.e., groups with only one observation. In our data, the number of such singletons differs depending on the type of IT expenditure we consider. In the following, we ensure that the number of observations is consistent across regressions *within* each table (but not necessarily across tables).

[18] IT intensity is defined, consistent with the baseline analysis, as IT expenditures per employee. The statistically insignificant results may stem from the fixed-cost nature of IT, which could obscure its relationship with firm's trading activities. For brevity, these results are not included in the main analysis of this subsection but are available upon request.

3.6.1 Investments vs. Operating Expenses

IT expenditures can be decomposed into operating expenses and investments. This distinction might be important. In fact, we might think of an analysis of investment into IT to be more closely comparable to previous studies in the literature that look at broad measures of technological change.

Results are reported in Table 3.6. In the first column, for comparison, we provide PPML estimates for total IT expenditures (including both investments and operating expenses) as dependent variable. Apart from being based on a different estimator (PPML rather than OLS), the sample is also different from our previous regressions, since the period for which IT expenditures can be decomposed is shorter than the full sample period. We continue to find positive and significant effects of import supply shocks on total IT expenditures independent on whether we consider contemporaneous or lagged effects. Similarly, in line with our previous findings, the estimated effect of export demand shocks continues to be insignificant.

In columns (2) and (3), we turn to firms' investment into IT and IT operating expenses, respectively. Importantly, we find statistically significant and economically large effects of contemporaneous export demand shocks on IT investments: a 1% increase in these demand shocks is predicted to increase firms' investment into IT in the same year by 0.264%; cf. the lower part of Table 3.6. The equivalent effects of export demand shocks on operating expenses are negative and significant. These contrasting effects may partly explain why we do not find any effects of export (demand shocks) on firms' total IT expenditures. Indeed, substitution across expenditure types is possible; when a firm increases IT investments, it can obtain a given level of IT for lower IT operating expenses. Moreover, higher IT investments result in a level of IT conditional on operating expenses in future periods and an increase in lagged export demand and thereby lagged IT investments may increase the current level of IT without having effect on current IT expenditures.

The positive and significant effect of exports on IT investments accords well with previous literature that have looked at various other types of technology upgrading, see e.g., Bustos (2011). As a firm observes a positive export demand shock, it increases IT investment, which in turn increases its stock of IT in the current year as well as in the years that follow. This indicates that firms perceive such demand shocks as somewhat persistent and therefore invest in the hope/expectation to realize the increased export potential in the (present and) following years.

For import (supply shocks), instead, we find significant and economically large effects on both investments into IT as well as operating expenses. Economic magnitudes are largest when we allow these effects to operate with a lag: for example, results reported in column (2) in the upper part of Table 3.6 predict that the elasticity of IT

Table 3.6: IT Investment vs. Operating Expenditures

Dependent variable:	IT expenditure	IT investment	IT operating expenses
	(1)	(2)	(3)
Log Export Demand (t-1)	-0.025	0.011	0.003
	(-0.324)	(0.051)	(0.039)
Log Import Supply (t-1)	0.548***	0.920***	0.406**
	(2.819)	(2.880)	(2.205)
Observations	2379	2379	2379
p-value, joint significance[a]	0.019	0.013	0.088
Dependent variable:	IT expenditure	IT investment	IT operating expenses
	(1)	(2)	(3)
Log Export Demand (t)	-0.063	0.264**	-0.098**
	(-1.216)	(2.369)	(-1.967)
Log Import Supply (t)	0.317*	0.593**	0.252
	(1.697)	(2.016)	(1.385)
Observations	2379	2379	2379
p-value, joint significance[a]	0.230	0.005	0.144

Notes: PPML estimates. All regressions contain firm fixed effects, industry-year fixed effects, as well interactions of base-year firm controls with year fixed effects. Robust t-statistics, clustered by firm, in parentheses. *** p<0.01, ** p<0.05, * p<0.1. [a] p-value from a test of joint significance of firm-level exports and imports.

investments to import supply shocks is close to one. The corresponding elasticity for IT operating expenses is also large (though only around half as big), and also highly statistically significant. Hence, the effect on IT demand due to an import supply shock is thus larger and more sluggish (positive effect on investment also with a lag) than for an export demand shock.

