universität wien

DISSERTATION | DOCTORAL THESIS

Titel | Title

Essays in International Trade

verfasst von | submitted by

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angestrebter akademischer Grad | in partial fulfilment of the requirements for the degree of

Doctor of Philosophy (PhD)

Wien | Vienna, 2025

Studienkennzahl lt. Studienblatt | Degree programme code as it appears on the student record sheet:	UA 794 370 140
Dissertationsgebiet lt. Studienblatt | Field of study as it appears on the student record sheet:	Diss.Gebiet: VWL, DK: Vienna Graduate School of Economics
Betreut von | Supervisor:	Univ.-Prof. Alejandro Cuñat, PhD Dr. Michael Reiter

Acknowledgements

This dissertation is the culmination of a personal journey, one filled with many challenges and many more moments of joy. It would not have been possible without the support, guidance, and encouragement of many individuals to whom I am profoundly grateful.

Foremost, I would like to thank my first supervisor, Alejandro Cuñat, for his unwavering support of me and my ideas from the first day of my graduate studies. His research insights and constructive feedback were invaluable for me to pursue questions that intrigued me the most. I have also benefited greatly from his patience, humor, and humility.

Next, I also express my sincerest gratitude to my co-supervisor, Michael Reiter. His approach to research, asking the right questions, and offering solutions have greatly helped me articulate ideas into research. His wholehearted guidance and encouragement were invaluable.

I am also deeply grateful to the the faculty members of the Department of Economics at the University of Vienna, especially Paul Pichler and Philipp Schmidt-Dengler for their academic advice and guidance, particularly in the final years of my studies. Florian Exler and Daniel Garcia gave me very helpful advice and feedback that helped improve my presentations.

I gratefully acknowledge the financial support from the Austrian Science Foundation (FWF) and the Anniversary Fund of the Austrian National Bank (OeNB).

I have been incredibly fortunate to be surrounded by intelligent, witty, and welcoming colleagues. I am thankful to Stefan Smutny, Fabian Prettenthaler, and Philipp Ulbing for being the best people to pursue my doctoral studies with. And even though he was halfway across the world, I am grateful to Paul Ko for the endless conversations that helped me navigate difficult days and enjoy the good ones.

I am eternally grateful to my very loving parents, Sushil and Anushri. The incessant support and encouragement they have offered unconditionally throughout the years have empowered me to pursue my passions and become everything I am today. I extend my heartfelt thanks to my brother, Aneesh, whose constant motivation and calm rationality have been my bedrock of growth. I hope I can continue to respect their love and support by pursuing excellence and contributing positively to the people around me.

I do not have enough words to express my love and gratitude to my fiancée, Edona. She has been the pillar of my strength and her endless support and encouragement have made this journey a very happy and memorable one, and more importantly, made me a more complete person.

Contents

Introduction

International trade is shaped by the rules, policies, and innovations that govern global markets. This thesis investigates how three significant developments - data usage restrictions, skilled migration regulations, and the introduction of central bank digital currencies (CBDCs) - may influence trade dynamics and market behavior. While these measures are designed with specific objectives, they often have broader, and sometimes unintended, consequences. Through three focused chapters, the thesis examines how these developments impact trade and firms' strategies, using theoretical models, empirical data, and simulations. The research aims to provide novel insights into how such changes are reshaping the landscape of international trade.

Consumer Data, Productivity, and Trade

Chapter 1 focuses on the growing significance of consumer data in the digital economy and the implications of regulatory restrictions on its usage. The rapid advancements in technology have made data a critical resource for firms, yet policies aimed at protecting consumer privacy, such as the European General Data Protection Regulation (GDPR), often introduce challenges for cross-border data flows and productivity. These restrictions can create unintended barriers for firms trying to enter foreign markets or enhance productivity. For example, Demirer et al. (2023) report that GDPR compliance raised data storage costs by about 20%

and led EU firms to significantly curtail data storage and processing relative to U.S. firms. Such regulations not only shape how firms collect, store, and transfer data but also influence their ability to compete and expand in international markets.

In this chapter, we develop a new understanding of how such data restrictions affect firm behavior, trade flows, and aggregate economic outcomes. We extend a standard trade model to include costs associated with data usage, exploring how they vary across regulatory environments. In line with the findings of Brynjolfsson and McElheran (2016), we incorporate market-specific data acquisition as a driver of productivity gains in that market. In our model, acquiring market-specific data lowers firms' marginal costs in that market. More productive exporters then invest more in this data, resulting in stricter selection into exporting and fewer overall exporters. To empirically test these dynamics, we use aggregated international trade data from COMTRADE and the data restriction index by Ferracane et al. (2018), to estimate the effects via a PPML gravity framework. Our findings show that stricter data regulations reduce bilateral trade flows, particularly in manufacturing industries reliant on the adaptation of products to local consumer preferences. Different sectors experience varying degrees of impact, as some industries rely more on data to adapt for each market. Overall, these results highlight how regulatory constraints on data can reduce the competitive advantage of firms in new markets, lowering international trade and reshaping the broader landscape of global economic activity.

Migrants of Influence: Skill Levels and the Effects on International Trade

Chapter 2, a joint work with Stefan Smutny, examines the role of migration in international trade, focusing on the distinctions between high-skilled and low-skilled

migrants. Migration policies that shape skilled labor flows play a crucial role in enhancing the human capital of destination countries while also influencing the competitive performance of both sending and receiving nations. In the early 21st century, OECD countries witnessed a substantial rise in migrant populations, particularly from Africa and Asia, with sizeable inflows originating from countries such as Mexico, India, Romania, China, and Poland. This migration surge stemmed from both "pull" factors – higher standards of living and "push" factors – instability, conflicts, or persecution. Notably, educational attainment among migrants also increased, especially at the tertiary level, with a significant upsurge observed among those from Asia, Africa, and Latin America (d'Aiglepierre et al., 2020). These shifts in migration flows and educational profiles have wide-ranging consequences for host countries, as immigrants bring distinct cultural, linguistic, and market insights that can shape trade patterns, spur innovation, and enhance the competitiveness of domestic industries.

A large body of literature demonstrates how migrants serve as conduits for critical market information and social networks, thereby reducing uncertainty for exporting firms (Gould, 1994; Head and Ries, 1998; Wagner et al., 2002). We add to this literature by looking at the effect of the skills of migrants on firm-level productivity and international trade. High- and low-skilled migrants bring very distinct forms of knowledge and expertise to host countries, affecting trade by lowering costs and bolstering firms' ability to compete abroad. By harnessing specialized skills, innovative capacity, and deeper familiarity with home markets, high-skilled workers complement the intrinsic productivity of firms while also facilitating connections between origin and destination countries. Although low-skilled migrants contribute significantly to the labor force, often filling essential roles in agriculture, construction, or services, their influence on firm-level productivity and trade costs is typically more modest.

Building on these insights, this chapter presents a model that accounts for firm heterogeneity and the skill-biased impacts of migration, illustrating how high-skilled migrants tend to generate larger productivity gains and more pronounced reductions in trade barriers than low-skilled migrants. Guided by the theoretical results of our model, we find empirical evidence that support this result, showing a stronger overall effect of high-skilled migrants on lowering trade barriers and enhancing export opportunities. These findings support the importance of policy design that recognizes the differentiated roles and contributions of both high- and low-skilled migrants can have on more efficient resource allocation, increased competitiveness, and sustainable economic growth.

Internationalizing Currencies and Trade Invoicing

Chapter 3 examines the adoption of new currencies for trade invoicing, a crucial step towards the global adoption of a currency. Following Eichengreen (2011), we note that while the US dollar dominates, a few other currencies (euro, yen, pound, Swiss franc) also play key international roles – serving in trade invoicing, global financial markets, and as reserve assets. Despite the USD's dominance, these other currencies have maintained their international roles, while the Chinese Renminbi (RMB) has only recently expanded beyond domestic use due to strategic policies by the People's Bank of China. These policies include establishing RMB settlement mechanisms and signing swap line agreements (Bahaj and Reis, 2022). Recent work by Boz et al. (2022) provide evidence that the dollar's international prominence is slowly eroding in favor of other currencies (e.g., increased use of the RMB), likely facilitated by greater financial integration and bilateral currency agreements.

Modern digital financial infrastructures and technological advancements, such as fast payment systems (FPSs) and central bank digital currencies (CBDCs),

can also affect the choice of invoice currency for cross-border payments. This chapter draws inspiration from the digital yuan pilot in China. By introducing the digital yuan and establishing cross-border payment trials with countries like Hong Kong, Thailand, and the United Arab Emirates (China is a founding member of the mBridge project (BIS Innovation Hub, 2022), which uses CBDCs to link the payment networks of the other countries), the aim is to reduce transaction costs, enhance payment efficiency, and encourage its use in international trade invoicing.

To study the effect of such recent financial developments on trade invoicing patterns, we use a three-country model of monopolistic competition to look at the firms' optimal choice of invoicing currency. We analyse a setup where one country issues a digital version of their currency as an alternative to the dominant currency. In doing so, we also account for exchange rate volatilities, firms' hedging strategies, and changes in transaction costs. Using numerical simulations, we find that some firms will switch to a new currency to invoice part of their exports to foreign markets when the financial costs and exchange rate volatility associated with that currency decrease. The findings are a starting point to study how better financial infrastructures and the digitalization of a currency could influence its adoption as an international currency, potentially reshaping global trade flows and diminishing dependence on a single dominant currency.

Consumer Data, Productivity, and Trade

1.1 Introduction

In today's digital age, data is fundamental to the global economy. With the internet user population expected to reach 66% of the world by the end of 2023, data volumes have surged.[1] Modern algorithms capture extensive user information, including location, browsing history, and purchasing patterns and firms rely on this data for decision-making, improving productivity, efficient resource allocation, and market adaptation.[2] Furthermore, as firms decide to enter new markets, the regulatory landscape regarding data usage in these destinations becomes a pivotal and cost-influencing factor that affects their market entry strategies.

Concerns about data misuse and overuse have led governments to implement comprehensive data-related regulations, shaping both domestic and international data practices. As a result, the use and transmission of data are now subject to increasingly strict oversight and compliance requirements. The European General Data Protection Regulation (GDPR), introduced in 2016, represents one of the most impactful privacy regulations, affecting over 20 million firms across multiple countries.[3] Ferracane et al. (2018) systematically document and assess the policies and regulations implemented by different countries, emphasizing the significant

[1] This represents a notable change from the 51% in 2018, according to forecasts by Cisco (2020).

[2] Agrawal et al. (2018) and Goldfarb and Tucker (2019) provide a broader discussion of how the production of goods and services in the economy has become progressively more dependent on data processing.

[3] Many countries have subsequently adopted a similar approach, with 157 countries implementing legislation to safeguard data and privacy as of early 2022, see Greenleaf (2022).

presence of strict data flow usage and access restrictions in China, Russia, Turkey, France, and Germany. These measures address issues like data privacy and security and represent a crucial turning point in the evolution of the digital era. Data-intensive firms, which are significant contributors to the modern economy, face challenges in adjusting their business models to comply with these regulations, incurring associated costs that may hinder the viability of data-driven strategies. Demirer et al. (2023) investigate the impact of GDPR on firm behaviour regarding data storage and processing. They find that in response to its implementation, firms based in the European Union reduced data storage by 26% and processing by 15% compared to their US counterparts, incurring a 20% increase in data costs on average.

This chapter investigates the relationship between such regulatory policies governing data and the economic performance of data-intensive firms, with a focus on their impact on international trade. To achieve this, we extend a standard trade model by allowing firms to enhance their market-specific productivity through additional data-related costs. This assumption is in line with Brynjolfsson and McElheran (2016) who provide causal evidence for an increase in productivity among manufacturing firms that adopt data-driven decision-making. We also introduce variations in these costs across countries to account for differences in data regulation restrictiveness, and empirically test the predictions of the model using gravity estimation techniques.

We establish three main results. First, we show that if firms can use data to boost their productivity when entering a new market, all exporting firms opt to use data, with the more productive ones using more of it. We also find that using market-specific data to become exporters makes the selection into exporting stricter for all firms. On the aggregate level, this translates to lower trade flows between countries as fewer firms find it profitable to export. Furthermore, we show that

the aggregate price index in the economy is inversely proportional to the level of restriction in data acquisition in place. The intuition behind our results can be summarized as follows: when exporting firms enter new markets, they choose to acquire market-specific data, driven by the advantage of reducing the marginal cost of production in that specific market. This, in turn, allows firms to charge more competitive prices, leading to higher sales within the target market. Increased sales generate higher revenue, offsetting the initial cost of acquiring market-specific data and resulting in a profitable outcome for all firms involved. However, this dynamic changes when the cost of obtaining market-specific data becomes high, often seen in markets with stringent data regulation and compliance policies. In response to the higher data acquisition costs, firms lower the amount of data they acquire, leading to higher product prices in the market, which, in turn, deter customers and result in decreased sales volumes. Overall, this results in a reduction in trade flows between pairs of countries when stricter data regulations are in place.

To evaluate these theoretical predictions, we utilize international trade data derived from COMTRADE, aggregated at the 2-digit level according to the Harmonized System Nomenclature 2017 edition,[4] combined with the data restriction index introduced by Ferracane et al. (2018). Their index spans 64 countries and encapsulates various digital policy restrictions - from limits on cross-border data transfers to rules governing how data can be used domestically. We empirically estimate the relationship between trade flows and data restriction index employing a Poisson Pseudo Maximum Likelihood (PPML) regression approach. We also include origin and destination fixed effects to control for unobserved variation. We document evidence of a decline in trade flows between countries in instances where the destination country has implemented more stringent data protection measures. This observed reduction in trade is particularly pronounced for the manufacturing

[4]Classification is based on the one provided by the World Customs Organization here, accessed on 16-Oct-2023.

sectors which depend heavily on tailoring their products to suit the requirements of specific markets. These sectors represent a diverse array of industries, including food and beverages, consumer goods (footwear, textiles, jewelry, and more), as well as pharmaceuticals, among others.

It is important to note that this chapter analyses the impact of utilizing market-specific data on international trade, placing a specific emphasis on the associated costs that are contingent on regulations and policies within distinct markets. We make a clear distinction between market-specific data and globally applicable data and focus on the former. When firms enter a new market, they augment their core technical expertise with data tailored to meet the specific market's demands. Market-specific data, limited in usability and scope to its region of origin, primarily influences productivity within that particular market. In sharp contrast, global data boasts universal applicability, akin to research and development findings, affecting productivity across geographical boundaries. To illustrate, consider the formulation of carbonated beverages such as Coca-Cola's Sprite, which varies from one country to another to suit distinct consumer taste preferences. For example, the sugar content in Sprite is 7.8gms/100 mL in Austria, increases to 10gms/100mL in Poland, and reaches 12gms/100mL in India, aligning with consumers' preferences in those regions.[5] This localized adaptation extends to the choice of sweeteners, ranging from corn starch-based to artificially synthesized sweeteners. Furthermore, the availability of various package sizes tailored to local preferences exemplifies the profound influence of market-specific data. In numerous such instances, firms adjust their products appropriately to cater to the unique preferences and characteristics of individual markets.

The remainder of the chapter proceeds as follows. Section 1.2 provides a review of related literature. The model and assumptions are described in Section 1.3 and

[5]See Action on Sugar (2015), Hashem et al. (2016), or Varsamis et al. (2017) for more details.

the equilibrium results in Section 1.4. Finally, comparative statics are presented in Section 1.5 and the empirical results are in Section 1.6. Section 1.7 concludes with a discussion, while all mathematical proofs and supplementary materials are provided in Section 1.A.

1.2 Related Literature

The literature on the economic impact of data is vast and growing. Many studies have shown that firms across all sectors harness data to boost their economic performance. Individual data, when combined with digital innovation and improved management techniques, drives up productivity for firms, provide access to favourable financing opportunities, and bolsters trade performance. Goldfarb and Trefler (2018) report that numerous large global firms, as determined by market capitalization, have integrated data as a foundational pillar of their operational framework. This strategic incorporation enables them to train artificial intelligence algorithms, which play a pivotal in investment planning and production decisions, and the execution of precision-targeted advertising campaigns.[6] Our model findings also show that more productive firms (which is a proxy for firm size in the model) tend to acquire and use larger volumes of data compared to their less productive counterparts.[7] These model predictions align with empirical evidence too, emphasizing that the firms aiming to harness the potential of artificial intelligence need large volumes of data for the training of their algorithms.[8]

[6] Iansiti and Lakhani (2020); Davenport and Ronanki (2018); European Parliament (2020) provide an overview of how firms use data in production and logistics processes. For evidence on firm size being an important determinant of technology adoption, see Gibbs and Kraemer (2004), Claessens and Tzioumis (2006), and Hall and Lerner (2010).

[7] In the context of the financial services industry, Farboodi et al. (2022) show that larger firms value data more and also process more of it for growth.

[8] These datasets are collected and evaluated on a large scale through big data methodologies and processed via cloud computing services. See Farahani et al. (2021), Iansiti and Lakhani (2020), Ramraj (2020), and OECD (2019, 2020) for some evidence.

Studies by Lileeva and Trefler (2010), Bustos (2011), and Topalova and Khandelwal (2011), among others, have examined the effect of trade liberalization events on firms' technology upgrading.[9] This body of literature typically assumes that firms can pay a fixed cost to achieve a uniform positive impact on their production technology. In contrast, the current chapter advances the research by incorporating non-linear productivity enhancements, wherein firms incur convex costs to acquire data. The data is modelled as market-specific, meaning the resulting productivity upgrade applies only to the specific market in question, rather than all other markets where the firm might be active. This market-specific dimension of productivity enhancement, to the best of our knowledge, has not been analysed in the literature. The costs associated with acquiring data are isomorphically modelled after the marketing costs in Arkolakis (2010). However, our study differs by focusing on the effect of data on firms' productivity rather than estimating the demand for their product in new export markets.

It is also crucial to emphasize the distinction between market-specific innovations and those resulting from research and development (R&D). The latter is a broad, exploratory process aimed at generating new processes and technologies, while the former involves targeted solutions designed to optimize and enhance products for the specific needs of a particular market. R&D often seeks breakthroughs applicable across multiple markets, whereas market-specific innovations are tailored to address the idiosyncratic requirements of a specific market. We distinguish our approach from existing literature on innovation[10] by focusing on market-specific innovations.

We also contribute to the literature that highlights the complementarity between a firm's decisions to export and invest in productivity. Previous studies [11] have

[9] Bloom et al. (2016) show that firms most affected by Chinese imports show heightened innovations.

[10] Most notably Atkeson and Burstein (2010), Aw et al. (2011), and Bustos (2011). For a comprehensive review of the literature on innovation and international trade, see Akcigit and Melitz (2022).

[11] See Costantini and Melitz (2007), Bustos (2011), and Topalova and Khandelwal (2011).

established conditions under which a reduction in the costs of exporting induces firms to simultaneously export and invest. This chapter expands the viewpoint and considers a scenario where firms can reduce their cost of production in a new export market by investing in data about that market.

The use of data by firms remains in its early stages, with significant variation in adoption across firms and sectors. Wu et al. (2020) provide evidence of firms leveraging data analytics to enhance existing technologies, finding that firms focused on process improvements are more likely to adopt these methods than those pursuing entirely new technologies.[12] In our model, larger firms invest more in market-specific data to enhance productivity, focusing on improving existing production technologies rather than creating new ones. Jones and Tonetti (2020) offer a theoretical framework for the increasing returns from nonrival data, emphasizing privacy and ownership concerns. This chapter builds on the non-rival nature of data, focusing instead on its role in boosting productivity when entering new markets.

Finally, we contribute to the growing body of literature examining the effect of data restriction on firm behaviour. Demirer et al. (2023) studied the effects of GDPR on firm behaviour regarding data storage and processing and finding that after its implementation, affected firms decreased their data storage and processing activities compared to their unaffected counterparts.[13] Ferracane et al. (2020) investigated how policies governing the movement and utilization of electronic data affect the productivity of firms in data-reliant sectors, revealing that stricter data regulations negatively affect downstream firms' performance. In our work, we expand on this research by considering the impact on firms engaged in bilateral trade, and we find that stricter data regulations lead to a reduction in trade flows.[14]

[12]For evidence of the positive association between artificial intelligence adoption and changes in firm size and investment, see Alekseeva et al. (2021).

[13]For a survey of literature on the different effects of the implementation of GDPR, see Johnson (2022). More recent literature has focused on the California Consumer Privacy Act and its effects on lending, for example, Canayaz et al. (2022); Doerr et al. (2023).

[14]The World Development Report, World Bank (2019), also addresses the significance of data

1.3 Model

In this section, we present a stylized theoretical model to examine firm-level decisions regarding entry into export markets. We analyse a scenario involving two symmetrical countries engaged in bilateral trade liberalization. Each country has a single monopolistically competitive industry, with differentiated goods produced by firms employing increasing returns to scale production technologies. Firms use labour as their sole input factor, as described by Krugman (1979), and exhibit heterogeneous productivities while facing fixed entry and exporting costs, as in Melitz (2003). To examine the impact of data restrictions enforced by various nations on firm behaviour, we expand upon these models by incorporating data acquisition by firms to boost their productivity in those countries.

In the digital economy, a substantial portion of consumer interactions occurs on online platforms that amass vast quantities of data from users' digital activities. We posit that within a specific country, all this data about individual consumers is consolidated into a single, exhaustive dataset. In this dataset, each consumer is represented as a unique data point, enabling the aggregation of information about a wide spectrum of attributes. Now, let's consider foreign firms expanding into new markets as exporters, where understanding local consumers and their preferences hinges on the information contained within the dataset. To access this, foreign firms often employ methods such as sending data requests to the dataset or, in some instances, engaging in data scraping, an automated process of data retrieval from websites and online sources.

restrictions in influencing economic and social development, emphasizing the need for balanced data policies to harness the benefits of data while safeguarding privacy and security.