3.6.2 Types of IT: Equipment, Software and IT Services

IT expenditures encompass different types of IT, which might react very differently to firms' trading opportunities. For example, expenditures on software may include business management systems (such as enterprise resource planning (ERP) software), e-commerce applications, virtual private network (VPN) software, etc. Some of these types of software might be crucial when expanding internationally because they allow for faster and more reliable communication along the supply chain. We may also expect some effects of trade on firms' expenditures on IT equipment (such as servers, communication equipment and network equipment). However, remember that IT equipment only accounts for a small share of overall expenditures.

Results are reported in Table 3.7. First, consider shocks to firms' importing possibilities. We find that the positive effects of such shocks on firms' IT expenditures, as seen in our analysis this far, are driven by positive effects on software expenditures;

Table 3.7: Exports, Foreign Sourcing, and Types of IT Expenditures

Dependent variable:	IT expenditure	Software	IT services	IT equipment
	(1)	(2)	(3)	(4)
Log Export Demand (t-1)	-0.133**	0.000	-0.217	-0.115
	(-1.989)	(0.002)	(-1.178)	(-1.043)
Log Import Supply (t-1)	0.365*	0.624***	0.324	0.311
	(1.655)	(2.727)	(1.059)	(1.256)
Observations	2621	2621	2621	2621
p-value, joint significance[a]	0.033	0.024	0.345	0.324
Dependent variable:	IT expenditure	Software	IT services	IT equipment
	(1)	(2)	(3)	(4)
Log Export Demand (t)	-0.091*	-0.151*	-0.116	-0.058
	(-1.757)	(-1.954)	(-1.118)	(-0.884)
Log Import Supply (t)	0.220	0.431*	-0.422	0.167
	(1.154)	(1.893)	(-1.284)	(0.848)
Observations	2621	2621	2621	2621
p-value, joint significance[a]	0.213	0.105	0.008	0.633

Notes: PPML estimates. All regressions contain firm fixed effects, industry-year fixed effects, as well interactions of base-year firm controls with year fixed effects. Robust t-statistics, clustered by firm, in parentheses. *** p<0.01, ** p<0.05, * p<0.1. [a] p-value from a test of joint significance of firm-level exports and imports.

cf. column (2). Once more, we also find these effects to be strongest once we allow them to operate with a lag. The effects of import supply shocks on IT equipment and purchases of IT services are also positive, but statistically insignificant.

Next, consider shocks to firms' exporting opportunities. Once more, our findings are inconsistent with a scale effect: none of the estimates are positive and significant, independent on which type of IT expenditure we consider. Instead, we find *negative* and significant effects of export demand shocks on firms' software expenditures. While this finding might seem striking, it is well in line with the negative estimate unveiled in the regression for IT operating expenses in Table 3.6: in fact, software expenditures are often operating expenses, e.g., because licenses have to be renewed.

3.6.3 Estimates from a Distributed Lag Model

In the previous two sections, we have shed light on our findings by considering the components of IT expenditures. Next, instead, we re-consider the dynamics in the relationship between trade shocks and firms' IT expenditures.

Note that the fixed effect estimator that we apply in this paper to the study of firms' IT expenditures assumes strict exogeneity of the explanatory variables. Given the construction of the instrumental variables, it is reasonable to assume that future values of the instruments are uncorrelated with current shocks to IT expenditures (i.e.,

ϵ_{it} in Equation (3.4.1)). However, the assumption that the error term in our empirical model is uncorrelated with excluded lags of the instruments (Export demand$_{ft-\ell}$, Import supply$_{ft-\ell}$) may be violated. In particular, our models this far include either one-year lags of these variables (upper part of each table) or contemporaneous effects (in the lower part of each table). However, there are reasons to believe that contemporaneous effects and lagged effects operate at the same time. To address this concern, we next estimate a distributed lag model.

Since the dynamic relationship between trade shocks and firms' IT expenditures might differ for operating expenses and IT investments, we focus on these two components in the following. Results from the distributed lag model for IT investments and IT operating expenses can be found in columns (1)–(3) and (4)–(5) of Table 3.8, respectively. For each dependent variable, we start with a model containing only the contemporaneous effects, and then continue to include first-order and second-order lags in the following two columns.

Results in Table 3.8 reinforce our findings in Table 3.6. Considering import supply shocks, we continue to find positive effects on both IT investments as well as operating expenses. Moreover, these effects seem to operate with a one-year lag: conditional on this one-year lag, the contemporaneous effect and second-year lag are either insignificant (column (3)) or only marginally significant (column (6)). Considering export demand shocks, we once more find large positive contemporaneous effects, but only for IT investments. For operating expenses, all estimated effects of export demand shocks are statistically insignificant, though oftentimes negative (in line with Table 3.6).

3.7 Conclusion

Information technology (IT) has proven important for the performance of firms and economies. Accordingly, obtaining a better understanding of the determinants of IT expenditures is of key importance for policy makers. The present paper contributes to the existing literature, cf. the Introduction, by analysing the impact of international trade on IT expenditures at the firm-level.

In particular, we exploit Danish data including a repeated survey of firms' IT expenditures (2002-2015) to ask whether firm-level trade expansions/contractions – imports and exports separately – affect firm-level IT expenditures among two-way trading firms. First, we document positive within-firm conditional correlations between imports (exports) and IT expenditures. Second, we apply well-established measures of exogenous firm-level export demand shocks and import supply shocks to ask if these positive correlations capture causal effects. For imports, we find causal

Table 3.8: Estimates from a Distributed Lag Model

Dependent variable:	IT Investments			IT Operating Expenses		
	(1)	(2)	(3)	(4)	(5)	(6)
Log Export Demand (t)	0.288***	0.307***	0.302***	-0.079	-0.064	-0.049
	(2.648)	(3.179)	(3.241)	(-1.640)	(-1.606)	(-1.230)
Log Export Demand (t-1)		-0.035	0.105		0.049	0.030
		(-0.175)	(0.561)		(0.606)	(0.395)
Log Export Demand (t-2)			-0.126			0.036
			(-0.546)			(0.623)
Log Import Supply (t)	0.550*	0.222	0.204	0.277	0.019	0.037
	(1.936)	(0.868)	(0.820)	(1.491)	(0.165)	(0.331)
Log Import Supply (t-1)		0.556*	0.558*		0.439***	0.231**
		(1.802)	(1.921)		(2.884)	(1.975)
Log Import Supply (t-2)			-0.033			0.209*
			(-0.145)			(1.695)
Observations	2332	2332	2332	2332	2332	2332
p-value, joint significance[a]	0.003	0.001	0.001	0.219	0.018	0.094

Notes: PPML estimates. All regressions contain firm fixed effects, industry-year fixed effects, as well interactions of base-year firm controls with year fixed effects. Robust t-statistics, clustered by firm, in parentheses. *** p<0.01, ** p<0.05, * p<0.1. [a] p-value from a test of joint significance of firm-level exports and imports.

and sizeable effects on IT expenditures. Import supply shocks are found to positively affect imports (first-stage estimates), but not (with statistically significance) size measures of the firm (sales, employment, or fixed assets). Hence, the positive effect on IT expenditures seems not to be driven by a general expansion of firm-level activity, but rather by changes in the composition of activities within the firm (e.g., if increased import is driven by offshoring less IT intensive tasks) or from the increased complexity of buying internationally (relative to domestically). When we decompose IT expenditures into software, IT services and IT equipment, we find from reduced form regressions that the positive effect of the import supply shock on IT expenditures seems primarily to be driven by the software component. Surprisingly, for export demand shocks – that positively affect firm-level size measures as well as exports – we find no causal effect on IT expenditures. Only when we consider sub-categories of IT expenditures (IT investments vs. IT operating expenditures) we find a positive causal effect of exports demand shocks on the sub-category IT investments, which is counterbalanced by a negative effect on operating expenses.