1.3.1 Enhancement Costs

We now construct a cost function for data acquisition through extraction requests, exhibiting increasing marginal costs, indicating rising expenses with higher data acquisition. Note that this cost structure also preserves the non-rival nature of data, that multiple firms can access the same dataset simultaneously without diminishing its availability to other firms. Let D represent the number of data requests made by a foreign firm into this consumer database and L denote the population of the destination country. Suppose $n(D)$ is the probability that data on a specific consumer is extracted after D requests have been sent. Obviously, $n(0) = 0$.

Assumption 1: Each data request sent by a firm extracts data on L^{α}, $\alpha \in [0, 1]$ of the country's consumers.

The parameter α plays a pivotal role in determining the effectiveness of the data extraction method. When $\alpha = 0$, each data request sent by the firm extracts information on a single consumer only in the destination market. This scenario represents a highly inefficient process for a firm aiming to gather comprehensive consumer data. In contrast, when $\alpha = 1$, the firm gains complete access to the entire consumer dataset, allowing them to extract detailed information on all consumers with a single request. This represents a highly effective data extraction method, enabling the firm to swiftly acquire a complete understanding of the local consumer base. Furthermore, the parameter α has implications for data extraction across markets of varying sizes. Lower α values enable a firm to acquire data on an equivalent number of consumers in two different potential markets using the same number of data requests, regardless of the market's size. This implies that the effectiveness of the data extraction method remains relatively unaffected by the market's size. Conversely, higher α values indicate that firms can efficiently expand their data extraction efforts in significantly larger markets while maintaining the same number of data requests. This suggests that the data extraction method

exhibits greater efficiency in larger markets, allowing firms to collect comprehensive consumer data more rapidly and cost-effectively.

Assumption 2: The probability that a data request extracts data on a consumer for the first time is $(1 - n(D))^{\beta}$, $\beta \in [0, 1]$.

Since $n(D)$ is the probability that data on a specific consumer is extracted after D requests have been sent, then $1 - n(D)$ is the probability that the consumer's data remains undiscovered, even after D requests have been made. The parameter β plays a crucial role in determining the diminishing returns of the firm's data extraction efforts. A higher value of β indicates that the data extraction process exhibits diminishing returns, meaning that the likelihood of extracting new data decreases sharply with each additional request. This implies that while initial data extractions are likely to access a significant amount of information, the rate of finding new data falls considerably as the firm sends more requests. As the firm sends more requests, the probability of accessing entirely new data diminishes, leading to a slower rate of discovering new consumer insights. In essence, the parameter β quantifies the speed at which the data extraction method becomes less efficient as more requests are made. Higher values of β suggest a more rapid decline in the efficiency of data acquisition, while lower values indicate a slower rate of diminishing returns. The value of β can also be interpreted in the context of data accessibility and data-sharing agreements between countries. Lower β values suggest greater ease of access to data and more favourable data-sharing agreements, allowing the firm to efficiently extract data on a larger scale.

Combining the assumptions above, the number of consumers whose data will be extracted with new data requests is $L^{\alpha}(1 - n(D))^{\beta}$. Assuming that the function $n(D)$ is continuous and differentiable, the marginal change in the number of consumers whose data is extracted though new requests is $n'(D)L$. Equating the

two, we get:

$$n'(D)\,L = L^{\alpha}\left(1 - n(D)\right)^{\beta}$$
$$\implies D = \frac{1-(1-n)^{1-\beta}}{1-\beta} L^{1-\alpha}$$

This expression gives us the number of data requests that need to be sent to the dataset of a market of size L to extract data on a fraction n of the consumers in that market. The acquisition of consumer data through these data requests incurs labour costs for the firm. We assume that each data request sent necessitates a labour cost represented by θw, where $\theta > 0$ denotes a small proportion of the wage w. Consequently, the total labour cost for a firm extracting data on a fraction n of the consumers in a market of size L is:

$$f_d(n, L) = \theta w \frac{1-(1-n)^{1-\beta}}{1-\beta} L^{1-\alpha} \tag{1.1}$$

This cost function exhibits two useful properties:

$$\frac{\partial f_d(n, L)}{\partial n} = \theta w (1-n)^{-\beta} L^{1-\alpha} > 0 \tag{1.2}$$
$$\frac{\partial^2 f_d(n, L)}{\partial n^2} = \beta\theta w (1-n)^{-\beta-1} L^{1-\alpha} > 0 \tag{1.3}$$

The marginal cost of extracting data on new consumers (equation (1.2)) is always positive, indicating that the cost of acquiring additional data increases as more data is acquired. As the proportion of consumers whose data has already been extracted grows, the remaining data becomes scarcer and more challenging to acquire, leading to a steady rise in marginal costs as shown in equation (1.3). This arises from the inherent difficulty in accessing previously unacquired data compared to data that has already been acquired. Firms make decisions about the optimal level of data

acquisition by balancing these costs against the benefits, which we describe next.

1.3.2 Supply

The economy is populated with L units of labour, which are provided inelastically to the firms as the unique factor of production. There is a continuum of these firms, each producing a unique variety ω. To enter the market, all firms pay a sunk entry cost equal to $f_e > 0$ units of labour, and then learn their idiosyncratic productivity $\varphi > 0$. A firm with higher productivity can be thought of as either producing a standardized variety at a lower marginal cost or producing a higher-quality variety at the same cost. In the current product differentiation model, representing productivities in either of these forms yields equivalent results. Firms draw their initial productivity from a known Pareto distribution function $G(\varphi) = 1 - \varphi^{-a}$ with $a > 1$.

After learning their productivity, firms choose whether to stay and produce or to forego the cost and exit the industry. Firms supply their product by using a technology of production which has a constant marginal cost of $1/\varphi$, also measured in terms of labour. Firms can increase their productivity in a specific market by paying to access consumer data from that market. When a firm with productivity φ acquires a fraction n of the data, we assume that the enhanced productivity now is:

$$\Phi(\varphi, n) = \left(\varphi^{\sigma-1} + \varphi^{\beta}(\sigma - 1)\, n\right)^{\frac{1}{\sigma-1}}, \quad n \in [0, 1] \tag{1.4}$$

This productivity enhancement through data exhibits scale effects, where more data yields more valuable insights; and diminishing returns, as the value of additional data wanes with volume. The cost the firms incurs to acquire a fraction n of the available data is $f_d(n)$ from equation (1.1). Then, firms' total costs to produce

an output q can now be categorized as:

$$TC\left(q,\varphi,n\right)=f_{d}\left(n\right)+\frac{q}{\Phi\left(\varphi,n\right)},\quad n\in[0,1] \tag{1.5}$$

Furthermore, we also assume that a firm seeking to enter the export market encounters an initial fixed cost of f_x after learning its initial productivity level. As outlined above, firms may additionally choose to invest in data acquisition, that can lowering their marginal production costs in this export market. Apart from these, we assume that there are no other uncertainties relating to exports. Furthermore, we employ the established iceberg trade cost model, that is, $\tau > 1$ units of a good must be shipped from the origin country to guarantee the delivery of a single unit in the destination country. To ensure factor price equalization across countries and effectively isolate the influence of trade on firm selection independently of wage discrepancies, we assume that both countries share identical characteristics.

However, there is one key difference that plays a pivotal role in our model. Firms have the ability to use market-specific data to enhance their productivity, but this capability is unique to foreign firms. In other words, we assume that only foreign firms can access and utilize consumer data to effectively lower their marginal production costs. This assumption is based on the following intuition: When firms in the domestic market decide to enter the industry, they incur the initial startup costs, f_e, and this provides them not only with their idiosyncratic productivity but also crucial information about consumer preferences, market structure, and other essential factors necessary for producing their final product. Conversely, when foreign firms seek to establish a presence in the same market, they must find ways to learn and adapt to this new market. They need to gather data on local consumers and adjust their production methods to align with the specific demands of the domestic market. Exporting firms, when operating in a foreign market, must invest resources in acquiring market-specific data to influence their marginal costs.

We model these resources as the costs of acquiring market-specific data. The firms that are only active in their domestic market behave in a manner consistent with the established framework outlined in Melitz (2003), while those that export to the foreign market adopt a different set of strategies, which we characterize in a subsequent section.

1.3.3 Demand

Each country is populated by a continuum of consumers of measure L. They derive utility from the consumption of a continuum of goods, indexed by ω, which takes the form of a CES utility function:

$$U = \left[\int_{\omega\in\Omega} y(\omega)^{\rho} d\omega\right]^{1/\rho}, \quad 0 < \rho < 1$$

where Ω denotes the set of goods available to the consumers in the country. The elasticity of substitution between any two goods is $\sigma = 1/(1-\rho) > 1$. Following Dixit and Stiglitz (1977), the behaviour of consumers in this setup is equivalent to one where they consume an aggregate good $Y \equiv U$ with an associated aggregate price index:

$$P = \left[\int_{\omega\in\Omega} p(\omega)^{1-\sigma} d\omega\right]^{1/(1-\sigma)}$$

The optimal consumption and expenditure decisions for each variety ω can then be written as:

$$y(\omega) = Y\left[\frac{p(\omega)}{P}\right]^{-\sigma}; \;\; r(\omega) = R\left[\frac{p(\omega)}{P}\right]^{1-\sigma}$$

where $R = P \times Y = \int_{\omega\in\Omega} r(\omega)\, d\omega$ denotes the aggregate expenditure.

1.4 Results

Faced with the CES preferences of the consumers and strictly convex data acquisition costs,[15] we can now characterize firm behaviour in the following propositions:

Proposition 1.4.1. *For a firm of type φ, there exists a cutoff φ_d^* such that the optimal data choice will be:*

$$n^*(\varphi) = \begin{cases} 0, & \varphi < \varphi_d^* \\ 1 - \dfrac{c^{1/\beta}}{\varphi}, & \varphi \geq \varphi_d^* \end{cases}$$

where $c = (\rho w)^\sigma \frac{\theta L^{1-\alpha}}{R P^{\sigma-1}}$ and $\rho = \frac{\sigma}{\sigma-1}$. Furthermore, the profit-maximizing price charged by the firm will be:

$$p^*(\varphi) = \begin{cases} \dfrac{\rho w}{\varphi}, & \varphi < \varphi_d^* \\ \dfrac{\rho w}{\Phi(\varphi)}, & \varphi \geq \varphi_d^* \end{cases}$$

To make the notation less cumbersome, I replace $\Phi(\varphi, n^*(\varphi))$ by $\Phi(\varphi)$ for the remainder of the chapter. The enhanced productivity $\Phi(\varphi)$ is a strictly increasing transformation of φ and is bounded above and can be graphically represented as in Figure 1.1.

[15] When the cost to acquire data is linear, i.e. $\beta = 0$, the results are analogous to Bustos (2011). For the remainder of the chapter we assume that $\beta \neq 0$.

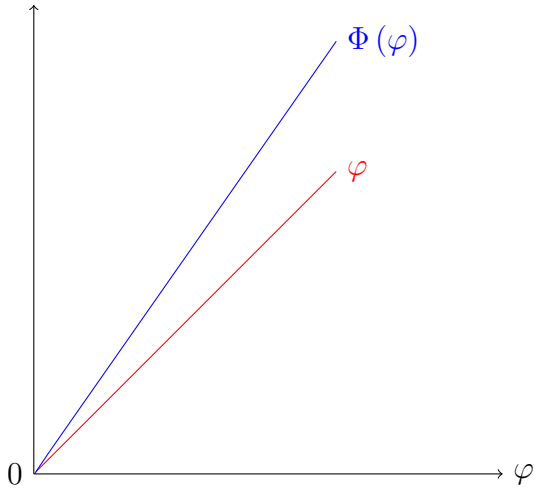

Figure 1.1: Productivity enhancement from data acquisition

The firms charge the same markup over marginal cost, $\sigma/(\sigma-1)$. The effective price goes down with the enhanced productivity but firms now generate higher revenues by selling more units of output. More productive firms will sell more output, charge lower prices, and earn higher revenues. For any $\varphi_1 < \varphi_2$, we have:

$$\frac{q(\varphi_1)}{q(\varphi_2)} < 1 \; ; \quad \frac{p(\varphi_1)}{p(\varphi_2)} > 1 \; ; \quad \frac{r(\varphi_1)}{r(\varphi_2)} < 1$$

Proposition 1.4.2. *All active firms that can acquire data will find it profitable to do so in order to enhance their productivity.*

Therefore, if available, all firms find it profitable to acquire data to enhance productivity as the costs incurred are outweighed by the increase in profits. We now characterize the volume of data acquired by firms in the following proposition:[16]

[16]This result is in line with other findings in the literature. Farboodi et al. (2022) find that larger firms are the ones that acquire and use the most amount of data.

Proposition 1.4.3. *The volume of data acquired by firms is a function of their initial drawn productivity. For* $\varphi_1, \varphi_2 \geq \varphi^*$ *such that* $\varphi_1 > \varphi_2$*, then* $n^*(\varphi_1) > n^*(\varphi_2)$.

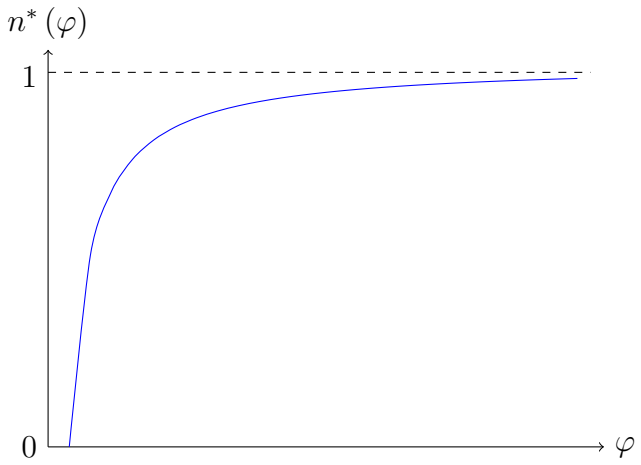

Figure 1.2: Volume of data acquired as a function of firm productivity

With the firms' behaviour characterized, we now look at the equilibrium in the open economy. Firms charge a price $p_d(\varphi) = \rho w \varphi^{-1}$ in the domestic market. However, in the foreign market, firms charge price $p_x(\varphi) = \tau \rho w \Phi(\varphi)^{-1}$. They still charge the same markup but now over the data enhanced marginal cost of production and further scaled up by τ to reflect the trade costs. The pricing policy, $p(\varphi)$ for a firm with an initial productivity φ is to charge $p_d(\varphi)$ on the domestic market and $p_x(\varphi)$ on the foreign market. Revenue earned by a firm in the domestic market and the export market are then going to be $r_d(\varphi) = RP^{\sigma-1} p_d(\varphi)^{1-\sigma}$ and $r_x(\varphi) = RP^{\sigma-1} p_x(\varphi)^{1-\sigma}$ respectively. By the symmetry assumption, the aggregate expenditure in every country will also represent the aggregate revenue of firms in any country, and thus also aggregate income. Therefore, the total revenue of the firm, $r(\varphi)$, will be $r_d(\varphi)$ if the firm only serves the domestic market and $r_d(\varphi) + r_x(\varphi)$ if the firm serves both the domestic and the international markets. The profits a firm makes varies with the market it is active in. On the domestic

market, the profit is $\pi_d(\varphi) = r_d(\varphi)/\sigma - f_e$ while the profit on the foreign market is $\pi_x(\varphi) = r_x(\varphi)/\sigma - f_x - f_d(n^*(\varphi))$ where f_e is the sunk cost of entering the domestic market, f_x is the sunk cost of entering the international market, and $f_d(\cdot)$ is the cost of acquiring data from the international market. The total profit of the firm, $\pi(\varphi)$, will be $\pi_d(\varphi)$ if the firm only serves the domestic market and $\pi_d(\varphi) + \pi_x(\varphi)$ if the firm serves both the domestic and the international market.

Proposition 1.4.4. *The cutoff productivity levels for entering the domestic market and the exporter market are given by:*

$$\varphi^* = \frac{\rho w}{P}\left(\frac{\sigma f_e}{R}\right)^{\frac{1}{\sigma-1}}$$
$$\Phi(\varphi_x^*) = \tau\varphi^*\left(\frac{f_x + f_d(n^*(\varphi_x^*))}{f_e}\right)^{\frac{1}{\sigma-1}}$$

These cutoffs are the levels of initial drawn productivity at which firms are indifferent between entering the domestic and the international market respectively. Assume that $\tau[f_x/f_e]^{\frac{1}{\sigma-1}} > 1$. It is then straightforward to establish that $\varphi_x^* > \varphi^*$. Thus, we get the following partition of productivities:

$$\begin{aligned}
\varphi < \varphi^* &: \quad \text{Exit the domestic market} \\
\varphi^* \leq \varphi < \varphi_x^* &: \quad \text{Enter the domestic market but do not export} \\
\varphi \geq \varphi_x^* &: \quad \text{Enter the domestic and the international market}
\end{aligned}$$

The equilibrium distribution of productivity levels of all active firms is given by $g(\varphi)/[1 - G(\varphi^*)]\ \forall\ \varphi \geq \varphi^*$. The ex-ante probability of entering the market is given by $1 - G(\varphi^*)$. Then the probability of one of these firms becoming an exporter will be $\mathfrak{p}_x = [1 - G(\varphi_x^*)]/[1 - G(\varphi^*)]$. If M is the equilibrium mass of firms in either country, then the mass of exporting firms is $M_x = \mathfrak{p}_x M$ and the

varieties available for consumption in any country are $M_t = M + M_x$.

All firms that are exporters will find it profitable to acquire and use data to lower their marginal cost of production in the foreign market. This is reflected in the difference in the price these firms charge on the two markets. Note that the lowering of the marginal costs only applies to the foreign market the firm is serving, not the domestic market (there are no firms that only serve the foreign market, all active firms serve the domestic market but some export internationally too). The average productivity of all active firms will be:

$$\widetilde{\Phi} = \left(\frac{1}{1 - G(\varphi^*)} \int_{\varphi^*}^{\infty} \Phi(\varphi)^{\sigma-1} g(\varphi) \, d\varphi \right)^{\frac{1}{\sigma-1}}$$

and the average productivity of all exporting firms will be:

$$\widetilde{\Phi}_x = \left(\frac{1}{1 - G(\varphi_x^*)} \int_{\varphi_x^*}^{\infty} \Phi(\varphi)^{\sigma-1} g(\varphi) \, d\varphi \right)^{\frac{1}{\sigma-1}}$$

where

$$\Phi(\varphi) = \begin{cases} \varphi, & \varphi^* \leq \varphi \leq \varphi_x^* \\ \Phi(\varphi, n^*(\varphi)), & \varphi_x^* < \varphi \end{cases}$$

Average revenue and profits across all firms within a country will be, respectively:

$$\overline{r} = r_d\left(\widetilde{\Phi}\right) + \mathfrak{p}_x r_x\left(\widetilde{\Phi}_x\right), \qquad \overline{\pi} = \pi_d\left(\widetilde{\Phi}\right) + \mathfrak{p}_x \pi_x\left(\widetilde{\Phi}_x\right)$$

The aggregate price and the aggregate revenue in the country will be, respectively:

$$P = M_t^{\frac{1}{1-\sigma}} p\left(\widetilde{\Phi}_t\right), \qquad R = M_t r_d\left(\widetilde{\Phi}_t\right)$$

Equilibrium in this model will be pinned down by an entry cutoff is a φ^*, an average expected profit for an entrant, $\overline{\pi}$, and a mass M of firms such that the labour markets clear, that the profit for the firm at the entry cutoff is zero, and that the free entry condition holds.

Proposition 1.4.5. *In an economy when firms can pay to acquire market-specific data to increase their productivity in that market, equilibrium is characterized by the following conditions:*

$$\overline{\pi} = \underbrace{\left[\left(\frac{\widetilde{\Phi}}{\varphi^*}\right)^{\sigma-1} - 1\right] f_e}_{\substack{\text{expected profits from} \\ \text{entering the industry}}} + \mathfrak{p}_x \underbrace{\left(\left[\left(\frac{\widetilde{\Phi}_x}{\varphi_x^*}\right)^{\sigma-1} - 1\right] f_x - f_d\left(n^*\left(\widetilde{\Phi}_x\right)\right)\right)}_{\text{expected profits from entering foreign market}} \tag{ZCP}$$

$$\overline{\pi} = \frac{f_e}{1 - G\left(\varphi^*\right)} \tag{FE}$$

$$wL = R \tag{LMC}$$

When firms have the option of acquiring data about a foreign market to lower their market specific marginal costs, all exporting firms exercise this option. A lower marginal cost of production increases potential profits for exporters and this results in the export cut-off of initial productivity to go up making the resulting market less competitive but with a lower aggregate price index.

Proposition 1.4.6. *In an economy when firms can pay to acquire market-specific data to increase their productivity in that market, the mass of active firms in equilibrium will be:*

$$M = \frac{wL}{\sigma\left[\overline{\pi} + f_e + \mathfrak{p}_x\left(f_x + f_d\left(n^*\left(\widetilde{\Phi}_x\right)\right)\right)\right]}$$

The mass of firms active in equilibrium is clearly less than in the traditional model.

As more productive firms acquire more data, they enhance their market-specific productivity more and generate higher profits. Consequently, the expected profits for an active firm go up and more firms forego the entry costs and fewer firms become productive.

1.5 Comparative Statics

In this section we study the influence of changes in the parameters that determine data restrictiveness on the productivity cut-offs, the distribution of data acquired, aggregate prices in the economy, the mass of active firms in the domestic market, and the mass of exporter firms. Because of the structure of our data acquisition costs, it is impossible to derive closed form solutions for some of the variables of interest in our model, especially the export productivity cut-off as it is characterized by an implicit function in Proposition 1.4.4. We will therefore use the implicit function theorem to carry out those comparative statics, and also provide a numerical example.

Recall that the cost of acquisition parameters α measures the fraction of the market that can be reached with each data request, and β captures the difficulty of extracting data on new consumers with each data request. A regulation to make data gathering and use more difficult is equivalent to a decrease in α and an increase in β.