While IT expenditures are employed here as a proxy for a firm's IT resources, it is crucial to reflect on how this measure aligns with the concept of capital. IT resources, as captured by expenditures, embody elements of both capital and operational costs, making them distinct from traditional notions of capital that are primarily associated with durable, long-term investments. A clear advantage of IT expenditures as a proxy is its broadness as it captures all types of IT, whereas other studies in the literature

often focus on specific types of IT (e.g., a binary measure of e-commerce). The broadness implies that substitution across different types of IT is captured, which may be particularly important over longer time periods as in the present paper where new types of IT replace older types of IT. Despite this advantage, IT expenditures is not an ideal proxy. In particular, the level of IT resources available to a firm will - beyond current IT expenditures also - be affected by IT investments in previous years. One possible approach to this challenge would be to compute/estimate the level of IT resources available to the firm as the sum of current IT operating expenses and the stock of IT capital derived from previous (and current IT investments) using the perpetual inventory method.[19] However, for IT technology – which develops fast and makes old versions obsolete – it may be particular difficult to obtain a reliable depreciation rate (even if conducted across the sub-categories of IT expenditures). Another and less ambitious approach would be to control for lagged values of IT investments in the regressions. It is also important to note that the data on firms' IT expenditures employed in this paper do not include general employee costs on IT but only account for FTEs for software development, which could understate the full scale of a firm's IT resources. Such advances are left for future research.

Another agenda for future research is to further exploit the trade aspect by utilizing the details of the trade data. Properties of the trade partner (gravity variables; e.g., distance measures or IT level of the partner country) may be important for the effects of trade on IT expenditures. Similarly, it may be important whether trade expansion is driven by adding products and countries to the portfolio (extensive margin expansion, which certainly adds complexity to the business) or by simply trading more within existing trade relations.

[19] Even previous operating expenses may effect the current level of IT resources, e.g., purchase of IT equipment (not classified as investments) or IT consultant services that facilitated implementation of new software.

3.8 References

Abramovsky, L., Griffith, R., 2006. Outsourcing and offshoring of business services: How important is ICT? Journal of the European Economic Association 4 (2-3), 594–601.

Aghion, P., Bergeaud, A., Lequien, M., Melitz, M. J., 05 2024a. The Heterogeneous Impact of Market Size on Innovation: Evidence from French Firm-Level Exports. The Review of Economics and Statistics 106 (3), 608–626.

Aghion, P., Bergeaud, A., Lequien, M., Melitz, M. J., Zuber, T., 05 2024b. Opposing Firm-Level Responses to the China Shock: Output Competition versus Input Supply. American Economic Journal: Economic Policy 16 (2), 249–269.

Akcigit, U., Melitz, M., 2022. Chapter 6 – International trade and innovation. In: Gopinath, G., Helpman, E., Rogoff, K. (Eds.), Handbook of International Economics: International Trade, Volume 5. Vol. 5 of Handbook of International Economics. Elsevier, 377–404.

Akerman, A., Gaarder, I., Mogstad, M., 07 2015. The Skill Complementarity of Broadband Internet. The Quarterly Journal of Economics 130 (4), 1781–1824.

Akerman, A., Leuven, E., Mogstad, M., 2022. Information frictions, internet, and the relationship between distance and trade. American Economic Journal: Applied Economics 14 (1), 133–163.

Andrews, D., Nicoletti, G., Timiliotis, C., 2018. Digital technology diffusion: A matter of capabilities, incentives or both?

Angrist, J. D., Pischke, J.-S., 2009. Mostly Harmless Econometrics: An Empiricist's Companion. No. 8769 in Economics Books. Princeton University Press.

Aw, B. Y., Roberts, M. J., Xu, D. Y., June 2011. R&D Investment, Exporting, and Productivity Dynamics. American Economic Review 101 (4), 1312–44.

Bloom, N., Garicano, L., Sadun, R., Van Reenen, J., 2014. The distinct effects of information technology and communication technology on firm organization. Management Science 60 (12), 2859–2885.

Borusyak, K., Hull, P., Jaravel, X., 2022. Quasi-experimental shift-share research designs. The Review of Economic Studies 89 (1), 181–213.

Bresnahan, T. F., Brynjolfsson, E., Hitt, L. M., 02 2002. Information Technology, Workplace Organization, and the Demand for Skilled Labor: Firm-Level Evidence. The Quarterly Journal of Economics 117 (1), 339–376.

Brynjolfsson, E., Jin, W., Wang, X., 2023. Information technology, firm size, and industrial concentration. NBER Working paper 31065, National Bureau of Economic Research.

Bugamelli, M., Pagano, P., 2004. Barriers to investment in ICT. Applied Economics 36 (20), 2275–2286.

Bustos, P., 2011. Trade liberalization, exports, and technology upgrading: Evidence on the impact of MERCOSUR on Argentinian firms. American Economic Review 101 (1), 304–340.

Cardona, M., Kretschmer, T., Strobel, T., 2013. ICT and productivity: conclusions from the empirical literature. Information Economics and Policy 25 (3), 109–125.

Cassiman, B., Golovko, E., Martínez-Ros, E., 2010. Innovation, exports and productivity. International Journal of Industrial Organization 28 (4), 372–376.

Chen, M., Martincus, C. V., 2022. Digital technologies and globalization: A survey of research and policy applications. Tech. rep., Inter-American Development Bank.

Chen, Z., Zhang, J., Zheng, W., 2017. Import and innovation: Evidence from Chinese firms. European Economic Review 94, 205–220.

Choi, C., 2010. The effect of the internet on service trade. Economics Letters 109 (2), 102–104.

Clarke, G. R. G., Wallsten, S. J., 2006. Has the Internet Increased Trade? Developed and Developing Country Evidence. Economic Inquiry 44 (3), 465–484.

Coelli, F., Moxnes, A., Ulltveit-Moe, K. H., 2022. Better, faster, stronger: Global innovation and trade liberalization. Review of Economics and Statistics 104 (2), 205–216.

DeStefano, T., De Backer, K., Moussiegt, L., 2017. Determinants of digital technology use by companies.

Dhyne, E., Konings, J., Van den bosch, J., Vanormelingen, S., 2021. The return on information technology: Who benefits most? Information Systems Research 32 (1), 194–211.

Freund, C. L., Weinhold, D., 2004. The effect of the internet on international trade. Journal of International Economics 62 (1), 171–189.

Gaulier, G., Zignago, S., 2010. BACI: International Trade Database at the Product-Level. The 1994-2007 Version. Working Papers 2010-23, CEPII.

Gierten, D., Viete, S., Andres, R., Niebel, T., 2021. Firms going digital: Tapping into the potential of data for innovation. OECD Digital Economy Papers 320.

Giotopoulos, I., Kontolaimou, A., Korra, E., Tsakanikas, A., 2017. What drives ict adoption by smes? evidence from a large-scale survey in greece. Journal of Business Research 81, 60–69.

Haller, S. A., Siedschlag, I., 2011. Determinants of ict adoption: Evidence from firm-level data. Applied Economics 43 (26), 3775–3788.

Hummels, D., Jørgensen, R., Munch, J., Xiang, C., 2014. The wage effects of offshoring: Evidence from Danish matched worker-firm data. American Economic Review 104 (6), 1597–1629.

Lashkari, D., Bauer, A., Boussard, J., 2024. Information technology and returns to scale. American Economic Review 114 (6), 1769–1815.

Lileeva, A., Trefler, D., 2010. Improved access to foreign markets raises plant-level productivity... for some plants. The Quarterly Journal of Economics 125 (3), 1051–1099.

Malgouyres, C., Mayer, T., Mazet-Sonilhac, C., 2021. Technology-induced trade shocks? Evidence from broadband expansion in France. Journal of International Economics 133, 103520.

Ricci, L. A., Trionfetti, F., 2012. Productivity, networks, and export performance: Evidence from a cross-country firm dataset. Review of International Economics 20 (3), 552–562.

Wakelin, K., 1998. Innovation and export behaviour at the firm level. Research Policy 26 (7), 829–841.

3.A Appendix

3.A.1 Data Appendix

3.A.1.1 Data on IT Expenditures

According to Denmark Statistics, the response rate for the IT survey is 95%, with non-response being partly due to bankruptcy and other changes in firm demographics. In cases where IT expenditures are not recorded in firms' financial statements, firms are asked to give a best estimate of their expenditures. Expenditures are recorded before depreciation, and excluding taxes. IT products which are purchased for direct re-sale are not included in the statistics.

For the period 2007–2015, IT expenditures can be divided into different types of IT, namely:

(i) hardware (e.g. computers, tablets, printers etc.)