Proposition 1.5.1. *The optimal volume of data acquired by firms is increasing in α and decreasing in β.*

The optimal volume of data acquired by a firm is increasing in α, that is, as the fraction of the market that can be reached with each data request increases, firms choose to acquire more data. On the flip side, if it becomes harder to extract data on new consumers with these data requests, firms have less incentive to acquire more

data. The price charged by the firm is inversely proportional to its productivity, which in turn is directly proportional to the amount of data it acquires. Therefore, when a country's regulations make it more difficult for firms to get data about the consumers, firms will respond by charging a higher price in that market than they would if the regulations were more lax. Since the productivity enhancements that the firms receive by using data is specific to the foreign market, prices charged by domestic firms stay unaffected by a change in data usage regulations.

Proposition 1.5.2. *The productivity cutoff to be an active firm is unchanged by changes in data regulation, while the productivity cutoff to be an exporting firm is lower when data regulations are stricter.*

When the data regulations become stricter, exporting firms charge a higher price but still generate lower revenue and profits because they sell fewer units of output. This pushes down the expected profits on the export market and as a result, the productivity level at which firms are indifferent between only serving the domestic market and becoming exporters also comes down. This leads to an increase in the mass of active firms in the market as there are more exporters, but all of them are going to charge a higher price. Consumers have a larger variety of products available to them, but foreign products become more expensive.

1.6 Data and Empirical Analysis

To test the model predictions empirically, we use two data sources. To analyze the effect of data restrictions, we need a precise and measurable collection of policy data pertaining to the regulatory framework governing data usage in various countries. To that end, we utilize an extensive, recently published database of data policies provided by the European Centre for International Political Economy (ECIPE) as presented by Ferracane et al. (2018). The policies analysed are those that impose

costs on businesses heavily dependent on data. To be included in the database, the authors require that a policy "(i) creates a more restrictive regime for online vs. offline data users; (ii) implies different treatment between domestic and foreign users; and (iii) is applied in a manner considered disproportionately burdensome to achieve a certain policy objective".[17] This comprehensive index is highly relevant to this chapter as it directly addresses the costs and challenges faced by foreign firms when faced with the complexities of data policies in their efforts to leverage market-specific data.[18]

We obtain the trade data from The Atlas of Economic Complexity classified with the Harmonized System (HS, 1992). We use the country-partner-product level trade flows (products at 4-digit level) data and aggregate it up to 2-digit industry level. As a result, we get 21 sectors, which are listed in the appendix (Table 1.3). This dataset also provides us with time-invariant covariates (distance measures between trading partners, shared borders, shared language, and shared colonial ties) and are included in our gravity estimations. Since the data for the restriction index is only available for the year of 2016, we consequently only use trade data for that year for the estimation.

The empirical estimation strategy we use is the well established structural gravity framework. We first run the following baseline regression to estimate the effect of data restrictions on total manufacturing trade flows accounting for origin and destination fixed effects:

$$y_{ij} = \exp\big(\delta_i + \delta_j + \beta_1 x_{ij} + \gamma_1 \cdot \ln \text{dist}_{ij} + \gamma_2 \cdot \text{cntg}_{ij} + \gamma_3 \cdot \text{lang}_{ij} + \gamma_4 \cdot \text{clny}_{ij}\big) \times \varepsilon_{ij} \tag{1.6}$$

[17] The countries covered by this index are listed Table 1.2 in the appendix.

[18] In a related paper, Ferracane et al. (2020) find that stringent data regulations can significantly hurt productivity in data-reliant downstream industries.

The variable y_{ij} corresponds to the nominal bilateral international trade flows between origin country i and destination country j, $\ln \text{dist}_{ij}$ is the natural logarithm of the distance between trading countries i and j, cntg_{ij} is an indicator variable which shows the presence of contiguous borders between trading countries i and j, lang_{ij} is an indicator variable for the existence of a common official language between countries i and j, and clny_{ij} is an indicator for the presence of colonial ties between countries i and j. The variables δ_i and δ_j are the origin and destination fixed effects, which will account for all other observable and unobservable origin-sector and destination-specific characteristics that may influence bilateral trade. Our variable of interest is x_{ij} which we create as an indicator function which takes the value 1 when the data restriction in the destination country is (weakly) higher than the one in the origin country and 0 otherwise. This will help us interpret the coefficient as the percentage change in trade flows between country-pairs when a destination country has higher data restrictions compared to a destination country which might have lower data restrictions for a fixed origin country. Furthermore, we believe that this effect is going to vary across the different sectors as they have heterogeneous data intensities in their production. To this end, we also run the following modified sector-level regression:

$$y_{ij,k} = \exp\Bigg(\delta_{i,k} + \delta_{j,k} + \sum_{k=1}^{21} \beta_k \left(x_{ij} \cdot \mathbb{I}_k\right) + \gamma_1 \cdot \ln \text{dist}_{ij} + \gamma_2 \cdot \text{cntg}_{ij} + \gamma_3 \cdot \text{lang}_{ij} + \gamma_4 \cdot \text{clny}_{ij}\Big) \times \varepsilon_{ij,k} \tag{1.7}$$

To make the coefficients across sectors statistically comparable, we interact each one of these sectors with the data restriction index which is denoted by $\mathbb{I}_k$ for each sector k. The variables $\delta_{i,k}$ and $\delta_{j,k}$ are now the origin-sector and destination-sector fixed effects while $y_{ij,k}$ now corresponds to the nominal bilateral international trade flows between origin country i and destination country j in sector k. Both of these

estimations are performed using the PPML estimator and are hence formulated in multiplicative form. We tabulate our statistically significant findings from both estimations in Table 1.1.[19]

The results in the first two columns correspond to the estimation equation (1.6) while those in the last two columns correspond to the estimation equation (1.7). We can clearly see that country pairs where the destination has a higher data restriction than the origin have less trade flows than the country pairs where the destination has lower data restrictions. Furthermore, when we look at the sector-level results, we see that the industries that rely heavily on personalization, namely food and beverages, chemical industry products, leather products, paper products, textile products, footwear, jewellery, arms and ammunition, and other manufactures. While trade flow of most of these industries are expected to have a negative impact when the destination has a higher data restriction, two of them stand out. The negative impact on chemical industry products is mainly driven by the inclusion of pharmaceuticals in that industry. With the extra layers of security and privacy surrounding any trade of arms and ammunitions between countries, the negative coefficient isn't unexpected.

[19]The full regression results are presented in Table 1.4 in the appendix.

	Total Trade Flows	Sector-level Trade Flows
Higher Data Restriction	−0.129 (0.0649)***	
Food and Beverages		−0.721 (0.192)***
Chemical Industry Products		−0.178 (0.0703)**
Leather Products		−0.614 (0.337)*
Paper Products		−0.326 (0.157)**
Footwear		−0.659 (0.262)**
Jewellery		−0.387 (0.219)*
Other Manufactures		−0.107 (0.210)*
Observations	93,826	93,796
Fixed Effects	*Origin*	
	Destination	
		Origin-sector
		Destination-sector
Pseudo R^2	0.9403	0.9215

Notes: Standard errors for the baseline regression are clustered at the destination level, while for the sector-level regression, they are clustered at the destination-sector level; $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 1.1: Estimating Effect of Data Restrictions on Trade Flows with Data Restrictions

1.7 Conclusion

Consumer-specific data serves as a powerful tool for firms seeking to enhance their products and services. By tapping into the wealth of available data, firms can better cater to their customers' needs and preferences, ultimately driving business growth and competitiveness. At the same time, governments across the world are

imposing restrictions to the cross-border flows of digital information. Driven by concerns over privacy, security, and law enforcement, governments are implementing policies and regulations that raise the costs for firms to acquire and use consumer data.

This chapter analyses the impact of changes in restrictions and regulations on data usage within a country on the entry choices made by firms operating in the market. Specifically, we focus on firms that rely on data to enhance their productivity in that market. Our model predicts that when accessing data becomes more difficult in a specific country, it reduces the number of foreign firms operating in that country. This, in turn, decreases the variety of goods available to consumers and lowers aggregate trade flows with other countries.

In our empirical analysis, we find support for this mechanism and additionally show that manufacturing sectors relying on market-specific adaptations experience a negative impact on trade flows to destination countries with stricter data restrictions. While recent literature has examined the effects of data privacy and ownership from a consumer's perspective, this chapter provides an early analysis of data usage by exporting firms in determining their market selection and how it changes when countries adopt stricter data regulations.

Appendix

1.A Supplementary Material

1.A.1 Proof of Proposition 1.4.1

Proof. The convexity of the data cost function ensures that acquiring the entirety of the dataset is prohibitively expensive for the firms and when we solve the profit maximization problem, we only need to consider the restriction $n \geq 0$. Firm of type φ solves the following maximization problem:

$$\begin{aligned}
&\max_{p,n} \pi(\phi) = p(\varphi)\, y(\varphi) - w\left[f_e + f_d(n) + \frac{y(\varphi)}{\Phi(\varphi, n)}\right] \\
&\qquad \text{s.t.} \quad 0 \leq n \\
&\mathcal{L}(p, n) = RP^{\sigma-1} p(\varphi)^{1-\sigma} - w\left[f_e + \frac{1-(1-n)^{1-\beta}}{1-\beta}\theta L^{1-\alpha} + \right. \\
&\qquad\qquad \left. + \frac{RP^{\sigma-1} p(\varphi)^{-\sigma}}{\Phi(\varphi, n)}\right] + \lambda n
\end{aligned}$$

FOC with respect to p:

$$\begin{aligned}
&\frac{\partial \mathcal{L}}{\partial p}: \quad (1-\sigma)\, p(\varphi)^{-\sigma} + \frac{w\sigma}{\Phi(\varphi, n)} p(\varphi)^{-\sigma-1} = 0 \\
&\Longrightarrow p^*(\varphi) = \left(\frac{\sigma}{\sigma-1}\right) \cdot \frac{w}{\Phi(\varphi, n^*(\varphi))}
\end{aligned}$$

FOC with respect to n:

$$\frac{\partial \mathcal{L}}{\partial n}: \quad -w\left[(1-n)^{-\beta}\theta N^{1-\alpha} - \frac{RP^{\sigma-1}p(\varphi)^{-\sigma}\Phi_2(\varphi,n)}{\Phi^2(\varphi,n)}\right] + \lambda = 0$$

Complementary slackness condition:

$$\lambda n(\varphi) = 0 \quad \text{and} \quad \lambda \geq 0$$

Notice that there exists φ^*, s.t. $\forall\ \varphi \leq \varphi^*$, the FOC with respect to n holds only for some $\lambda > 0 \implies n(\varphi) = 0$ (the constraint $n(\varphi) \geq 0$ is binding). However, $\forall\ \varphi > \varphi^*$, the constraint is not binding and the corresponding $n(\varphi) \in (0,1)$ is actually the solution to the FOC with respect to n for $\lambda = 0$. Thus, for $\varphi \leq \varphi^*$, $n(\varphi) = 0$. For all $\varphi > \varphi^*$, the optimal $n(\varphi)$ is given by:

$$n^*(\varphi) = 1 - \frac{\left(\left(\frac{w\sigma}{\sigma-1}\right)^{\sigma}\frac{\theta N^{1-\alpha}}{RP^{\sigma-1}}\right)^{\frac{1}{\beta}}}{\varphi}$$

□

1.A.2 Proof of Proposition 1.4.2

Proof. Consider a firm of type φ. Then, the profits of this firm when it uses data and when it does not are, respectively:

$$\begin{aligned}
\pi_{data}(\varphi) &= RP^{\sigma-1}p_{data}^{*}(\varphi)^{1-\sigma} - w\left[f_e + f_d(n^*) + \frac{RP^{\sigma-1}p_{data}^{*}(\varphi)^{-\sigma}}{\Phi(\varphi)}\right] \\
\pi(\varphi) &= RP^{\sigma-1}p^{*}(\varphi)^{1-\sigma} - w\left[f_e + \frac{RP^{\sigma-1}p^{*}(\varphi)^{-\sigma}}{\varphi}\right] \\
\implies \Delta\pi &= RP^{\sigma-1}\left[\left(\frac{\sigma}{\sigma-1}\cdot\frac{w}{\Phi(\varphi)}\right)^{1-\sigma} - \left(\frac{\sigma}{\sigma-1}\cdot\frac{w}{\varphi}\right)^{1-\sigma}\right] - wf_d(n^*) - \\
&\quad - wRP^{\sigma-1}\left[\frac{p_d^{*}(\varphi)^{-\sigma}}{\Phi(\varphi)} - \frac{p^{*}(\varphi)^{-\sigma}}{\varphi}\right] \\
&= RP^{\sigma-1}\left(\frac{\sigma w}{\sigma-1}\right)^{1-\sigma}\left[\Phi(\varphi)^{\sigma-1} - \varphi^{\sigma-1}\right] - wf_d(n^*) - \\
&\quad - wRP^{\sigma-1}\left[\left(\frac{\sigma}{\sigma-1}\cdot\frac{w}{\Phi(\varphi)}\right)^{-\sigma}\frac{1}{\Phi(\varphi)} - \left(\frac{\sigma}{\sigma-1}\cdot\frac{w}{\varphi}\right)^{-\sigma}\frac{1}{\varphi}\right] \\
&= RP^{\sigma-1}\left(\frac{\sigma w}{\sigma-1}\right)^{1-\sigma}\left[\frac{\Phi(\varphi)^{\sigma-1} - \varphi^{\sigma-1}}{\sigma}\right] - wf_d(n^*) \\
&= RP^{\sigma-1}\left(\frac{\sigma w}{\sigma-1}\right)^{1-\sigma}\left(\frac{\sigma}{\sigma-1}\right)^{-1}\varphi^{\beta}n^* - wf_d(n^*) \\
&= \frac{\theta N^{\alpha}}{c}\varphi^{\beta}n^*w - wf_d(n^*) \\
&= \frac{\theta N^{\alpha}w}{1-\beta}\underbrace{\left[\frac{1-\beta n^*}{(1-n^*)^{\beta}} - 1\right]}_{\text{positive since } \beta<1}
\end{aligned}$$

Thus, all firms find it profitable to acquire data when it is available to them. □

1.A.3 Proof of Proposition 1.4.3

Proof. First recall that the optimal data choice as shown in Proposition 1.4.1 is:

$$\begin{aligned} n^*(\varphi) &= 1 - \frac{c^{1/\beta}}{\varphi} \\ \implies \frac{\partial n^*(\varphi)}{\partial \varphi} &= \frac{c^{1/\beta}}{\varphi^2} \quad > 0 \end{aligned}$$

Therefore, more productive firms will acquire more data. The asymptotic behaviour of $n^*(\varphi)$ is immediately evident. □

1.A.4 Proof of Proposition 1.4.4

Proof. Consider a firm of type φ. It will be indifferent between exiting and producing in the domestic market when:

$$\begin{aligned} & \pi_d(\varphi^*) = 0 \\ \implies & \left(\frac{\varphi^*}{\rho w} \cdot P\right)^{\sigma-1} \frac{R}{\sigma} = f_e \\ \implies & \varphi^* = \frac{\rho w}{P}\left(\frac{\sigma f_e}{R}\right)^{\frac{1}{\sigma-1}} \end{aligned}$$

All firms with $\varphi \geq \varphi_x^*$ will export, where:

$$\begin{aligned} & \pi_x(\varphi_x^*) = 0 \\ \implies & \left(\frac{\Phi(\varphi_x^*)}{\tau \rho w} \cdot P\right)^{\sigma-1} \frac{R}{\sigma} = f_x + f_d\left(n^*(\varphi_x^*)\right) \\ \implies & \Phi(\varphi_x^*) = \tau \varphi^* \left(\frac{f_x + f_d\left(n^*(\varphi_x^*)\right)}{f_e}\right)^{\frac{1}{\sigma-1}} \end{aligned}$$

□

1.A.5 Proof of Proposition 1.4.5

Proof. We have that:

$$
\begin{aligned}
r_d(\varphi) &= RP^{\sigma-1}\left[\frac{\sigma}{\sigma-1}\frac{w}{\varphi}\right]^{1-\sigma} \\
\implies \frac{r_d\left(\widetilde{\Phi}\right)}{r_d(\varphi^*)} &= \left(\frac{\widetilde{\Phi}}{\varphi^*}\right)^{\sigma-1} \\
\implies \pi_d\left(\widetilde{\Phi}\right) &= \frac{r_d\left(\widetilde{\Phi}\right)}{\sigma} - f_e = \left(\frac{\widetilde{\Phi}}{\varphi^*}\right)^{\sigma-1}\frac{r_d(\varphi^*)}{\sigma} - f_e
\end{aligned}
$$

But we know that for the entry cutoff firm

$$
\begin{aligned}
\pi_d(\varphi^*) &= 0 \\
\implies \pi_d(\varphi^*) &= \frac{r_d(\varphi^*)}{\sigma} - f_e = 0 \\
\implies r_d(\varphi^*) &= \sigma f_e \\
\implies \pi_d\left(\widetilde{\Phi}\right) &= \left[\left(\frac{\widetilde{\Phi}}{\varphi^*}\right)^{\sigma-1} - 1\right] f_e
\end{aligned}
$$

Similarly,

$$
\begin{aligned}
r_x(\varphi) &= RP^{\sigma-1}\left[\frac{\sigma}{\sigma-1}\frac{\tau w}{\Phi(\varphi)}\right]^{1-\sigma} \\
\implies \frac{r_x\left(\widetilde{\Phi}_x\right)}{r_x(\varphi_x^*)} &= \left(\frac{\widetilde{\Phi}_x}{\varphi_x^*}\right)^{\sigma-1} \\
\implies \pi_x\left(\widetilde{\Phi}_x\right) &= \frac{r_x\left(\widetilde{\Phi}_x\right)}{\sigma} - f_x - f_d\left(n^*\left(\widetilde{\Phi}_x\right)\right) \\
&= \left(\frac{\widetilde{\Phi}_x}{\varphi_x^*}\right)^{\sigma-1}\frac{r_x(\varphi_x^*)}{\sigma} - f_x - f_d\left(n^*\left(\widetilde{\Phi}_x\right)\right)
\end{aligned}
$$

But we know that for the export cutoff firm

$$\begin{aligned}
&\pi_x\left(\varphi_x^*\right) = 0 \\
\implies &r_x\left(\varphi_x^*\right) = \sigma\left[f_x + f_d\left(n^*\left(\varphi_x^*\right)\right)\right] \\
\implies &\pi_x\left(\widetilde{\Phi}_x\right) = \left[\left(\frac{\widetilde{\Phi}_x}{\varphi_x^*}\right)^{\sigma-1} - 1\right] f_x + \left(\frac{\widetilde{\Phi}_x}{\varphi_x^*}\right)^{\sigma-1} f_d\left(n^*\left(\varphi_x^*\right)\right) - f_d\left(n^*\left(\widetilde{\Phi}_x\right)\right)
\end{aligned}$$

Then, the equilibrium conditions are:

$$\overline{\pi} = \underbrace{\left[\left(\frac{\widetilde{\Phi}}{\varphi^*}\right)^{\sigma-1} - 1\right] f_e}_{\substack{\text{expected profits from} \\ \text{entering the industry}}} + \mathfrak{p}_x \underbrace{\left(\left[\left(\frac{\widetilde{\Phi}_x}{\varphi_x^*}\right)^{\sigma-1} - 1\right] f_x - f_d\left(n^*\left(\widetilde{\Phi}_x\right)\right)\right)}_{\text{expected profits from entering foreign market}} \tag{ZCP}$$

$$\overline{\pi} = \frac{f_e}{1 - G\left(\varphi^*\right)} \tag{FE}$$

(1.8)

□

1.A.6 Proof of Proposition 1.4.6

Proof. We have that:

$$
\begin{aligned}
R &= M\overline{r} \\
\text{and} \quad \overline{r} &= r_d\left(\widetilde{\Phi}\right) + \mathfrak{p}_x r_x\left(\widetilde{\Phi}_x\right) \\
\text{and} \quad \overline{\pi} &= \pi_d\left(\widetilde{\Phi}\right) + \mathfrak{p}_x \pi_x\left(\widetilde{\Phi}_x\right) \\
\text{and} \quad r_d\left(\widetilde{\Phi}\right) &= \sigma\left[\pi_d\left(\widetilde{\Phi}\right) + f_e\right] \\
\text{and} \quad r_x\left(\widetilde{\Phi}_x\right) &= \sigma\left[\pi_x\left(\widetilde{\Phi}_x\right) + f_x + f_d\left(n^*\left(\widetilde{\Phi}_x\right)\right)\right] \\
\text{Then,} \quad \overline{r} &= \sigma\left[\pi_d\left(\widetilde{\Phi}\right) + f_e + \mathfrak{p}_x\left(\pi_x\left(\widetilde{\Phi}_x\right) + f_x + f_d\left(n^*\left(\widetilde{\Phi}_x\right)\right)\right)\right] \\
&= \sigma\left[\overline{\pi} + f_e + \mathfrak{p}_x\left(f_x + f_d\left(n^*\left(\widetilde{\Phi}_x\right)\right)\right)\right] \\
\implies M &= \frac{wL}{\sigma\left[\overline{\pi} + f_e + \mathfrak{p}_x\left(f_x + f_d\left(n^*\left(\widetilde{\Phi}_x\right)\right)\right)\right]}
\end{aligned}
$$

□

1.A.7 Proof of Proposition 1.5.1

Proof. From Proposition 1.4.1, we have that:

$$
\begin{aligned}
n^*(\varphi) &= 1 - \frac{\left((\rho w)^\sigma \theta L^{1-\alpha} R^{-1} P^{1-\sigma}\right)^{1/\beta}}{\varphi} \\
\implies \frac{\partial n^*(\varphi)}{\partial \alpha} &= \frac{\left((\rho w)^\sigma \theta L^{1-\alpha} R^{-1} P^{1-\sigma}\right)^{1/\beta}}{\varphi} \cdot \frac{\log L}{\beta} \\
\text{and} \quad \frac{\partial n^*(\varphi)}{\partial \beta} &= -\frac{\left((\rho w)^\sigma \theta L^{1-\alpha} R^{-1} P^{1-\sigma}\right)^{1/\beta}}{\varphi} \cdot \frac{\log\left(\left((\rho w)^\sigma \theta L^{1-\alpha} R^{-1} P^{1-\sigma}\right)^{1/\beta}\right)}{\beta^2}
\end{aligned}
$$