(ii) telecommunication equipment (e.g. phones, smartphones, transmission equipment, GPS equipment)

(iii) other IT equipment

(iv) standard software (including software packages, application software, operation systems, cloud computing etc.)

(v) specialized software (i.e., software specifically developed for the company)

(vi) service contracts and IT consultancy (e.g., service support for hardware and software, IT design and development, service contracts, webhosting and homepages)

(vii) telecommunication services (e.g., telephone bills, internet services incl. broadband)

(viii) rental of IT equipment (e.g., rental of hardware)

(ix) other IT services

We aggregate these components as follows: IT equipment is the sum of (i) – (iii); Software is the sum of (iv) and (v); IT services is the sum of (vi) – (ix). Notably, software expenditures include both purchases of software as well as expenditures on software licenses.

Moreover, for the same period, total IT expenditures can be broken down into investments ("aktiverede udgifter") and direct expenses ("direkte udgifter"). Investment here refers to expenditures on IT which have been recorded as an asset in the

financial year and will be gradually expensed over multiple years, typically through depreciation or amortization. This may include purchased IT equipment but also certain types of software, and even IT consultancy. For direct expenses, the entire cost has been recorded as an expense in the specified accounting year, rather than being spread out over multiple periods. Practically all firms report direct expenses on IT, whereas non-zero investments in IT are reported only by 59 percent of firms in our sample.

Table A.1: Sample Restrictions

Description of Sample Restriction	Number of Firms	Number of Observations	Average Employment
Manufacturing firms in IT survey, with more than 10 Employees	2932	8224	297
Non-missing Export Demand Shock (t)	2136	6935	342
Non-missing Import Supply Shock (t)	1925	6572	358
Non-missing Export Demand and Import Supply Shock in (t-1)	1805	6298	365
Positive Exports and Imports in year (t)	1733	6087	375
Positive Exports and Imports in year (t-1)	1702	6011	378
IT expenditures > 0	1675	5905	380
Drop singletons etc.	966	5140	423

Notes: The table reports the number of firms, firm-year observations, and average firm employment, after successive sample restrictions. The first row is the starting sample, including all manufacturing firms with at least 10 employees, which report to the IT expenditure survey, and which can be matched to other firm statistics registers. The last row restricts the sample to those observations which are part of the regression analysis. In particular, this step drops singleton observations of firms.

3.A.1.2 Additional Summary Statistics

Table A.2: Summary Statistics: Types of IT, and Investment vs. Operating Expenses

	Mean	SD	Observations
Panel A: Full Sample			
Overall IT expenditure	22,012	138,874	2,998
Investment, indicator	0.586	0.493	2,998
Investment share	0.140	0.197	2,998
Software share	0.329	0.256	2,998
IT equipment share	0.0593	0.0988	2,998
IT services share	0.612	0.265	2,998
Panel B: Top-Exporters			
Overall IT expenditure	91,392	300,134	598
Investment, indicator	0.737	0.440	598
Investment share	0.170	0.189	598
Software share	0.387	0.249	598
IT equipment share	0.0569	0.0949	598
IT services share	0.557	0.263	598
Panel B: Top-Importers			
Overall IT expenditure	91,440	300,275	598
Investment, indicator	0.726	0.447	598
Investment share	0.173	0.191	598
Software share	0.365	0.258	598
IT equipment share	0.0624	0.111	598
IT services share	0.573	0.272	598

Notes: Panel A reports summary statistics for all firm-year observations in the sample; Panels B and C report summary statistics for top-exporters and top-importers, respectively. Top-traders are defined, for each year, as the top-quintile of the distribution of firm-level exports or imports. Notably, the set of top-importers and top-exporters is partly overlapping, but some firms belong to only one of the two categories.

3.A.2 Empirical Appendix

3.A.2.1 First Stage Results and Additional Results on Workings of the IV

Table A.3: First Stage Estimates

Dependent variable:	Log Exports (t-1)	Log Imports (t-1)	Log Exports (t-1)	Log Imports (t-1)
	(1)	(2)	(3)	(4)
Log Export Demand (t-1)	0.296***		0.288***	0.136***
	(6.687)		(6.377)	(3.981)
Log Import Supply (t-1)		0.196***	0.059	0.171***
		(3.868)	(1.550)	(3.464)
Observations	5140	5140	5140	5140
R^2	0.929	0.938	0.929	0.939
p-value, joint significance[a]			0.000	0.000

Notes: First stage results. All regressions contain firm fixed effects, industry-year fixed effects, as well interactions of base-year firm controls with year fixed effects. Robust t-statistics, clustered by firm, in parentheses. *** p<0.01, ** p<0.05, * p<0.1. [a] p-value from a test of joint significance of firm-level exports and imports.

Table A.4: Export Demand, Import Supply, and Firm's Trading Behaviour

	Number Of Export Destinations (t-1)			Number Of Export Products (t-1)			Number Of Export Markets (t-1)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Log Export Demand (t-1)	0.109***		0.107***	0.118***		0.114***	0.168***		0.162***
	(5.977)		(5.794)	(5.130)		(4.917)	(6.476)		(6.175)
Log Import Supply (t-1)		0.032**	0.015		0.067***	0.048**		0.063***	0.039
		(2.256)	(1.090)		(2.900)	(2.110)		(2.641)	(1.642)
Observations	5140	5140	5140	5140	5140	5140	5140	5140	5140
R^2	0.945	0.944	0.946	0.886	0.884	0.886	0.932	0.929	0.932
p-value, joint significance[a]			0.000			0.000			0.000
	Number Of Import Origins (t-1)			Number Of Import Products (t-1)			Number Of Import Markets (t-1)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Log Export Demand (t-1)	0.057***		0.042***	0.101***		0.082***	0.113***		0.091***
	(4.163)		(3.225)	(5.790)		(4.854)	(6.217)		(5.291)
Log Import Supply (t-1)		0.096***	0.099***		0.147***	0.140***		0.162***	0.156***
		(5.264)	(5.549)		(7.648)	(7.168)		(6.993)	(7.085)
Observations	5140	5140	5140	5140	5140	5140	5140	5140	5140
R^2	0.918	0.920	0.922	0.925	0.926	0.927	0.935	0.937	0.938
p-value, joint significance[a]			0.000			0.000			0.000

Notes: [a] p-value from a test of joint significance of firm-level exports and imports.

3.A.2.2 Additional Results: Fixed Assets

Table A.5: Fixed Assets – OLS Results

Dependent variable:	Log Fixed Assets			Log Fixed Assets per Employee		
	(1)	(2)	(3)	(4)	(5)	(6)
Log Export (t-1)	0.126***		0.100***	0.057***		0.047**
	(5.312)		(4.483)	(2.921)		(2.468)
Log Import (t-1)		0.139***	0.105***		0.056***	0.040**
		(5.981)	(5.127)		(2.666)	(2.000)
Observations	5140	5140	5140	5140	5140	5140
R^2	0.959	0.959	0.960	0.899	0.899	0.899
p-value, joint significance[a]			0.000			0.006

Notes: OLS estimates from the empirical model in Equation (3.4.1). All regressions contain firm fixed effects, industry-year fixed effects, as well interactions of base-year firm controls with year fixed effects. Robust t-statistics, clustered by firm, in parentheses. *** p<0.01, ** p<0.05, * p<0.1. [a] p-value from a test of joint significance of firm-level exports and imports.

Table A.6: Fixed Assets: Reduced Form Estimates

Dependent variable:	Log Fixed Assets			Log Fixed Assets per Employee		
	(1)	(2)	(3)	(4)	(5)	(6)
Log Export Demand (t-1)	0.049*		0.044*	0.020		0.016
	(1.937)		(1.740)	(0.878)		(0.695)
Log Import Supply (t-1)		0.036*	0.029		0.029	0.028
		(1.885)	(1.527)		(1.192)	(1.145)
Observations	5140	5140	5140	5140	5140	5140
R^2	0.958	0.958	0.958	0.899	0.899	0.899
p-value, joint significance[a]			0.0477			0.412

Notes: OLS estimates from the empirical model in Equation (3.4.1). All regressions contain firm fixed effects, industry-year fixed effects, as well interactions of base-year firm controls with year fixed effects. Robust t-statistics, clustered by firm, in parentheses. *** p<0.01, ** p<0.05, * p<0.1. [a] p-value from a test of joint significance of firm-level exports and imports.