Clearly, $n^*(\varphi)$ is increasing in α and decreasing in β. □

ISO code	Country	ISO code	Country	ISO code	Country	ISO code	Country
ARG	Argentina	DNK	Denmark	ITA	Italy	PHL	The Philippines
AUS	Australia	ECU	Ecuador	JPN	Japan	POL	Poland
AUT	Austria	ESP	Spain	KOR	South Korea	PRT	Portugal
BEL	Belgium	EST	Estonia	LTU	Lithuania	PRY	Paraguay
BGR	Bulgaria	FIN	Finland	LUX	Luxembourg	ROU	Romania
BRA	Brazil	FRA	France	LVA	Latvia	RUS	Russia
BRN	Brunei	GBR	United Kingdom	MEX	Mexico	SGP	Singapore
CAN	Canada	GRC	Greece	MLT	Malta	SVK	Slovakia
CHE	Switzerland	HKG	Hong-Kong	MYS	Malaysia	SVN	Slovenia
CHL	Chile	HRV	Croatia	NGA	Nigeria	SWE	Sweden
CHN	China	HUN	Hungary	NLD	Netherlands	THA	Thailand
COL	Colombia	IDN	Indonesia	NOR	Norway	TUR	Turkey
CRI	Costa-Rica	IND	India	NZL	New Zealand	TWN	Taiwan
CYP	Cyprus	IRL	Ireland	PAK	Pakistan	USA	United States
CZE	Czech Republic	ISL	Iceland	PAN	Panama	VNM	Vietnam
DEU	Germany	ISR	Israel	PER	Peru	ZAF	South Africa

Table 1.2: Countries covered by the Digital Trade Restrictiveness Index

Table 1.3: Harmonized System Nomenclature 2017 edition

Section 1 Animal Products	- Live animals - Meat and edible meat offal - Fish and crustaceans; molluscs and other aquatic invertebrates - Dairy produce; birds' eggs; natural honey; edible products of animal origin, not elsewhere specified or included - Products of animal origin, not elsewhere specified or included
Section 2 Vegetable Products	- Live trees and other plants; bulbs, roots and the like; cut flowers and ornamental foliage - Edible vegetables and certain roots and tubers - Edible fruit and nuts; peel of citrus fruit or melons - Coffee, tea, maté and spices - Cereals - Products of the milling industry; malt; starches; inulin; wheat gluten - Oil seeds and oleaginous fruits; miscellaneous grains, seeds and fruit; industrial or medicinal plants; straw and fodder - Lac; gums, resins and other vegetable saps and extracts - Vegetable plaiting materials; vegetable products not elsewhere specified or included
Section 3 Fat and Oil Products	- Animal or vegetable fats and oils and their cleavage products; prepared edible fats; animal or vegetable waxes
Section 4 Food and Beverages	- Preparations of meat, of fish or of crustaceans, molluscs or other aquatic invertebrates - Sugars and sugar confectionery - Cocoa and cocoa preparations - Preparations of cereals, flour, starch or milk; pastrycooks' products - Preparations of vegetables, fruit, nuts or other parts of plants - Miscellaneous edible preparations - Beverages, spirits and vinegar - Residues and waste from the food industries; prepared animal fodder - Tobacco and manufactured tobacco substitutes

Section 5 Mineral Products	- Salt; sulfur; earths and stone; plastering materials, lime and cement - Ores, slag and ash - Mineral fuels, mineral oils and products of their distillation; bituminous substances; mineral waxes
Section 6 Chemical Products	- Inorganic chemicals; organic or inorganic compounds of precious metals, of rare-earth metals, of radioactive elements or of isotopes - Organic chemicals - Pharmaceutical products - Fertilisers - Tanning or dyeing extracts; tannins and their derivatives; dyes, pigments and other colouring matter; paints and varnishes; putty and other mastics; inks - Essential oils and resinoids; perfumery, cosmetic or toilet preparations - Soap, organic surface-active agents, washing preparations, lubricating preparations, artificial waxes, prepared waxes, polishing or scouring preparations, candles and similar articles, modelling pastes, "dental waxes" and dental preparations with a basis of plaster - Albuminoidal substances; modified starches; glues; enzymes - Explosives; pyrotechnic products; matches; pyrophoric alloys; certain combustible preparations - Photographic or cinematographic goods - Miscellaneous chemical products
Section 7 Plastic Products	- Plastics and articles thereof - Rubber and articles thereof
Section 8 Leather Products	- Raw hides and skins (other than furskins) and leather - Articles of leather; saddlery and harness; travel goods, handbags and similar containers; articles of animal gut (other than silk-worm gut) - Furskins and artificial fur; manufactures thereof
Section 9 Wood and Straw Products	- Wood and articles of wood; wood charcoal - Cork and articles of cork - Manufactures of straw, of esparto or of other plaiting materials; basketware and wickerwork
Section 10 Paper Products	- Pulp of wood or of other fibrous cellulosic material; recovered (waste and scrap) paper or paperboard - Paper and paperboard; articles of paper pulp, of paper or of paperboard - Printed books, newspapers, pictures and other products of the printing industry; manuscripts, typescripts and plans

Section 11	- Silk
Textile Products	- Wool, fine or coarse animal hair; horsehair yarn and woven fabric
	- Cotton
	- Other vegetable textile fibers; paper yarn and woven fabrics of paper yarn
	- Man-made filaments
	- Man-made staple fibers
	- Wadding, felt and nonwovens; special yarns; twine, cordage, ropes and cables and articles thereof
	- Carpets and other textile floor coverings
	- Special woven fabrics; tufted textile fabrics; lace; tapestries; trimmings; embroidery
	- Impregnated, coated, covered or laminated textile fabrics; textile articles of a kind suitable for industrial use
	- Knitted or crocheted fabrics
	- Articles of apparel and clothing accessories, knitted or crocheted
	- Articles of apparel and clothing accessories, not knitted or crocheted
	- Other made up textile articles; sets; worn clothing and worn textile articles; rags
Section 12	- Footwear, gaiters and the like; parts of such articles
Footwear and Headgear	- Headgear and parts thereof
	- Umbrellas, sun umbrellas, walking-sticks, seat-sticks, whips, riding-crops and parts thereof
	- Prepared feathers and down and articles made of feathers or of down; artificial flowers; articles of human hair
Section 13	- Articles of stone, plaster, cement, asbestos, mica or similar materials
Ceramic Products	- Ceramic products
	- Glass and glassware
Section 14	- Natural or cultured pearls, precious or semi-precious stones, precious metals,
Jewellery	metals clad with precious metal and articles thereof; imitation jewellery; coin

Section 15 Base Metal Products	- Iron and steel - Articles of iron and steel - Copper and articles thereof - Nickel and articles thereof - Aluminium and articles thereof - Lead and articles thereof - Zinc and articles thereof - Tin and articles thereof - Other base metals; cermets; articles thereof - Tools, implements, cutlery, spoons and forks, of base metal; parts thereof of base metal - Miscellaneous articles of base metal
Section 16 Machinery and Appliances	- Nuclear reactors, boilers, machinery and mechanical appliances; parts thereof - Electrical machinery and equipment and parts thereof; sound recorders and reproducers, television image and sound recorders and reproducers, and parts and accessories of such articles
Section 17 Transportation Equipment	- Railway or tramway locomotives, rolling-stock and parts thereof; railway or tramway track fixtures and fittings and parts thereof; mechanical (including electro-mechanical) traffic signalling equipment of all kinds - Vehicles other than railway or tramway rolling-stock, and parts and accessories thereof - Aircraft, spacecraft, and parts thereof - Ships, boats and floating structures
Section 18 Optical and Surgical Instruments	- Optical, photographic, cinematographic, measuring, checking, precision, medical or surgical instruments and apparatus; parts and accessories thereof - Clocks and watches and parts thereof - Musical instruments; parts and accessories of such articles
Section 19 Arms and Ammunition	- Arms and ammunition; parts and accessories thereof
Section 20 Other Manufactures	- Furniture; bedding, mattresses, mattress supports, cushions and similar stuffed furnishings; lamps and lighting fittings, not elsewhere specified or included; illuminated signs, illuminated name-plates and the like; prefabricated buildings - Toys, games and sports requisites; parts and accessories thereof - Miscellaneous manufactured articles

Section 21 Art Work and Collectibles	- Works of art, collectors' pieces and antiques
Section 22 Unclassified Products	- Manufactures not classified in any of the above

	Trade Flows	Clustered SEs	Trade Flows	Clustered SEs
Log Distance	−0.798	0.0418***	−0.877	0.0405***
Common language	0.0955	0.0831	0.0855	0.0829
Contiguity	0.417	0.0794***	0.529	0.0818***
Colony	−0.123	0.129	0.0467	0.122
Higher Data Restriction	−0.129	0.0649***		
Animal Products			0.343	0.359
Vegetable Products			0.438	0.354
Fat and Oil Products			0.282	0.287
Food and Beverages			−0.721	0.192***
Mineral Products			0.140	0.220
Chemical Industry Products			−0.178	0.0703**
Plastics and Rubbers			−0.0384	0.117
Leather Products			−0.614	0.337*
Wood and Straw Products			−0.327	0.362
Paper Products			−0.326	0.157**
Textile Articles			−0.169	0.143
Footwear			−0.659	0.262**
Ceramic Products			−0.114	0.124
Jewellery			−0.387	0.219*
Base Metal Products			−0.00169	0.113
Machinery and Appliances			−0.150	0.145
Transportation Equipment			−0.0786	0.321
Optical and Surgical Instruments			−0.180	0.137
Arms and Ammunition			−0.720	0.453
Other Manufactures			−0.210	0.107*
Art Work and Collectibles			−0.185	0.259
Unclassified			−0.0134	0.232
Constant	23.00	0.349***	28.36	0.295***
Observations	93,826		93,796	
Origin fixed effects	✓			
Destination fixed effects	✓			
Origin-sector fixed effects			✓	
Destination-sector fixed effects			✓	
Pseudo R^2	0.9403		0.9215	

Notes: Standard errors for the baseline regression are clustered at the destination level, while for the sector-level regression they are clustered at the destination-sector level; $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 1.4: Estimating Effect of Data Restrictions on Trade Flows with Data Restrictions

Migrants of Influence: Skill Levels and the Effects on International Trade

This is a joint work with Stefan Smutny.

2.1 Introduction

In the early 21st century, the OECD countries have experienced a substantial increase in migrant populations, particularly from Africa and Asia, with significant inflows originating from major countries such as Mexico, India, Romania, China, and Poland. This phenomenon extended globally, reflecting the effect of “pull" factors, attracting those seeking higher standards of living, and “push" factors, compelling individuals to move due to instability, conflicts, or persecution. Additionally, there has been a notable rise in the educational attainment of migrants, especially in tertiary education, with a significant upsurge observed among migrants from Asia, Africa, and Latin America.[1]

The shifting global landscape of migration, characterized by a growing migrant population and their improved education levels, has a profound impact on both host and source countries. Immigrants bring a wealth of languages, cultures, and market insights from their home countries. This richness of cultural and market knowledge becomes a valuable resource that directly benefits firms involved in international trade. By tapping into this resource, firms can refine their products and marketing

[1]For precise quantitative data, please see d’Aiglepierre et al. (2020).

strategies, better meeting diverse customer preferences, and consequently, enhancing their export opportunities.

In order to participate in international trade effectively, firms must gather specific information related to their target markets.[2] This involves a fundamental understanding of consumer tastes and preferences, both domestic and international competitors, social, economic, and political environment, business culture and practices, language of commerce, legislation, and regulations, among other key factors. Without this essential information, the uncertainty in international trade increases, resulting in higher costs for firms and acting as a significant barrier to successful trade initiatives. Similarly, while firms in host countries hire foreign-born workers, they are faced with heterogeneity in incoming immigrants in the form of different ages of arrival and educational background that may result in different impacts on hiring firms.

Despite the extensive body of research on the economic implications of migration, there has been a noticeable gap in understanding the divergent effects of high-skilled and low-skilled migrants on international trade. This paper aims to address this specific research gap. To address these complexities, this paper builds a tractable model of international trade that considers firm heterogeneity and allows for both high- and low-skilled migrant workers to enter the production technology of the firm and also affect the iceberg trade costs. It explores the implications of such hiring at both the firm and aggregate levels, particularly focusing on trading patterns and export choices. Understanding the distinct influences of high-skilled and low-skilled migrants on international trade is of paramount importance, particularly for policymakers. Such insight can inform the development of migration policies, trade

[2]Various studies have examined other mechanisms that facilitate trade by reducing communication costs, including the advent of the telegraph (Juhász and Steinwender, 2018; Steinwender, 2018), mobile telephones (Jensen, 2007; Allen, 2014), broadband internet access (Malgouyres et al., 2021; Akerman et al., 2022), lower telephone call rates (Fink et al., 2005; Portes and Rey, 2005), and translation technologies (Brynjolfsson et al., 2019; Molnar, 2019).

agreements, and economic development strategies. Tailoring policies to harness the positive contributions of both high-skilled and low-skilled migrants can result in more efficient resource allocation, heightened competitiveness, and sustainable economic growth.

Numerous studies have demonstrated that migration serves as a valuable channel through which firms can effectively mitigate these trade barriers. In their seminal work, Gould (1994) shows that US bilateral trade is increasing with immigrant's home countries. A similar conclusion has been found by Head and Ries (1998) and Wagner et al. (2002) for Canada. These effects can even be observed historically too. Investigating US trade in the late nineteenth and early twentieth century, Dunlevy and Hutchinson (1999) show that immigration increases imports significantly. A substantial body of literature has since explored the various channels through which migration reduces trade barriers and stimulates international trade between countries.

The distinction between high-skilled and low-skilled migrants is evident through their educational backgrounds, training, and specialized expertise. High-skilled migrants possess specialized skills, expertise, and technological knowledge that can have a significant impact on both the countries they migrate to and those they leave behind. Their contributions extend beyond the labour market, encompassing innovation, entrepreneurship, and increased productivity. In the context of international trade, high-skilled migrants play a pivotal role in creating and maintaining trade networks, facilitating the exchange of knowledge, and shaping the competitive advantages of host countries. Their ability to integrate into global business networks and engage in strategic collaborations can enhance trade flows and promote the development of high-value-added industries.

Low-skilled migrants also play a crucial yet distinct role in bolstering the economies of both their home countries and the nations they move to. They

often occupy essential positions in industries such as agriculture, construction, and services, effectively addressing labour shortages and promoting economic growth. In the context of international trade, low-skilled migrants can impact trade dynamics by influencing labour costs, expanding the labour force, and strengthening labor-intensive sectors.

This paper makes two primary contributions. Firstly, we develop a theoretical model of international trade that incorporates firm heterogeneity and skill-biased productivity. Secondly, we empirically assess the theoretical hypotheses by combining trade and migration data. Using structural gravity estimation techniques, our analysis shows that total migration decreases trade costs, with high-skilled migrants exhibiting a more pronounced reduction compared to low-skilled migrants. In our theoretical model of bilateral trade, we assume that immigrants with varying skill levels enhance firm productivity and concurrently reduce trade costs between their host and home countries. High-skilled migrants not only complement the firm's inherent productivity with advanced technical, innovative, and managerial skills but also offer deeper insights into their home markets and facilitate connections between the two countries. In contrast, low-skilled migrants primarily boost the firm's labour productivity. Building upon this theoretical foundation, our empirical analysis yields robust evidence demonstrating the positive impact of migrants in lowering trade costs. Using detailed migration data from 20 OECD countries along with bilateral trade data, we illustrate the significance of immigrants' skill levels in this reduction, highlighting that higher-skilled immigrants exert a more substantial negative effect on trade costs.

The rest of the paper is organized as follows. Section 2.2 reviews the related literature. Section 2.3 lays out the theoretical framework. Section 2.4 outlines the empirical strategy and provides an econometric analysis of the theoretical predictions. Section 2.5 concludes.

2.2 Related Literature

The literature has extensively examined the beneficial impact of migrants on international trade. Rauch (1999) theorizes that immigrants reduce trade costs by building business networks (information channels) and by carrying over a preference for home-country goods that boosts demand in destination markets. Additionally, it has a secondary impact by enhancing US preferences for products originating from the immigrants' home countries. Girma and Yu (2002) highlight the importance of accounting for colonial ties. They found that, for the UK, only immigrants from non-Commonwealth countries positively affect trade. Finally, Felbermayr and Toubal (2012) have shown evidence of trade cost reduction through high skilled migration by analysing 29 OECD countries.[3]

More recent research has taken different approaches to better understand the causality of these findings and their underlying mechanisms. Recent studies for the UK (Ottaviano et al., 2018), France (Marchal and Nedoncelle, 2019), and Canada (Cardoso and Ramanarayanan, 2022) have found increased productivity in service-producing firms and reduced fixed costs due to migration into these countries. Additionally, research by Parsons and Vézina (2018); Olney and Pozzoli (2021); Ariu (2022) uses natural experiments to reach similar conclusions. However, these studies either do not distinguish between the skill level of migrants or primarily focus on low-skilled migrant flows, often originating from developing countries. As a result, our understanding of how foreign workers of different skill levels contribute to trade promotion remains limited. In this paper, we provide more supporting evidence that migrants across all skill levels contribute to the reduction of trade costs and add to the literature by showing that a greater skill level corresponds to a more substantial decrease in these costs.

[3] A lot of the literature uses log linearized estimations of the gravity equation. Furthermore, the literature acknowledges the difficultly in identifying the direction of the effect because of endogeneity issues and poor data quality, see Felbermayr et al. (2015).

The literature categorizes how migrants can influence trade by bringing information about their country of origin (network effect), introducing new skills and general knowledge for production (knowledge diffusion effect), or enhancing diversity at the firm or country level (diversity effect). Rauch and Trindade (2002) highlight Chinese networking effects on trade efficiency, while Combes et al. (2005) find networks involving migrants and firms amplifying trade between French regions. Bahar and Rapoport (2018) demonstrate the knowledge diffusion effect, revealing that greater immigration from countries exporting a specific product increases the likelihood of the host country independently exporting that product, with high-skilled migrants having a particularly strong influence. Bahar et al. (2022) identify increased exports due to knowledge and technology transfer from returning Yugoslavian refugees. Orefice et al. (2021) explore how immigrants boost exports, emphasizing diversity's impact in sectors with complex production and teamwork collaboration. We contribute to this body of literature by introducing skill diversity among immigrant workers at the firm-level in our theoretical model, and empirically investigating its impact on reducing information asymmetry in international trade. Our results align with prior research, demonstrating that all migrants contribute to reducing trade costs, and there exists a positive correlation between the extent of cost reduction and their skill level.

White (2007) examines the influence of immigrants on Danish imports and exports, emphasizing the impact of factors such as immigration policy changes and the homogeneity of the host country's population. Melitz (2008) explores the role of a common language in bilateral trade, distinguishing between direct communication and translation as facilitators of trade, with direct communication being more significant. Analysing data from 1995 to 2008 in Spanish provinces, Peri and Requena-Silvente (2010) find that immigrants significantly boost exports by increasing the number of transactions, especially for culturally distant countries

and differentiated goods. Work by Felbermayr and Jung (2009) is in a similar vein to ours, they find a substantial trade-boosting effect of migration, with a 0.11% increase in bilateral trade for each one-percent rise in the bilateral migrant population, highlighting that medium-skilled migrants have limited impact. We extend their research by introducing a tractable theoretical model of international trade that accounts for migrants' skill levels and demonstrate a positive correlation between skill level and trade enhancement.

Immigration has a wide-ranging impact on various economic factors, as supported by a large body of empirical research. Studies have highlighted the positive effects of immigration on total factor productivity and wage premiums (Ottaviano and Peri, 2012; Peri, 2012), substantial knowledge spillovers resulting from immigration, leading to increased innovation in host countries (Hunt and Gauthier-Loiselle, 2010; Bahar and Rapoport, 2018). However, there has been relatively less attention given to understanding how the varying skills of immigrant workers influence firms' export behaviours. This challenge has been exacerbated by limited access to comprehensive data on both employees and employers. Yet, recent studies, utilizing data from Denmark and Sweden, have provided valuable insights. For instance, Hiller (2013) and Hatzigeorgiou and Lodefalk (2016) have established that the employment of immigrant workers has a positive impact on a firm's export sales, underscoring the potential benefits that companies can derive from hiring foreign employees. We contribute to this literature by employing gravity estimation to analyse trade flows, with a particular emphasis on examining how the skill levels of migrant workers influence these trade patterns. This project also contributes to the literature of firm-level models of international trade[4] and incorporates the insights presented in the work by Burstein and Vogel (2017) to incorporate skill-biased productivity

[4]Bernard and Jensen (1999); Eaton and Kortum (2002); Bernard et al. (2003); Melitz (2003) are seminal contributions, having notably emphasized the pivotal role of firm-level analysis, encompassing both theoretical and empirical dimensions.

into the model.

2.3 Model

In this section, we present our theoretical model of international trade featuring heterogeneous firms, akin to the models proposed by Hopenhayn (1992) and Melitz (2003). We start with the description of consumers, who also serve as the labour force, and subsequently describe firm behaviour. Our model represents an economy encompassing S countries, and we denote an origin country by i and a destination country by j.

2.3.1 Consumers

Each country $i \in S$ is populated by an exogenous L_i measure of consumers, who provide their labour inelastically, which we assume is the only factor of production. Consumers have CES preferences over all the varieties. Hence, a representative consumer in a country $j \in S$ gets utility U_j from the consumption of goods shipped by all other firms in all other countries, defined by:

$$U_j = \left(\sum_{i \in S} \int_{\Omega_i} q_{ij}(\omega)^{\frac{\sigma-1}{\sigma}} d\omega \right)^{\frac{\sigma}{\sigma-1}}$$

where $q_{ij}(\omega)$ is the quantity consumed in the country j of variety ω, σ is the elasticity of substitution across the varieties, and Ω_i is the endogenous set of varieties originating in the country i.

2.3.2 Firms

There is a continuum Ω of possible varieties, and each firm produces a distinct variety $\omega \in \Omega$ and acts as a monopolistic competitor on the product market. Denote the set of varieties produced by firms in a country i by $\Omega_i \subset \Omega$. Suppose that there is a mass M_i of firms from a country i and that firms must incur a fixed cost $f_{ij} > 0$ to export to each destination j. Consistent with existing literature, we assume that during transportation, a fraction of the traded goods is lost, necessitating the firms to ship $\tau_{ij} > 1$ units from country i to j for every one unit to successfully reach the destination. Each firm in country i draws an initial productivity z from an exogenous cumulative distribution $G(z)$ and produces its variety using the technology:

$$q_i(z) = z\left[\phi_H(z)\, l_{i,H}^{\frac{\theta-1}{\theta}} + \phi_U l_{i,U}^{\frac{\theta-1}{\theta}}\right]^{\frac{\theta}{\theta-1}} \tag{2.1}$$

where $l_{i,H}$ and $l_{i,U}$ are high- and low-skilled labour, $\phi_H(z)$ and ϕ_U are skill-specific labour productivities. We align with the literature on immigration, wherein firms engage both high-skilled and low-skilled workers under a constant elasticity of substitution aggregate. To accommodate the potential interaction between firm productivity and skill, we use an otherwise conventional production function featuring skill-specific labour productivity dependent on firm productivity in the "nested CES" form, as above. The distinguishing feature lies in its allowance for the productivity of high-skilled workers to vary with firm productivity. For example, if we assume $\phi'_H(z) > 0$, that would imply that high-skilled labour tends to be more productive in high-productivity firms, thereby giving rise to a complementary relationship between skill and productivity. From an analytical perspective, this diverges from the conventional outcome of a constant-elasticity association between wages and the supply of skilled labour.[5] The parameter θ is the elasticity of substitution between high-skilled and low-skilled labor in the firms' production

[5]See Card (2009) or Borjas (2014) for example.

technology. A high value of θ would imply that firms can easily adjust to changes in the relative availability of high- versus low-skilled labor.

In the rest of the paper, we identify a firm by its productivity, as firms with the same productivity in a given country exhibit similar behaviour. At times, we also identify firms by their variety ω, since each firm produces a unique variety. This substitution is equivalent and does not affect the results.

2.3.3 Equilibrium

We first start with solving the optimization problem for a consumer in country j. This consumer maximizes utility over a bundle of goods produced by all firms in all other countries subject to the aggregate budget constraint:

$$\begin{aligned} &\max_{q_{ij}} \left[\sum_i \int_{\Omega_i} q_{ij}(\omega)^{\frac{\sigma-1}{\sigma}} d\omega \right]^{\frac{\sigma}{\sigma-1}} \\ &\text{s.t.} \sum_i \int_{\Omega_i} p_{ij}(\omega) q_{ij}(\omega) d\omega \leq Y_j \end{aligned}$$

Then, the optimal quantity demanded of the good ω is:

$$q_{ij}(\omega) = p_{ij}(\omega)^{-\sigma} Y_j P_j^{\sigma-1} \tag{2.2}$$

where $P_j \equiv \left(\sum_i \int_{\Omega_i} p_{ij}(\omega)^{1-\sigma} d\omega \right)^{\frac{1}{1-\sigma}}$ is the Dixit-Stiglitz price index. Also, the amount spent on variety ω is simply the product of the quantity and the price:

$$x_{ij}(\omega) = p_{ij}(\omega)^{1-\sigma} Y_j P_j^{\sigma-1}$$

Aggregating up across all firms in country j, we get:

$$X_{ij} \equiv \int_{\Omega_i} x_{ij}(\omega)\, d\omega = Y_j P_j^{\sigma-1} \int_{\Omega_i} p_{ij}(\omega)^{1-\sigma}\, d\omega \tag{2.3}$$

This is the total flow of goods from country i to country j and it depends on the aggregate price index in country j, denoted by P_j, the total expenditure in country j, denoted by Y_j, and the prices charged by the producing firms for of each of the varieties ω, denoted by $p_{ij}(\omega)$ which we will characterize below.

We now turn to the firms. If the wages for the high- and low-skilled labour are $w_{i,H}$ and $w_{i,U}$ respectively, we must have that the ratio of the wages be equal to the ratio of their marginal products (from equation (2.1)):

$$\begin{aligned} \frac{w_{i,H}}{w_{i,U}} &= \frac{\partial q_i(\omega)/\partial l_{i,H}}{\partial q_i(\omega)/\partial l_{i,U}} = \frac{\phi_H(z)}{\phi_U} \cdot \frac{l_{i,H}^{\frac{-1}{\theta}}}{l_{i,U}^{\frac{-1}{\theta}}} \\ \implies \frac{l_{i,H}}{l_{i,U}} &= \left(\frac{\phi_H(z)}{\phi_U}\right)^{\theta} \left(\frac{w_{i,H}}{w_{i,U}}\right)^{-\theta} \end{aligned}$$

which is the firm's relative demand for high- and low-skilled labour. The second term comes from the standard result that a firm's relative demand for labour is inversely proportional to the relative wage with elasticity of substition across skills θ. However, since we allow the skill-specific productivities to vary with skill levels and also with the productivity of the firm, the relative demand for high- and low-skill labour also varies with skill-biased productivity and shows up in the first term. This gives us a within-firm share of high- and low-skilled labour:

$$\pi_{i,H}(z) = \frac{\phi_H(z)^{\theta} w_{i,H}^{-\theta}}{\phi_H(z)^{\theta} w_{i,H}^{-\theta} + \phi_U^{\theta} w_{i,U}^{-\theta}}$$
$$\pi_{i,U}(z) = \frac{\phi_U^{\theta} w_{i,U}^{-\theta}}{\phi_H(z)^{\theta} w_{i,H}^{-\theta} + \phi_U^{\theta} w_{i,U}^{-\theta}}$$

The marginal cost of production is then the share-weighted wage bill normalized by the firm's productivity, i.e. $W_i(z) = w_{i,H}\pi_{i,H}(z) + w_{i,U}\pi_{i,U}(z)$. Furthermore, as a measure of the skill diversity at the firm-level, we define a CES aggregate of the different skill types, a "skill index", as: $\Phi_i(z) = \left[\phi_H(z)\pi_{i,H}(z)^{\frac{\theta-1}{\theta}} + \phi_U \pi_{i,U}(z)^{\frac{\theta-1}{\theta}}\right]^{\frac{\theta}{\theta-1}}$ which now gives us the marginal cost of production for the firm in country i as $z\Phi_i(z)$.

We now determine the prices that a firm charges. A firm producing variety ω in country i has to pay a fixed market entry cost f_{ij} to export to a destination country j where it faces a demand $q_{ij}(\omega)$ for its product. It also faces the standard iceberg shipping costs, τ_{ij}.[6] Then, the firm sets a price $p_{ij}(\omega)$ to maximize profits according to the following optimization problem:

$$\max_{p_{ij}(\omega)} \sum_j \left(p_{ij}(\omega) q_{ij}(\omega) - \frac{W_i(\omega)}{\omega \Phi_i(\omega)} \tau_{ij} q_{ij}(\omega) - f_{ij} \right)$$
$$\text{s.t.} \quad q_{ij}(\omega) = p_{ij}(\omega)^{-\sigma} Y_j P_j^{1-\sigma}$$

The first order condition implies that a firm in country i producing variety ω

[6] We assume that $\tau_{ij} > 1 \; \forall i \neq j$ and that $\tau_{ii} = 1$. This reflects frictionless shipping for firms when they sell their product domestically. Similarly, we assume that $f_{ij} > 0 \; \forall i \neq j$ and that $f_{ii} = 0$ for algebraic simplification.

and selling to destination j will charge a price:

$$p_{ij}(\omega) = \frac{\sigma}{\sigma - 1} \frac{W_i(\omega)}{\omega \Phi_i(\omega)} \tau_{ij}$$

which is a constant mark-up over the marginal cost of production. Then, the total revenue of a firm conditional on exporting is:

$$x_{ij}(\omega) = p_{ij}(\omega) q_{ij}(\omega) = \left(\frac{\sigma}{\sigma - 1} \frac{W_i(\omega)}{\omega \Phi_i(\omega)} \tau_{ij} \right)^{1-\sigma} Y_j P_j^{\sigma - 1}$$

Average price charged by firms in i selling to j is:

$$\begin{aligned} \int_{\Omega_i} p_{ij}(\omega)^{1-\sigma} d\omega &= \int_{\Omega_i} \left(\frac{\sigma}{\sigma - 1} \frac{W_i(\omega)}{\omega \Phi_i(\omega)} \tau_{ij} \right)^{1-\sigma} d\omega \\ &= \left(\frac{\sigma}{\sigma - 1} \right)^{1-\sigma} \tau_{ij}^{1-\sigma} \int_{\Omega_i} \left(\frac{W_i(\omega)}{\omega \Phi_i(\omega)} \right)^{1-\sigma} d\omega \\ &= \left(\frac{\sigma}{\sigma - 1} \right)^{1-\sigma} \tau_{ij}^{1-\sigma} M_i \tilde{z}_i^{\sigma - 1} \end{aligned} \tag{2.4}$$

where Ω_i is the set of varieties produced by firms located in country $i \in S$, $\tilde{z}_i$ is a modified average productivity of firms in country i, and M_i is the measure of exporting firms in country i. Plugging in the result from equation (2.4) into the trade flows in equation (2.3) gives us a gravity-like equation:

$$X_{ij} = \left(\frac{\sigma}{\sigma - 1} \right)^{1-\sigma} \tau_{ij}^{1-\sigma} M_i \tilde{z}_i^{\sigma - 1} Y_j P_j^{\sigma - 1} \tag{2.5}$$

The threshold firm in country i that will be indifferent between exporting to destination j or not will be such that:

$$\frac{1}{\sigma} \left(\frac{\sigma}{\sigma - 1} \frac{W_i(z)}{z \Phi_i(z)} \tau_{ij} \right)^{1-\sigma} Y_j P_j^{\sigma - 1} = f_{ij}$$

This equation determines, implicitly, a threshold of productivity above which the firms will find it profitable to incur the fixed cost of exporting to destination country j. Denote that threshold by $z_{ij}^{\star}$. To simplify our model further, we assume that the firm productivities are distributed according to a Pareto distribution[7]. Assuming a Pareto distribution with the shape parameter θ_i, we can re-write the gravity equation as:

$$X_{ij} = \frac{\theta_i}{\theta_i + 1 - \sigma} \left(\frac{\sigma}{\sigma - 1} \right)^{1-\sigma} \tau_{ij}^{1-\sigma} M_i \left(z_{ij}^{\star} \right)^{\sigma - \theta_i - 1} Y_j P_j^{\sigma - 1} \tag{2.6}$$

We assume that $\theta_i > \sigma - 1$ (this parametric assumption is necessary in order for trade flows to be finite). As a consequence of assuming the distributional form, θ_i will dictate heterogeneity in the firms – as θ_i increases, the probability that the productivity is below any given z increases, i.e. the heterogeneity of producers is decreasing in θ_i.

We posit that the impact of migrant workers varies depending on their countries of origin. For instance, a Norwegian or Danish worker in a German firm may yield different outcomes compared to an Australian or Brazilian worker. Moreover, it is unrealistic to assume that high- and low-skilled workers exert identical effects at the firm level. We model the expansion of immigrant worker employment as a decrease in iceberg trade costs. To account for the variable impact of high-skilled versus low-skilled immigrant workers on these costs, we assume that the share of high-skilled workers in the host country is the sole factor affecting the reduction in iceberg costs between the host and home countries:

$$\tau_{ij} = \frac{\tau_{ij}^{\star}}{\left(\int_{\Omega_i} \pi_{ij,H} \left(\omega \right) d\omega \right)^{\eta}}$$

[7]This was first proposed by Chaney (2008).

where $\pi_{ij,H}(\omega)$ is the fraction of within-firm share of high-skilled workers from country j in a firm in country i, η is the iceberg cost elasticity of high skilled workers, and $\tau_{ij}^{\star}$ is the usual trade cost. The iceberg costs clearly decrease as firms in country i hire more high-skilled workers from country j across all firms.

2.4 Empirical Analysis

2.4.1 Stochastic Formulation of the Gravity Equation

As we attempt to estimate the effects of an increase in the share of high-skilled workers influx on trade flows, we must define the gravity as a stochastic function of observable and unobservable factors. For estimation, we can follow the convention to define trade costs as an exponential function of observable trade costs and an idiosyncratic error term ν_{ij} such that:

$$\left(\frac{1}{\tau_{ij}}\right)^{\sigma-1} = \exp\left(\eta \ln(\pi_{ij}) - \gamma \ln(Z_{ij})\right)\nu_{ij},$$

where $\pi_{ij} := \int_{\Omega_i} \pi_{ij,H}(\omega)\, d\omega$ and $\tau_{ij}^{\star} := Z_{ij}^{\gamma}$. Here, Z_{ij} constitutes a vector of trade costs. We can therefore re-write equation (2.6), i.e. the total trade flows from country i to country j as:

$$\begin{aligned} X_{ij} = \exp\Bigg[&(1-\sigma)\ln\left(\frac{\sigma}{\sigma-1}\right) + \ln\left(\frac{\theta_i M_i}{\theta_i + 1 - \sigma}\right) + (\sigma - \theta_i - 1)\ln\left(z_{ij}^{\star}\right) \\ &+(\sigma-1)(\eta\ln(\pi_{ij}) - \gamma\ln(Z_{ij})) + \ln(Y_j) + (\sigma-1)\ln(P_j)\Bigg]\nu_{ij}, \end{aligned} \tag{2.7}$$

where ν_{ij} captures an error factor. In order to simplify the expression, we will define $\varepsilon_{ij} := \exp[(1-\sigma)\ln(\sigma/(1-\sigma)) + (\sigma-1)\ln(z_{ij}^{\star})]\nu_{ij}$. Note that, as shown in Head and Mayer (2014), $z_{ij}^{\star}$ is a constant. We further need to assume

$\mathbb{E}(\varepsilon_{ij}|\theta_i, M_i, Y_j P_j, \pi_{ij}, Z_{ij}) = 1$. Next, we define origin and destination fixed effects such that multilateral resistances are absorbed:

$$\delta_i := \exp\left[\ln\left(\frac{\theta_i M_i}{\theta_i + 1 - \sigma}\right) - \theta_i \ln\left(z_{ij}^{\star}\right)\right],$$
$$\delta_j := \exp\left[\ln(Y_j) + (\sigma - 1)\ln(P_j)\right]$$

We can then re-write the gravity equation so that:

$$X_{ij} = \exp\left[\beta \ln(\pi_{ij}) - (\sigma - 1)\gamma \ln(Z_{ij}) + \delta_i + \delta_j\right]\varepsilon_{ij},$$

where $\beta := (\sigma - 1)\eta$. The implied moment condition is:

$$\mathbb{E}(X_{ij}|\cdot) = \lambda_{ij} := \exp\left[\beta \ln(\pi_{ij}) - (\sigma - 1)\gamma \ln(Z_{ij}) + \delta_i + \delta_j\right] \tag{2.8}$$

Note that, besides β, the unknown parameters δ_i and δ_j are also being estimated.

2.4.2 Data

We utilize two primary sources of data for our analysis. Firstly, we acquire standard international trade statistics from the World Trade Organization (WTO). In addition to our dependent variable, which comprises bilateral trade flows, this dataset includes a diverse set of commonly employed variables related to bilateral trade costs.

Our second source of data originates from the Institute for Employment Research (IAB) tracking international migration, with a specific focus on temporary migration, migrant integration, and migration policies. The dataset is a collaborative effort involving 15 European research councils and is extensively documented by Brücker et al. (2013). The IAB has assembled a macro-dataset that

encompasses 20 OECD countries. The dataset includes comprehensive information regarding migration patterns, including gender, country of origin, and skill levels, spanning the years 1980 to 2010 in five-year intervals. Skill levels are determined through the method outlined by Defoort and Rogers (2008). Gender shares are estimated by using Barro and Lee (2013) to the United Nations data (UNDESA (2011)) on world population by gender.

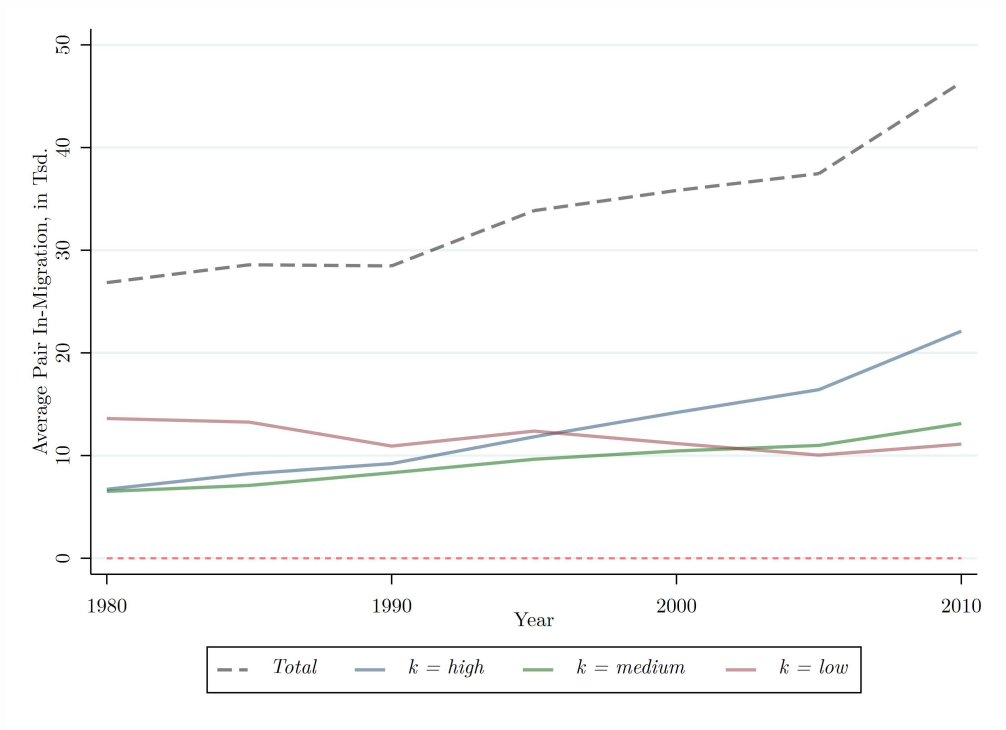

Figure 2.1: Average pair in-migration for different skill levels

Notes: Averages are reported in thousands. Note that k defines the level of migrant skill such that $k = \{total, high, medium, low\}$.

Our analytical model formulates a gravity equation for exports, which is characterized by the influence of skill-specific in-migration and incorporates the conventional multilateral resistance factors. To achieve this, we harmonize the

two datasets in a way that aligns the trade data with the migration data.[8] This matching process results in a dataset comprising 2,006 dyadic observations across seven distinct time periods. It is noteworthy that the dyadic relationships are not perfectly symmetrical, meaning that for certain origin countries, only a subset of destination countries is included in our dataset. This results in an unbalanced panel.

Figure 2.1 depicts the average pairwise migration flows across time. We observe a clear incline of high and medium skilled workers, whereas the average pairwise migration of low skilled individuals remains constant.

2.4.3 Estimation

We will estimate a standard two-way fixed effects gravity model of the moment condition (2.8) such that

$$X_{ij} = \exp\Big[\beta \ln(\pi_{ij}) + \psi \ln(Z_{ij}) + \delta_i + \delta_j\Big]\, \varepsilon_{ij},$$

where we define $\psi := (1-\sigma)\gamma$. As heteroskedasticity is a prevalent characteristic of trade and migration data, we have $\mathbb{E}(\ln(\varepsilon_{ij})|\theta_i, M_i, Y_j P_j, \pi_{ij}, Z_{ij}) \neq 0$. Hence, instead of log-linearizing the model such that it can be estimated with OLS, we will follow Silva and Tenreyro (2006) and estimate the model with PPML. This allows the model to remain in its multiplicative form. Both Fernández-Val and Weidner (2016) and Weidner and Zylkin (2021) have shown that β is consistently estimated by a two-way FE-PPML estimator. Building on Davis (2002), Baltagi et al. (2014) argue that the unbalancedness of data does not affect the estimation of two-way gravity models. Weidner and Zylkin (2021) have however shown that typical clustered standard errors might be off-centered and biased. We will therefore

[8] This means that we merge the two datasets such that the ij pair of the trade dataset matches the ji pair of the migration dataset.

additionally report bias-corrected standard errors.[9]

Note that, in order to compare different skill levels, we must stack our sample by skill and introduce another grouping variable. We therefore introduce Π_{ijk} as the total number of migrants from j to i for skill level $k = \{\textit{total, high, medium, low}\}$. Note that this means that $\ln(\pi_{ij}) = \mathbb{1}_k \ln(\Pi_{ijk})$ if $k = \textit{high}$. Hence, our estimation function can now be written as

$$X_{ijkt} = \exp\left[\sum_k \left\{\beta_k[\mathbb{1}_k \ln(\Pi_{ijkt})] + \psi_k \mathbb{1}_k \ln(Z_{ijk})\right\} + \delta_{ik} + \delta_{jk}\right] \varepsilon_{ijkt}$$
$$\text{for } t = 1980, 1985, ..., 2010$$

where we estimate the gravity equation for each t separately. We report the coefficients of this specification in Figure 2.3. The corresponding Table 2.1 presents additional information on the estimation results. The empirical model controls for a variety of classical bilateral trade costs. We also include a control for colonial ties to account for the potential bias presented in Girma and Yu (2002). Our estimation is robust against panel unbiasedness. Running the same analysis for a balanced panel, Figure 2.2 provides evidence that the results remain qualitatively consistent, with very similar quantitative outcomes. Our model seems to predict the data especially well for observations in the 21st century. This is to be expected as during this period, we observe an incline in international migration. For our latest sample, we find that a 1% increase in the overall migration flows increases trade flows by about 0.21%. For high skilled migration flows, we estimate this coefficient to be 0.25%. Note that, as predicted by our model, the point estimates are decreasing in the skill level.

[9] Here, we follow the procedure suggested by Weidner and Zylkin (2021).

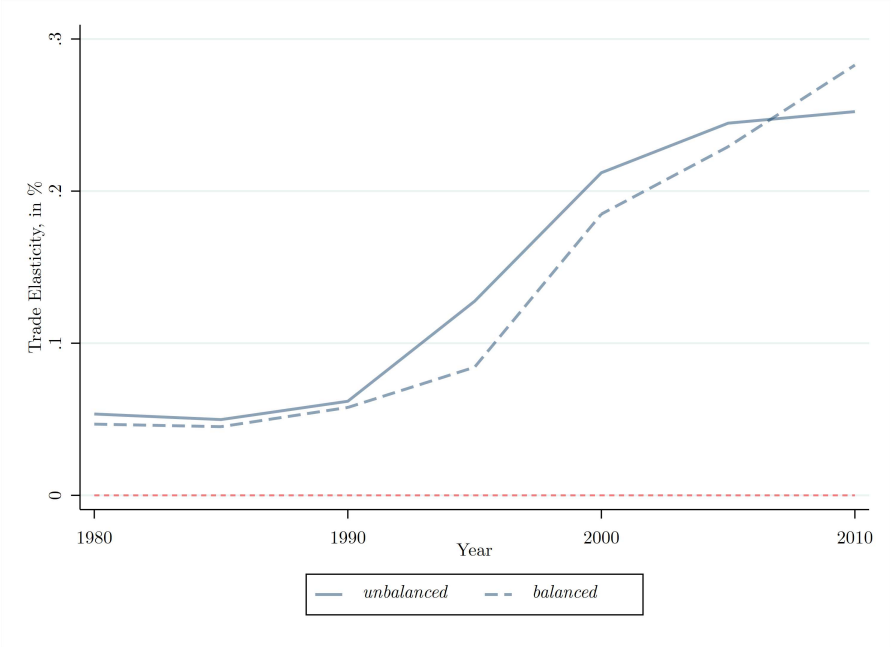

Figure 2.2: Coefficients of the gravity estimation for high-skilled migrants with a balanced and unbalanced panel

Notes: The balanced panel consists of 240 observations for each t. The number of observations for the unbalanced panel is either 272 or 306, depending on t.

Next, we can further investigate these effects by gender. Our dataset enables us to analyze migration patterns independently for males and females. As extensively documented in the existing body of research, exemplified by sources like Barbulescu and Bidwell (2013) and Cortes and Pan (2018), significant occupational heterogeneity exist between genders. Hence, it is an interesting exercise to test our model with respect to gender. n a qualitative analysis, discernible distinctions between genders do not emerge. This is evident in the results presented in Figures 2.4 and 2.5. Notably, in both female and male populations, the coefficients for high-skilled migrants surpass those for low-skilled migrants. Furthermore, in quantitative terms, these effects exhibit a similar magnitude to the overall outcomes depicted in Figure 2.3. We conclude that our main results presented above are not driven by skilled migration of a particular gender.

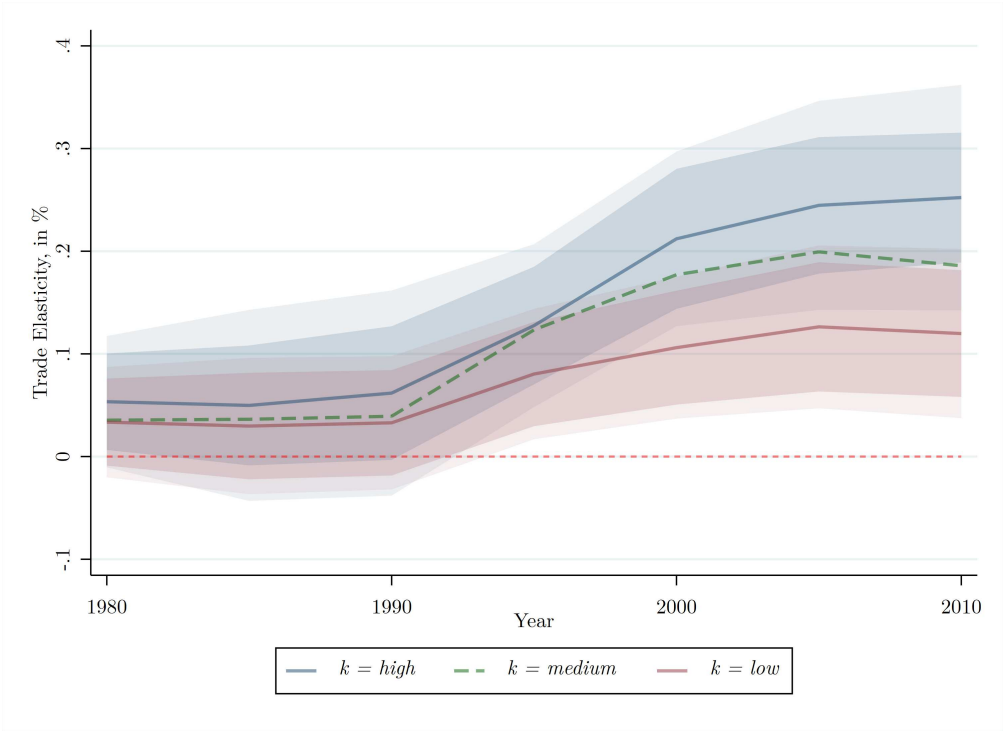

Figure 2.3: Coefficients of the gravity estimation by level of migrant skills

Notes: Darker shaded areas represent 90% destination-skill clustered standard errors. The lighter shaded areas report the 90% bias-corrected standard errors suggested by Weidner and Zylkin (2021).

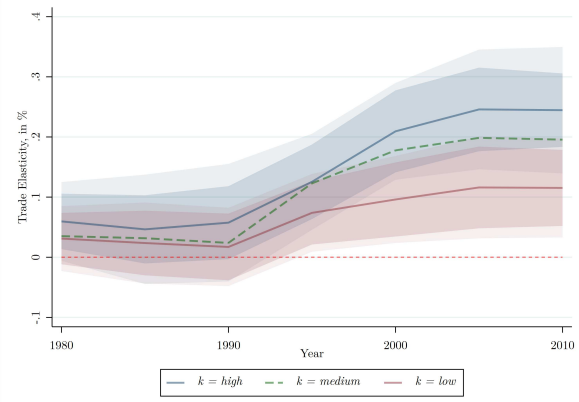

Figure 2.4: Female migrants

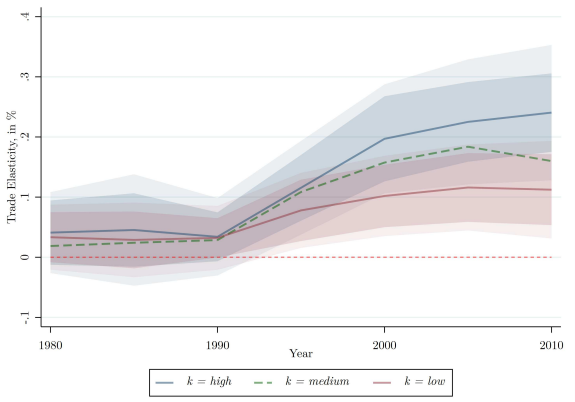

Figure 2.5: Male migrants

Notes: Darker shaded areas represent 90% destination-skill clustered standard errors. The lighter shaded areas report the 90% bias-corrected standard errors suggested by Weidner and Zylkin (2021).

	(i)	(ii)	(iii)	(iv)
Total In-migration: $\ln(\Pi_{ijkt})$	0.0409	0.0528	0.1783	0.2055
	(0.0269)	(0.0382)	(0.0345)***	(0.0360)***
By migrant skill levels:				
$k = high$	0.0535	0.0618	0.2121	0.2523
	(0.0285)*	(0.0396)	(0.0415)***	(0.0385)***
$k = medium$	0.0355	0.0393	0.1772	0.1859
	(0.0333)	(0.0372)	(0.0346)***	(0.0343)***
$k = low$	0.0335	0.0329	0.1061	0.1198
	(0.0258)	(0.0312)	(0.0337)***	(0.0375)***
Year t	1980	1990	2000	2010
Mean Trade Flows (in Mio. $)	463	1,180	3,250	5,330
Observations	1,088	1,088	1,224	1,088
Pseudo R^2	0.98	0.98	0.98	0.97

Notes: Standard errors are in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 2.1: Effect of Migrant Skill Levels on In-migration

2.5 Conclusion

Immigration significantly influences host countries by enhancing diversity, expanding global connections, and facilitating knowledge exchange, thus elevating productivity, especially in sectors that can effectively utilize immigrant knowledge and diversity. This, in turn, results in improved export performance, influencing vital policies and strategies for resource allocation in the interconnected global landscape. Immigrants are not just an additional labour force; they bring valuable knowledge about their home countries, fostering trade networks and enhancing product quality, thereby acting as a source of specific human capital for host country firms.

This paper makes two significant contributions to understanding the impact of migrants on international trade. Firstly, we introduce a tractable theoretical model of international trade that considers firm heterogeneity and skill-biased productivity. By incorporating skill-biased productivity at the firm level and trade costs varying with the proportion of high-skilled immigrants, we derive a testable gravity equation. Using a comprehensive migration dataset and employing structural gravity estimation techniques, we demonstrate the positive effect of migration in reducing trade costs. Our findings also highlight the prominent role of high-skilled migrants in achieving a more pronounced reduction in trade costs compared to low-skilled migrants. This empirical evidence substantiates the theoretical model's premise that high-skilled immigrants, with their insights into foreign markets and enhanced connections, play a key role in diminishing trade barriers.

Internationalizing Currencies and Trade Invoicing

3.1 Introduction

The importance and effects of the internationalization of a currency plays a central role in open-economy macroeconomics. While the rise of an international currency is hinged upon the economic size and the openness of the issuing country, historical events show that the state of its financial markets are hugely impactful in this process. Eichengreen (2011) documents that the delayed internationalization of the U.S. dollar (USD) was mainly related to its underdeveloped financial market in the early days, despite the United States being the leading economy globally. Similarly, the usage of Chinese Renminbi (RMB) remains mostly within domestic markets due to China's still-developing financial infrastructure, even though China is the world's second-largest economy and a major player in international trade.

Financial factors, including the depth and liquidity of financial markets, robust regulatory frameworks, and access to cross-border financial instruments, are crucial for currency internationalization. Recent developments suggest potential shifts in the global currency landscape, particularly with the RMB gaining traction in East Asia. The Chinese government has implemented measures to bolster RMB internationalization, such as establishing RMB payment systems, signing bilateral swap agreements, and enabling controlled convertibility through Hong Kong. A prominent example of these efforts is the People's Bank of China's (PBoC) involvement in the BIS-led mBridge project, which leverages distributed ledger technology to enhance cross-border payments. The project, conducted alongside

central banks from Hong Kong, Thailand, and the UAE, aims to make cross-border payments faster, cheaper, and more transparent using central bank digital currencies (CBDCs).[1] By potentially improving transaction efficiency and reducing costs, mBridge could represent a novel pathway for the RMB's internationalization.

While these macroeconomic initiatives are crucial for the internationalization of any currency, understanding the micro-level dynamics that influence the firms' currency choices is important as well. Relying on exogenous assumptions about currency choice fails to account for key firm-level strategic considerations, such as hedging strategies, interactions between domestic and international financial conditions, and exchange rate risks. Moreover, transaction costs, exchange rate expectations, and the availability of financial instruments play a critical role in determining invoicing currencies in an endogenous and dynamic manner. This chapter addresses these complexities by developing a three-country model of monopolistic competition, where firms set prices strategically while facing exchange rate uncertainties. Firms may invoice in the dominant global currency, their local currency, or a third "rising" currency, aiming to maximize expected profits. Crucially, the model reflects the reality that a significant portion of firms' production costs are denominated in foreign currencies. This aligns with empirical evidence showing that nominal exchange rate shocks have a far greater impact on import and wholesale prices than on consumer prices.[2] By capturing these dynamics, the model provides a more comprehensive framework for understanding the strategic drivers of invoicing currency choice internationalization.

The results of the model reflect firstly a straightforward hedging rationale, suggesting that firms are more likely to invoice in a particular currency if a substantial portion of their costs is denominated in that currency. Additionally, the

[1]The BIS Innovation Hub (2022) provides further details of project mBridge, including its technical aspects.

[2]See Goldberg and Knetter (1997), Campa and Goldberg (2005), Gopinath et al. (2010) and Burstein and Gopinath (2014) for more comprehensive work in this context.

optimal choice of invoicing currency is influenced by exchange rate characteristics. For instance, firms tend to prefer invoicing in more stable currencies to mitigate unnecessary exchange rate risks, especially when certain currencies exhibit high volatility. Furthermore, exchange rate correlations play a pivotal role, as firms are more likely to invoice in the vehicle currency if it is highly correlated with a third currency, enhancing the momentum of the vehicle currency. This endogenous determination of invoicing currency provides a better understanding of how financial factors and exchange rate dynamics influence firms' strategic decisions, thereby contributing to a more nuanced understanding of currency internationalization and its macroeconomic implications.

Using the Frankel-Wei regression framework, recent work by Ho et al. (2005), Henning (2013), and Subramanian and Kessler (2013) indicate the apparent emergence of an RMB bloc in East Asia, at least among some emerging economies within the region. This shift is further supported by Balasubramaniam et al. (2011), who argue that regional trade agreements and the increasing use of the RMB in bilateral trade settlements are fostering its internationalization. Bahaj and Reis (2022) examine the influence of central bank policies in promoting the global adoption of a currency. Their study focuses on the establishment of 38 swap line agreements between People's Bank of China (PBoC) and various other countries' central banks between 2009 and 2018. They demonstrate how these swap lines reduced the volatility of RMB borrowing costs and greatly improved the usage of RMB for settling international trade between countries. The likelihood of using RMB by these countries, after entering into a swap agreement, increased to about 14% and thus also increasing its share in country payments by about 1.3 percentage points. The results obtained in this chapter are in tune with these results, which suggest that central bank policies aimed at stabilizing foreign currency borrowing costs may make that currency more attractive for financing trade, hence fostering

internationalization.

The choice of invoicing currency has important consequences for the transmission of macroeconomic policies. Betts and Devereux (2000) show that monetary and fiscal shocks affect consumption and welfare differently depending on the invoicing currency choice. Work by Boz et al. (2022) focuses on the distribution and evolution of invoicing currencies in international trade. It outlines a recent gradual diversification away from traditional USD dominance toward a more balanced currency basket, including the RMB and other emerging currencies. The diversification is driven by regional trade agreements, bilateral financial arrangements, and especially the growing economic stature of emerging markets. This also means that, in the case of firms whose locations are in a region with active financial integration and support for a variety of currencies, there will be greater diversity in the use of currencies for invoicing, which would make international trade resistant to exchange rate shocks and less dependent on one single currency. The results of this chapter align with these empirical findings on changes in invoicing practices, we numerically show that firms will choose a basket of currencies to invoice their exports while accounting for transaction costs and exchange rate volatilities.

The rest of the chapter is organized as follows: section 3.2 lays out the basics of theoretical underpinnings, followed by section 3.3 that provides the results of an endogenous choice of invoicing currency followed by some numerical simulations for intuition in section 3.4, section 3.5 provides a final discussion while section 3.A has the technical details of the derivations.

3.2 Model

In this section, we construct a theoretical framework to study the interaction between firms' endogenous choices of invoicing currency and the associated financial

costs. Building on the substantial literature on currency selection in international trade Bacchetta and Van Wincoop (2005), Novy (2006), and Goldberg and Tille (2008), we present a new mechanism through which financial costs determine currency choice by firms. Using a three-country sticky price model similar to Novy (2006), we show that firms strategically select invoicing currencies that minimize their overall financial costs, favoring those with lower transaction fees. Furthermore, this preference is driven by the objective to maximize profits while also accounting for exchange rate volatility.

Our model, unlike those proposed by Bacchetta and Van Wincoop (2005) and Goldberg and Tille (2008), abstracts away from industry heterogeneity and focuses on financial costs associated with invoicing in different currencies for both intermediate and final goods trade. While simplifying the model, this abstraction lends itself for numerical simulations and empirical testing across different industries and economic contexts. By focusing on the effects of financial costs on invoicing currency choice in a tractable framework, our model can provide a better understanding of usage of different currencies in international trade, offering practical implications to policymakers and firms. On the one hand, our results can serve as a starting point for a framework for financial regulation that will support the uptake of a currency in invoicing trade, and, on the other, help understand how firms adjust their choices to limit exposure to financial risk and maintaining their competitive positions in international trade. Predictions from our model can also be used as a starting point for further detailed empirical testing of the mechanisms that determine currency choice in invoicing.

3.2.1 Model World

There are three countries in the world, indexed 1, 2, and 3. Each country is populated with firms that produce unique tradable goods in the continuum $[0, 1]$

such that firms in country 1 produces tradable goods in the range $[0, n_1]$, while firms in country 2 produces tradable goods in the range $[n_1, n_2]$, and country 3 produces tradable goods in the range $[n_2, n_3]$, with $n_3 = 1$.

3.2.2 Consumers

Consumers in each country $j = \{1, 2, 3\}$ maximize a Dixit-Stiglitz consumption index defined over all tradable goods as:

$$C_j \equiv \left(\int_0^1 (c_{ij})^{\frac{\rho-1}{\rho}} \, \mathrm{d}i \right)^{\frac{\rho}{\rho-1}}$$

where c_{ij} is the consumption of good i by a consumer in country j. The parameter $\rho > 1$ is the elasticity of substitution, and we assume that it is the same across countries. The price index, which is defined as the minimum level of expenditure for one unit of composite consumption, is:

$$P_j = \left(\int_0^1 (p_{ij})^{1-\rho} \, \mathrm{d}i \right)^{\frac{1}{1-\rho}}$$

where p_{ij} is the price of good c_{ij}. The demand function for good c_{ij} is then

$$c_{ij} = \left(\frac{p_{ij}}{P_j} \right)^{-\rho} C_j$$

3.2.3 Firms

Firms in each country $j = \{1, 2, 3\}$ combine intermediate inputs from all three countries to produce the final tradable output using a Cobb-Douglas production technology:

$$Y_j = N_{j1}^{\alpha_{j1}} N_{j2}^{\alpha_{j2}} N_{j3}^{\alpha_{j3}}$$

where $N_{j1}, N_{j2},$ and N_{j3} denote the intermediate goods imported from countries $1, 2,$ and 3 respectively, with α_{j1}, α_{j2}, and α_{j3} being their corresponding weights in the production process. Therefore, N_{jj} denotes the domestic input factors of production. The production technology is further assumed to exhibit constant returns to scale, that is, $\alpha_{j1} + \alpha_{j2} + \alpha_{j3} = 1$.

3.3 Endogenous Choice of Invoicing Currency

Suppose country 1 is the issuer of the dominant currency and country 2 is the issuer of the rising currency. Firms must pay for intermediate inputs in the currency of their country of origin but can price exported goods in any of the three currencies. Transactions in each of the three currencies incur additional financial costs, which are assumed to be proportional to the volume of goods exchanged and are therefore modeled as a markup. We denote f_i as the proportional cost associated with settling an invoice in country i's currency. Let R_h denote the producer-currency price of intermediate inputs from country h for all $h = \{1, 2, 3\}$. Define the nominal exchange rate e_{jh} as the price of country h's currency in country j's currency units with $e_{jj} = 1$ for all $j = \{1, 2, 3\}$ and $h = \{1, 2, 3\}$.[3]

With this notation, the cost function associated with a firm in country 3, denominated in country 3's currency can be written as:

$$\text{costs}_3 = e_{31}R_1\left(1 + f_1\right)N_{31} + e_{32}R_2\left(1 + f_2\right)N_{32} + e_{33}R_3\left(1 + f_3\right)N_{33}$$

The technical appendix shows that by minimizing these costs, firms face the

[3]Note that the derivations for all the following results and analytical definitions are available in the Technical Appendix.

following costs:

$$\text{costs}_3 = \left[\frac{e_{31}R_1\left(1+f_1\right)}{\alpha_{31}}\right]^{\alpha_{31}}\left[\frac{e_{32}R_2\left(1+f_2\right)}{\alpha_{32}}\right]^{\alpha_{32}}\left[\frac{e_{33}R_3\left(1+f_3\right)}{\alpha_{33}}\right]^{\alpha_{33}}Y_3$$

Then, the marginal cost can be written as:

$$M_3 = \frac{\text{costs}_3}{Y_3} = \left[\frac{e_{31}R_1\left(1+f_1\right)}{\alpha_{31}}\right]^{\alpha_{31}}\left[\frac{e_{32}R_2\left(1+f_2\right)}{\alpha_{32}}\right]^{\alpha_{32}}\left[\frac{e_{33}R_3\left(1+f_3\right)}{\alpha_{33}}\right]^{\alpha_{33}}$$

Now, consider the exports from a firm in country 3 to consumers in country 2. Given that the firm has constant marginal costs, it can maximize its profits with respect to each individual consumer separately without taking into account the amount sold to other consumers. The firm can choose to invoice these exports between the dominant currency, the rising currency, and its own home currency. The expected profits in each of these three choices will be, respectively:

$$\mathbb{E}\left[\pi_{32}^{(1)}\right] = \mathbb{E}\left[\left(e_{31}p_{32}^{(1)}\left(1-f_1\right)-M_3\right)\left(\frac{e_{21}p_{32}^{(1)}}{P_2}\right)^{-\rho}C_2\right]$$

$$\mathbb{E}\left[\pi_{32}^{(2)}\right] = \mathbb{E}\left[\left(e_{32}p_{32}^{(2)}\left(1-f_2\right)-M_3\right)\left(\frac{e_{22}p_{32}^{(2)}}{P_2}\right)^{-\rho}C_2\right]$$

$$\mathbb{E}\left[\pi_{32}^{(3)}\right] = \mathbb{E}\left[\left(e_{33}p_{32}^{(3)}\left(1-f_3\right)-M_3\right)\left(\frac{e_{23}p_{32}^{(3)}}{P_2}\right)^{-\rho}C_2\right]$$

where $\pi_{32}^{(k)}$ denotes the nominal profits for a firm in country 3 exporting to country 2 denominated in the currency of country 3 by charging the consumer in country 2 are price $p_{32}^{(k)}$ for $k = \{1, 2, 3\}$. The superscript k in $\pi_{32}^{(k)}$ and $p_{32}^{(k)}$ is used to denote the invoicing is being done in the currency of country k. Similar to intermediate inputs, firms have to incur extra financial costs, which depend on their choice of

currency for invoicing their exports. This is reflected in the profit functions as a reduction in their revenues. The product of the price $p_{32}^{(k)}$ with the exchange rate e_{3k} converts the revenue for the firm into its domestic currency while the product of the price $p_{32}^{(k)}$ with the exchange rate e_{2k} converts the price faced by a consumer in country 2 from currency of country k into the currency of country 2. Firms act as monopolistic competitors and set their prices before exchange rates are known. The optimal prices that maximize these profits are:

$$
\begin{aligned}
p_{32}^{(1)} &= \frac{\rho}{\rho-1}\frac{K}{(1-f_1)}\frac{\mathbb{E}\left[e_{31}^{\alpha_{31}}e_{32}^{\alpha_{32}}e_{33}^{\alpha_{33}}e_{21}^{-\rho}\right]}{\mathbb{E}\left[e_{31}e_{21}^{-\rho}\right]} \\
p_{32}^{(2)} &= \frac{\rho}{\rho-1}\frac{K}{(1-f_2)}\frac{\mathbb{E}\left[e_{31}^{\alpha_{31}}e_{32}^{\alpha_{32}}e_{33}^{\alpha_{33}}e_{22}^{-\rho}\right]}{\mathbb{E}\left[e_{32}e_{22}^{-\rho}\right]} \\
p_{32}^{(3)} &= \frac{\rho}{\rho-1}\frac{K}{(1-f_3)}\frac{\mathbb{E}\left[e_{31}^{\alpha_{31}}e_{32}^{\alpha_{32}}e_{33}^{\alpha_{33}}e_{23}^{-\rho}\right]}{\mathbb{E}\left[e_{33}e_{23}^{-\rho}\right]}
\end{aligned}
$$

where K is a constant. Plugging these prices back into the profit functions, we get that:

$$
\begin{aligned}
\mathbb{E}\left[\pi_{32}^{(1)}\right] &= G\cdot(1-f_1)^{\rho}\cdot\left(\mathbb{E}\left[e_{31}^{\alpha_{31}}e_{21}^{-\rho}\right]\right)^{\rho}\left(\mathbb{E}\left[e_{31}^{\alpha_{31}}e_{32}^{\alpha_{32}}e_{21}^{-\rho}\right]\right)^{1-\rho} \\
\mathbb{E}\left[\pi_{32}^{(2)}\right] &= G\cdot(1-f_2)^{\rho}\cdot\left(\mathbb{E}\left[e_{31}\right]\right)^{\rho}\left(\mathbb{E}\left[e_{31}^{\alpha_{31}}e_{32}^{\alpha_{32}}\right]\right)^{1-\rho} \\
\mathbb{E}\left[\pi_{32}^{(3)}\right] &= G\cdot(1-f_3)^{\rho}\cdot\left(\mathbb{E}\left[e_{32}^{\rho}\right]\right)^{\rho}\left(\mathbb{E}\left[e_{31}^{\alpha_{31}}e_{32}^{\alpha_{32}+\rho}\right]\right)^{1-\rho}
\end{aligned}
$$

where G is a constant. Since the profits depend on the various exchange rates multiplicatively, we need to assume some structure of their stochastic properties. We assume that the exchange rates are jointly log-normally distributed, that is:

$$
\ln\begin{pmatrix}e_{31}\\ e_{32}\end{pmatrix}\sim\mathcal{N}\left(\begin{bmatrix}\mu_{31}\\ \mu_{32}\end{bmatrix},\begin{bmatrix}\sigma_{31}^2 & \sigma_{12}\\ \sigma_{12} & \sigma_{32}^2\end{bmatrix}\right)
$$

For simplicity and analytic tractability, we further assume that $\mu_{31} = \mu_{32} = 0$. The variances are always positive, i.e. $\sigma_{31}^2, \sigma_{32}^2 > 0$ whereas the covariance, σ_{12}, can be negative too.

A firm in country 3 has a choice of three currencies to invoice its exports to country 2, namely $p_{32}^{(1)}$ (dominant currency pricing, DCP), $p_{32}^{(2)}$ (rising currency pricing, RCP), and $p_{32}^{(3)}$ (producer currency pricing, PCP). If the expected profits $\mathbb{E}\left[\pi_{32}^{(2)}\right]$ are larger than $\mathbb{E}\left[\pi_{32}^{(1)}\right]$ and $\mathbb{E}\left[\pi_{32}^{(3)}\right]$, then firms will choose the rising currency to invoice its exports to consumers in country 2. The invoicing decision made by firms in country 3 are outlined in the proposition below and the intuition behind the different mechanisms at play are demonstrated using simulations that follow:

Proposition 3.3.1. *Consider a firm in country* 3 *exporting its final good to country* 2. *Even when the invoicing costs associated with using the rising currency (f_2) are higher than the costs associated with the dominant (f_1) and the producer (f_3) currencies, the firm is more likely to use the rising currency for invoicing when:*

(a) the share of costs $\alpha_{32} > 1/2$,

(b) ratio of exchange rate volatility, $\sigma_{31}^2/\sigma_{32}^2 > 1$, and

(c) the covariance of the exchange rates, $\sigma_{21} > 0$.

3.4 Numerical Simulations

Doing some back of the envelope calculations for this exercise, we use the parameter values of $\sigma_{12} = 0.25$, $\sigma_{31} = 0.75$, and $\sigma_{32} = 0.5$ for the stochastic distribution of the exchange rates. As for the proportional financial costs, we assume that there is a 1% proportional cost associated with using the dominant currency, a 6% proportional cost associated with using the rising currency, and a 2% proportional cost associated

with using the producer currency. Our tractable modelling framework allows us to understand this result numerically. First, we simplify the invoicing decision for the firm in country 3 to get the following necessary conditions:

- RCP over PCP:

$$\left(\frac{1}{2}-\alpha_{33}\right)\cdot\sigma_{31}^2+\alpha_{33}\cdot\sigma_{12}+\log\left(\frac{1-f_2}{1-f_3}\right)>\left(\frac{1}{2}-\alpha_{32}\right)\cdot\sigma_{32}^2+\alpha_{32}\cdot\sigma_{12}$$

- DCP over RCP:

$$\left(\frac{1}{2}-\alpha_{32}\right)\cdot\sigma_{32}^2+\log\left(\frac{1-f_1}{1-f_2}\right)>(1-\alpha_{31}-\alpha_{32})\cdot\sigma_{21}$$

- DCP over PCP:

$$\left(\frac{1}{2}-\alpha_{33}\right)\cdot\sigma_{31}^2+\log\left(\frac{1-f_1}{1-f_3}\right)>(1-\alpha_{31}-\alpha_{32})\cdot\sigma_{12}$$

Using these inequalities and their pairwise comparisons, we can now plot the regions where each of the currencies is preferred, to get the Figure 3.1.

The first determining factor is the firms' share of imports from different countries. Firms in country 3 would choose to invoice their final goods in the rising currency (represented by the red region in the figure) when their reliance on intermediate goods from country 2, denoted by α_{32}, is high. This choice minimizes the currency mismatch between their revenues and costs, thus reducing exchange rate risks and maximizing profits. Conversely, firms that depend more heavily on intermediate goods from country 1, represented by α_{31}, tend to prefer the dominant currency (represented by the green region in the figure) for invoicing their exports to country 2. This basic hedging argument ensures that their costs are better matched with their revenue streams. Combining all possible combinations, this plot shows that

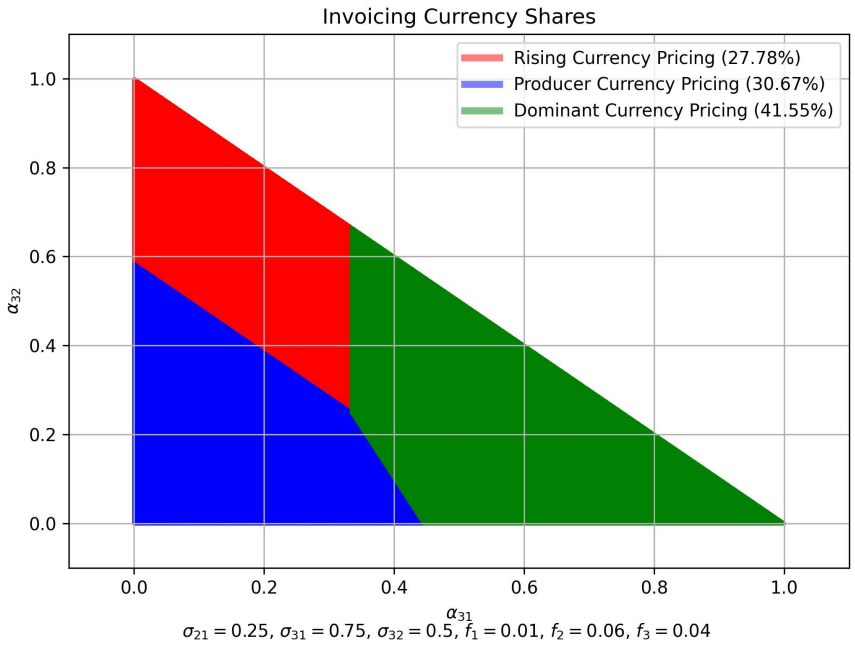

Figure 3.1: Invoicing Currency Shares

about 40% of the final goods trade from country 3 to country 2 is invoiced in the dominant currency, while both the rising currency and producer currency account for about 30% of the share each.

Consider now the case of the rising currency, issued by country 2. The invoicing preferences of firms changes as country 2 undertakes various measures to support an increased usage of its currency in international trade. We perform two such simulations to provide an understanding of the mechanisms that determine currency usage in our model.

It is clear from Figure 3.2 that a reduction in invoicing costs for the rising currency leads to an increase in its share of total exports from country 3 to country 2. Specifically, as these costs decline, the rising currency's share can grow significantly, potentially capturing up to 60% of the invoicing share when its costs align with those of the dominant currency. This shift is accompanied by a

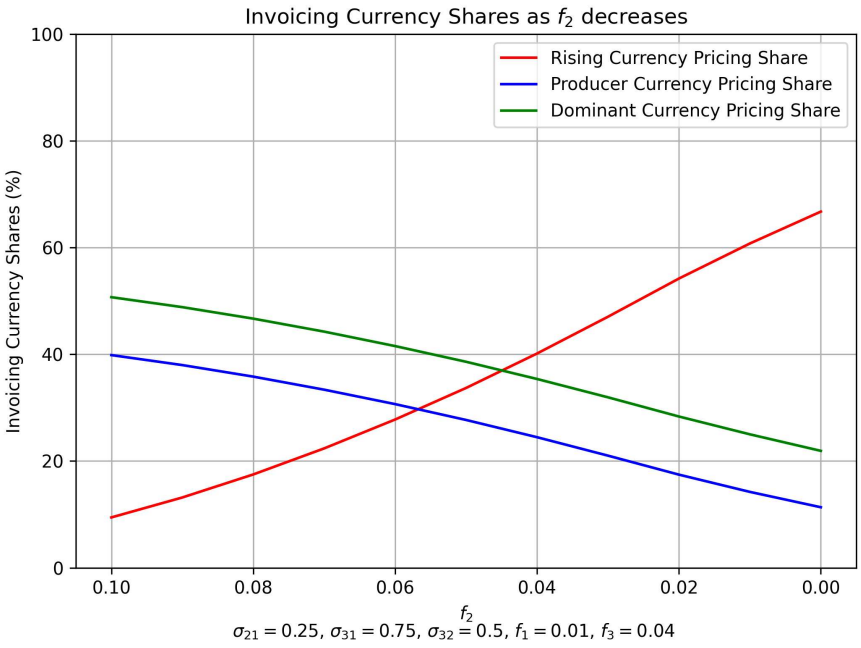

Figure 3.2: Decreasing Costs

corresponding decrease in the shares attributed to both the producer currency and the dominant currency, highlighting the rising currency's growing attractiveness under favorable cost conditions. However, it is important to note that such a high share of invoicing in the rising currency only materializes when the associated costs are nearly negligible.

The financial costs associated with cross-border payments can be reduced through various mechanisms. If country 2 were to adopt an efficient and fast payment systems accessible to international firms, that can minimize the number of intermediaries, such as correspondent banks, thereby speeding up settlements and lowering exchange rate risks and delays. Signing central bank swap lines with partner countries can expand access to foreign currency, reducing liquidity issues and lowering the costs of currency conversion. Furthermore, usage of blockchain and related distributed ledger technologies could augment transparency, shorten transaction times, and

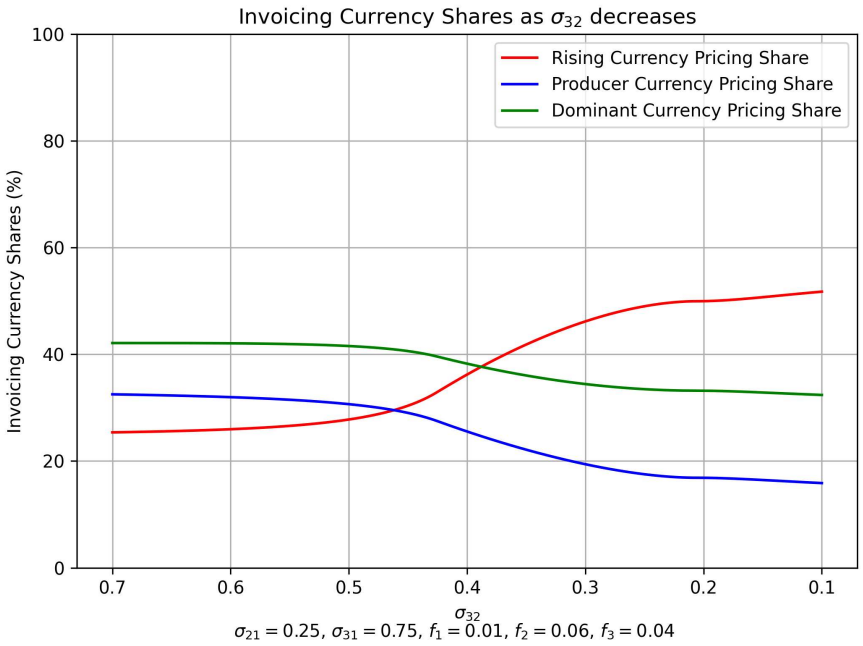

Figure 3.3: Decreasing Volatility

cut costs by eliminating intermediaries that add delays and expenses to cross-border payments. By aligning its payment infrastructure to a common regulatory framework across other countries can also bring operational costs down. Any measure that improves interoperability and automate settlement processes can lead to a reduction in errors and the need for manual intervention. The country issuing the rising currency can undertake many such measures that can significantly lower the financial barriers of cross-border payments, promoting increased usage of its currency in international trade.

Another important factor that plays a crucial role in firms' invoicing decisions is the exchange rate volatility. Reduced volatility lowers the exchange rate risk, making the rising currency a more stable and appealing option for firms seeking to minimize financial uncertainties. Figure 3.3 shows the results of a simulation when there is a decrease in the volatility of the rising currency relative to the

producer currency - this further incentivizes firms to use the rising currency for invoicing. A decline in exchange rate volatility of the rising currency translates into an increase of its share in total exports from country 3 to country 2. When the volatility of the exchange rate declines, the share of exports invoiced in the rising currency may increase significantly, even going as far up as 50% of the invoicing share. This increase in the share is accompanied by a reduction in the shares of both the producer currency and the dominant currency, demonstrating how the stable exchange rate conditions can contribute to the rising currency's attractiveness. However, it should be noted that such a high share of invoicing in the rising currency only happens at a very low level of exchange rate volatility.

The introduction of fast payment networks by country 2 could greatly contribute to the stabilization of exchange rate volatility, thereby making cross-border transactions more efficient, fast, and secure. Such networks might shorten settlement periods, thus lowering firms' exposure to downturns in exchange rates while lowering uncertainty and settlement risk. The relatively lower transaction costs which come from these payment infrastructure may also give trading patterns regularity and predictability and encourage exchange rate stability. In addition, the potential interlinking of fast payment systems with stablecoins or CBDCs may result in faster financial transactions that cut down on reliance on correspondent currencies for smooth transactions. The prospective adoption of CBDCs by country 2 offers another possible intervention for reducing exchange rate volatility and hence increasing the usage of its currency internationally. If country 2 were to issue the digital version of its national currency, the CBDCs could serve as a safe and efficient vehicle for cross-border transactions. CBDCs would allow for better control, maintenance, and transmission of monetary policy measures. This control should stabilize expectations and reactions from the market, which would, in turn, help dampen sudden movements in exchange rates. Country 2 could, through

CBDCs, instill restored confidence among international traders and investors for a more stable and resilient exchange rate system.

3.5 Conclusion and Discussion

International currencies are quite rare. All the current major global currencies have acquired that status through the direct intervention of specific policies as well circumstances working to their advantage. Through a set of favorable events globally and prudent policy internally, the U.S. was able to reposition itself from being reliant on the British pound to being the issuer of the dominant currency in a little over a decade.[4] Currently, we are witnessing China's rise as the leading global exporter and its contemporary policy measures which are intended to increase the international use of RMB. We focus on two key implications of policy measures aimed at internationalizing the RMB - lowering the costs associated with its use and reducing its exchange rate volatility. Both of these implications play key roles in currency internationalization, through higher usage in settlement of invoices in international trade. Along with numerical simulations, the model presented shows that as the associated financial costs and the corresponding exchange rate volatility for a rising currency go down, some firms will find it optimal to use this currency to invoice a share of their final goods exports. However, for this shift to be large enough to capture a substantial share in the global economy, both the costs and exchange rate volatility have to go down by a significant factor. The next steps for this chapter include a more detailed theoretical analysis of global behavior, along with empirical verification of these results.

[4]See Eichengreen (2011) for a detailed discussion.

Appendix

3.A Technical Appendix

Suppose country 1 is the issuer of the dominant currency and country 2 is the issuer of the rising currency. We assume that firms have to pay for the intermediate inputs in the currency of their country of origin. However, when exporting internationally, they can choose to price the final goods in any of the three currencies. Transactions in each of the three currencies incur transaction costs, which are assumed to be proportional to the volume of goods exchanged and are therefore modeled as a markup. We denote f_i as the proportional cost associated with settling an invoice in country i's currency. Let R_h denote the producer-currency price of intermediate inputs from country h for all $h = \{1, 2, 3\}$. Define the nominal exchange rate e_{jh} as the price of country h's currency in country j's currency units with $e_{jj} = 1$ for all $j = \{1, 2, 3\}$ and $h = \{1, 2, 3\}$.

With this notation, the cost function associated with a firm in country 3, denominated in country 3's currency can be written as:

$$\begin{aligned}
\text{costs}_3 &= e_{31} R_1 (1 + f_1) N_{31} + e_{32} R_2 (1 + f_2) N_{32} + e_{33} R_3 (1 + f_3) N_{33} \\
&= e_{31} R_1 (1 + f_1) \left(Y_3 N_{32}^{-\alpha_{32}} N_{33}^{-\alpha_{33}} \right)^{\frac{1}{\alpha_{31}}} + \\
&\quad e_{32} R_2 (1 + f_2) \left(Y_3 N_{31}^{-\alpha_{31}} N_{33}^{-\alpha_{33}} \right)^{\frac{1}{\alpha_{32}}} + \\
&\quad e_{33} R_3 (1 + f_3) \left(Y_3 N_{31}^{-\alpha_{31}} N_{32}^{-\alpha_{32}} \right)^{\frac{1}{\alpha_{33}}}
\end{aligned}$$

Taking derivatives with respect to $N_{3,1}$ and setting it equal to zero, we get:

$$\begin{aligned}
\frac{\partial \text{ costs}_3}{\partial N_{31}} &:= e_{32}R_2\left(1+f_2\right)\frac{\alpha_{31}}{\alpha_{32}}\left(Y_3 N_{31}^{-\alpha_{31}} N_{33}^{-\alpha_{33}}\right)^{\frac{1}{\alpha_{32}}} N_{31}^{-1} + \\
&\qquad e_{33}R_3\left(1+f_3\right)\frac{\alpha_{31}}{\alpha_{33}}\left(Y_3 N_{31}^{-\alpha_{31}} N_{32}^{-\alpha_{32}}\right)^{\frac{1}{\alpha_{33}}} N_{31}^{-1} = 0 \\
\implies \quad & e_{32}R_2\left(1+f_2\right)\frac{N_{32}}{\alpha_{32}} + e_{33}R_3\left(1+f_3\right)\frac{N_{33}}{\alpha_{33}} = 0
\end{aligned}$$

Similarly, we get the other two FOCs as:

$$\begin{aligned}
& e_{31}R_1\left(1+f_1\right)\frac{N_{31}}{\alpha_{31}} + e_{33}R_3\left(1+f_3\right)\frac{N_{33}}{\alpha_{33}} = 0 \\
\implies & N_{33} = -\left(\frac{\alpha_{33}}{\alpha_{31}}\right)\frac{e_{31}R_1\left(1+f_1\right)}{e_{33}R_3\left(1+f_3\right)}N_{31} \\
& e_{31}R_1\left(1+f_1\right)\frac{N_{31}}{\alpha_{31}} + e_{32}R_2\left(1+f_2\right)\frac{N_{32}}{\alpha_{32}} = 0 \\
\implies & N_{32} = -\left(\frac{\alpha_{32}}{\alpha_{31}}\right)\frac{e_{31}R_1\left(1+f_1\right)}{e_{32}R_2\left(1+f_2\right)}N_{31}
\end{aligned}$$

Substituting these back into the equation for $Y_3 = N_{31}^{\alpha_{31}} N_{32}^{\alpha_{32}} N_{33}^{\alpha_{33}}$:

$$\begin{aligned}
Y_3 &= N_{31}^{\alpha_{31}}\left[-\left(\frac{\alpha_{32}}{\alpha_{31}}\right)\frac{e_{31}R_1\left(1+f_1\right)}{e_{32}R_2\left(1+f_2\right)}N_{31}\right]^{\alpha_{32}}\left[-\left(\frac{\alpha_{33}}{\alpha_{31}}\right)\frac{e_{31}R_1\left(1+f_1\right)}{e_{33}R_3\left(1+f_3\right)}N_{31}\right]^{\alpha_{33}} \\
\implies Y_3 &= \left[\frac{e_{31}R_1\left(1+f_1\right)}{\alpha_{31}}\right]^{1-\alpha_{31}}\left[\frac{e_{32}R_2\left(1+f_2\right)}{\alpha_{32}}\right]^{-\alpha_{32}}\left[\frac{e_{33}R_3\left(1+f_3\right)}{\alpha_{33}}\right]^{-\alpha_{33}} N_{31} \\
\implies N_{31} &= \left[\frac{e_{31}R_1\left(1+f_1\right)}{\alpha_{31}}\right]^{\alpha_{31}-1}\left[\frac{e_{32}R_2\left(1+f_2\right)}{\alpha_{32}}\right]^{\alpha_{32}}\left[\frac{e_{33}R_3\left(1+f_3\right)}{\alpha_{33}}\right]^{\alpha_{33}} Y_3
\end{aligned}$$

Solving similarly for N_{32} and N_{33} we get:

$$N_{32} = \left[\frac{e_{31}R_1\left(1+f_1\right)}{\alpha_{31}}\right]^{\alpha_{31}} \left[\frac{e_{32}R_2\left(1+f_2\right)}{\alpha_{32}}\right]^{\alpha_{32}-1} \left[\frac{e_{33}R_3\left(1+f_3\right)}{\alpha_{33}}\right]^{\alpha_{33}} Y_3$$

$$N_{33} = \left[\frac{e_{31}R_1\left(1+f_1\right)}{\alpha_{31}}\right]^{\alpha_{31}} \left[\frac{e_{32}R_2\left(1+f_2\right)}{\alpha_{32}}\right]^{\alpha_{32}} \left[\frac{e_{33}R_3\left(1+f_3\right)}{\alpha_{33}}\right]^{\alpha_{33}-1} Y_3$$

Plugging in these values back, we get the optimal cost function:

$$\text{costs}_3 = \left[\frac{e_{31}R_1\left(1+f_1\right)}{\alpha_{31}}\right]^{\alpha_{31}} \left[\frac{e_{32}R_2\left(1+f_2\right)}{\alpha_{32}}\right]^{\alpha_{32}} \left[\frac{e_{33}R_3\left(1+f_3\right)}{\alpha_{33}}\right]^{\alpha_{33}} Y_3$$

Then, the marginal cost can be written as:

$$M_3 = \frac{\text{costs}_3}{Y_3} = \left[\frac{e_{31}R_1\left(1+f_1\right)}{\alpha_{31}}\right]^{\alpha_{31}} \left[\frac{e_{32}R_2\left(1+f_2\right)}{\alpha_{32}}\right]^{\alpha_{32}} \left[\frac{e_{33}R_3\left(1+f_3\right)}{\alpha_{33}}\right]^{\alpha_{33}}$$

Now, consider the exports from a firm in country 3 to country 2. The firm can choose to invoice these exports between the dominant currency, the rising currency, and the home currency. The expected profits in each of these three choices will be,

respectively:

$$\begin{aligned}
\mathbb{E}\left[\pi_{32}^{(1)}\right] &= \mathbb{E}\left[\left(e_{31}p_{32}^{(1)}\left(1-f_1\right)-M_3\right)\left(\frac{e_{21}p_{32}^{(1)}}{P_2}\right)^{-\rho}C_2\right] \\
&= P_2^{\rho}C_2\cdot\mathbb{E}\left[e_{31}e_{21}^{-\rho}\left(1-f_1\right)\left(p_{32}^{(1)}\right)^{1-\rho}-M_3e_{21}^{-\rho}\left(p_{32}^{(1)}\right)^{-\rho}\right] \\
\mathbb{E}\left[\pi_{32}^{(2)}\right] &= \mathbb{E}\left[\left(e_{32}p_{32}^{(2)}\left(1-f_2\right)-M_3\right)\left(\frac{e_{22}p_{32}^{(2)}}{P_2}\right)^{-\rho}C_2\right] \\
&= P_2^{\rho}C_2\cdot\mathbb{E}\left[e_{32}e_{22}^{-\rho}\left(1-f_2\right)\left(p_{32}^{(2)}\right)^{1-\rho}-M_3e_{22}^{-\rho}\left(p_{32}^{(2)}\right)^{-\rho}\right] \\
\mathbb{E}\left[\pi_{32}^{(3)}\right] &= \mathbb{E}\left[\left(e_{33}p_{32}^{(3)}\left(1-f_3\right)-M_3\right)\left(\frac{e_{23}p_{32}^{(3)}}{P_2}\right)^{-\rho}C_2\right] \\
&= P_2^{\rho}C_2\cdot\mathbb{E}\left[e_{33}e_{23}^{-\rho}\left(1-f_3\right)\left(p_{32}^{(3)}\right)^{1-\rho}-M_3e_{23}^{-\rho}\left(p_{32}^{(3)}\right)^{-\rho}\right]
\end{aligned}$$

To find the optimal price, we take the derivative of the profits w.r.t the prices and set it equal to 0:

$$\begin{aligned}
&\frac{\partial\mathbb{E}\left[\pi_{32}^{(1)}\right]}{\partial p_{32}^{(1)}} = \mathbb{E}\left[\left(1-\rho\right)e_{31}e_{21}^{-\rho}\left(1-f_1\right)\left(p_{32}^{(1)}\right)^{-\rho}+\rho M_3e_{21}^{-\rho}\left(p_{32}^{(1)}\right)^{-\rho-1}\right]=0 \\
&\quad\Longrightarrow\left(\rho-1\right)\left(1-f_1\right)\left(p_{32}^{(1)}\right)^{-\rho}\mathbb{E}\left[e_{31}e_{21}^{-\rho}\right]=\rho\left(p_{32}^{(1)}\right)^{-\rho-1}\mathbb{E}\left[M_3e_{21}^{-\rho}\right] \\
&\quad\Longrightarrow p_{32}^{(1)}=\frac{\rho}{\rho-1}\frac{1}{\left(1-f_1\right)}\frac{\mathbb{E}\left[M_3e_{21}^{-\rho}\right]}{\mathbb{E}\left[e_{31}e_{21}^{-\rho}\right]} \\
&\quad\Longrightarrow p_{32}^{(1)}=\frac{\rho}{\rho-1}\frac{K}{\left(1-f_1\right)}\frac{\mathbb{E}\left[e_{31}^{\alpha_{31}}e_{32}^{\alpha_{32}}e_{33}^{\alpha_{33}}e_{21}^{-\rho}\right]}{\mathbb{E}\left[e_{31}e_{21}^{-\rho}\right]}
\end{aligned}$$

Similarly:

$$p_{32}^{(2)} = \frac{\rho}{\rho-1}\frac{K}{(1-f_2)}\frac{\mathbb{E}\left[e_{31}^{\alpha_{31}}e_{32}^{\alpha_{32}}e_{33}^{\alpha_{33}}e_{22}^{-\rho}\right]}{\mathbb{E}\left[e_{32}e_{22}^{-\rho}\right]}$$
$$p_{32}^{(3)} = \frac{\rho}{\rho-1}\frac{K}{(1-f_3)}\frac{\mathbb{E}\left[e_{31}^{\alpha_{31}}e_{32}^{\alpha_{32}}e_{33}^{\alpha_{33}}e_{23}^{-\rho}\right]}{\mathbb{E}\left[e_{33}e_{23}^{-\rho}\right]}$$

where $K = \left[\frac{R_1(1+f_1)}{\alpha_{31}}\right]^{\alpha_{31}}\left[\frac{R_2(1+f_2)}{\alpha_{32}}\right]^{\alpha_{32}}\left[\frac{R_3(1+f_3)}{\alpha_{33}}\right]^{\alpha_{33}}$. Plugging back these optimal prices back into the profit functions we get:

$$\begin{aligned}
\mathbb{E}\left[\pi_{32}^{(1)}\right] &= \mathbb{E}\left[\left(e_{31}e_{21}^{-\rho}\frac{\rho}{\rho-1}K\frac{\mathbb{E}\left[e_{31}^{\alpha_{31}}e_{32}^{\alpha_{32}}e_{33}^{\alpha_{33}}e_{21}^{-\rho}\right]}{\mathbb{E}\left[e_{31}e_{21}^{-\rho}\right]} - e_{21}^{-\rho}Ke_{31}^{\alpha_{31}}e_{32}^{\alpha_{32}}e_{33}^{\alpha_{33}}\right)\times\right. \\
&\qquad \left.\left(\frac{\rho}{\rho-1}\frac{1}{(1-f_1)}K\frac{\mathbb{E}\left[e_{31}^{\alpha_{31}}e_{32}^{\alpha_{32}}e_{33}^{\alpha_{33}}e_{21}^{-\rho}\right]}{\mathbb{E}\left[e_{31}e_{21}^{-\rho}\right]}\right)^{-\rho}P_2^{\rho}C_2\right] \\
&= P_2^{\rho}C_2\left(\frac{\rho}{\rho-1}\right)^{-\rho}\frac{K^{1-\rho}}{(1-f_1)^{-\rho}}\times \\
&\quad \left(\frac{\rho}{\rho-1}\mathbb{E}\left[e_{31}e_{21}^{-\rho}\right]\frac{\mathbb{E}\left[e_{31}^{\alpha_{31}}e_{32}^{\alpha_{32}}e_{33}^{\alpha_{33}}e_{21}^{-\rho}\right]}{\mathbb{E}\left[e_{31}e_{21}^{-\rho}\right]} - \mathbb{E}\left[e_{31}^{\alpha_{31}}e_{32}^{\alpha_{32}}e_{33}^{\alpha_{33}}e_{21}^{-\rho}\right]\right)\times \\
&\quad \left(\frac{\mathbb{E}\left[e_{31}^{\alpha_{31}}e_{32}^{\alpha_{32}}e_{33}^{\alpha_{33}}e_{21}^{-\rho}\right]}{\mathbb{E}\left[e_{31}e_{21}^{-\rho}\right]}\right)^{-\rho} \\
&= \frac{G}{(1-f_1)^{-\rho}}\cdot\mathbb{E}\left[e_{31}^{\alpha_{31}}e_{32}^{\alpha_{32}}e_{33}^{\alpha_{33}}e_{21}^{-\rho}\right]\left(\frac{\mathbb{E}\left[e_{31}^{\alpha_{31}}e_{32}^{\alpha_{32}}e_{33}^{\alpha_{33}}e_{21}^{-\rho}\right]}{\mathbb{E}\left[e_{31}e_{21}^{-\rho}\right]}\right)^{-\rho} \\
&= \frac{G}{(1-f_1)^{-\rho}}\cdot\mathbb{E}\left[e_{31}^{\alpha_{31}}e_{32}^{\alpha_{32}}e_{21}^{-\rho}\right]\left(\frac{\mathbb{E}\left[e_{31}^{\alpha_{31}}e_{32}^{\alpha_{32}}e_{21}^{-\rho}\right]}{\mathbb{E}\left[e_{31}e_{21}^{-\rho}\right]}\right)^{-\rho} \\
&= G\cdot(1-f_1)^{\rho}\cdot\left(\mathbb{E}\left[e_{31}e_{21}^{-\rho}\right]\right)^{\rho}\left(\mathbb{E}\left[e_{31}^{\alpha_{31}}e_{32}^{\alpha_{32}}e_{21}^{-\rho}\right]\right)^{1-\rho}
\end{aligned}$$

where $G = \frac{P_2^\rho C_2}{\rho - 1} \left(\frac{\rho}{\rho - 1}\right)^{-\rho} K^{1-\rho}$. Similarly,

$$\mathbb{E}\left[\pi_{32}^{(2)}\right] = G \cdot (1 - f_2)^\rho \cdot (\mathbb{E}\left[e_{31}\right])^\rho \left(\mathbb{E}\left[e_{31}^{\alpha_{31}} e_{32}^{\alpha_{32}}\right]\right)^{1-\rho}$$
$$\mathbb{E}\left[\pi_{32}^{(3)}\right] = G \cdot (1 - f_3)^\rho \cdot \left(\mathbb{E}\left[e_{32}^{\rho}\right]\right)^\rho \left(\mathbb{E}\left[e_{31}^{\alpha_{31}} e_{32}^{\alpha_{32}+\rho}\right]\right)^{1-\rho}$$

Assume, for simplicity and analytical tractability, that the exchange rates are jointly log-normally distributed, that is:

$$\ln \begin{pmatrix} e_{31} \\ e_{32} \end{pmatrix} \sim \mathcal{N}\left(\begin{bmatrix} \mu_{31} \\ \mu_{32} \end{bmatrix}, \begin{bmatrix} \sigma_{31}^2 & \sigma_{12} \\ \sigma_{12} & \sigma_{32}^2 \end{bmatrix}\right) \quad \text{and that} \quad \mu_{31} = \mu_{32} = 0.$$

The moment generating function of the distribution then is:

$$\mathbb{E}\left[e_{31}^r e_{32}^s\right] = \exp\left[\frac{1}{2}\left(r^2\sigma_{31}^2 + 2rs\sigma_{12} + s^2\sigma_{32}^2\right)\right] \quad \forall r, s \in \mathbb{R}$$

A firm in country 3 will prefer to use the rising currency to invoice its exports to country 2 if the following two conditions hold:

$$(i) \quad \mathbb{E}\left[\pi_{32}^{(2)}\right] > \mathbb{E}\left[\pi_{32}^{(1)}\right]$$
$$\implies (1 - f_2)^\rho \left(\mathbb{E}\left[e_{31}\right]\right)^\rho \left(\mathbb{E}\left[e_{31}^{\alpha_{31}} e_{32}^{\alpha_{32}}\right]\right)^{1-\rho} > (1 - f_1)^\rho \left(\mathbb{E}\left[e_{31} e_{21}^{-\rho}\right]\right)^\rho \left(\mathbb{E}\left[e_{31}^{\alpha_{31}} e_{32}^{\alpha_{32}} e_{21}^{-\rho}\right]\right)^{1-\rho}$$

Using the moment generating function and taking natural logarithms on both sides of both equation, we get:

$$\begin{aligned}
&\rho \log\left(1-f_2\right)+\frac{\rho}{2}\left[\sigma_{31}^2\right]+\frac{(1-\rho)}{2}\left[\alpha_{31}^2\sigma_{31}^2+2\alpha_{31}\alpha_{32}\sigma_{12}+\alpha_{32}^2\sigma_{32}^2\right] \\
&> \rho \log\left(1-f_1\right)+\frac{\rho}{2}\left[\left(1-\rho\right)^2\sigma_{31}^2+2\rho\left(1-\rho\right)\sigma_{12}+\rho^2\sigma_{32}^2\right] \\
&\qquad +\frac{(1-\rho)}{2}\left[\left(\alpha_{31}-\rho\right)^2\sigma_{31}^2+2\left(\alpha_{31}-\rho\right)\left(\alpha_{32}+\rho\right)\sigma_{12}+\left(\alpha_{32}+\rho\right)^2\sigma_{32}^2\right] \\
\implies &\left(\frac{1}{2}-\alpha_{31}\right)\cdot\sigma_{31}^2+\left(\alpha_{31}-\alpha_{32}\right)\cdot\sigma_{21}+\log\left(\frac{1-f_2}{1-f_1}\right)>\left(\frac{1}{2}-\alpha_{32}\right)\cdot\sigma_{32}^2 \\
&\qquad \text{and} \quad (ii) \quad \mathbb{E}\left[\pi_{32}^{(2)}\right]>\mathbb{E}\left[\pi_{32}^{(3)}\right] \\
\implies &\left(1-f_2\right)^{\rho}\left(\mathbb{E}\left[e_{31}\right]\right)^{\rho}\left(\mathbb{E}\left[e_{31}^{\alpha_{31}}e_{32}^{\alpha_{32}}\right]\right)^{1-\rho}>\left(1-f_3\right)^{\rho}\left(\mathbb{E}\left[e_{32}^{\rho}\right]\right)^{\rho}\left(\mathbb{E}\left[e_{31}^{\alpha_{31}}e_{32}^{\alpha_{32}+\rho}\right]\right)^{1-\rho}
\end{aligned}$$

Using the moment generating function and taking natural logarithms on both sides of both equation, we get:

$$\begin{aligned}
&\rho \log\left(1-f_2\right)+\frac{\rho}{2}\left[\sigma_{31}^2\right]+\frac{(1-\rho)}{2}\left[\alpha_{31}^2\sigma_{31}^2+2\alpha_{31}\alpha_{32}\sigma_{12}+\alpha_{32}^2\sigma_{32}^2\right] \\
&> \rho \log\left(1-f_3\right)+\frac{\rho^3}{2}\left[\sigma_{32}^2\right]+\frac{(1-\rho)}{2}\left[\alpha_{31}^2\sigma_{31}^2+2\alpha_{31}\left(\alpha_{32}+\rho\right)\sigma_{12}+\left(\alpha_{32}+\rho\right)^2\sigma_{32}^2\right] \\
&\implies \alpha_{31}\cdot\sigma_{21}+\log\left(\frac{1-f_2}{1-f_3}\right)>\left(\frac{1}{2}-\alpha_{32}\right)\cdot\sigma_{32}^2
\end{aligned}$$

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Abstract

This thesis explores three critical developments in the global economy and their effects on international trade. The first chapter examines how data usage restrictions, such as the GDPR, influence trade flows and firm productivity. The second chapter investigates the role of skilled migration in reducing trade barriers. The third chapter analyzes how modern financial innovations, including central bank digital currencies (CBDCs), impact trade invoicing practices.

The first chapter evaluates the trade and productivity implications of data collection restrictions. These regulations, by increasing costs and limiting data-driven efficiencies, create barriers to market entry and diminish firm competitiveness. Through theoretical modeling and empirical analysis, we find that stricter data policies significantly reduce bilateral trade flows, particularly in data-intensive industries.

The second chapter assesses the differential impacts of high- and low-skilled migrants on international trade. High-skilled migrants enhance trade by contributing specialized expertise, while low-skilled migrants address labor shortages. Our empirical findings show that migration lowers trade costs overall, with high-skilled migrants playing a more significant role in this reduction.

The third chapter explores the influence of financial innovations, such as fast payment systems and CBDCs, on trade invoicing. Numerical simulations demonstrate that lower transaction costs and stable ex-

change rates facilitated by digital financial infrastructure promote the adoption of emerging currencies for trade invoicing, reducing reliance on dominant global currencies.

Zusamenfassung

Diese Dissertation untersucht drei entscheidende Entwicklungen in der Weltwirtschaft und deren Auswirkungen auf den internationalen Handel. Das erste Kapitel analysiert, wie Beschränkungen der Datennutzung, wie die DSGVO, Handelsströme und die Produktivität von Unternehmen beeinflussen. Das zweite Kapitel untersucht die Rolle qualifizierter Migration bei der Reduzierung von Handelsbarrieren. Das dritte Kapitel analysiert, wie moderne finanzielle Innovationen, einschließlich digitaler Zentralbankwährungen (CBDCs), die Praktiken der Fakturierung des internationalen Handels beeinflussen.

Im ersten Kapitel werden die Handels- und Produktivitätsauswirkungen von Beschränkungen bei der Datenerhebung untersucht. Diese Vorschriften schaffen durch erhöhte Kosten und eingeschränkte datenbasierte Effizienz Barrieren für den Markteintritt und verringern die Wettbewerbsfähigkeit von Unternehmen. Theoretische Modellierungen und empirische Analysen zeigen, dass strengere Datenrichtlinien die bilateralen Handelsströme erheblich reduzieren, insbesondere in datenintensiven Branchen.

Das zweite Kapitel bewertet die unterschiedlichen Auswirkungen von hoch- und niedrigqualifizierten Migranten auf den internationalen Handel. Hochqualifizierte Migranten fördern den Handel durch spezialisierte Expertise, während niedrigqualifizierte Migranten Arbeitskräftemängel ausgleichen. Unsere empirischen Ergebnisse zeigen, dass Migration die

Handelskosten insgesamt senkt, wobei hochqualifizierte Migranten eine bedeutendere Rolle bei dieser Reduzierung spielen.

Das dritte Kapitel untersucht den Einfluss finanzieller Innovationen wie schnellen Zahlungssystemen und CBDCs auf die Handelsfakturierung. Numerische Simulationen zeigen, dass durch digitale Finanzinfrastruktur ermöglichte niedrigere Transaktionskosten und stabile Wechselkurse die Nutzung aufstrebender Währungen für die Handelsfakturierung fördern und die Abhängigkeit von dominanten Weltwährungen verringern.