Table A.7: Fixed Assets: IV Estimates

Dependent variable:	Log Fixed Assets			Log Fixed Assets per Employee		
	(1)	(2)	(3)	(4)	(5)	(6)
Log Export (t-1)	0.164**		0.088	0.069		-0.025
	(1.995)		(0.710)	(0.889)		(-0.188)
Log Import (t-1)		0.183*	0.140		0.148	0.171
		(1.866)	(1.014)		(1.093)	(0.917)
Observations	5140	5140	5140	5140	5140	5140
R^2	0.036	0.033	0.058	0.010	-0.006	-0.015
First stage F, exports	44.68		25.17	44.68		25.17
First stage F, imports		14.95	14.12		14.95	14.12
Kleibergen-Paap rk Wald	44.68	14.95	3.793	44.68	14.95	3.793
LM under-identification	35.83	15.07		35.83	15.07	
– p value	0.000	0.000		0.000	0.000	
p-value, joint significance[a]			0.054			0.478

Notes: OLS estimates from the empirical model in Equation (3.4.1). All regressions contain firm fixed effects, industry-year fixed effects, as well interactions of base-year firm controls with year fixed effects. Robust t-statistics, clustered by firm, in parentheses. *** p<0.01, ** p<0.05, * p<0.1. [a] p-value from a test of joint significance of firm-level exports and imports.

AARHUS BSS SCHOOL OF BUSINESS AND SOCIAL SCIENCES
AARHUS UNIVERSITY

Declaration of co-authorship[1]

Date: 27.09.2024

This declaration concerns the following article/manuscript:

Title:	Firms' Trading Activities and IT Expenditures
Authors:	Ying Dai, Ina Charlotte Jäkel, Allan Sørensen

The article/manuscript is:

- ☐ Published, state full reference:
- ☐ Accepted, state journal:
- ☐ Invited for revision, state journal:
- ☐ Submitted
- ☒ In preparation

Date of the current version of the manuscript, if not published or accepted: 27.09.2024

Please fill out Table 1 regarding contribution to the manuscript for all authors. The respective author has contributed to the elements:

A. Research idea: Identifying, developing, specifying, and formulating the overarching research question and aim.
B. Theory: Organizing theoretical perspectives, developing arguments and hypotheses, specifying theoretical model.
C. Research design: Developing and planning design for test or exploration of the research question.
D. Data collection: Preparing and organizing data collection, data collection, preparing data for analysis and storage.
E. Data analysis: Application of empirical techniques to analyze or synthesize study data including providing support for interpretations such as visualizations etc.
F. Writing: Drafting and revising manuscript presenting the research idea and results

of this article/manuscript as follows:

4 Has essentially delivered this part.
3 Major contribution
2 Equal contribution
1 Minor contribution
0 Did not contribute to this part.
N/A Not relevant or not applicable

[1] Attribution of authorship should be based on criteria a-d adopted from the Vancouver guidelines (see also rules and guidelines from Aarhus University) and all individuals who meet these criteria should be recognized as authors. The co-author has contributed:

a) to the conception or design of the work, or the acquisition, analysis, or interpretation of data for the work, *and*
b) drafting the work or revising it critically for important intellectual content, *and*
c) to the final approval of the version to be published, *and*
d) agrees to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

AARHUS BSS SCHOOL OF BUSINESS AND SOCIAL SCIENCES
AARHUS UNIVERSITY

Table 1. Individual contributions and signature of each co-author[1]

Author	Extent of contribution (4-0) per element (A.-F.)						Signature of the author[2]
	A. Research Idea	B. Theory	C. Research Design	D. Data Collection	E. Data Analysis	F. Writing	
Ying Dai	2	0	2	4	3	2	
Ina Charlotte Jäkel	2	0	2	0	1	2	
Allan Sørensen	2	4	2	0	0	2	

[1]More rows can be added for additional authors.
[2]All authors must confirm the declaration either by signature or email.

If relevant, you may add more information on the work and collaboration such as open science practices or more detailed specifications of authors' contributions here: