Essays on Product Customization, Digital Technologies, and International Trade

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AM	additive manufacturing
CES	constant elasticity of substitution
CIA	cash-in-advance
CPC	Cooperative Patent Classification
DC	documentary collections
DLT	distributed ledger technology
ECB	European Central Bank
EDI	electronic data interchange
EP	European Patent
EPO	European Patent Office
GDP	gross domestic product
GVC	global value chain
ICOs	initial coin offerings
ICT	information and communication technologies
i.i.d.	independently and identically distributed
IT	information technology
IPC	International Patent Classification
IPRs	intellectual property rights
KYC	know your customer
LC	letter of credit
LRUM	linear random utility model
MNE	multinational enterprise
MP	method of payment
MPF	multi-product firm
OA	open account
OECD	Organisation for Economic Co-operation and Development
QAM	quadratic address model
RTB	Red-Tape Barriers
TIC	technologies de l'information et de la communication
UN	United Nations
UNCTAD	United Nations Conference on Trade and Development
USPTO	United States Patent and Trademark Office
WIPO	World Intellectual Property Organization
WTO	World Trade Organization
4IR	Fourth Industrial Revolution

Preface

> "[T]he Internet of Things, artificial intelligence, 3D printing and Blockchain have the potential to profoundly transform the way we trade, who trades and what is traded."[1]
>
> Roberto Azevêdo, World Trade Organization (WTO) (2018, p. 3)

Over the past decades, innovations in information and communication technologies (ICT) have facilitated information sharing over large distances and have also contributed to growing fragmentation of production (Baldwin 2016, p. 5; Fort 2017, p. 667ff.). ICT and manufacturing are becoming increasingly interconnected in recent years. Thereby, boundaries between physical and virtual worlds get blurred (Schwab 2015). Examples include 3D printing for tailor-made production (The Economist 2018) or streamlining document handling and financial intermediation along entire global value chains (GVCs) through blockchain (Ganne 2018, p. 17ff.).[2] These digital technologies are expected to have remarkable real effects on economic growth and labor markets.[3] In particular, their impact on international trade and GVCs is under discussion among academics, policy makers, and the general public.[4]

This dissertation contains three chapters: Chapter 1 develops a theoretical model to analyze demand and supply side mechanisms of product customization. The modeling of manufacturing technology mirrors features of digital technologies such as 3D printing. Chapter 2 analyzes patent data to examine and compare prevalence of customization across technical fields. Furthermore, the chapter looks specifically at patents related to 3D printing and incorporates the main empirical findings in a theoretical set-up. Therefore, the first two chapters contribute to discussions on how digital technologies - inter alia 3D printing but also artificial intelligence and big data - might influence "what is traded" (WTO 2018, p. 3) internationally: customized or differentiated goods, physical goods and data.

Chapter 3 studies how the level of ICT and administrative barriers in destination countries

[1]In foreword by Roberto Azevêdo to the World Trade Report 2018 (WTO 2018, p. 3).

[2]For definitions of 3D printing and blockchain see sections 2.1 and 3.2.1, respectively.

[3]Acemoglu and Restrepo (2017, 2018a) and Dauth et al. (2017) discuss labor market effects. European Commission (2020) provides estimates for impacts of digital technologies on economic growth.

[4]See, for instance, Baldwin (2016), De Baker et al. (2018), Fort (2017), and WTO (2018).

affect trade finance and the occurrence of trade intermediation through digital platforms. The theoretical set-up of trade intermediation through a platform that bundles administrative and financial transactions models how blockchain could affect "the way we trade" (WTO 2018, p. 3). Thereby, increased transparency and efficiency can impact participation of firms and countries - "who trades" (WTO 2018, p. 3) - in GVCs.

The first part of this dissertation relates to technological advancements of computer numerical control machines that have increased the flexibility of production processes. These developments are also reflected by a growing literature in economics on multi-product firms and flexible manufacturing processes (e.g. Bernard et al. 2011; Carballo et al. 2018; Eckel and Neary 2010). However, beyond the flexibility to produce a variety of differentiated products, recent technological advances facilitate product customization: Upon individual data input, for instance based on a 3D scan, firms can easily modify production to result in goods tailored to individual specifications and needs. This is common practice in the hearing aid industry and is also applied in dentistry (Freund et al. 2020, p. 2). Further examples include personalized footwear or so-called precision medicine (The Economist 2018, 2020).

In contrast to proliferation, i.e. an increase in differentiated products, customization ensures that consumers get their perfect match (Hsu et al. 2014, p. 10, fn.1). Hence, not only do supply side factors affect firms' production decisions, the latter will also crucially depend on how much consumers care about getting their "ideal version" (Carballo et al. 2018, p. 34). Concerning juxtaposition of product customization and differentiation, the theoretical literature seems scarce: Articles focus either on consumers that buy exclusively if tailored to their needs (Carballo et al. 2018) or on set-ups with oligopolistic market structures (Loginova 2010; Syam and Kumar 2006). Chapter 1 therefore aims to extend this literature.

Chapter 1 analyzes determinants of firms' choice between product differentiation and customization in a theoretical model. It studies how preferences of consumers, market size, and firms' productivity can impact their decision to offer customized goods. The modeling of the production technology for customization is primarily inspired by technical features of additive manufacturing (3D printing) which make it adequate for product customization (Weller et al. 2015, p. 46ff.). That the adoption of 3D printing could cause an increase in trade flows is shown by Freund et al. (2020, p. 10) for the hearing aid industry. Chapter 1 is thereby related to discussions on how 3D printing affects global trade and *what* kind of goods are traded, e.g. differentiated or customized goods.

The theoretical model in chapter 1 studies brands' decision to offer mass-produced differentiated versions, to adopt technologies that allow customization or both. The partial equilibrium model combines a spatial *intra*-brand dimension and an *inter*-brand dimension based on a multinomial logit model (Anderson et al. 1992). On the demand side, consumers are characterized by an ideal specification on a Salop (1979a) type circle but also differ in the preferences for brands. They incur costs as long as they do not get their individualized product. When facing differentiated and customized products, consumers buy the latter whenever the absence of these costs at least compensate potentially higher prices for the custom good.

On the supply side, firms decide between proliferation and customization: There are fixed costs for every differentiated version a firm offers. This leads to economies of scale. On the other hand, the customization technology is characterized by sunk costs and economies of scope. Chapter 1 discusses different versions of the model. These versions feature symmetric or heterogeneous firms as well as consumers that form expectations on or observe the exact distance to the differentiated good.

Results are mainly robust to different specifications of the modeling: An expansion of market size, for instance, due to trade liberalization or growing sensitivity to costs by consumers increase firms' incentives to offer customized goods. Yet, if several brands tailor products to their clients, their goods become more similar on one dimension. Hence, it depends on the role of *branding* in the market whether firms are willing to adopt the customization technology. If heterogeneity in preferences is low, it is relatively more attractive for high productivity firms to offer personalization as they are able to cope with increased price competition.

Technical features make 3D printing suitable for production of custom goods such that it is of growing importance in several industries (Freund et al. 2020; Weller et al. 2015). Nevertheless, empirical studies on the adoption of this technology across industries are still scarce. Likewise, there is limited evidence whether 3D printing is indeed among the main production methods for custom goods. Chapter 2 therefore provides an empirical study on customization. In this context, the aim is to analyze time trends and application areas of customization.

However, there is limited data availability on the firm-product level regarding customization: While there are very precise product classifications such as the *Harmonized System (HS)*, those data do not show whether a product is finally tailored to a customer. Relatedly, information on firms' usage of technologies that are adequate for individualization is scarce. This is also due to the novelty of the technological advances that cause delayed reflection of adoption rates in (survey) data. But precisely because of that novelty, it seems particularly helpful to study latest data on inventions of firms. Chapter 2 therefore approaches the study on prevalence of customization over time and sectors by analyzing patent data provided by the European Patent Office (EPO).[5] Major advantages such as timely availability, global coverage, detailed information and classifications (Organisation

[5]The data source for patent data in this dissertation is the Worldwide Patent Statistical Database (PATSTAT) provided by the EPO.

for Economic Co-operation and Development (OECD), p. 27) allow to examine in which technical fields customization seems (most) frequent.

To that end, chapter 2 develops a keyword search and text analysis of patent abstracts in order to classify innovations related to customization.[6] The analysis establishes some stylized facts. The data supports that customization gains relevance: There is an increasing trend of patenting associated with customization over the past decades. The largest share of these patent filings prevail in digital and communication technologies. Moreover, inventions that mention customization keywords are mostly related to automation, big data, and artificial intelligence (AI). Intuitively, tailoring products to individuals requires information. Interaction and communication are facilitated with innovations in ICT. The study is complemented with an analysis of patenting in additive manufacturing. As the text analysis in chapter 2 suggests that customization inventions are also associated with automation, the model in chapter 2 builds on theoretical insights of chapter 1 but modifies and extends the set-up to capture automation of tasks such as in Acemoglu and Restrepo (2018b).

The findings in chapter 2 support a connection between customization, big data and AI. AI and 3D printing are also classified as "enabling technologies" (Ménière et al. 2020, p. 19) of the *Fourth Industrial Revolution* (4IR). Following the *Third Industrial Revolution*, where electronics and ICT played a major role for automation, the distinctive features of the *Fourth Industrial Revolution* are the blurring boundaries between virtual and physical worlds (Schwab 2015). Blockchain belongs to an 4IR "core technology field" (Ménière et al. 2020, p. 19) and is a distributed ledger technology (DLT). Ganne (2018) and Patel and Ganne (2020) provide discussions of recent applications of DLT to international trade. Examples include several platforms for digital document handling along GVCs but also for financial intermediation. Financial frictions and delays associated with administrative procedures hamper participation in GVCs especially of firms in countries with weak contract enforcement (Antràs 2020; Demir and Javorcik 2020; Djankov et al. 2010). Chapter 3 therefore analyzes how the emergence of DLT could affect international trade.

Chapter 3 consists of an empirical and theoretical part. Methodologically, the empirical part in chapter 3 is similar to the approach in chapter 2: In order to proxy the spread of DLT, the analysis relies on patent data. Inventions are classified as related to DLT based on combinations of technical classifications and keywords as in Jordan and Bitton (2019). The usage of patent data is motivated by the availability of data on recent innovations. One caveat is that there are open source solutions, probably especially for permissionless blockchains. Nonetheless, given the outlook on future market value of the technology,

[6]See Dechezleprêtre et al. (2021) and Mann and Puettmann (2020) for similar approaches to identify patents related to automation.

inventors still have an interest in seeking protection for their blockchain inventions (The Economist 2017). The data analysis in chapter 3 reveals that there has been a rapid increase in patent applications related to DLT over the time span 2015-2018 where filings at least doubled from year to year. The major jurisdictions where patents are filed are also the main exporters of ICT services. A further text analysis of DLT patents recognizes references to keywords related to financial services, cross-border activities or smart contracts.[7]

The theoretical part in chapter 3 is motivated by recent examples of DLT applications to international trade that include ocean carriers, ports, banks, and trading partners on the platform (Patel and Ganne 2020, p. 41ff.). It formalizes these features of DLT in a two country model where every exporter is assumed to match with one trading partner in the importing country. As in Petropoulou (2008b, 2011), information frictions in the destination country result in a positive likelihood that direct bilateral matching is unsuccessful. There is, however, a monopolist who offers trade intermediation services for a commission rate but ensures successful matching if both partners are on the same platform (Petropoulou 2008b, 2011). Chapter 3 extends this baseline model of Petropoulou (2008b, 2011) in several ways to account for financial intermediation and document handling on a digital platform.

If importers and exporters trade directly, they agree on open account (OA) or cash-in-advance (CIA) terms depending on the level of contract enforcement in the trading countries (Antràs and Foley 2015; Schmidt-Eisenlohr 2013). The model also accounts for delays at the border (Djankov et al. 2010) and shipping time (Berman et al. 2012). The model in chapter 3 introduces dependency of post-shipment terms on the level of ICT innovations. Bank intermediation is modeled as letter of credit (LC) that eliminates voluntary default (Schmidt-Eisenlohr 2013, p. 101). In practice, letter of credit requires exchange of documents between different parties, i.e. importers, exporters, and banks, that - if paper based - could cause inefficiencies and delays.[8]

On a blockchain, the letter of credit turns digital: With smart contracts automating payments upon arrival of the goods and digitized customs documents directly handled on the platform, administrative delays are assumed to be eliminated. Even with intermediation, firms do not match with probability one as both partners need to be part of the same platform. This reflects that blockchain and automation through smart contracts increase transparency and time efficiency, but network size and interoperability of DLTs are crucial for trading partners to benefit.

The model yields first insights: An active platform enables less productive firms to participate in international trade and causes aggregate trade flows to increase. Nevertheless, the monopolistic platform provider extracts the additional surplus. Information frictions

[7]For a definition of smart contracts see section 3.2.1.

[8]For detailed discussions on CIA, OA, and LC see section 3.2.

and geographical distance might act as substitutes or complements for the effect on platform size.

Finally, this dissertation relates to discussions on the impact of digital technologies on international trade. The theoretical models on product customization and trade intermediation through blockchain offer first insights on economic mechanisms. The empirical discussions and text analyses of patent data are approaches to capture the spread of customization and blockchain across time and technical fields. Blockchain, 3D printing, AI or big data are only a few examples of digital technological advances that will likely have vast effects on economies. The three chapters thereby analyze specific aspects that might alter the choice of firms to customize goods in global markets, how firms manage global transactions, and which firms and countries participate in GVCs in the future.

Chapter 1

Product Customization and International Trade

1.1 Introduction

Consumers value goods that are customized. Over the past years, rapid advances in new technologies such as additive manufacturing have reduced costs associated with customization. Not only are these developments likely to affect trade and the structure of global value chains (GVCs), but also technology choices and production decisions of single firms: Brands that used to offer mass-produced differentiated versions could potentially adopt technologies that enable (mass) customization. Recent examples of customized products include footwear, clothing, medical products, and motor vehicles.[1] Thereby, brands let customers choose among several differentiated products, offer perfectly tailored designs, or both.

These brands supply multiple versions, i.e. they act as multi-product firms (MPFs) in international markets. There is a growing literature on MPFs in international trade (Eckel and Neary 2010; Bernard et al. 2011; Dhingra 2013; Mayer et al. 2014). Bernard et al. (2010, p. 81) show evidence for the importance of product switching, dropping and adding: 80% of MPFs change their product mix at least once in a five year span. These intra-firm adjustments have been related to firm or firm-product attributes. However, discussions about the role of product customization within MPFs seem to be relatively scarce. Carballo et al. (2018) consider customization but not the choice between customized and differentiated versions that consumers might face in goods markets.

This chapter wants to fill this gap: The theoretical model allows firms to choose among production plans that either feature economies of scale and lead to offering mass-produced

[1] See The Economist (2018, 2020), Agnew (2019), Freudmann (2020), Freund et al. (2020), and Williams (2019) for examples and discussions.

differentiated versions or exploit economies of scope that allow mass customization.[2] The theoretical model is thereby able to capture differences between a simple increase in product variety, i.e. proliferation, and (mass) customization. As in Hsu et al. (2014, p. 10, fn.1), customization means that the consumer's "ideal version" (Carballo et al. 2018, p. 34) is offered with probability one.[3]

In many goods markets, consumers can choose between a wide range of brands that offer each a set of differentiated or customized versions. While consumers care about the *branding*, they also prefer to have a specification - e.g. size, shape or color - that is closest to their ideal version. The purchase decision will therefore be modeled as a nested discrete choice problem: The consumer decides first on the brand and then on the optimal version within that brand.

For the latter decision, the buyer trades off price differences and costs associated with the distance to the ideal version as in a standard Salop (1979a) framework. The intra-brand dimension therefore follows the literature on spatial competition, e.g. Hadfield (1991). However, it is not about firms being allocated along the (unit) circle but products that multi-product firms locate along the circumference.

The spatial *intra*-brand dimension is combined with a multinomial logit model that captures the *inter*-brand dimension. Consumers have idiosyncratic preferences for a brand. When deciding from which brand they will buy, they take (expected) costs into account. Two versions of the formation of purchase decisions are analyzed: First, when it is based on expected distances to brands' closest versions and second, when consumers are able to perfectly predict the distance to the closest versions.

The partial equilibrium model yields first predictions that are mainly robust to different specifications: The adoption of the customization technology is more likely the larger the market and the more sensitive consumers are to costs. The former effect is increasing in the productivity of the firm. The heterogeneity of preferences in an industry has a differential effect: While high productivity firms are more likely to adopt the customization technology in markets where preference heterogeneity is relatively low, the opposite is true for industries characterized by high variation in consumers' tastes.

Recently, several multinational enterprises (MNEs) opened plants in developed countries with highly automated production processes.[4] In several cases, automation includes usage of 3D printers (additive manufacturing).[5] The digitization of manufacturing processes as

[2]There is also a discussion on offering both, differentiated and customized, versions. See section 1.3.2 and section 1.5.2.

[3]In the following, the term "ideal version" as in Carballo et al. (2018, p. 34) denotes versions that are tailored to consumers.

[4]De Baker et al. (2018, p. 8) define "*botsourcing* [as] [...] firms replacing humans with robots by building new factories in the home country, which are based on highly automated production plans".

[5]"Additive manufacturing (AM), also known as 3D printing, uses computer-aided design to build objects layer by layer. This contrasts with traditional manufacturing, which cuts, drills, and grinds away

well as the production of integral goods reduce production steps and might thereby affect structures of global value chains (WTO 2018, p. 8). Its flexibility makes additive manufacturing especially attractive for customization (Weller et al. 2015, p. 47). Therefore, also closeness to consumers and lead time could become key in production and location decisions of MNEs. Ongoing debates on prevalence and effects of potential *botsourcing* on goods and labor markets show relevance and pertinence.[6] For the moment, the open economy dimension of the model will (only) be captured by an increase in market size. Changing fixed, marginal, and trade costs, will certainly affect the location decisions of MNEs but go beyond the scope of the current chapter.

Examples are mostly referring to customization for final goods' consumers, but the model can be easily applied to tailoring products to intermediate goods or downstream producers as long as downstream producers do not have any market power.

This chapter is organized as follows: After a brief review of the related literature in section 1.2, the theoretical modeling of the consumers' (section 1.3) and producers' (section 1.4) optimization problems are introduced. The subsequent section 1.5 discusses results for the optimal pricing, differentiation and technology choice. Finally, section 1.6 concludes.

1.2 Literature

This chapter is related to several strands of research, in particular, to literature on localized competition, (nested) multinomial logit models, customization, multi-product firms (in international trade) and empirics on product variety.

Most models of localized competition go back to Hotelling (1929) and Salop (1979a) where firms locate along the unit line or on the (unit) circle. Examples include discussions on heterogeneous firms (Vogel 2008, 2011) or on market preemption and entry deterrence (e.g. Bonanno (1987), Judd (1985), Salop (1979b), and Schmalensee (1978)) in spatial models.

In contrast to those papers, it is the *intra*-brand and not the *inter*-brand dimension that is localized in this setting: Monopolistic competition between firms is captured by a multinomial logit model, but these firms allocate *their products* along their market area which is the unit circle. This modeling is related to Hadfield (1991, p. 532ff.) where a monopolist allocates retail outlets equidistantly along a circle. However, the latter framework is extended to include aspects of customization and, importantly, *inter-brand* competition.

Concerning customization, a novel feature of the set-up is that firms may invest sunk

unwanted excess from a solid piece of material [...]" (ASTM International 2021).

[6] See, for instance, discussions in De Baker et al. (2018), WTO (2018, p. 107ff.), Carbonero et al. (2018) or section 2.2 in chapter 2.

costs to locate at the center of the unit circle. Thus, they can serve all consumers who are uniformly distributed along the circumference at constant marginal costs. Grossman and Helpman (2002, p. 112ff.) use a circular structure to model firm's choice between integration and outsourcing. The midpoint is associated with an input that is "“standardized” or “generic” [...]; [...] not particularly well suited for any of the final producers, but [...] equally productive in all uses" (Grossman and Helpman 2002, p. 114).[7] The nature of the origin as being equidistant to any point on the circle's circumference is also utilized in this chapter.

In addition, the modeling of the customization technology is also related to the literature on flexible manufacturing, in general (e.g. Eaton and Schmitt 1994), and in international trade, in particular (Eckel 2009; Eckel and Neary 2010). Product differentiation in section 1.4.1, though, abstracts from the existence of a flexible manufacturing technology. Whenever the customization technology is adopted, production plans feature "*strong economies of scope*" (Eaton and Schmitt 1994, p. 877) where one base product is tailored to the consumer's need.[8]

Customization is notably discussed in management and marketing literature where it is frequently modeled as (a duopoly of) firms choosing locations on the unit circle or the unit interval (e.g Dewan et al. 2003; Loginova 2010; Syam and Kumar 2006). Loginova (2010) develops a duopoly model where two brands locate at the end points of a unit line. Not only do consumers differ in terms of their most preferred varieties but they also have varying levels of familiarity with the brand. Loginova (2010) argues that interaction with the brand that is necessary for customization is costly and might cause "frustration and information overload" (Loginova 2010, p. 298) because of the difficulties to specify the ideal variety for production. This is related to Syam et al. (2008, p. 386) who find that buyers are "regret averse" and are likely to choose in the end a specification that is close to the standardized mass-produced goods. Loginova (2010, p. 304) notes that frictions associated with missing knowledge about brands relax price competition among the two brands and only one of the brands offers customized goods in equilibrium. Even though interaction costs could be incorporated in the current framework, it will be abstracted from them for tractability. Moreover, with new digital technologies customization might not require consumers to specify their ideal version in advance, e.g. they do not need to know their exact footprint for a custom shoe beforehand because it is scanned in-store (The Economist 2018).[9]

[7]A similar set-up is analyzed in a working paper by Bar-Isaac et al. (2021).

[8]Note that literature frequently refers to standardization and customization (e.g. Dewan et al. 2003; Hsu et al. 2014; Loginova 2010). However, here, usage of product differentiation and customization is preferred in order to avoid mixing terminology for production plans and consumer's specification, i.e. to what extend inputs for proliferation might be customized (Hsu et al. 2014, p. 16) or inputs for customization standardized.

[9]Consumers could yet associate costs with sharing personal information and data.

The literature on customization in an international trade context is relatively scarce. Carballo et al. (2018, p. 37) assume that consumers will only buy the firm's product if it is offered in their ideal version, others (e.g. Hsu et al. 2014, p. 12ff.) allow firms to serve only a (sub)set of clients with their customized versions. Both assumptions are relaxed: First, consumers might buy versions that are not perfectly tailored to their ideal specification if the full price is low enough. On the other hand, customization is non-exclusive upon adoption of the specific brand: While there might still be consumers that prefer to buy a brand's differentiated version if both types of versions are offered, those consumers could still get their ideal version with probability one.[10]

Grossman and Helpman (2005)'s model on customization in the context of outsourcing intermediate goods production also includes spatial elements: Intermediate goods suppliers are located on a unit circle. Producers form outsourcing decisions based on the observable total number of suppliers in the developing and developed country (Grossman and Helpman 2005, p. 138). This is related to the expectation based purchase decision in section 1.3.1. The appearance of new technologies might also affect whether components are outsourced or produced in-house.[11]

The degree of inter-brand competition is affected by a measure for heterogeneity in consumers' preferences in a multinomial logit model (Anderson et al. 1992; McFadden 1977). Fajgelbaum et al. (2011) and Verhoogen (2008) apply these kinds of models to an international trade context. The idea of a nested choice follows Fajgelbaum et al. (2011), where consumers choose a product within a nest of given quality.

Hsu et al. (2014) study the effect of competition on customization. The main differences from the framework in this chapter are that firms are located on one circle, that firms are restricted to decide on a customization scope around their location, and that there is price discrimination for the customized good in Hsu et al. (2014). The latter assumption also causes the sales' share of customized versions to increase when competition intensifies (Hsu et al. 2014, p. 14): That is, because the circle gets more crowded, firms are located closer to each other which increases price competition. Price discrimination for customized versions relaxes the competitive pressure. Contrary to that, in the current framework, the degree of competition is mainly governed by the heterogeneity in preferences in an industry. Hsu et al. (2014, p. 17) find a negative correlation between distance to the next sea ports in China and the city's customization share in the data and point to a relationship between customization and trade.[12]

[10] See the discussion of different cases in section 1.3.

[11] See results of an ICT survey by *Institut national de la statistique et des études économiques* (Insee) (2019a), Arlbjørn and Mikkelsen (2014) or the modeling of firms' integration and outsourcing decisions in Grossman and Helpman (2002).

[12] Hsu et al. (2014, p. 16) argue that a high degree of product proliferation in downstream industries might require custom production of upstream industries and thereby cause differences between customization shares across countries along GVCs.

Since brands will offer at least one variety, they act as multi-product firms as in Eckel et al. (2015), Bernard et al. (2011), Eckel and Neary (2010), and Shaked and Sutton (1990). Dhingra (2013) studies the impact of trade liberalization on product and process innovation. She discusses effects of trade liberalization where an increase in market size induces firms to conduct process innovations due to existing economies of scale. On the other hand, the increase in competition leads firms to reduce the number of varieties offered and consequently the "visibility of a brand" (Dhingra 2013, p. 2579) which intensifies inter-brand competition.

Neiman and Vavra (2019) study "The Rise of Niche Consumption" over the past 15 years. Based on the AC Nielsen Homescan Data they show that individual concentration of spending has increased.[13] Households tend to concentrate their spending on a few products. At the same time, aggregate concentration has decreased. This latter trend is caused by adding new varieties, i.e. proliferation, which results from heterogeneity across consumers. Neiman and Vavra (2019, p. 14ff.) develop a model featuring heterogeneous mark-ups: firms facing a large consumer base aim at increasing profits given that consumer set (the intensive margin) while smaller firms target extending their consumer base (the extensive margin). In contrast, this chapter takes individual spending concentration to the extreme such that there is a discrete choice among differentiated versions of a brand. Therefore, there is only the extensive margin effect as demand of every consumer is fixed to one.

Finally, a recent study estimates that, by 2030, 3D printing might reduce trade in footwear by up to 15% (McKinsey Global Institute 2019, p. 124), while Freund et al. (2020, p. 9) find a significant boost in exports of hearing aids due to lower production costs. Findings in Freund et al. (2020, p. 26f.) suggest that adoption of 3D printing affects trade differentially depending on products' weight: While the authors find a significant rise in exports of light products, imports of heavier products have decreased. This could potentially be because goods that face higher trade costs, e.g. because of their weight, are then printed closer to consumers (Freund et al. 2020, p. 26). This chapter does not take a stance on that. However, understanding the mechanisms, demand and supply side effects of customization technologies could potentially prove valuable to understand size, direction, and intensity of their impact on trade and global value chains.

1.3 Consumers

Consider a sector from the manufacturing industry with a set $\mathcal{M}$ of active brands. Consumers will buy one unit of a brand $b \in 1, \ldots, \mathcal{M}$ in that sector. Those consumers of mass L are uniformly distributed along the unit circle. Consumers are described by a

[13] For applications of this data set see also Faber and Fally (2017) and Handbury (2019).

location $z \in [0,1]$ in the circular characteristic space. This location z describes their *ideal* version for that sector. Therefore, all active brands will mirror the circular preference space and decide on the allocation of products along the brand's unit circle. The unidimensional characteristic space is exhaustive, i.e. it captures all possible versions in that industry. That is, there will be no change in the length of the closed characteristics space, $C = [0,1]$, when, for instance, trade liberalization causes the mass of consumers, L, to grow.[14]

For example, take the color wheel and consumers who are uniformly distributed along it with particular preferences for a specific - *ideal* - color for their pair of shoes. Manufacturers face the set of potential buyers who differ on this unidimensional preference space and consequently offer shoes that vary along the continuum of colors. Brands therefore mirror the preference space (color wheel) and allocate their products along the circumference.[15]

As in Hsu et al. (2014), Loginova (2010) and Dewan et al. (2003), it is assumed that consumers know their location, z, their *ideal* version, in the preference space. The assumption is reasonable when technologies such as additive manufacturing are considered where consumers do not need any prior knowledge of their own ideal version. This might, however, be less clear when they would need to specify their ideal type or evaluate their (expected) "*fit costs*" (Dewan et al. 2003, p. 1057). Problems associated with regret aversion (Syam et al. 2008) and overchoice (Gourville and Soman 2005) could arise.[16]

The combination of a geographical and a random utility model is inspired by the model in Anderson et al. (1992, p. 345ff.). $\tilde{p}^b_z$ is the location specific price a consumer would (expect) to pay. y is the level of income that is spent on that sector.[17] Consumers' discrete choice problem is nested. They choose the brand and the closest differentiated or, if available, customized version.

Consumer j's conditional indirect utility at location z when buying one unit of brand $b \in 1, \ldots, \mathcal{M}$ is

$$V^b_{j|z} = y - \tilde{p}^b_{|z} + \mu\epsilon^b_{j|z} \tag{1.1}$$

[14]Bar-Isaac et al. (2021, p. 8) argue that moving along the radius of a circle is a measure for vertical differentiation. It is difficult, though, to think of empirical analogs for changes in the circumference, C.

[15]See figures A.1 and A.2 for graphical illustrations.

[16]See discussion on vertical differentiation below. If there would be problems with overchoice, an increase in the number of differentiated versions offered would potentially even aggravate these problems. Predictions on the positive effect of an increase in the number of versions on consumers' welfare could be weakened or even reversed.

[17]It is equivalent to the "effective reservation price" in Salop (1979a, p. 142) for the customized version.

where $\forall z \in [0,1]$, $\epsilon^b_{j|z}$, the idiosyncratic taste shocks, are independently and identically distributed (i.i.d.) according to the double exponential distribution.[18] Heterogeneity in preferences for brands is captured by μ (Fajgelbaum et al. 2011, p. 729; Anderson et al. 1992, p. 345; McFadden 1977, p. 10ff.) which is thereby a weight for the *inter*-brand dimension. A higher μ is equivalent to a lower correlation between taste shocks, $\epsilon^b_{j|z}$ and $\epsilon^{\tilde{b}}_{j|z}$. Hence, consumers perceive differences between firms in an industry, *branding*, as important.

If the inter-brand dimension does not matter, i.e. brands are perceived as perfect substitutes, $\mu \to 0$ in equation (1.1), consumers would buy from the brand that offers the lowest location dependent price (Anderson et al. 1992, p. 345). Only this localized dimension matters and the set-up collapses to a model of spatial competition with heterogeneous firms as, for instance, in Vogel (2008). The parameter $\mu > 0$ could also be interpreted as a measure of imperfect information (Perloff and Salop 1986), overlaying the signal of the location dependent prices of a brand.[19]

On the other hand, *intra*-brand competition features some local dimension as prices depend on the location. In the literature, $\tilde{p}^b_{|z}$ is often referred to as *delivered* or *full* price (Hadfield 1991, p. 532; Anderson et al. 1992, p. 345ff.).[20] It includes the brand's mill price and potential "*fit costs*" (Dewan et al. 2003, p. 1057).[21] The former will depend on the technology that the brand uses. The latter costs will, by definition, equal zero in case of customization.

Brands will not be able to price discriminate even when they offer customization.[22] Therefore, upon adoption of the customization technology, the *delivered* price is independent of the consumer's location. If, however, $\tilde{p}^b_{T|z} = \tilde{p}^b_T, \forall z$, i.e. prices are independent of the location of the consumer, only the *inter*-brand dimension matters and the set-up collapses to a standard multinomial logit model (Anderson et al. 1992, p. 39ff.; Fajgelbaum et al. 2011, p. 727ff.). Intuitively, if all brands in the given industry were to adopt the customization technology and therefore $\tilde{p}^b_{C|z} = p^b_C, \forall z, b$ in equation (1.1), consumers will only care about the *inter*-brand dimension: their idiosyncratic preference for a particular

[18] See Anderson et al. (1992, p. 39ff.) for more details on the double exponential distribution and the multinomial logit model.

[19] In a more general sense, μ could be interpreted as an industry-wide inverse measure for "brand familiarity" (Loginova 2010, p. 299).

[20] In the following, *delivered* and *full* price are used interchangeably.

[21] Note that the literature uses different terms to denote the costs that consumers incur when not getting their *ideal* version. Inter alia, they are named "transport costs" (e.g. Salop 1979a, p. 142; Anderson et al. 1992, p. 189) to focus on the spatial dimension, "*shopping costs*" (Vogel 2008, p. 426), or "adaptation costs" (Eckel 2009, p. 1452) when considering the producer side. In the following, the term "*fit costs*" from Dewan et al. (2003, p. 1057) is used to denote the *costs*, that consumers incur when the version the brand offers does not *fit* the ideal specification. In contrast to Carballo et al. (2018, p. 39, fn. 20), the "burden of adaptation" needs to be carried by consumers and not by firms.

[22] See detailed discussion in section 1.4.2.

brand and the lowest mill price.
Given location z and the location dependent price $\tilde{p}^b_{|z}$, the consumer will buy from the brand that yields the highest indirect utility. The probability that this will be brand b is given by

$$P^b(z) = Prob(V^b_{j|z} = \max_{\tilde{b} \in 1,\dots,\mathcal{M}} V^{\tilde{b}}_{j|z}), \forall b \in 1, \dots \mathcal{M} \tag{1.2}$$

Since at any z there is a mass L of consumers, the expected demand for brand b at z is

$$D^b(z) = LP^b(z) \tag{1.3}$$

Since the $\epsilon^b_{j|z}$ are i.i.d. according to the double exponential distribution, equation (1.3) can be rewritten as

$$D^b(z) = LP^b(z) = L\frac{e^{-\frac{\tilde{p}^b(z)}{\mu}}}{\sum_{\tilde{b}=1}^{\mathcal{M}} e^{-\frac{\tilde{p}^{\tilde{b}}(z)}{\mu}}} \tag{1.4}$$

which indicates the share of consumers at z that will demand brand b. When L is large enough, which is assumed in the following, $D^b(z)$ serves as a good approximation for the aggregate demand (Anderson et al. 1992, p. 34). The denominator could be interpreted as a weighted *delivered* price index. If all *delivered* prices were the same, the demand share would simply equal $\frac{1}{\mathcal{M}}$. Obviously, at any z, summing demand over all brands yields the mass L as every consumer buys at least and at most one unit.[23]
Given the choice of the brand, the consumer chooses the product version based on the observed technology, degree of differentiation, and resulting (expected) prices of the brand. Thereby, it is observable whether a firm produces differentiated products with the increasing returns to scale production function ($T = \{D\}$), invested in the customization technology ($T = \{C\}$), or whether it uses both technologies ($T = \{D, C\}$). An example of a customization technology would be additive manufacturing as mentioned in section 1.1. If the latter technology is adopted, it is non-exclusive, i.e. it allows mass customization:[24] Any consumer at any location z that decides to buy from a brand that adopted this technology, knows that the *ideal* version is offered with probability one. However, the decision on the choice of the differentiated or customized version clearly depends on the minimum (*delivered*) price. The case of consumers buying *ideal* versions

[23]For a given location z:

$$\sum_{\tilde{b}=1}^{\mathcal{M}} D^{\tilde{b}}(z) = \sum_{\tilde{b}=1}^{\mathcal{M}} L\frac{e^{-\frac{\tilde{p}^{\tilde{b}}(z)}{\mu}}}{\sum_{\tilde{b}=1}^{\mathcal{M}} e^{-\frac{\tilde{p}^{\tilde{b}}(z)}{\mu}}} = L$$

[24]To keep the model tractable and in light of further technological advances, it is assumed in the following that mass customization is feasible. However, there are debates on the current extent of mass customization through 3D printing (Weller et al. 2015, p. 44).

customized for neighboring consumers is excluded as it would counter the original idea of customization and most technologies that require information on the specific buyer.[25] Furthermore, customers know the number of differentiated products, n_D^b, a brand offers. When the customization technology is adopted, $n_C^b = \infty$.[26] They also observe the price for the differentiated versions, p_D^b, and their customized version, p_C^b. Note that there might be intra-brand heterogeneity among differentiated versions. In that case p_D^b can be interpreted as the average mill price for differentiated versions that consumers observe.[27] As long as the consumer does not get the personal *ideal* version, there are *fit costs* that are convex in the distance to the differentiated product. The *delivered* price, i.e. the price including *fit costs*, is defined as

$$\tilde{p}_{D|z}^b = p_D^b + t[d(n_D^b, z)]^\alpha \tag{1.5}$$

where $t > 0$ is a weight for the *fit costs*, $\alpha \geq 2$, and $\tilde{p}_{D|z}^b$ indicates that the *delivered* price depends on the consumer's location.[28]

$$d(n_D^b, z) = \min_{i \in 1, \ldots n_D^b} |z_i^b - z| \tag{1.6}$$

measures the distance to the next differentiated version, where $z_i^b \in [0,1], \forall i \in 1, \ldots n_D^b$ defines the location of the differentiated version i on the brand's unit circle. To keep the model tractable, consumers know *a priori* that brands allocate their differentiated versions equispaced along their market area of unit length.[29]

Derivations of the case where consumers observe their exact location vis-à-vis the next differentiated product do not lead to closed-form solutions. In the following, there is therefore a brief discussion on expectation based purchase decisions.

1.3.1 Expectation Based Purchase Decision

Assume that consumers know the technology a brand is using, the number of differentiated versions, n_D^b, and prices, p_T^b. However, they do not observe the distance to the next closest differentiated version such that the value of equation (1.6) remains unknown for

[25] Oxford University Press (2021a) defines "customize [as to] [m]odify (something) to suit a particular individual [...]".

[26] Examples include offering the continuum of colors (see figure A.1) or sizes.

[27] See discussion on intra-brand competition and symmetry within brands in section 1.4.1.

[28] As described above, the term "*fit costs*" is taken from Dewan et al. (2003, p. 1057). However, in contrast to the authors, here it includes not only the "sensitivity" (Dewan et al. 2003, p. 1057) parameter t, but t multiplied by the distance $[d(n_D^b, z)]^\alpha$.

[29] Consumers might also simply expect or assume that versions are equispaced even when they are unable to observe or predict their precise location vis-à-vis the next closest differentiated good. However, then, ex-ante demand (the *fit costs* they expect) might not equal the actual (ex-post) realization. See discussion in section 1.3.1.

the consumer when making the purchase decision.[30] In reality, this assumption captures the idea of *trial and error* when shopping differentiated versions.

However, when consumers observe that the differentiated versions are allocated equidistantly along the unit circumference, they can form expectations as the distance can only fall within the interval $[0, \frac{1}{2n_D^b}]$. The expected *full* price that, for obvious reasons, is independent of the location equals:[31]

$$\tilde{p}_D^b = p_D^b + \bar{t}\bar{x}(n_D^b) \tag{1.7}$$

where $\bar{t}\bar{x}(n_D^b)$ captures expected *fit costs*. In principle, one could also assume a specification where all consumers are sufficiently loss-averse to evaluate the *full* price at the maximum possible distance to a version, i.e. $\tilde{p}_D^b = p_D^b + t(2n_D^b)^{-\alpha}$.

On the one hand, it seems more intuitive to argue that the consumer knows the personal *ideal* type but not the distance to the next differentiated version. On the other hand, the statement could be reversed and the expectation based purchase decision interpreted as a scenario where consumers are perfectly aware of the location of brands' differentiated versions but do not know their own *ideal* version. In both cases, *delivered* prices are based on expectations and might therefore differ from the actual ex-post price.

Consumer j's conditional indirect utility from equation (1.1) at any location $z \in [0, 1]$ would take the following values $\forall b \in 1, \dots, \mathcal{M}$

$$V_{j|z}^b = y - \tilde{p}_T^b + \mu\epsilon_{j|z}^b = \begin{cases} y - p_D^b - \bar{t}\bar{x}(n_D^b) + \mu\epsilon_{j|z}^b & \text{if } T = D \\ \\ y - p_C^b + \mu\epsilon_{j|z}^b & \text{if } T = C \end{cases} \tag{1.8}$$

The assumption on the distribution of $\epsilon_{j|z}^b$ persists. Brand b's demand share in equation (1.4) is constant across locations and equals

$$D^b = L\frac{e^{-\frac{\tilde{p}_T^b}{\mu}}}{\sum_{\tilde{b}=1}^{\mathcal{M}} e^{-\frac{\tilde{p}_T^{\tilde{b}}}{\mu}}} = Le^{-\frac{\tilde{p}_T^b}{\mu}}\mathcal{P} \tag{1.9}$$

where $\mathcal{P}$ could be interpreted as a *delivered* price index.

In the discrete choice literature, the indirect utility function is regularly some version of the following form: $V_{j|z}^b = y - p_z^b + a^b + \mu\epsilon_{j|z}^b$ (see e.g. Anderson et al. (1992, p. 146)) where a^b captures vertical differentiation across brands: Given a value for $\epsilon_{j|z}^b$ and p_z^b, all

[30] This is similar to Grossman and Helpman (2005, p. 138) where final good producers observe the "thickness", i.e. the amount of suppliers, in a market only.

[31] See appendix A.2 for the full derivation.

$$\tilde{p}_D^b \equiv \mathbb{E}_{\hat{z}}[\tilde{p}_{D|\hat{z}}^b] = p_D^b + t\mathbb{E}_{\hat{z}}[(\hat{z})^\alpha], \bar{x}(n_D^b) \equiv (\frac{1}{2n_D^b})^\alpha, \bar{t} \equiv \left(\frac{1}{\alpha+1}\right)t < t$$

customers prefer the brand where a^b is highest. For consistency of equation (1.8) and the discrete choice literature, a^b takes values in the interval $[-\bar{t}\overline{x}(n_D^b), 0]$. As a result, proliferation (i.e. a decrease in the expected *fit costs*) can be interpreted as an increase in perceived quality of a brand.[32]

However, as discussed in section 1.2, there might be potential regret aversion (Syam et al. 2008) or the problem of overchoice (Gourville and Soman 2005) that might complicate the consumer's choice problem. By choice of the preference space, R^1, options vary on one dimension only and are therefore compatible (Berger et al. 2007, p. 462; Gourville and Soman 2005, p. 383): Consumers do not need to trade off different features against each other, e.g. versions vary either in color or shape. An increase in the range of colors makes it more likely that the consumer gets the most preferred *ideal* color and a brand that offers a wider range of colors is perceived as being of higher quality.

Dhingra (2013, p. 2556) argues that proliferation might exacerbate *inter*-brand competition as the product space gets more concentrated but that it might also relax competitive pressure because a brand gets more "visible". If a brand offers many versions, its visibility is high and consumers expect a low *delivered* price in equation (1.7). However, in the limiting case of $n_D^b \to \infty$ or $n_C^b = \infty, \forall b$, i.e. adoption of customization by all active firms in the market, price competition is intensified.

While the assumption of an expectation based purchase decision seems restrictive, it allows closed form solutions in section 1.5.1. Section 1.5.2 analyzes the scenario where consumers do observe their exact location and shows that results are mainly robust in spite of the specifications.

However, when the exact location is not observed by the consumer, the (expected) *delivered* price in equation (1.7) is the same and constant for any consumer which excludes cases where demand for differentiated and customized products might coexist as described in the next subsection.

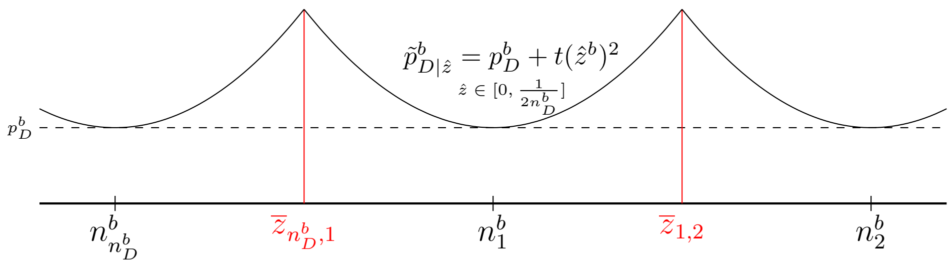
1.3.2 Exact Location Based Purchase Decision

In contrast to the previous subsection, in the following it is assumed that consumers know their *ideal* version and observe exactly the distance to the next closest differentiated product.

It is abstracted from interaction costs for the customization technology. If these costs were constant across brands they would simply reduce the maximum price producers could charge for the customized version. However, Loginova (2010, p. 298) argues that co-designing requires brand familiarity. In this case, interaction costs would indeed depend on a brand specific variable. To keep the model tractable existence of interaction costs or the need for brand familiarity are not considered in this chapter.

[32] See also discussion in section 2.4.

Figure 1.1: Price Function for Differentiated Versions



Notes: Equispaced differentiated versions priced at p^b_D; *Delivered* price $\tilde{p}^b_{D|\hat{z}}$; Indifferent consumers at $\overline{z}_{n^b_D,1}$, $\overline{z}_{1,2}$; Assumption of quadratic *fit costs*, $\alpha = 2$.

As the brand's market area is the unit circle and n^b_D differentiated versions are allocated equispaced along the circumference, the distance between differentiated versions is $\frac{1}{n^b_D}$. The maximum distance at which a buyer might be located vis-à-vis the next differentiated version is $\frac{1}{2n^b_D}$. Therefore, equation (1.6) can only take values in the interval $[0, \frac{1}{2n^b_D}]$. The lower limit is equivalent to the case where the consumer's preference exactly equals the specification of a differentiated version of the brand. The upper limit happens whenever the consumer's preference is exactly in between two differentiated versions.
Consequently, by symmetry, equation (1.6) can be expressed as

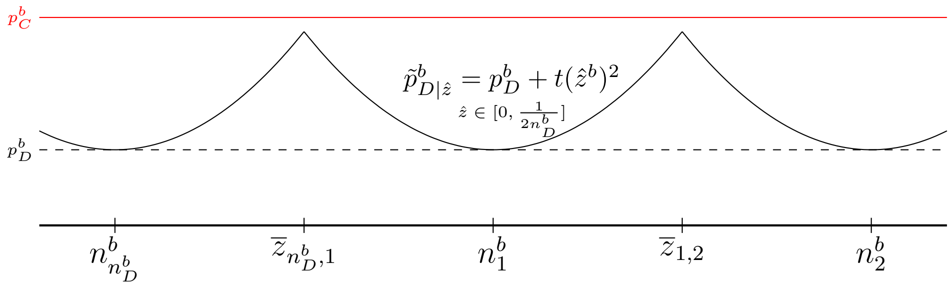
$$d(n^b_D, z) = \min_{i \in 1,\dots n^b_D} |z^b_i - z| \equiv \hat{z}^b \in [0, \frac{1}{2n^b_D}] \tag{1.10}$$

Figure 1.1 illustrates the case where brand b offers n^b_D differentiated products that are allocated equispaced along the circle. Consumers at the maximum distance and with resulting maximum *fit costs* are exactly indifferent between buying the differentiated versions that is located left or right to their location. In contrast to location z that describes the *ideal* version in the general preference space, $\hat{z}^b$ is dependent on the given brand as it defines the distance to the next closest differentiated version of a brand and is a function of the number of differentiated versions, n^b_D. If $z^b_i = z^{\tilde{b}}_i, \forall b, \tilde{b} \in 1, \dots, \mathcal{M}$, i.e. symmetry among brands concerning any location of the differentiated versions, the brand index could be dropped even *a priori*.
Consider the circular market area of brand b and assume that this firm adopted both technologies. Consumers face the (expected) mill prices p^b_C and p^b_D for the customized and differentiated versions, respectively. While they would not incur any *fit costs* for the former, for the latter versions they incur *fit costs* that are convex in distance.
Given preferences for brands, consumers compare the versions' *delivered* prices.

$$\tilde{p}^b_D = p^b_D + t(\hat{z}^b)^\alpha, \qquad \forall \hat{z}^b \in [0, \frac{1}{2n^b_D}] \tag{1.11}$$

$$\tilde{p}^b_C = p^b_C, \quad \forall \hat{z}^b \in [0, \frac{1}{2n^b_D}] \tag{1.12}$$

Figure 1.2: Demand for Product Differentiation Only (**Case 1**)



Notes: Equispaced differentiated versions priced at p^b_D; *Delivered* price $\tilde{p}^b_{D|\hat{z}}$; Indifferent consumers at $\overline{z}_{n^b_D,1}$, $\overline{z}_{1,2}$; Assumption of quadratic *fit costs*, $\alpha = 2$.

They buy the version with minimum *delivered* price, where

$$\begin{aligned}\tilde{p}^b_{\hat{z}} &= \min\{\tilde{p}^b_D, \tilde{p}^b_C\} \\ &= \min\{p^b_D + t(\hat{z}^b)^\alpha, p^b_C\}\end{aligned} \tag{1.13}$$

On both sides of each differentiated version of the brand, i.e. $2 * n^b_D$ times, only three configurations might arise.[33]

Case 1:

$$p^b_D + t\frac{1}{(2n^b_D)^\alpha} < p^b_C \tag{1.14}$$

This is equivalent to stating that

$$p^b_D + t(\hat{z}^b)^\alpha < p^b_C, \quad \forall \hat{z}^b \in [0, \frac{1}{2n^b_D}] \tag{1.15}$$

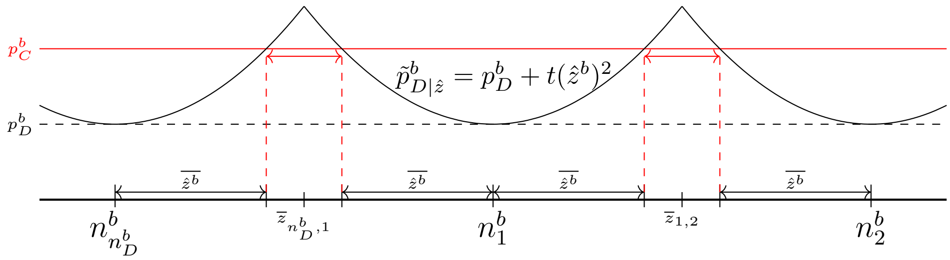
The *delivered* price for the differentiated version is lower than the customized version at any distance $\hat{z}^b \in [0, \frac{1}{2n^b_D}]$. Even the consumer with the maximum *fit costs* for the differentiated version would need to bear a lower *delivered* price, $p^b_D + t(2n^b_D)^{-\alpha}$ than for the customized version, p^b_C. There will be no demand for the customized version of brand b (at any $\hat{z}^b$). See figure 1.2 above for a graphical illustration.

Case 2:

$$\begin{gathered}p^b_D + t(\hat{z}^b)^2 \geq p^b_C \\ \text{for some } \hat{z}^b \in [0, \frac{1}{2n^b_D})\end{gathered} \tag{1.16}$$

[33] When indifferent between customized and differentiated versions, clients are assumed to buy the differentiated version.

Figure 1.3: Demand for Customized and Differentiated Versions (**Case 2**)



Notes: Equispaced differentiated versions priced at p_D^b; *Delivered* price $\tilde{p}^b_{D|\hat{z}}$; Customized versions priced at p_C^b; Assumption of quadratic *fit costs*, $\alpha = 2$.

As the function $\tilde{p}_D^b = p_D^b + t(\hat{z}^b)^\alpha, \alpha \geq 2$ is monotonically increasing on $\hat{z}^b \in [0, \frac{1}{2n_D^b})$, there is a single crossing point with the constant function p_C^b. Define $\overline{\hat{z}^b}$ as the distance to the closest differentiated version at which consumers are indifferent between buying the differentiated or the customized version.

$$\begin{aligned} p_D^b + t(\overline{\hat{z}^b})^\alpha &= p_C^b \\ t\overline{\hat{z}^b}^\alpha &= p_C^b - p_D^b \\ \overline{\hat{z}^b} &= \left(\frac{p_C^b - p_D^b}{t}\right)^{\frac{1}{\alpha}} \in [0, \frac{1}{2n_D^b}) \end{aligned} \tag{1.17}$$

As the root cannot be negative and $t > 0$, p_C^b needs to be larger than the mill price for the differentiated version, $p_C^b > p_D^b$.

As depicted in figure 1.3, all consumers at locations $\hat{z}^b : 0 \leq \hat{z}^b \leq \overline{\hat{z}^b}$ will buy the differentiated version. On the other hand, all consumers at locations above $\overline{\hat{z}^b}$ but below $\frac{1}{2n_D^b}$ will buy their *ideal* version. Considering the high *fit costs* those consumers would need to bear, the minimum price is p_C^b. Note that this is different to Hsu et al. (2014, p. 12) where firms decide on the segment for which bespoke products can be produced and consumers that are outside of that range are simply not able to get their specification. Here, it is the consumer's deliberate choice to either buy the differentiated or customized version even when getting the customized version from the brand is possible.

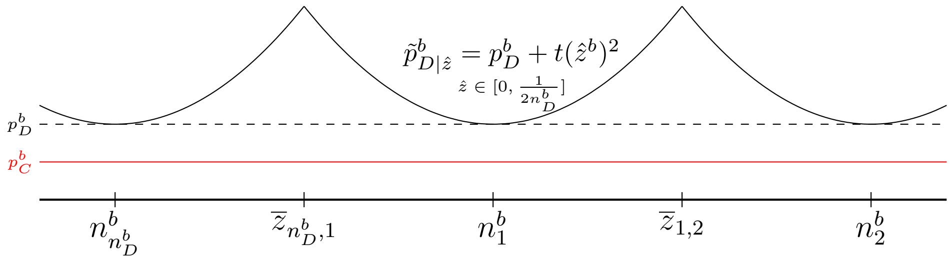
Case 3:

$$p_D^b > p_C^b \tag{1.18}$$

The price for the differentiated version is greater than the price for the customized version even at distance $\hat{z}^b = 0$. Consequently, there would be no demand for the differentiated version of brand b (at any $\hat{z}^b$) as shown in figure 1.4.

Producers will decide on the technology and the (mill) price they charge and, if necessary, on the number of differentiated versions as discussed in the following section.

Figure 1.4: Demand for Customized Versions Only (**Case 3**).



Notes: Equispaced differentiated versions priced at p^b_D; *Delivered* price $\tilde{p}^b_{D|\hat{z}}$; Customized versions priced at p^b_C; Assumption of quadratic *fit costs*, $\alpha = 2$.

1.4 Producers

In the given sector, there are many potential entrants. There is free entry. By paying the sunk entry costs, f_E, a firm establishes a brand. Brands are risk neutral.

As discussed in section 1.3, the parameter μ is an inverse measure for the correlation between the idiosyncratic taste shocks, $\epsilon^b_{j|z}$ (Fajgelbaum et al. 2011, p. 729; McFadden 1977, p. 10ff.; Anderson et al. 1992, p. 345). When $\mu > 0$ and a brand's action of distinguishing itself from competitors is costless, there will be horizontal differentiation across labels due to *branding*.[34] In contrast to Dhingra (2013, p. 2560), there is no assumption on within-brand and across-brand substitutability beyond μ.[35] The existing differentiation allows brands to exert some control over prices. Price competition between brands is governed by the parameter μ. In case of $\mu \to 0$, there is low variation in preferences and price competition will be intensified. In the limit, prices would equal marginal costs and the most productive brand will serve the entire market.

Due to the existing heterogeneity in preferences whenever $\mu > 0$, any brand b has its own circular market area of unit length. However, firms are small in the market such that they take market aggregates (e.g. the price index) as given. There is multi-product-monopolistic competition, i.e. monopolistic competition between brands that offer multiple products along the preference space.[36] The brand decides on the adoption of the technology, $T = \{D, C, DC\}$, taking optimal differentiation and prices into account. Due to the multinomial logit set-up, optimal mill prices will be independent of the number of differentiated versions. Whether brands choose sequentially n^{b*}_T and then p^{b*}_T or make both decisions simultaneously lead to similar results.

The technology choice is a simple short run comparison of optimal profits with a fixed

[34] The argument follows Dhingra (2013, p. 2555) who refers to the marketing literature.

[35] Contrary to Ben-Akiva et al. (1989), there is also no assumption on the geographic distance between brands.

[36] Amir et al. (2016) analyzes prices and welfare in a multi-product monopoly setting. Hadfield (1991, p. 533f.) discusses the case of a monopolist who establishes retail outlets to serve a circular market.

number of competitors in the market. If technologies are mutually exclusive, brand b adopts the customization technology if and only if the latter results in larger profits.

$$\Pi_D^{b^*}(n_D^{b^*}, p_D^{b^*}) \leq \Pi_C^{b^*}(p_C^{b^*}) \tag{1.19}$$

Similarly, if simultaneous production with both technologies is possible, the technology (mix) is adopted that satisfies $T = \underset{T=\{D,C,DC\}}{\operatorname{argmax}} \{\Pi_D^{b^*}(n_D^{b^*}, p_D^{b^*}), \Pi_C^{b^*}(p_C^{b^*}), \Pi_{DC}^{b^*}(n_D^{b^*}, p_D^{b^*}, p_C^{b^*})\}$. In the following subsections, profit functions for product differentiation and customization will be defined. Results will be discussed in section 1.5.

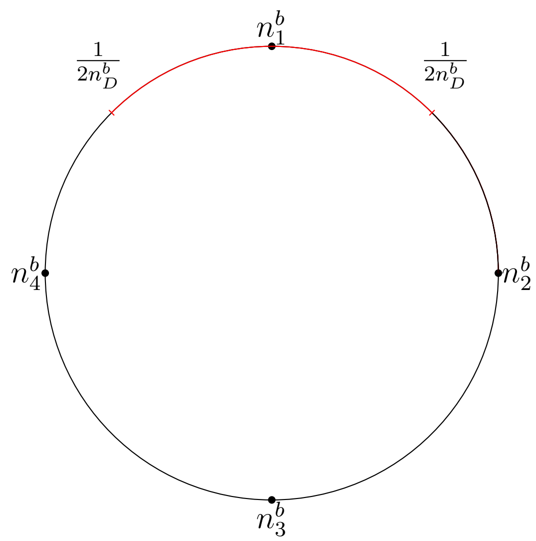
Note that when discussing comparative static results in section 1.5, trade liberalization is equivalent to an increase in the mass of consumers, L. However, trade liberalization could also affect firms' location choices. Production of customized versions might be more skill intensive than production of differentiated versions. In a two country setting where countries differ in endowments of low and high skilled labor as well as capital, one could interpret the sunk costs, f_E, as being paid in terms of skilled labor to establish headquarter services in the home country.

1.4.1 Product Differentiation

Facing the circular preference space, brand b allocates its n_D^b differentiated versions equispaced along its market area. These locations are defined by $z_i^b \in [0,1], \forall i \in 1, \dots n_D^b$. See figure 1.5 for a graphical illustration.

Offering a differentiated product entails fixed costs, f_D, that need to be paid per variety. Hence, production of differentiated versions features economies of scale. Per-unit costs, $c_{iD}^b = c_D^b \forall i \in 1, \dots, n_D^b$, are equal across differentiated versions, constant, and

Figure 1.5: Example of Brand b offering $n_D^b = 4$ Differentiated Versions.



independent of brand's total number of differentiated versions, $c_{iD}^b \perp n_D^b, \forall i$. Differentiated products are mass-produced and production processes are intensive in low skilled labor. In an open economy setting with countries that differ in the endowment of skilled workers, manufacturing of these versions would be located in the country that has the comparative advantage. A simple way to incorporate that in the model is to think of f_D as being paid in terms of the wage for low skilled labor.

Re-anchoring costs are zero. The latter assumption implies that whenever a new differentiated version is added, all existing versions will be rearranged such that they are, again, equispaced along the circumference. While this might seem restrictive for the supply side, it is consistent with symmetry on the demand side; Brands face a potential set of consumers, L, at any $z \in [0,1]$. As consumers are uniformly distributed and marginal as well as fixed costs are constant along the circle, firms will allocate their differentiated products equispaced along the unit circle. The equispaced allocation of products is an implication whenever consumers know about their exact location vis-à-vis the closest differentiated versions. However, when consumers only observe the number of versions offered and form expectations, firms are indifferent where to allocate the versions. However, there is no clear (theoretical) explanation for why they would allocate all versions on one side of the circular market. Neiman and Vavra (2019) find increasing concentration of individual household's spending but decreasing concentration in aggregate spending driven by the heterogeneity of consumers' preferences.

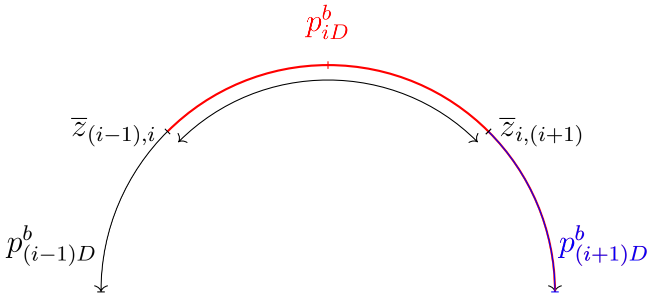
While there is some empirical support for symmetry, there is also a technical reason for it. The dimension of the preference space, R^1, the circumference of the circle, is smaller than $n_D^b - 1$ when $n_D^b > 2$. Absent symmetry and zero re-anchoring costs, there would exist localized competition: The location of a new version does not affect all versions equally around the circle but only the market area of the two neighboring versions. This counters the condition of variants being strong gross substitutes that is needed for the compatibility of the linear random utility model (LRUM) with the quadratic address model (QAM) (Anderson et al. 1992, p. 114).[37]

Due to symmetry on demand and supply side, resulting mill prices, $p_{iD}^b = p_D^b \forall i \in 1,\ldots,n_D^b$ are also identical for all differentiated versions of a brand. Distance between equispaced versions along the unit circle is $\frac{1}{n_D^b}$. With equal mill prices, the indifferent consumer, $\overline{\hat{z}^b}$, will be located exactly in-between two version, at the maximum distance $\frac{1}{2n_D^b}$.

However, once prices would differ across locations, the indifferent consumer would no longer be located at $\overline{\hat{z}^b} = \frac{1}{2n_D^b}$. The indifference condition would be a function of the

[37] The fact that simple discrete choice theorems do not hold with localized competition is also discussed in Anderson et al. (1989), where the authors leave the "equivalence problem [of aggregated demand systems] [...] for the intermediate case of partially localized competition [to future research]" (Anderson et al. 1989, p. 32).

Figure 1.6: Localized Competition Between Differentiated Versions.



Notes: Differentiated versions priced at $p^b_{(i-1)D}, p^b_{iD}, p^b_{(i+1)D}$; Indifferent consumers denoted by $\overline{z}_{(i-1),i}$ and $\overline{z}_{i,(i+1)}$.

difference in the prices of the (two) neighboring differentiated versions as depicted in figure 1.6.[38] In order to keep the model tractable and to ensure that variants are gross substitutes, marginal costs are not allowed to differ across differentiated versions.

The assumption of constant marginal costs within multi-product firms is similar to settings in Ottaviano and Thisse (2011, p. 943) and Allanson and Montagna (2005, p. 590). It contrasts, conversely, with models that consider multi-product firms and flexible manufacturing systems where firms have a *core competence* and rising marginal costs the further away the product is from the core (Eckel and Neary 2010, p. 189). The set-up also differs from Nocke and Yeaple (2006, p. 4) who argue that marginal costs of all products are rising as a response to a new product line.

The choice of the unit circle restricts the brand's product differentiation to be unidimensional, e.g. the color wheel for a certain type of shoe.[39] It would be implicitly assumed that producing this product in a different color does not significantly alter marginal costs.

There is *intra-brand* competition among the n^b_D differentiated versions on the circle that, by symmetry on the demand and supply side, have each a market area of $\frac{1}{n^b_D}$. On both sides of each version, i.e. $2 * n^b_D$ times, buyers of brand b's products have a maximum distance of $\frac{1}{2n^b_D}$ to the closest version. Brand b's demand share of the total mass L of consumers at any z will depend on the *inter*-brand competition, i.e. on existing heterogeneity in preferences and on productivity of the brand relative to its competitors.

The general form of the profit function is therefore:

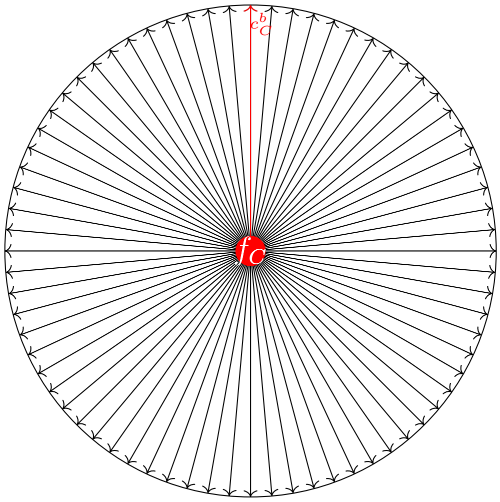
$$\max_{n^b_D, p^b_D} \Pi^b_D = 2n^b_D(p^b_D - c^b_D)L \int_0^{\frac{1}{2n^b_D}} D^b(p^b_D, n^b_D)_{\hat{z}^b} L d\hat{z}^b - n^b_D f_D - f_E \tag{1.20}$$

The distance to the closest differentiated version and consequently the *delivered* price will depend on the number of versions offered. The demand function, $D^b(n^b_D, p^b_D)_{\hat{z}^b}$, expresses

[38]The indifferent consumer is decisive only when the case of exact location based purchase decisions is considered.

[39]See figure A.1 for a graphical illustration.

Figure 1.7: Brand b paying sunk costs f_C to offer customized versions at marginal costs c_C^b.



that the integral over demand shares at any distance $\hat{z}^b$ will therefore depend not only on the mill price, p_D^b, but also on n_D^b.[40] Note that in section 1.3.1 demand on the brand's unit circle is constant across locations, $\hat{z}^b$, and revenue in equation (1.20) collapses to $(p_D^b - c_D^b)D^b(p_D^b, n_D^b)$.

1.4.2 Product Customization

Besides the possibility to offer mass-produced differentiated versions, brands might adopt a technology that enables mass customization. Upon adoption, this technology allows to serve all consumers along the entire circle at constant marginal costs, c_C^b. In a graphical representation as shown in figure 1.7, it is equivalent to paying sunk costs, f_C, in order to locate inside the Salop circle and serve the consumers at constant marginal costs, c_C^b.[41] The production plan features "*strong economies of scope*" (Eaton and Schmitt 1994, p. 877) if all customized versions are produced starting from one single product.

Suppose that the customization technology is intensive in capital and that there exists capital-skill complementarity. Sunk costs, f_C, could be thought as being paid in terms of the wage for skilled workers. If customization requires interaction with and therefore closeness to consumers, it is likely to be located in (or close to) the brand's domestic market. Especially, when brands see the reduction in lead time as a key driver for technology and location choices.

Above, there were frequent references to additive manufacturing (AM), in general, or, 3D

[40]Equation (1.20) implicitly assumes that there is symmetry for the $2 * n_D^b$ intervals.

[41]One could think of these marginal costs to be proportional to the radius, i.e. $\tilde{c}_C^b = c_C^b \frac{1}{2\pi}$, where $r = \frac{1}{2\pi}$ is the radius of the unit circle. However, since variations in the length of the preference space (circumference) are not considered, the proportionality does only affect numerical results.

printers, in particular.[42] The modeling of customization is not limited to these (specific) technologies as long as production of customized versions comes at constant marginal costs, allows mass customization (in the future) and entails sunk costs.
Some firms might adopt the customization technology while others stick to differentiation. Hence, if brand b offers customized versions, the resulting profit function has the following form:

$$\max_{p_C^b} \Pi_C^b = (p_C^b - c_C^b) \int_0^1 \frac{e^{-\frac{p_C^b}{\mu}}}{\sum_{\tilde{b}=1}^{\mathcal{M}} e^{-\frac{\tilde{p}^{\tilde{b}}(z)}{\mu}}} L dz - f_C \tag{1.21}$$

There are no *fit costs* for consumers of brand b, i.e. $p_C^b = \tilde{p}_{C|z}^b$, at any location $z \in [0,1]$. Depending on whether competitors adopted the customization technology as well, consumers might need to bear *fit costs* when buying from other brands. The denominator might therefore depend on the location z. When all brands offer customization, revenues in equation (1.21) collapse to $(p_C^b - c_C^b)D^b(p_C^b)L$.
Note that the existence and the feature of the customization technology is taken as given. That is, investments in research and development or in-house innovation processes are not modeled. This would require a dynamic approach which goes beyond the scope of this analysis. The *Enquête TIC auprès des entreprises* conducted by the *Institut national de la statistique et des études économiques* (Insee) finds that in 2018 more than half of surveyed French firms that applied 3D printing used their own 3D printers while more than half also used external services (Insee 2019a). Hence, there seems to be mixed evidence on whether firms use in-house or external services for additive manufacturing technologies.
Furthermore, so far, there is no explicit relation imposed on marginal costs of product differentiation and customization. The results from the French survey might potentially reflect an imperfect but possibly positive association between brands' productivity for differentiation and customization when 3D printing is conducted in-house. Later, when influences of changes in productivity on the technology choice are analyzed, independent marginal costs, $c_D^b \perp c_C^b$, as well as a positive mapping between them, $c_C^b(c_D^b) : \frac{\partial c_C^b(c_D^b)}{\partial c_D^b} > 0$, are discussed.

1.5 Results

In the following, results on optimal pricing and technology choice are discussed. The assumption that consumers do not observe their exact location vis-à-vis the closest differentiated version but form an expectation based purchase decision yields closed form

[42] See, for instance, Weller et al. (2015) or Lund and Bughin (2019) on characteristics of AM technologies.

solutions in the case of symmetric brands (section 1.5.1). Section 1.5.2 presents results for the case of exact location based purchase decisions. See appendix A.2 for proofs and derivations.

1.5.1 Expectation Based Purchase Decision

When consumers form expectation based purchase decisions, brand b's demand share is constant at any location z. Recall that consumers demand at least and at most one unit in the industry. Given the expression for the demand share in equation (1.9) and $\tilde{p}_D^b = p_D^b + \bar{t}\bar{x}(n_D^b)$, the profit function equals

$$\max_{n_D^b, p_D^b} \Pi_D^b = (p_D^b - c_D^b) L \frac{e^{-\frac{\tilde{p}_T^b}{\mu}}}{\sum_{\tilde{b}=1}^{\mathcal{M}} e^{-\frac{\tilde{p}_T^{\tilde{b}}}{\mu}}} - n_D^b f_D - f_E \tag{1.22}$$

Maximizing equation (1.22) with respect to p_D^b yields the optimal price

$$p_D^{b^*} = \mu + c_D^b \tag{1.23}$$

It is independent of the number of differentiated products. This is different to a monopoly version of the model where the price is increasing in n_D^b: A monopolist maximizes subject to the restriction that consumers at maximum distance are still willing to buy the product (Hadfield 1991, p. 533) and thereby extracts the entire surplus from these consumers.
In equation (1.23), there is a constant optimal *margin*, $p_D^{b^*} - c_D^b = \mu$, compared to a constant relative mark-up as in the case of a CES function (Besanko et al. 1990, p. 404). The *margin* equals the inverse measure of the correlation in idiosyncratic taste shocks. In markets where there is more variation in preferences, brands can charge higher prices. As in Fajgelbaum et al. (2011, p. 736, fn. 19), the optimal *margin* is independent of the potential existence of per-unit or iceberg trade costs. This is important when mass-produced (or even customized) versions are imported into the domestic market. Differences in prices across brands will be solely driven by differences in their productivity.
The first order condition with respect to the optimal number of differentiated versions yields

$$(p_D^b - c_D^b)\left(-\frac{1}{\mu}\frac{\partial \bar{t}\bar{x}(n_D^b)}{\partial n_D^b}\right) D^b(n_D^b, p_D^b) L = f_D \tag{1.24}$$

An increase in the number of differentiated versions reduces the (expected) distance to the next differentiated version and thereby the (expected) *delivered* price for all consumers.

$$\frac{\partial D^b}{\partial n_D^b} = -\frac{1}{\mu}\frac{\partial \tilde{p}_D^b}{\partial n_D^b} = -\frac{1}{\mu}\frac{\partial \bar{x}(n_D^b)}{\partial n_D^b} > 0 \tag{1.25}$$

The reduction in $\tilde{p}_D^b$ causes brand b's market share at any z to grow (*inter-brand* dimension). For optimality, the beneficial effect of adding a new version on demand shares needs to exactly equal the costs for establishing that version, f_D (see equation (1.24)). When the optimal price is given by equation (1.23), the optimal number of differentiated versions is determined by

$$\alpha\bar{t}\frac{\overline{x}(n_D^{b^*})}{n_D^{b*}}D^b(n_D^{b^*}, p_D^{b^*})L = f_D \tag{1.26}$$

Symmetry across and within brands

If brands are perfectly symmetric, i.e. $c_D^b = c_D, \forall b \in 1, \ldots \mathcal{M}$, market shares are evenly distributed across all active brands and equal $D^b = D = \frac{1}{\mathcal{M}}$. $L^b = \frac{L}{\mathcal{M}}$ is the uniform mass of consumers for each brand. Then, there exists a closed form solution for the optimal number of differentiated versions.[43]

$$n_D^* = \left(\frac{\alpha\bar{t}L}{2^\alpha \mathcal{M} f_D}\right)^{\frac{1}{1+\alpha}} \tag{1.27}$$

The optimal degree of differentiation, n_D^*, is decreasing in the number of competitors in the market, $\mathcal{M}$, and the fixed costs for establishing a version, f_D. If the mass of consumers, L or L^b, rises, the representative brand faces higher demand at any z. This allows to cover fixed costs for additional versions and therefore an extension of the brand's product line with a resulting further increase in demand. Consequently, brands offer more differentiated products in larger markets.

When buyers get more sensitive to *fit costs*, i.e. if the value of $\bar{t}$ increases, firms provide optimally more products. Suppose that the weight of the *fit costs* is positively associated with the income level in a market. If the expected distance to a version is interpreted as a measure for perceived quality of a brand, there is higher demand for quality in richer markets, where the brand's unit circle would be optimally more crowded.[44]

Note that from equation (1.27), when fixed costs for the differentiated version approach zero, $f_D \to 0$, the optimal differentiation tends towards infinity, $n_D^* \to \infty$, and consumers can get their *ideal* version. Absent sunk costs, i.e. $f_C = 0$, results are isomorphic to the adoption of the customization technology.

Equation (1.27) also nests an adapted version of the optimality result of the "isolated" multi-product-monopolist in Hadfield (1991, p. 533), when sufficiently loss-averse buyers are considered who evaluate the *delivered* price at the maximum possible distance to a differentiated version.[45]

Given *inter-brand* symmetry, optimal prices and differentiation, maximized profits amount

[43] n_D^* is not necessarily an integer value unless the integer function is applied. To keep it simple, the integer problem is not considered for the moment.

[44] See the discussion on vertical differentiation in discrete choice models in section 1.3.1.

[45] In the case of a monopolist, $\mathcal{M} = 1$, and buyers who put the weight $\bar{t}$ on *fit costs* and evaluate the *delivered* price at the maximum distance, $\tilde{p}_D^b = p_D^b + \bar{t}(\frac{1}{2n_D^b})^\alpha$.

to

$$\Pi_D^* = L^b \left(\mu - (\alpha\bar{t})^{\frac{1}{1+\alpha}} \left(\frac{f_D}{2L^b} \right)^{\frac{\alpha}{\alpha+1}} \right) \tag{1.28}$$

If the multi-product firm pays f_C in order to supply *customized* versions, maximizing profits in equation (1.21) leads to:

$$p_C^{b*} = \mu + c_C^b \tag{1.29}$$

Not only is the optimal *margin* constant across brands but also across technologies. If brands have uniform marginal costs, optimal profits from customization are

$$\Pi_C^* = \mu \frac{L}{\mathcal{M}} - f_C = \mu L^b - f_C \tag{1.30}$$

Clearly, producing with the customization technology leads to positive (short-run) profits only if sunk costs are low enough such that $f_C < \mu\frac{L}{\mathcal{M}}$. Hence, there needs to be minimum levels of heterogeneity in preferences, μ, and market share, L^b, that generate sufficient revenues to cover at least sunk costs, f_C.
Brands will adopt the customization technology if and only if

$$\frac{f_C}{f_D} \leq \left(\frac{\alpha\bar{t}L}{2^\alpha \mathcal{M} f_D} \right)^{\frac{1}{1+\alpha}} = n_D^* \tag{1.31}$$

The left hand side are fixed costs of establishing a differentiated version relative to sunk costs of customization. The ratio needs to be smaller than the optimal n_D^* to incentivize customization: Due to the symmetry assumption, market shares and consequently revenues are identical for both production processes such that the technology is chosen that promises minimum total fixed or sunk costs, $\min\{n_D^* f_D, f_C\}$.
Given the exogenous supply side parameters and the weight of *fit costs*, $\bar{t}$, there is a threshold value for the mass of consumers, $\overline{L}$, that equalizes profits of both production processes:

$$\begin{aligned} \overline{L}: \quad \Pi_D^* &= \Pi_C^* \\ \overline{L} &= f_C^{(1+\alpha)} \left(\frac{2^\alpha \mathcal{M}}{\alpha\bar{t} f_D^\alpha} \right) \end{aligned} \tag{1.32}$$

For any $L > \overline{L}$, Π_C^* is larger than Π_D^*: While a larger mass of consumers expands demand at any location z, it also raises the optimal number of differentiated versions. The latter reduces Π_D^*, whereas f_C is, by definition, independent of L. When market size grows through trade liberalization, customization becomes more attractive. More competing brands in the market have the opposite effect. $\Pi_C^* - \Pi_D^*$ is increasing in L, but at a decreasing rate: Growth in market size leads to an under-proportionate increase in n_D^*.[46]

[46]The elasticity of n_D^* with respect to L is $\frac{dln(n^*)}{dln(L)} < 1$.

To sum up, adoption of the customization technology is more likely, the larger the market, consumers' sensitivity to *fit costs*, or fixed costs, f_D. More competitors in the market or higher sunk costs, f_C, dampen attractiveness of choosing $T = C$.
By symmetry, either none or all firms switch to the new technology. The assumption of symmetry was for the sake of simplicity and to afford first insights based on closed form solutions. However, there is empirical evidence that firms differ in productivity (Melitz 2003, p. 1695). In the following, multi-product firms can therefore differ in marginal costs, c_D^b and c_C^b, though, symmetry across differentiated products of a brand, i.e. $c_{iD}^b = c_D^b, \forall i \in 1, \ldots n_D^b, \forall b$ is still retained.

Symmetry within and heterogeneity across brands

Since there is multi-product-monopolistic competition between brands, a single brand takes market aggregates as given. Results for the optimal prices are therefore identical to equation (1.23) and equation (1.29). This implies that independent of asymmetry in marginal costs there is a constant *margin* across brands and across technologies. However, as marginal costs differ, firms charge different prices which affects the choice of differentiation and market shares.[47] The optimal number of differentiated products is determined by equation (1.24). The condition is not explicitly solvable for the optimal number of differentiated products $n_D^{b^*}$. Hence, the implicit function theorem is applied for comparative static analyses.
The positive effects of market size, L, and the weight of the *fit costs*, $\bar{t}$, on optimal differentiation are robust to the case of heterogeneous brands: A larger mass of consumers augments revenues given market shares and thereby allows to cover additional fixed costs. This effect is increasing in the productivity of the firm: The lower the marginal costs of a brand, the larger the rise in differentiated versions as a response to the expansion in market size. In Dhingra (2013, p. 2557), high-productivity exporters benefit most from larger markets. They are able to cope with the competitive pressure caused by trade liberalization and expand their product range.[48]
In order to avoid reduction in demand, brands' optimal differentiation increases as a response to a rise in the sensitivity to *fit costs*, t. In addition, the intuitive negative impact of f_D on proliferation extends to the current framework.
However, with heterogeneity across firms, the measure of dissimilarity in preferences, μ,

[47]Note that if firms were assumed to differ in fixed costs, mill prices would be the same across brands and technologies. For $T = C$, market shares, revenues, and profits would be identical. For $T = D$, *delivered* prices would be smaller for firms with low fixed costs that face consequently higher demand.
[48]However, the current framework abstracts from free entry in Dhingra (2013).

marginal costs, c_D^b, and the (so-called) *delivered* price index

$$\mathcal{P} = \left[\sum_{\tilde{b}=1}^{\mathcal{M}} e^{-\frac{\tilde{p}_T^{\tilde{b}}}{\mu}}\right]^{-1} \tag{1.33}$$

also have an impact on the choice of differentiation. The differentiation weighted price index, $\mathcal{P}$, depends positively on prices charged by competing brands. Ceteris paribus, if competitors get less productive, brand b's consumer base, $L^b = D^b L$, at any $z \in [0,1]$ expands. Due to higher demand and revenues, the brand can cover additional fixed costs and optimal differentiation increases. Intuitively, higher marginal costs lowers the degree of differentiation within a brand.

More variation in preferences across consumers, or, put differently, a reduction in the correlation between taste shocks, $\epsilon_{j|z}^b$, are expressed by a rise in μ. The idiosyncratic taste shock gets more weight in the indirect utility function of the consumer (see equation (1.1)). The importance of the *branding* makes consumers, ceteris paribus, less responsive to the *delivered* price, i.e. to (expected) *fit costs*. On the other hand, profit maximizing firms will be able to charge a higher *margin*, which, other things being equal, decreases demand for a given brand but also causes the aggregate *delivered* price index to rise. Without further assumptions on relative productivity and resulting prices of a brand, there are no clear predictions on the direction of the effect on proliferation. But, at the optimum, only the direct effect of μ on brand's demand is decisive for its sign.

For $\frac{\partial D^b}{\partial \mu} > 0$, the *delivered* price of brand b needs to be larger than the demand-weighted average price:[49] More variation in preferences, a higher μ, reduces the importance of mill prices and (expected) distances for consumers' choice. Since marginal costs map one to one into mill prices and more productive firms offer more differentiation, this benefits less productive firms. Their demand shares go up as a response to higher variation in preferences at the expense of demand for products from high productivity firms. Low productivity firms can therefore cover additional fixed costs and intensify proliferation which lowers *delivered* prices and increases their market shares further. Brands that charge *delivered* prices below the demand weighted average, i.e. high productivity brands, see their expected demand decrease as a response to increased heterogeneity in preferences. Their optimal n_D^{b*} shrinks. The correlation of preferences across brands might depend on the specific industry. Hence, variations in μ might yield interesting hypotheses on the differential incentives to adopt customization across industries.[50]

In the short run, firms compare profits they would generate with either technology,

[49] See the derivations in appendix A.2 or Anderson et al. (1992, p. 346f.) for a general discussion. A more restrictive version is that the difference in the *delivered* price and the demand weighted average *delivered* price needs to be larger than the *margin* $\mu > 0$.

[50] An interpretation along the lines of "imperfect information" in Perloff and Salop (1986, p. 184): A rise in the measure for imperfect information in an industry benefits those brands that charge higher prices.

$T = \{D, C\}$.[51] Brand b adopts the customization technology if and only if

$$\Pi_C^{b^*}(p_C^{b^*}) \geq \Pi_D^{b^*}(n_D^{b^*}, p_D^{b^*}) \iff \Pi_C^{b^*}(p_C^{b^*}) - \Pi_D^{b^*}(n_D^{b^*}, p_D^{b^*}) \geq 0$$

Proposition 1.1 *Incentives to adopt the customization technology are increasing in market size for those brands whose optimal mill price for customized versions, $p_C^{b^*} = c_C^b + \mu$, is below the optimal delivered price for differentiated versions, $\tilde{p}_D^{b^*}$.*

The underlining intuition is as follows: Optimal profits from customization, $\Pi_C^{b^*}$, clearly rise as a response to larger markets. The brand can generate additional revenues at any location z. There are three channels, though, that affect optimal profits from differentiation, $\Pi_D^{b^*}$: First, given market shares, growth in market size increases revenues (as for $\Pi_C^{b^*}$). Second, due to $\frac{\partial n_D^{b^*}}{\partial L} > 0$, the expected *delivered* price decreases due to lower expected *fit costs* which causes demand for brand b, D^b, and consequently $\Pi_D^{b^*}$ to rise. Third, the optimal proliferation comes at additional costs for establishing those versions, $\frac{\partial n_D^{b^*}}{\partial L} f_D > 0$, which clearly reduces optimal profits, $\Pi_D^{b^*}$. At the optimum, the latter two effects compensate each other. The difference in optimal profits increases when the rise in revenues as a response to trade liberalization is larger from customization than from product differentiation. This is the case whenever $\tilde{p}_C^b > \tilde{p}_D^b \iff c_C^b - c_D^b < \bar{t}x(n_D^{b^*})$, i.e. the expected *fit costs* are higher than the difference in the marginal costs. The customized version would yield the minimum price and, given pricing of competitors, market shares of brand b expand.

Since customization offers consumers' *ideal* version with probability one, there are no *fit costs* and consequently no effect of the weight $\bar{t}$ on $\Pi_C^{b^*}$. However, when consumers are more sensitive to distance, demand for differentiated version reduces, ceteris paribus, such that a brand would optimally need to invest more in differentiation. Adoption of $T = C$ becomes more likely.

Proposition 1.2 *If $c_C^b \perp c_D^b$: Incentives to adopt the customization technology are increasing (decreasing) in c_D^b (c_C^b).*

A rise in c_D^b reduces market shares and, by independence, profits generated from differentiation, $\Pi_D^{b^*}$, only. Lower marginal costs for customization have the opposite effects on $\Pi_C^{b^*}$. In both cases, $\Pi_C^{b^*} - \Pi_D^{b^*}$ rises.

Proposition 1.3 *If $c_C^b : \frac{\partial c_C^b(c_D^b)}{\partial c_D^b} > \frac{D^b(p_D^{b^*}, n_D^{b^*})}{D^b(p_C^{b^*})}$: Incentives to adopt the customization technology are increasing in the productivity of the firm.*

Suppose there is a positive association between marginal costs and a change in productivity affects demand for customized versions more than for differentiated versions. A reduction in c_D^b causes $\Pi_C^{b^*}$ to rise more than $\Pi_D^{b^*}$: $\Pi_C^{b^*} - \Pi_D^{b^*}$ is increasing in the productivity of the firm.

[51] The number of competitors is kept fixed in the short run.

Proposition 1.4 *If* $c_C^b : \frac{\partial c_C^b(c_D^b)}{\partial c_D^b} > \frac{D^b(p_D^{b^*}, n_D^{b^*})}{D^b(p_C^{b^*})}$, *the incentives to adopt the customization technology as a response to larger markets is increasing in the productivity of a brand if the direct effect on the difference of the profits is larger than the increase in demand due to a higher degree of differentiation.*

An expansion in market size, L, generates additional revenues (direct effect). Given the condition imposed on marginal costs, the effect is decreasing in marginal costs, c_D^b. But marginal costs affect profits from differentiation also indirectly through proliferation: Lower marginal costs, c_D^b, are associated with a higher degree of differentiation and market shares. Therefore, choosing $T = C$ as a response to a rise in L is increasing in the productivity of the firm only if the direct effect on optimal revenues dominates the indirect effect through proliferation and market shares.
Finally, the impact of heterogeneity in preferences, μ, on technology choice is discussed.[52] As mentioned above the direction of the effect of μ on the brand's demand share depends on the prices (or productivity) relative to those of the competitors.

Proposition 1.5 *Suppose* $\tilde{p}_C^{b^*} < \tilde{p}_D^{b^*}$*:*
If $\tilde{p}_C^{b^*} < \sum_{\tilde{b}=1}^{\mathcal{M}}(\tilde{p}_T^{b^*})D^{\tilde{b}}$, *an increase in* μ *reduces incentives to adopt the customization technology.*
If $\tilde{p}_C^{b^*} > \sum_{\tilde{b}=1}^{\mathcal{M}}(\tilde{p}_T^{b^*})D^{\tilde{b}}$, *an increase in* μ *makes adoption of the technology more likely if*

$$\frac{D^b(p_C^{b^*})}{D^b(p_D^{b^*}, n_D^{b^*})} > \frac{\tilde{p}_D^{b^*} - \sum_{\tilde{b}=1}^{\mathcal{M}}(\tilde{p}_T^{b^*})D^{\tilde{b}}}{\tilde{p}_C^{b^*} - \sum_{\tilde{b}=1}^{\mathcal{M}}(\tilde{p}_T^{b^*})D^{\tilde{b}}} \tag{1.34}$$

If correlation in preferences is low (high μ), brands can charge higher optimal *margins* because consumers get less responsive to prices. Whenever $\tilde{p}_C^{b^*} < \tilde{p}_D^{b^*}$, a rise in μ is, given market shares, associated with an increase in revenue. Call it the "*within-brand-revenue-effect*". However, as described above, a change in the correlation of the idiosyncratic taste shock, ϵ_j^b, affects market shares: The reduction in sensitivity to prices, distances, and consequently productivity of a brand benefits low productivity firms at the expense of high productivity firms. Call it the "*across-brand-market-share-effect*". Whether the latter effect is positive depends on pricing relative to the demand weighted average prices of competitors. If $\tilde{p}_C^{b^*} < \sum_{\tilde{b}=1}^{\mathcal{M}} \tilde{p}_T^{\tilde{b}^*} D^{\tilde{b}}$, an increase in μ necessarily reduces demand shares for $T = C$. This effect always dominates the positive *within-brand-revenue-effect*. If variation in preferences rises, a brand that has below average demand weighted prices will have less incentives to adopt the new technology. This is independent of whether the price for the differentiated versions is below or above the average.
In contrast, if the price for customized versions is above the average, equation (1.34) in proposition 1.5 defines the condition under which aggregate "*within-brand-revenue-effect*" and "*across-brand-market-share-effect*" are positive. The relative demand shares need to

[52] See appendix A.2 for a detailed overview.

be larger than the ratio of deviations from the average price.
Equation (1.34) implies that across markets that vary in μ, high (low) productivity firms are more likely to adopt the customization technology when the correlation between tastes is relatively high (low). The intuition for the result becomes clearer with the example of a market characterized by low μ: Upon adoption of $T = C$, a brand would charge the optimal price $p_C^{b^*} = \mu + c_C^b$. A decrease in μ means that brands are perceived as more similar, price differences and the *fit costs* for $T = D$ become more important. In the limit with $\mu \to 0$, there is tough price competition and the brand with the lowest marginal costs could capture the entire market. Hence, a decrease in μ makes the adoption of the customization technology more attractive for high productivity firms: Given their productivity, they can charge a low price p_C^b that allows them to increase their demand. On the other hand, with the high sensitivity to *fit costs*, if they would offer mass-produced differentiated versions, the decrease in μ would increase their optimal $n_D^{b^*}$ and lead to additional fixed costs.
The next section discusses robustness of results when consumers observe the exact location vis-à-vis the closest differentiated version.

1.5.2 Exact Location Based Purchase Decision

If consumers observe the exact location vis-à-vis the closest differentiated version, demand will differ along locations $z \in [0, 1]$. As differentiated versions are equispaced along the circumference of unit length, the distance can only take values within $\hat{z}^b \in [0, \frac{1}{2n_D^b}]$. If technologies are mutually exclusive, profits associated with product differentiation would equal

$$\max_{n_D^b, p_D^b} \Pi_D^b = 2n_D^b(p_D^b - c_D^b) \int_0^{\frac{1}{2n_D^b}} L \frac{e^{-\frac{p_D^b + t(\hat{z}^b)^\alpha}{\mu}}}{\sum_{\tilde{b}=1}^{\mathcal{M}} e^{-\frac{\tilde{p}_D^{\tilde{b}}(\hat{z}^b)}{\mu}}} d\hat{z}^b - n_D^b f_D \tag{1.35}$$

The denominator of the demand share can be interpreted as the inverse of a *delivered* price index, $\tilde{\mathcal{P}}_{\hat{z}^b}$, which, in contrast to previous sections, depends on location $\hat{z}^b$. By assumption of monopolistic competition, brands take it as given. Optimal prices for differentiated versions are still given by marginal costs and the optimal *margin*, μ.

$$p_D^{b^*} = \mu + c_D^b \tag{1.36}$$

The first order condition with respect to optimal differentiation yields

$$0 = \left[2 \int_0^{\frac{1}{2n_D^b}} e^{-\frac{p_D^{b^*} + t(\hat{z}^b)^\alpha}{\mu}} \tilde{\mathcal{P}}_{\hat{z}^b} d\hat{z}^b - \frac{f_D}{L\mu}\right] - \frac{1}{n_D^b} e^{-\frac{p_D^b + t(\frac{1}{2n_D^b})^\alpha}{\mu}} \tilde{\mathcal{P}}_{\frac{1}{2n_D^b}} \tag{1.37}$$

The first term in brackets shows that, given the market area of each version on the brand's circle, an increase in n_D^b allows to generate additional revenue from the new version net

of fixed costs. The second term, however, expresses that introducing a new version will reduce the market area of every existing version. This effect is well known in the literature on multi-product firms (see, for instance, Eckel and Neary 2010, p. 189).
Note that if it is assumed that there is complete symmetry between brands, i.e. $c_D^b = c_D^{\tilde{b}}, \forall b, \tilde{b} \in 1, \ldots, \mathcal{M}$, the first exactly counterbalances the last term in equation (1.37): Intuitively, the potential market area of a brand is fixed to the circumference of the circle. If, by increasing n_D^b, brand b does not attract new consumers, e.g. because demand shares remain unchanged to $\frac{L}{\mathcal{M}}$, there is no effect on brand's revenue but only fixed costs f_D. Introducing new differentiated versions cannot be optimal.
Results from the previous section are robust: An increase in market size, L, sensitivity to *fit costs*, t, or reductions in fixed or marginal costs, c_D^b, f_D, lead to a higher optimal number of differentiated versions. Moreover, the expansion in n_D^{b*} as a response to an increase market size is increasing in the productivity of the brand.
However, since *full* prices, $\tilde{p}_D^b(\hat{z}^b)$ are no longer constant across locations, $\hat{z}^b$, a change in μ affects demand for a version differently across locations. Assuming that n_D^{b*} is already sufficiently large:[53]

Proposition 1.6 *An increase in μ will cause n_D^{b*} to rise if*

$$\int_0^{\frac{1}{2n_D^{b*}}} \left(\sum_{\tilde{b}=1}^{\mathcal{M}} (\tilde{p}^{\tilde{b}}(\hat{z}^b)) D_{\hat{z}^b}^{\tilde{b}} - \tilde{p}_D^{b*}(\hat{z}^b) \right) D^b(p_D^{b*}, n_D^{b*})_{\hat{z}^b} d\hat{z}^b < \underbrace{(p_D^{b*} - c_D^b)}_{\mu} \int_0^{\frac{1}{2n_D^{b*}}} D^b(p_D^{b*}, n_D^{b*})_{\hat{z}^b} d\hat{z}^b$$

To get the intuition of this result assume, for simplicity, that the deviation is constant across $\hat{z}^b$. If the brand has below average (demand-weighted) productivity, it will gain market shares through a rise in μ because pricing gets relatively less important in the consumers' purchase decision. The left hand side is negative, the right hand side is always positive and the condition will be always fulfilled. On the other hand, when the brand has above average (demand-weighted) productivity, the left hand side will be positive. Then, an increase in μ leads to proliferation only if the deterioration of market shares is dominated by the direct effect of a higher *margin* on aggregated revenues.
Optimal profits and prices for the customization technology are given by

$$\Pi_C^{b*} = \mu \int_0^1 \frac{e^{-\frac{\mu + c_C^b}{\mu}}}{\sum_{\tilde{b}=1}^{\mathcal{M}} e^{-\frac{\tilde{p}^{\tilde{b}}(z)}{\mu}}} L dz - f_C \tag{1.38}$$

$$p_C^{b*} = \mu + c_C^b \tag{1.39}$$

The propositions from the previous subsection are robust to the specification of exact-location-based consumer decision with the exception that it is not about the constant

[53] I.e. $\frac{1}{n_D^{b*}}$ is small enough to neglect the effect at the upper limit $\frac{1}{2n_D^{b*}}$ that results from the application of the Leibniz rule, see appendix A.2.

demand, $D^b(p_D^{b*}, n_D^{b*})$, but about the aggregate over all locations,

$$\int_0^{\frac{1}{2n_D^{b*}}} D(p_D^{b*}, n_D^{b*})_{\hat{z}^b} d\hat{z}^b.$$

Proposition 1.5 generalizes to the following proposition.

Proposition 1.7 *An increase in μ makes the adoption of the customization technology more likely if*

$$\int_0^{\frac{1}{2n_D^{b*}}} D^b(p_C^{b*}) \left[\tilde{p}_C^{b*} - \sum_{\tilde{b}=1}^{\mathcal{M}} (\tilde{p}_T^{b*}) D_{\hat{z}^b}^{\tilde{b}}\right] d\hat{z}^b > \int_0^{\frac{1}{2n_D^{b*}}} D^b(p_D^{b*}, n_D^{b*})_{\hat{z}^b} \left[\tilde{p}_D^{b*} - \sum_{\tilde{b}=1}^{\mathcal{M}} (\tilde{p}_T^{b*}) D_{\hat{z}^b}^{\tilde{b}}\right] d\hat{z}^b$$

Technology Mix

When clients are able to perfectly foresee their location on the brand's unit circle, demand for differentiated and customized versions might coexist (see **Case 2** in section 1.3.2). If a brand decides to produce with both technologies, the resulting profit function is

$$\begin{aligned} \Pi_{DC}^b = {} & 2n_D^b L(p_D^b - c_D^b) \int_0^{\left(\frac{p_C^b - p_D^b}{t}\right)^{\frac{1}{\alpha}}} D^b(p_D^b, n_D^b)_{\hat{z}^b} d\hat{z}^b - n_D^b f_D \\ & + 2n_D^b L(p_C^b - c_C^b) \int_{\left(\frac{p_C^b - p_D^b}{t}\right)^{\frac{1}{\alpha}}}^{\frac{1}{2n_D^b}} D^b(p_C^b)_{\hat{z}^b} d\hat{z}^b - f_C \end{aligned} \tag{1.40}$$

subject to

$$\left(\frac{p_C^b - p_D^b}{t}\right)^{\frac{1}{\alpha}} \leq \frac{1}{2n_D^b} \tag{1.41}$$

As described above (see figure 1.3), at locations $\hat{z}^b \in [0, \left(\frac{p_C^b - p_D^b}{t}\right)^{\frac{1}{\alpha}})$, there is demand for the differentiated version because the *delivered* price including the *fit costs* is lower than the price charged for the customized version. However, consumers at $\hat{z}^b \in [\left(\frac{p_C^b - p_D^b}{t}\right)^{\frac{1}{\alpha}}, \frac{1}{2n_D^b}]$, would need to bear such high *fit costs* that they demand customized versions. An increase (decrease) in p_D^b (p_C^b) expands the market share of customized versions *within* a brand. Obviously, whenever $p_C^b < p_D^b$, there is no demand for the differentiated version.
From the optimality conditions, the ratio of market shares *within* a brand is given by

$$\frac{\int_{\left(\frac{p_C^b - p_D^b}{t}\right)^{\frac{1}{\alpha}}}^{\frac{1}{2n_D^b}} D^b(p_C^b)_{\hat{z}^b} d\hat{z}^b}{\int_0^{\left(\frac{p_C^b - p_D^b}{t}\right)^{\frac{1}{\alpha}}} D^b(p_D^b, n_D^b)_{\hat{z}^b} d\hat{z}^b} = \frac{\mu - (p_D^b - c_D^b)}{(p_C^b - c_C^b) - \mu} \tag{1.42}$$

It depends on the relative differences between μ and *margins*, $p_T^b - c_T^b$.
Note that, given the difference $\left(\frac{p_C^b - p_D^b}{t}\right)^{\frac{1}{\alpha}}$, the upper boundary of differentiated versions

is fixed.[54] Proliferation consequently reduces the market share of customized versions within brand b. In that case, optimal differentiation, $n_D^{b^*}$ should be lower than in the previous section with mutually exclusive technologies.

1.6 Conclusion

There is anecdotal evidence that firms complement their offer of mass-produced differentiated products with versions that consumers can *customize*. Consumers and producers' choice problems reflect trade-offs between prices and *fit costs* on the demand side and economies of scale and scope on the supply side. The discrete choice model is able to capture these trade-offs. It yields first predictions on the effect of a change in demand and supply side parameters on the likelihood of the adoption of the customization technology. The latter is more likely the larger the market and the more sensitive consumers are to *fit costs*. Moreover, more productive brands have higher incentives to adopt the customization technology as a response to an expansion in market size. If variation in preferences in an industry is low, high productivity firms are more likely to offer customization.
As mentioned in the introduction (section 1.1), there are ongoing discussions on the prevalence of *botsourcing*. Therefore, future work should analyze the role of labor costs and the open economy dimension beyond a simple increase in market size. A potential closing wage gap between developing and developed countries, complementarities between capital and the skill level of workers as well as potential spillover effects in mass production and customization are crucial aspects for a model that features the location choice of MNEs.
Clearly, one aim is to support the theory with data and to test the models' predictions on market size and productivity. In the medium to long run, effects of customization technologies such as additive manufacturing on the market structure are further points to consider. Especially, when it comes to technologies that enable in-store production, 3D hubs, or even "prosumers", i.e. "a person who both consumes and produces a particular commodity" (Collins Dictionary 2021b). A related question is whether 3D printing will reduce barriers to entry for firms (WTO 2018, p. 3).
Furthermore, representing investment decisions in R&D is out of this chapter's range. However, whether customization services are provided in-house or externally (see Insee 2019a), and result from own R&D investments or joint ventures are empirically and theoretically interesting aspects to study. From a theoretical angle, the analysis should extend beyond a short run comparison of profits but allow entry of firms. Moreover, the model should be extended to oligopolistic market structures. This could also have effects on consumer welfare which was not considered so far.

[54] Especially if the boundary is independent of n_D^b, i.e. $\left(\frac{p_C^b - p_D^b}{t}\right)^{\frac{1}{\alpha}} \perp n_D^b$.

Additive manufacturing might have significant effects on the existing structure of global value chains and the direction and sizes of trade flows. This work analyzed how the appearance of a technology that allows mass customization affects production decisions. It therefore extends a growing literature on the economic effects of digital technologies, in general, and additive manufacturing, in particular.

Chapter 2

Innovation and Customization

2.1 Introduction

Not only do firms offer consumers an increasing number of differentiated products in order to get closer to the consumers' taste but they also provide products that go beyond a close match: the perfect fit to the consumer's *ideal* version.[1] Recent advances in digital technologies are often named as enabling customization (WTO 2018, p. 91). However, empirical studies seem scarce. Therefore, this chapter analyzes patent data from the European Patent Office (EPO) in order to explore industry trends and geographical distribution of inventions related to customization. Patents are classified based on a keyword search among patent abstracts. These patent filings serve as a proxy for trends in customization. The data thereby allow to study relevant technical fields, industries, and countries. The analysis shows that there is an increase in patenting related to customization over the past 30 years. The number of granted inventions mentioning customization keywords was more than ten times higher in 2014 compared to 1990.

While a rise in product variety of multiproduct firms is denoted product proliferation, customized products or services guarantee that the consumer gets the *ideal* version with certainty.[2] Customization ensures zero *fit costs* for buyers and an additional value of being *unique*.[3] Results from a consumer survey suggest that 41% of respondents value personalization because of its uniqueness, 34% because of the precise *match*, and 28% because personalized products are reflecting their personality (Deloitte 2019, p. 17).

In practice, customization might range from a consumer's purchase of an in-store 3D printed personalized object (The Economist 2018) to customization of intermediate goods along global supply chains. The former highlights the importance of being close to con-

[1]See examples in section 1.1.

[2]This definition is also established in chapter 1. See also Hsu et al. (2014, p. 10, fn.1). Individualization, customization, and personalization will be used interchangeably. See discussion of synonyms in section 2.3 and in appendix B.1.

[3]For a definition of *fit costs*, see section 1.3.

sumers and the potential need for interaction or even co-creation. These factors could incentivize *nearshoring*, *insourcing* or *botsourcing* of firms and attenuate the role of distance and time.[4]

The analysis of patent data reveals that the largest share of patents that are associated with customization are filed in technical fields related to digital and communication technologies. Intuitively, customization requires information on and interaction or communication with (potential) purchasers. Information and communication technologies (ICT) facilitate information sharing between buyers and sellers along production chains independent of physical distance. In an international context, this could even attenuate *offshoring* activities and fragmentation of production but the role of distance and trade costs would depend crucially on whether products are (in)tangible. The share of ICT in customization inventions remains dominant over the entire time period considered. Yet, in recent years, customization patents related to automation and artificial intelligence are increasing. This reflects the potential of the so-called *Fourth Industrial Revolution* (4IR). The term refers to the blurring boundaries between physical and virtual worlds (Schwab 2015), in general, and for industrial production, in particular.

Given its technical features, 3D printing is often named as a potential driver for (mass) customization on the supply side (WTO 2018, p. 68). It is an example for an 4IR technology (Ménière et al. 2020). For instance, its flexibility in the production of custom goods caused the hearing aid industry to move from traditional to additive manufacturing processes (Freund et al. 2020, p. 3; Banker 2013). 3D printing can make production processes independent of intermediate parts, thereby localizing production and reducing lead times. It shortens supply chains especially for tailored products that usually involve many production steps (WTO 2018, p. 68). This could increase a firms' resilience during unexpected supply shocks, shortage or delivery problems. Together with the fact that it replaces tasks that were previously performed by humans, this technology could have significant effects on the structure of global value chains and labor markets.[5]

Additive manufacturing can be defined as "[t]echnologies involving the use or application of processes or apparatus that produce three-dimensionally shaped structures by selectively depositing successive layers of material one upon another" (Cooperative Patent Classification (CPC) 2021a, p.1). The "additive" nature of the process is different to "traditional" subtractive manufacturing that removes, for instance, by cutting excess material (waste) in order to get the desired pattern. This makes the former technology appealing for on-demand production. Moreover, there are no cost penalties associated with an increasing complexity of the product (Weller et al. 2015, p. 46). The high flexibility and the fact that there is no need for molds reduce lead times and allow rapid

[4]If *nearshoring* refers to the reversal of previous *offshoring* activities, this is often denoted *backshoring*, see De Baker et al. (2018, p. 3).

[5]Dechezleprêtre et al. (2021, p. 6f.) define 3D printing as part of automation technologies.

prototyping. The characteristics of additive manufacturing (AM) processes render it particularly attractive for small-scale production and product customization (see e.g. Lund and Bughin 2019; Weller et al. 2015). Patent data show that there is a steep increase in patent filings over the past years. Interestingly, the majority of personalization through AM is targeted to the health sector.

The previous chapter developed a theoretical model in order to analyze determinants of firms' choice between an increase in product variety and customization. The discrete choice problem yields results that are not dependent on a specific production technology. The analysis of patent data in this chapter suggests that customization seems associated with 4IR technologies. Introducing robots, 3D printing and/or applying artificial intelligence (AI) cause some of the tasks required for the production of custom goods to be automated. This chapter therefore extends the supply side to include Acemoglu and Restrepo (2018b)'s "[m]odelling [a]utomation" of tasks. For tractability, the demand side relaxes the assumption of a discrete choice problem and the exact location based purchase decision. It relies on a constant elasticity of substitution (CES) utility function (Dixit and Stiglitz 1977). Similar to the Melitz (2003) and Bustos (2011) type model in Koch et al. (2019), there is automation of some tasks on the supply side. However, in contrast to these models, the choice between two technologies implies a different level of product quality (Kugler and Verhoogen 2011). The model can therefore capture demand and supply side factors for firms' production choices.

There is scarcity of firm level data on the adoption of additive manufacturing. A notable exception is, for instance, the *Enquête sur les technologies de l'information et de la communication et le commerce électronique* (TIC 2018) conducted by the French *Institut national de la statistique et des études économiques* (Insee) in 2018.[6] However, the results give only a one-year cross-sectional impression on the adoption of additive manufacturing by French firms. Moreover, the survey does not contain any questions concerning customization to end consumers. But even when it comes to customization of intermediate goods along supply chains, the literature and data availability are scarce. This chapter tries to fill this gap by using patent data to spot customization inventions and to proxy firms' R&D output in AM. The expected economic value of being at the forefront of 4IR technologies is reflected by extensive programs at national and supranational levels to foster R&D in robotics and AI (International Federation of Robotics (IFR) 2021).

The article is organized as follows: After a brief review of the literature in section 2.2, section 2.3 presents stylized facts of the patent data analysis. Section 2.4 introduces the theoretical model. After outlook and discussion in section 2.5, section 2.6 concludes.

[6]See: "Robotique, impression 3D : des technologies propres à l' industrie", `https://www.insee.fr/fr/statistiques/3896461?sommaire=3856444` (June 12, 2021).

2.2 Literature

This chapter is related to several research areas. First, it relates to the literature on firms' adoption or innovation decisions for automation technologies (e.g. Acemoglu and Restrepo 2017; Dechezleprêtre et al. 2021). However, not only does this chapter focus on supply side mechanisms but it also analyzes how automation might affect the type of goods that can be produced and how demand side factors could induce adoption of new technologies. Second, the article relates to the vast literature that studies innovation in international markets (e.g. Bilir and Morales 2020; Coelli et al. 2020; Flach and Irlacher 2018) and to the growing empirical and theoretical literature that analyzes the relation between automation and international trade (Freund et al. 2020; Koch et al. 2019) as well as its impact on the location of production (De Baker et al. 2018; Krenz et al. 2018). Finally, the theoretical set-up is linked to the discrete choice model that was introduced in the previous chapter. A detailed discussion on related theoretical literature (e.g. Anderson et al. 1992; Hadfield 1991) can be found in section 1.2.

Previous research on automation focuses primarily on the supply side. In the framework provided by Acemoglu and Restrepo (2018b, 2019), part of a continuum of tasks required for production is automated. Acemoglu and Restrepo (2018b, p. 51) discuss how the "*productivity effect*", i.e. a rise in output caused by automation of tasks, and the "*displacement effect*" affect equilibrium wages. The latter effect captures the substitution of human labor in production which reduces labor demand and thereby equilibrium wages. The authors note that the impact of automation on wages might be negative especially for mediocre machines, i.e. those machines where the increase in productivity is weak, still sufficient for adoption but dominated by the impact through the reduction in the labor share (Acemoglu and Restrepo 2018b, p. 48, 52).

Koch et al. (2019, p. 11ff.) build on this framework in a theoretical context with heterogeneous firms which can pay (higher) fixed costs for adoption of robots. The technology is assumed to decrease marginal costs through lower rental rates for capital than hourly renumeration for labor. The set-up below models adoption of automation technology on the supply side as in Koch et al. (2019, p. 11ff.) and Acemoglu and Restrepo (2018b, p. 50). However, new technologies such as 3D printers also have an impact on the *type* of goods that are or could be produced (Freund et al. 2020, p. 5). In the theoretical model in section 2.4, a brand that switches from traditional to automation technologies is able to produce custom goods. A reduction in production costs and/or consumers' valuation of tailor-made products can induce adoption of automation technologies.

But beyond *displacing* tasks, automation potentially creates new ones. Acemoglu and Restrepo (2019, p. 4) label the creation of new tasks performed by human labor as the "*reinstatement effect*" of automation. Given that the range of tasks is fixed to the unit interval in the model below, there is only a *displacement effect*. Moreover, the share of tasks that can be automated is taken as given. This is only for tractability. Innovation in automation technologies could likely modify the range of tasks as well. This is difficult to measure empirically though, e.g. an "automation" patent identified in section 2.3 might, inter alia, simply raise the share of automatable tasks, change the type of tasks or improve their efficiency.

The model below is a partial equilibrium model and therefore does not yield predictions on the impact of customization on the equilibrium wage rate. However, when automation has a demand side effect through customization the *productivity effect* could likely be attenuated. Bessen (2018, p. 3) argues that personalization, higher product quality, or lower lead times could boost demand such that output and labor demand increases at the same time as the labor share in production decreases. This effect would be in line with the argument in Acemoglu and Restrepo (2018b, p. 48, 52), that negative employment effects through *displacement* could be compensated when machines are beyond average, e.g. able to increase demand through customization (better quality).

Exploiting a data set on the manufacturing sector in Spain, Koch et al. (2019, p. 4) provide *micro* evidence of a positive selection effect of more productive firms in robot adoption and an increase in labor employment of innovating firms. Yet, when controlling for productivity, skill intensity of firms has a negative effect on the likelihood to adopt robots (Koch et al. 2019, p. 4). The modelling of the supply side in section 2.4 draws on the Melitz (2003) (and Bustos (2011)) type model in Koch et al. (2019, p. 10ff.). Yet, in contrast to their model, automation is not restricted to affect the supply side only. The modelling of proliferation as an increase in *perceived* quality on the demand side associates the set-up with the literature on quality in international trade (e.g. Kugler and Verhoogen 2011).

Furthermore, there is the discussion whether and how automation and particularly 3D printing affect trade flows and the structure of global value chains (De Baker et al. 2018; Freund et al. 2020; WTO 2018). Examples of *reshoring* to developed countries are mostly based on anecdotal evidence or case studies and do not find consistent empirical evidence.[7] Oldenski (2015) analyzes potential reshoring activities by US multinationals. If at all, she finds evidence in favor of more offshoring than reshoring activities for US firms (Oldenski 2015, p. 3f.).

In order to study trade effects of 3D printing, Freund et al. (2020) focus on the hearing aid industry where - especially since the year 2007 - production processes are almost exclusively based on 3D printing (Banker 2013). The authors apply a difference-in-differences design to estimate the effect on country level exports, taking the year 2007 as cutoff: The control group encompasses exports classified as high-tech or as belonging to chapter 90 in the Harmonized System (HS) apart from hearing aids (HS 902140) (Freund et al. 2020, p.

[7] WTO (2018, p. 107ff.) provides a brief literature review.

8, fn. 10). They find a positive and significant effect on exports after 2007 (Freund et al. 2020, p. 9). Furthermore, the authors find that exports from middle and high income countries expanded at the same time as imports to countries with a revealed comparative disadvantage in the production of hearing aids increased and they relate that to improved and affordable access for people in these countries to hearing aids (Freund et al. 2020, p. 15). This indicates that AM might increase trade. The data in section 2.3.3 reflect that most patents classified as customization in AM are targeted to the health sector and an important share also specifically to hearing aids.

There is a growing literature using text analysis to classify patents in certain groups such as Dechezleprêtre et al. (2021), Hemous and Olsen (2014), and Mann and Puettmann (2020) for automation, Buarque et al. (2019) for artificial intelligence (AI), Bessen and Hunt (2007) for software, or Banholzer et al. (2019) for process and product innovations. The former rely on a combination of keywords and technical classification based on International Patent Classification (IPC) or Cooperative Patent Classification (CPC) symbols.[8] Similar to the classification of process and product innovations in Banholzer et al. (2019), the data set for customization invention below is not restricted to certain technical classifications a priori. On the contrary, after identifying these inventions, CPC codes actually allow to study their distributions across technological and industrial fields. In contrast to Banholzer et al. (2019), Bessen and Hunt (2007), and Mann and Puettmann (2020), however, there is no prior manual classification of patents to train an algorithm. Instead, a purely keyword based match as in Buarque et al. (2019, p. 3) and Dechezleprêtre et al. (2021, p. 6f.) is applied to the data. It differs from the approach of Dechezleprêtre et al. (2021) as they are inferring from keyword matches certain IPC and CPC classes for automation. In section 2.3.1, the keyword search is not restricted to any production method.

EPO's Worldwide Patent Statistical Database (PATSTAT) Online provides abstracts and titles of patents but not the text of the claims. The condition that keywords need to appear in the abstract is likely more restrictive than scanning all claims. The quantity of claims is usually - and also in this data set - skewed to the right.[9] The number of claims can also be interpreted as a quality measure (Squicciarini et al. 2013, p. 30ff.). However, more claims would also mechanically increase the likelihood of a keyword match. An ad-hoc keyword search among European Patents through the EP full text database

[8]The IPC is managed by the World Intellectual Property Organization (WIPO) (see `https://www.wipo.int/classifications/ipc/en` (May 14, 2021)). The CPC is a joint project between the European Patent Office (EPO) and the United States Patent and Trademark Office (USPTO) (see `https://www.cooperativepatentclassification.org` (May 14, 2021). It is more detailed than the IPC. This chapter uses CPC codes, see section 2.3.

[9]In contrast to the wording of the claims, the number of claims of a publication is provided in PATSTAT Online (see table TLS211_PAT_PUBLN, variable publn_claims).

shows that the number of matching documents in claims but not abstracts is more than four times larger than the reverse.[10] While there are also outlayers for the length of the abstract, mean and median are very close. Mann and Puettmann (2020, p. 8) argue that due to the "matter-of-fact language [of patent texts] [...], the occurrence of a word is more important than the frequency of its appearance". On the other hand, Dechezleprêtre et al. (2021, p. 7, 71) explicitly include a frequency threshold for keywords in their analysis, e.g. that a wordstem appears at least five times. Below, the classification of patents into customization is based on the *occurrence* and not on the *frequency* of a word(stem) as it seems difficult to justify a reasonable threshold value.[11]

2.3 Empirics

The analysis uses patent data provided by the European Patent Office (EPO) as a proxy for firms' innovative activity. This empirical section is divided into three parts: Based on a keyword search of patents' abstracts, the first step is to spot customization inventions. There is no prior condition on the industrial classification or whether the invention concerns, for instance, a production process, a manufacturing product, or services. In contrast, the second subsection categorizes patents as additive manufacturing (AM) entirely based on a technical classification, the Cooperative Patent Classification (CPC). Finally, the third subsection reports the main stylized facts of the analysis of customization and AM patents. Patents (imperfectly) reflect firms' investment in research and development (R&D).

A patent grants applicants the right to hinder unauthorized reproduction, usage or distribution of their invention in the jurisdiction and for the time the patent is valid (EPO 2020d). A filing therefore indicates in which jurisdictions firms see market potential for their invention (Coelli et al. 2020, p. 4). The procedure to obtain a patent is costly, patents should therefore be a proxy for innovations that are expected to have high market potential. Therefore, section 2.3.3 also studies where firms seek protection for their customization and AM patents. For patent grant, the European Patent Convention requires that "inventions [..] are new, involve an inventive step and are susceptible of industrial application" (Article 52(1) of the European Patent Convention).[12] Note that patenting an object produced by AM technology further demands that "it is not possible to define

[10]Based on search among European patents in EP AB2021/20 (retrieved on May 19, 2021.), see table in appendix B.1.

[11]Banholzer et al. (2019, p. 7, 51f.) classify claims in "process claims" based on whether a keyword is mentioned at least in the first two to five terms. Yet, certain very general phrases do reappear especially at the beginning of abstracts, e.g. "the invention relates", "problem to be solved", which limits the applicability of conditions on the first x words for patent abstracts.

[12]See `https://www.epo.org//law-practice/legal-texts/html/epc/2020/e/ar52.html` (June 12, 2021)

the claimed product other than in terms of the process of manufacture" (EPO 2020c). As argued in OECD (2009, p. 27), patents link firms' R&D activity as well as innovation and final application, for instance, in manufacturing processes. They can therefore be interpreted as output measures but also as inputs for new inventions, especially at the industry level. The former is important when customization inventions should be related to product customization for end consumers or intermediate goods producers.

Firm-level data on R&D investment in or adoption of new technologies such as 3D printers are scarce. Moreover, as adoption rates within a given industry might (yet) be low, there is the risk of little variation. The TIC 2018 survey reports that 3D printing is used by only 4% of enterprises with more than 10 employees in France, but by 16% of enterprises with 250 or more employees (Insee 2019a). Moreover, it seems difficult to find data on the product-level of customization, i.e. whether a product or service is perfectly tailored to a buyer or not. Finally, the analysis requires knowledge about the spread and distribution of the innovative activity in global markets. To overcome these challenges, patent data offers several advantages: It can capture recent trends in technologies such as 3D printing that potentially take some time until they are widely adopted for production.[13] There is detailed information on classification in technology fields similar to industry or sector classifications. The patent data further has a global reach. Finally, text analysis of abstracts enable keyword search. These texts should indicate the intended use, e.g. to produce or offer customized goods, of the invention.

The data source for this analysis is the PATSTAT Online 2020 Autumn Edition. The study includes only patents that are granted to make them more comparable in terms of quality. Patents filed under the Patent Cooperation Treaty (PCT) are excluded.

Applicants frequently search patent protection for the invention in more than one jurisdiction which inflates the number of applications related to one and the same invention in the data set. So called patent families allow to identify separate inventions. Hence, the focus of the current analysis lies on DOCDB simple patent families which is also common in the literature (e.g. Aghion et al. 2016, p. 15). Patent applications that share the DOCDB Family identifier claim the same priority.[14] Unless specified otherwise, patent family and invention denotes DOCDB patent family in the following.

In the data set, as members of the same patent family, several abstracts refer to the same invention but the wording might slightly differ across filings. Considering applications

[13] See section 2.2 for a discussion of papers that used a similar approach to identify patents related to digital technologies.

[14] Note that there is also the broader concept of INPADOC extended patent family where applications of the same extended family are related through similar (but not always identical) content. Patent applications that share the same identifier for an extended family will claim the same priority as at least one other member of this family (See `https://www.epo.org/searching-for-patents/helpful-resources/first-time-here/patent-families/inpadoc.html`)(August 31, 2020).

instead of inventions could therefore bias results. The assignment to technical fields and industries is therefore at the DOCDB patent family level.[15] The procedure associated with patent grant takes time and varies across jurisdictions (OECD 2009, p. 46). The data set is therefore restricted to applications up until 2016.[16] One important caveat of the analysis is that the usage of patent data can bias results towards industries where patenting is more common, possibly also due to strategic aspects (OECD 2009, p. 28).

2.3.1 Methodology: Classifying Customization Inventions

The usage of patent data is an attempt to proxy trends in customization. In order to identify patents related to customization, all patent applications were retrieved from PATSTAT Online where the following conditions are *all* met: the patent is filed between 1980 and 2016, it is granted, its abstract is in English and matches with at least one keyword or wordstem specified in the keyword list.[17] The majority of all patent filings in PATSTAT Online have English abstracts. This is convenient to not only study a single country but also the global dimension of filings. For consistency, the analysis considers English abstracts exclusively as translations can lead to additional noise. Given the level of detail, abstracts are considered more informative than patents' titles.

The choice of keywords relies on synonyms for customization reported in English and American dictionaries.[18] The expressions *build to order*, *engineer to order*, and *precision medicine* are included for the classification of inventions. The former two terms are especially used in engineering, the latter is obviously specific to medical sciences. While patents that match with theses words will likely be part of these specific fields, the match per se does not imply a certain production technology or the classification in process or product innovations. Hence, these terms are included in the further analysis.

There are 55.596 distinct applications in the data set that match with at least one of the keywords. These applications are partitioned in 39.886 distinct DOCDB patent families. Given that the theoretical model in section 2.4 is based on firms, the further analysis focuses on applications and inventions where at least one applicant is a company. This results in 45.499 applications and 30.946 DOCDB patent families.[19]

Table 2.1 summarizes the share of inventions that contain the respective word(stem)s

[15]Thereby, the condition is whether at least one application in the family is assigned to the respective class.

[16]OECD (2009, p. 46) reports that the procedure can take several years. After 2016, the number of applications drops remarkably. It is difficult to disentangle whether and to what extent this is because of decreasing patenting activity or simply due to the time lag.

[17]See table B.1 for the detailed list of word(stem)s.

[18]Sources: Oxford University Press (Lexico.com), Cambridge University Press (Cambridge Dictionary), Merriam-Webster, Collins Dictionary. See table B.2 for more details.

[19]Shares are equivalent to 81.84% and 77.59% of all applications and inventions in the data set, respectively. The average family size is slightly higher when companies are applicants.

Table 2.1: Share of Matching Inventions [%] to Word(stem)s

personalize	18.62
tailored	16.49
individualized	6.03
custom(ized)	62.93
made-to-order/measure	0.26
engineered-to-order	0.01
built-to-order	0.14
bespoke	0.08
precision-medicine	0.01

Notes: Data source: PATSTAT Online 2020 Autumn Edition; Share of granted inventions (DOCDB patent families), classified as customization, filed in 1980-2016, with English abstracts, and where at least one applicant is a company. For detailed list of wordstems see table B.1.

across all abstracts of the patent family. Aggregated over time, usage of word(stem)s related to personalized as well as customized and tailored seems most popular.[20] The wordcloud of abstracts (see figure 2.1) depicts many wordstems related to information and communication technologies, e.g. “comput”, “data”, “inform”, “communic” or “messag”.[21] Section 2.3.3 takes therefore a closer look at the technical fields of applications.

2.3.2 Methodology: Classifying 3D Printing Inventions

The invention of 3D printing is often attributed to patent US4575330 “Method and apparatus for production of three-dimensional objects by stereolithography” (Hull 1986) filed at the USPTO in 1984. Its abstract describes how layers are “automatically formed and integrated together to provide a step-wise laminar buildup of the desired objects” (Hull 1986). Even at the very beginning of additive manufacturing (AM), the technology was hence associated with automation and the flexibility to create (almost) any object. The chapter therefore includes the study of AM related patents in its analysis of customization trends. Other 4IR technologies such as robots also provide a high degree of flexibility.[22]

[20]There is some variation in the usage of the words over time (see figure B.1), e.g. the frequency of the term “tailor” has decreased over the past 40 years.

[21]The wordcloud is based on a maximum of 100 words across abstracts of all applications, removing punctuation, numbers, symbols, and English stopwords. The wordcloud reflects that there are some very general terms that reappear frequently in patent abstracts, independent of a specific topic, e.g. “invent” or “disclos”.

[22]For a discussion on so-called “*core*” and “*enabling*” technologies of the fourth industrial revolution (4IR) as well as their applications, see Ménière et al. (2020, p. 19f.).

Figure 2.1: Wordcloud of All Applications classified as Customization

Notes: Data source: PATSTAT Online 2020 Autumn Edition; Wordcloud is based on abstracts of granted applications, with English abstracts, classified as customization, filed in 1980-2016, and where at least one applicant is a company.

Nevertheless, production steps usually involve combining, processing, welding or cutting of intermediate inputs. Production of bespoke products would require adaption of inputs whereas AM processes already tailor output by the very nature of the layer-by-layer production. In theory, this is captured by an investment in the machine or R&D to serve the infinitum of versions along the preference space (see chapter 1) and the automation of tasks (see section 2.4).

The Cooperative Patent Classification (CPC) contains several symbols related to AM. All patents that were filed at least in the year 1980 were downloaded from PATSTAT Online given that they match at least with one of the CPC symbols in table 2.2.

Dechezleprêtre et al. (2021, p. 6) include 3D printing in their paper but rely on a text based classification with word(stem)s “3D print”, “additive manufacturing” or “additive layer manufacturing”. The approach of a purely CPC based classification comes with the risk of missing some patents that are (re)classified retrospectively, e.g. due to the fact that CPC symbols were introduced after the patent was filed. On the other hand, there are several synonyms for 3D printing such as rapid prototyping that might be missed by a text based search. Furthermore, it would not cover filings that mention only the method on which AM is based such as stereolithography (SLA), selective laser sintering (SLS) or fused deposition modeling (FDM).

The identification of customization inventions in section 2.3.1 focuses on identifying whether a patent targets customization in general without restricting technical fields. For this reason, applying a text based search is adequate. In contrast, inventions related

Table 2.2: CPC Section and Main Groups Related to Additive Manufacturing

Symbol	Name
B33	Additive manufacturing technology
B29C 64/00	Additive manufacturing, i.e. manufacturing of three-dimensional [3D] objects by additive deposition, additive agglomeration or additive layering, e.g. by 3D printing, stereolithography or selective laser sintering
B22F 10/00	Additive manufacturing of workpieces or articles from metallic powder
B22F 12/00	Apparatus or devices specially adapted for additive manufacturing; Auxiliary means for additive manufacturing; Combinations of additive manufacturing apparatus or devices with other processing apparatus or devices

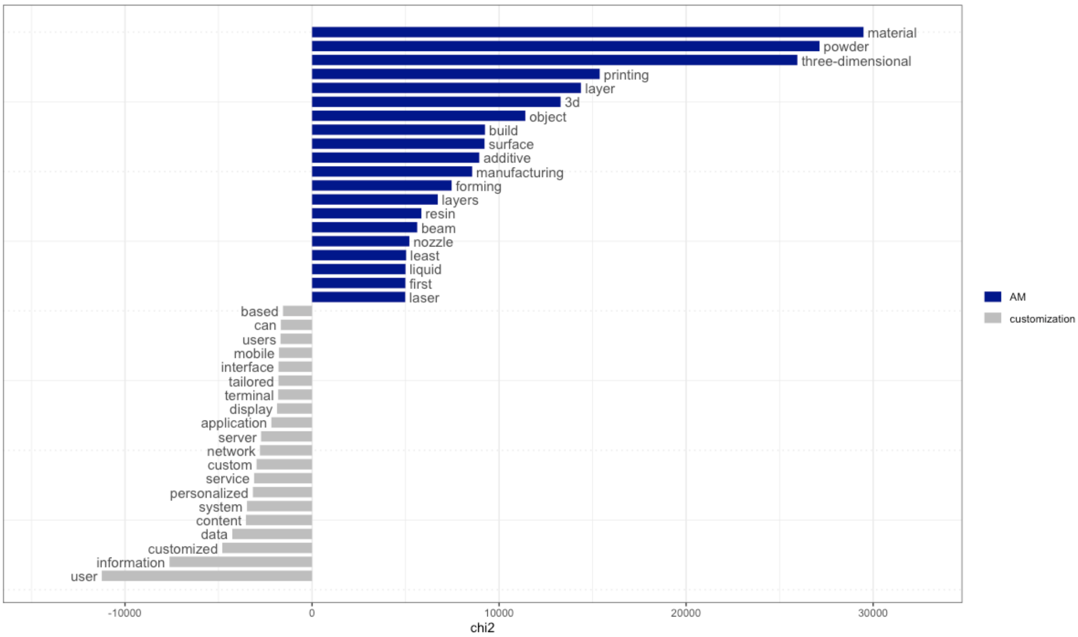
Source: Cooperative Patent Classification - Table, CPC definitions, `https://www.cooperativepatentclassification.org/cpcSchemeAndDefinitions/table` (May 15, 2021).

to AM are about a certain production technology. Based on the CPC symbols in table 2.2, the analysis below tries to spot potential applications of AM and its relation to customization.

The data set for AM encompasses fewer applications (15.444) and 7.632 distinct DOCDB patent families. For consistency, the data set is also restricted to granted patents with English abstracts where at least one applicant is a company. The wordcloud in figure B.2 refers to many more technical word(stem)s such as “form”, “powder”, “layer”, “surfac” than figure 2.1. Abstracts in AM do not frequently mention word(stem)s related to the application of the technology.

A direct comparison of the relative occurrence of words in abstracts of patents concerning additive manufacturing and customization is depicted in figure 2.2.[23] The figure shows that abstracts of the two data sets differ significantly. It is remarkably more probable that an AM patent mentions terms such as “material”, “powder”, or “object”, whereas customization patents are more likely to contain “information”, “customized”, or “user”. Obviously, the keyword search in section 2.3.1 is based on some of these words. However, figure 2.2 indicates that abstracts of AM patents are relatively unlikely to refer to personalization. By its technical features, 3D printing is a potential tool for customization. Yet, applicants are relatively unlikely to describe these applications in the abstracts.

Figure 2.2: Comparison of Terms' Frequency in Abstracts



Notes: Data source: PATSTAT Online 2020 Autumn Edition; "Keyness plot" (Welbers et al. 2017, p. 258f.) with quanteda package in R. Comparison of term frequencies in abstracts from applications classified as customization (gray) and AM (blue) as in section 2.3.1 and section 2.3.2.

2.3.3 Customization and 3D Printing: Stylized Facts

Figure 2.3 plots the number of granted inventions over time. Customization inventions are indicated in black, the red line depicts inventions that are linked to 3D printing. The green shaded area maps the overlap between both data sets. DOCDB patent families (inventions) are assigned to their earliest filing year.

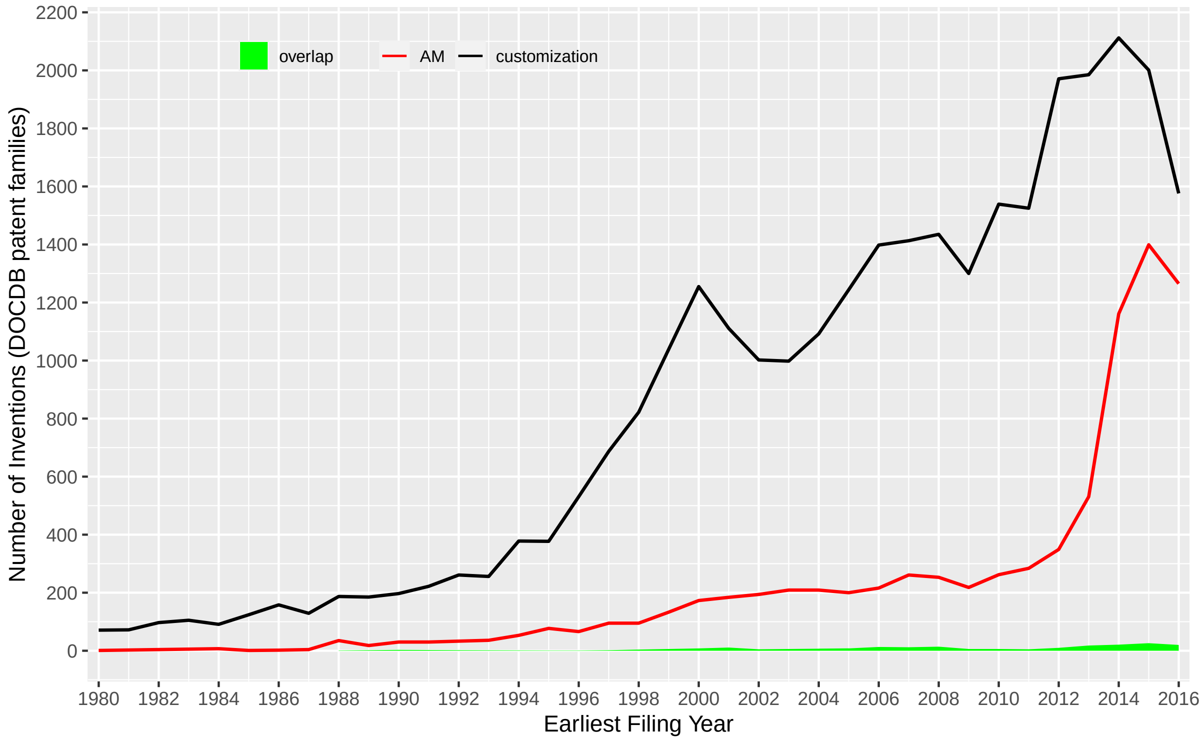
Inventions related to customization almost doubled over the second half of the 1990s. After a slump over the first years of the century, they reach a maximum in 2014. The drop in the past two years could indicate a reduction in (granted) filings or still a potential time lag due to administrative procedures. The widely discussed trend for customization (see discussion in section 2.1) is reflected by a rise in patent filings up to 2014 that mention respective keywords.

Stylized Fact 1. Time trend: The number of inventions related to customization has increased over the past two decades.

There is also a rise in patent filings related to 3D printing up to 2015. The level of granted filings is lower than for customization but the increase in past years is steeper. From 2012 to 2015, the number of granted inventions tripled. Note that only around 60% of all applications in the AM data set are granted and that the median filing year of all

[23]Figure 2.2 is generated with R package quanteda (see Welbers et al. 2017, p. 258f.).

Figure 2.3: Number of Granted DOCDB Patent Families assigned to Earliest filing Year



Notes: Data source: PATSTAT Online 2020 Autumn Edition; Classification in customization and AM inventions based on section 2.3.1 and section 2.3.2.

applications is 2014. This might be a potential indication for the growing relevance of the technology in the nearby future and that looking only at granted applications might not capture rising R&D activity and research output in AM.[24]

The flexibility of AM enables production of custom goods. However, there are only few applications that are contained in both datasets, i.e. inventions that are assigned to CPC symbols in table 2.2 and whose abstract contain at least one keyword in table B.1. The share of customization applications in the AM data set is equivalent to 3%, AM makes up around 1% of customization patents. This might be due to the technical nature of the descriptions of patent abstracts in AM (figure B.2) which limits the effectiveness of a keyword search. By its technical features (Weller et al. 2015) it is a technology *enabling* customization. Freund et al. (2020) analyze the hearing aid industry that produces with AM processes. In the current analysis, patents that are specifically assigned to hearing aids (CPC symbol: H04R 25/00) make up 13% of the overlapping data set, while more than half are related to health (A64). Note that even the anecdotal evidence on custom footwear produced by 3D printing (The Economist 2018) is mirrored by around 8% of these applications that are linked to footwear (A43).

Yet, concerning customization, the wordcloud in figure 2.1 suggests a strong link to ICT

[24]The number of all filed inventions grew by almost 80% from 2015 to 2016.

that is consistent with the distribution of customization inventions across CPC symbols.

Stylized Fact 2. The main share of "customization" patents are filed in digital and communication technologies.

The major shares of DOCDB patent families concerning personalization in general belong to "G06 Computing, Calculating; Counting" (28.68%) and "H04 Electric Communication Technique" (16.70%) (see table B.3). Importantly, the wordstem personal is not sufficient for inclusion in the data set as otherwise the number of patents would be inflated by abstracts mentioning personal computers.[25] Patentability of software or business methods at the United States Patent and Trademark Office (USPTO), for instance, became common in the 1990s (Cockburn and Wagner 2007, p. 2; Bessen and Hunt 2007, p. 158). Hence, the rapid rise in inventions could be driven by a change in legal conditions but also by technical progress as argued by Mann and Puettmann (2020, p. 6f.).[26]
Intuitively, personalization requires information about (potential) customers, their needs and preferences. Innovations in ICT and particularly customization inventions in ICT related areas might have triggered increased customization in other (manufacturing) industries because it allows to gain or share information about consumers and facilitates communication with purchasers.[27]
A recent slight increase in patenting in machinery and AM that mention customization keywords is not sufficient evidence for that. Yet, it could be that personalization in the remaining fields takes some time to be observable in patent data, for instance, due to the time lag of the administrative procedures or timely R&D.
Figures 2.4 and 2.5 depict the share of patent families belonging to respective technology sectors and fields as a share of all inventions in the customization data set.[28] The majority of patents belongs to the sector of electrical engineering where major fields are computer technology, digital communication, and IT methods for management. The data furthermore reflects that personalization seems important for medical technology where one would also expect a high preference for individualization on the demand side, i.e. that purchasers are more sensitive to *fit costs* (see section 1.3) or quality which allows customizing firms to charge higher prices (see section 2.4.1).
After a sharp rise in the 1990s, the share of ICT related inventions remains dominant

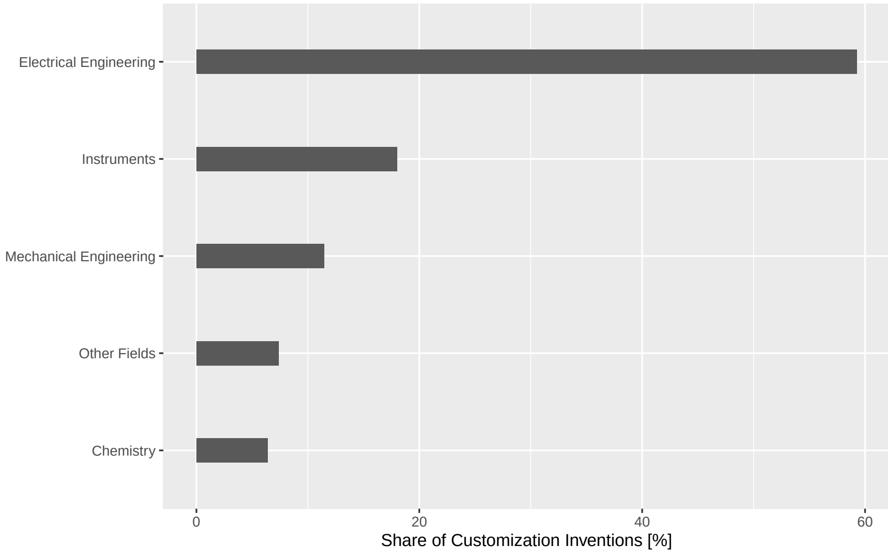
[25]The share of applications belonging to a certain CPC symbol depends very much on the level of aggregation. CPC is divided into section, classes, subclasses, groups, and main groups, see `https://www.cooperativepatentclassification.org/cpcSchemeAndDefinitions/table` (May 15, 2021).

[26]Note that the development of the black line in figure 2.3 would also mirror the dotcom bubble and its burst in the beginning of the century.

[27]See quote below in section 2.6.

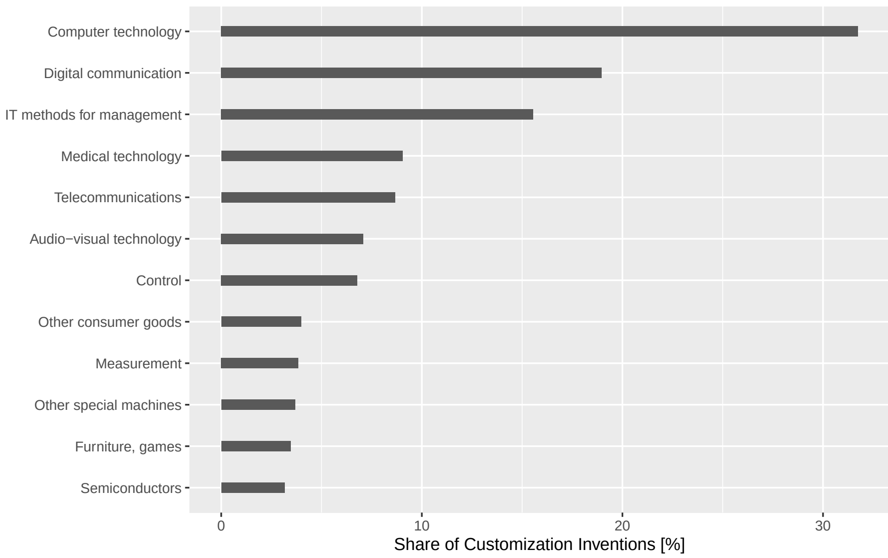
[28]Assignment of inventions to sectors and fields is based on the IPC8 - Technology Concordance (World Intellectual Property Organization (WIPO) 2019). It is not mutually exclusive. Figure 2.5 shows the twelve fields with the highest shares.

Figure 2.4: Technology Sectors (WIPO)



Notes: Data source: PATSTAT Online 2020 Autumn Edition; Classification in customization inventions as in section 2.3.1.

Figure 2.5: Technology Fields (WIPO)



Notes: Data source: PATSTAT Online 2020 Autumn Edition; Classification in customization inventions as in section 2.3.1.

and has even been increasing over the past years. Medical technology or machinery do not experience increases in relative terms. However, looking at absolute filings in these fields, there is an observable - though small - increase in the past five years. However, the dominance of ICT could merely reflect a higher propensity to patent in that sector compared to others (Dernis et al. 2015, p. 30). Yet, the share of ICT inventions in this data set is higher than what one would expect considering the share of electrical engineering in total patenting over the same time interval.[29]

Stylized Fact 3. The major share of "customization" inventions can be classified as mixed product-process patents. More than a third are pure process patents.

Patents can protect new products or processes. For the theory section below, it is crucial whether technologies differ in marginal costs (process productivity) or fixed costs or both. Banholzer et al. (2019, p. 6) provide a list of keywords to classify patents in process, product or mixed process-product patents.[30] Applied to the abstracts in this data set, most DOCDB patent families match with both process and product keywords (47.66%) or are pure process (36.78%) inventions. Around 8% contain only words related to product patents.[31] Banholzer et al. (2019, p. 14) argue that classification of patents in process patents based on abstracts is less restrictive than based on claims: Many abstracts contain the word "method" (around 50% in the current data set, see also in figure 2.1) but at the same time only a small share of claims contains process keywords. Given that Banholzer et al. (2019) find a smaller total share of process innovations based on all abstracts in their data set, customization inventions seem to be relatively more often protecting process innovations. In the theory section, adoption of the customization technology is modeled as affecting marginal costs of firms.

Stylized Fact 4. Customization inventions are associated with automation, big data, or artificial intelligence.

The so-called *Fourth Industrial Revolution* (Ménière et al. 2020; Schwab 2015) is often associated with production of custom goods. As patent data suggests there is a strong link between customization and ICT. ICT, or specifically big data, and artificial intelligence are complementary technologies to automation of production processes.[32] Assigning in-

[29]Data on total patenting by technology field (1980-2016) based on WIPO (2021a) statistics database.

[30]Their main analysis is based on claims where they also include relative measures of how many claims contain product vs. process keywords (Banholzer et al. 2019, p. 8).

[31]Banholzer et al. (2019, p. 6f.) are more strict in the analysis of patent abstracts: They classify a patent as process patent exclusively as soon as the abstract contains one match with the list of keywords, and all remaining patents as product patents. Here, this would consequently result in more than 80% process inventions and 15.56% product inventions.

[32]Ménière et al. (2020, p. 19f.) argue that ICT software and hardware are part of "*core technologies*" and account AI and additive manufacturing as "*enabling technologies*" of the *Fourth Industrial Revolution.*

Table 2.3: Share of Customization Inventions Across TOP 10 Application Authorities, 1980-2016 [%]

Application Authority	All Inventions	Automation	AI	Big Data
US	64.32	65.51	82.90	70.66
CN	22.22	23.00	17.53	18.81
EP	11.10	9.27	9.96	6.49
JP	6.52	4.41	3.25	3.39
KR	5.92	5.32	5.63	7.09
CA	5.48	4.37	3.25	4.34
TW	3.35	2.66	2.16	2.55
AU	2.41	1.99	1.95	2.50
GB	1.41	1.42	1.30	1.00
MX	1.22	1.00	0.65	00.73
All		13.30	14.58	1.49

Notes: Data source: PATSTAT Online 2020 Autumn Edition; Classification in customization inventions as in section 2.3.1.

ventions to different technology areas based on CPC codes and/or text search among abstracts following Buarque et al. (2019, p. 17) and World Intellectual Property Organization (WIPO) (2021b) for artificial intelligence (AI), Dechezleprêtre et al. (2021, p. 6) and UK IPO (2014b, p. 1) for automation and robotics (including AM) as well as UK IPO (2014a, p. 1f.) for big data shows that their absolute number has increased and covers around 30% of customization patents in 2016.

In terms of the geographical distribution, the majority of customization inventions are filed at the USPTO, followed by China and by filings at the European Patent Office (EPO).[33] Firms seek protection for their inventions in jurisdictions where they expect future sales or usage of the firms' patented products or processes. Filings for the US are over-proportionately related to 4IR technologies. There might be some home bias for patent filings of important US firms in the ICT sector. Yet, filings are not mutually exclusive but come at some costs. Firms seem to attribute a high market potential for their customization inventions in the US market, potentially indicating a high sensitivity to obtaining the *ideal version* by local purchasers. Ménière et al. (2020, p. 10) find the dominance of filings by the United States in technologies linked to the *Fourth Industrial Revolution* in general.

The increase in filings and granted inventions related to customization and 3D printing

[33]Note that even though the majority of *all* filings have abstracts in English, there might be some bias concerning the application authority due to the condition on patent abstracts being in English.

point to a rising relevance of personalization. Moreover, the high share of patents related to ICT as 4IR *core* technologies, big data and automation are an indication that there are changes in production processes. The following section adopts the theoretical model of the previous chapter to account for the stylized facts found in patent data.

2.4 Theory

The analysis of patent data in the previous section revealed that patent filings related to customization are especially prevalent in digital technologies and technical fields that are related to automation. This suggests a link between automation on the supply side and the offer of customized products or services. The distribution of filings and inventions across firms is skewed, few firms own many patents. The theoretical model is based on heterogeneous firms. One important caveat is that the set-up below focuses on the economic features of 4IR technologies, it does not model investment in R&D but *adoption* of the invention.

Chapter 1 developed a multinomial logit model where consumers choose between brands that either offer differentiated or customized products. When consumers do not receive the *ideal* version, they need to cover *fit costs*. For a given mill price, the *delivered* price is higher and resulting demand lower for the brand that offers fewer differentiated versions. In the indirect utility function, proliferation is therefore equivalent to an increase in quality (section 1.5.1).

This chapter builds on this equivalence result but relaxes the assumption of consuming a single product in an industry. Alongside the argument in the previous chapter, proliferation - and ultimately customization - are modeled as an increase in quality which closely relates the model to the literature on quality in international trade, especially to Kugler and Verhoogen (2011, p. 319ff.).

Depending on their nest(ed) structure, most models of multi-product firms can be classified in "market segmentation" and "market interlacing" (Allanson and Montagna 2005, p. 589): In the former case, the "nest" refers to a firm offering different variants of a product, while in the latter case the "nest" represents a product offered by differentiated firms.

2.4.1 Consumers

There is a representative consumer with a constant elasticity of substitution (CES) utility function.[34] Consumers derive utility from the consumption of differentiated products.

$$U = \left[\int_{\omega\in\Omega} \left(s\left(n(\omega)\right)x(\omega)\right)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \tag{2.1}$$

where $\sigma > 1$ is the elasticity of substitution between brands, $\omega \in \Omega$ is the index for the brands that are active in the market. $x(\omega)$ is the amount that consumers purchase from a given variety. Every firm offers exactly one variety but might further differentiate varieties in versions. One might think of competition between brands (firms) offering footwear (here: varieties) in different colors (here: versions). Theoretically, this is equivalent to assuming that equation (2.1) nests a sub-utility function on the brand level where demand for versions is determined by expected *fit costs* which are a function of the number of versions a brand offers.[35]

The function $s(n(\omega))$ captures the sensitivity of consumers to proliferation.[36] For the moment, it is a function defined on the support $[0, \infty)$. The following conditions are imposed:

$$s'_{n(\omega)}(n(\omega)) > 0 \qquad s(n(\omega) = 1) = \underline{s}(\omega), \underline{s}(\omega) > 0 \qquad \lim_{n\to\infty} s(n(\omega)) = 1 \tag{2.2}$$

That is, an increase in the number of versions that a firm is offering leads to an increase in the perceived quality of the product. The underlying idea is the expectation based purchase decision established in the previous chapter: Consumers do not observe the exact location vis-à-vis their *ideal* version but form an expectation about the *delivered* price, i.e. the expected distance in terms of *fit costs*. This implies that the *delivered* price of a brand is identical for all consumers.[37] Increased proliferation makes it a priori more likely that the consumer gets the *ideal* version which increases *perceived* quality of the brand. Note that, in any case, a consumer demands only one version of a given brand. They care about $n(\omega)$ only to the extent that it is a (quality) signal for proliferation.

The value of the function $s(n(\omega))$ is restricted to the domain $[\underline{s} > 0, 1]$. $\underline{s}(\omega)$ is the minimum level of quality attributed to variety ω when the brand offers only one version.

[34]The demand structure goes back to Dixit and Stiglitz (1977, p. 298ff.) and is applied to international trade as in Melitz (2003, p. 1698ff.) and considers quality in particular as in Kugler and Verhoogen (2011, p. 319ff.).

[35]In Allanson and Montagna (2005, p. 591), the sub-utility is a CES function over all firms' versions. Equation (2.1) should therefore be analogous to the case of brand specific quality weights but perfect substitutes on the *within* brand level.

[36]The incorporation of quality in the utility function follows Kugler and Verhoogen (2011, p. 319) who denote $q(\omega)$ as a general quality function.

[37]Note that in the discrete choice model in section 1.3, it is the idiosyncratic component $\epsilon^b_{j|z}$ which ensures that at any location $z \in [0, 1]$, the demand is strictly above zero for all brands.

The maximum quality is limited to 1. Put differently, as long as purchasers are not guaranteed that they get their *ideal* version, $n(\omega) \to \infty$, they discount the amount they consume.

Consumers maximize utility subject to the budget constraint. Demand is then given by

$$x(\omega) = X\left(s(n(\omega))\right)^{\sigma-1}\left(\frac{p(\omega)}{P}\right)^{-\sigma} \tag{2.3}$$

$p(\omega)$ is the price of variety ω and P is the aggregate price index.[38] For a given mill price, $p(\omega)$, consumers' demand is increasing in $n(\omega)$.

2.4.2 Producers

There are two production technologies, $T = \{D, C\}$, denoted as differentiation and customization technology. In order to establish a brand, firms need to pay sunk entry costs, f.[39] As in a standard Melitz (2003) model, upon paying the sunk entry costs, brands receive a productivity draw, ϕ, from a cumulative distribution function $G(\phi)$ with support $(0, \infty)$ (Melitz 2003, p. 1701).

Differentiation among brands is costless and firms will consequently develop horizontally differentiated brands. Every brand is small with respect to the market, its decisions do not affect market aggregates. It takes price index and aggregate demand as given. Brands are competing on the level of their variety but none of them is offering more than one variety. The latter is important to exclude strategic interaction between and within firms (Bernard et al. 2011, p. 1278, fn. 5).

Firms choose between the technology, $T = \{C, D\}$, and the number of versions, $n_D(\omega)$, $n_C(\omega) = \infty$, and the mill price, $p_D(\omega), p_C(\omega)$. There is no price discrimination, all versions are priced at the same mill price, $p_T(\omega)$. As motivated above, the choice of $n_T(\omega)$ is isomorphic to the choice of product quality. However, the supply side is further extended in order to include the aspect of automation.

For every differentiated version in $n_D(\omega)$, the firm entails fixed costs f_D which are constant across firms.[40] As in the previous chapter, this captures the idea that on the level of a differentiated version, there are economies of scale. The differentiated versions are produced with labor only. Marginal costs are given by $c_D(\phi)$. These marginal costs are constant and independent of the number of versions.[41]

[38] Note that as in Kugler and Verhoogen (2011, p. 319, 320, fn. 26), the price index is a quality adjusted price index.

[39] As in the previous chapter, firm and brand is used interchangeably. Any firm can only establish a single brand.

[40] Analyzing the role of heterogeneous "product productivity" (Hallak and Sivadasan 2013, p. 56) goes beyond the scope of this analysis.

[41] Allanson and Montagna (2005, p. 590) also assume fixed outlays per brands' versions and marginal costs that are independent of the range of versions. However, the authors further assume that marginal

Adoption of the customization technology, e.g. adoption of a 3D printer, enables mass customization. Paying sunk costs f_C therefore allows the firm to offer the infinitum of the variety's versions, $n_C(\omega) = \infty$, at equal marginal costs, $c_C(\phi)$.
Customization might involve automation of tasks (see section 2.3.3). Following the literature, notably Acemoglu and Restrepo (2018b, p. 50), and the extension in Koch et al. (2019, p. 12), it will be assumed that the production of one unit requires the combination of a continuum of tasks in a constant elasticity of substitution (CES) functional form with elasticity α. The output of the combination of tasks can be described as

$$\left(\int_{N-1}^{N} task_i^{\frac{\alpha-1}{\alpha}} di\right)^{\frac{\alpha}{\alpha-1}} \tag{2.4}$$

Complex tasks need to be performed by human labor while less complex tasks can be automated. Let $I \in [N-1, N]$ be the threshold for tasks that can be automated. Then, the output of a task is given by

$$task_i = \mathbb{1}[i \leq I]\eta_i k_i + \gamma_i l_i \tag{2.5}$$

where η_i, γ_i are the productivity of automation technologies and human labor, respectively. Automation technologies have a comparative advantage in lower indexed tasks, $\frac{d\frac{\gamma(i)}{\eta(i)}}{di} > 0$ (Acemoglu and Restrepo 2018b, p. 50). The input of automation capital and labor input are denoted k_i and l_i. For simplicity and in contrast to Koch et al. (2019, p. 12), it is abstracted from heterogeneity in productivity or the quality of tasks. The measures are economy wide and depend only on the task index i. Human labor earns an hourly wage w while the rent of automation capital amounts to r. $\frac{R}{\eta(I)} < \frac{W}{\gamma(I)}$ ensures that up to I it is more expensive to produce the task with labor than with capital (Acemoglu and Restrepo 2018b, p. 50). In an open economy version, input costs are country dependent. When tasks $i \leq I$ are automated, marginal costs can be described as

$$c_C(\phi) = \frac{1}{\phi}[\eta(N-1, I)r^{1-\alpha} + \gamma(I, N)w^{1-\alpha}]^{\frac{1}{1-\alpha}} \tag{2.6}$$

Accordingly, marginal costs for the differentiation technology where it is assumed that all tasks are performed by labor can be expressed as

$$c_D(\phi) = \frac{1}{\phi}[\gamma(N-1, N)w^{1-\alpha}]^{\frac{1}{1-\alpha}} \tag{2.7}$$

where $\eta(N-1, I) = (\int_{N-1}^{I} \eta_i^{\alpha-1} di)^{\frac{1}{\alpha}}, \gamma(I, N) = (\int_{I}^{N} \gamma_i^{\alpha-1} di)^{\frac{1}{\alpha}}$. Marginal costs are independent of the number of versions a firm offers.
The profit function of a firm with productivity ϕ and producing with the differentiation technology is given by:[42]

$$\max_{p_D, n_D} \pi_D(\phi) = (p_D - c_D(\phi))X\left(s(n_D)\right)^{\sigma-1}\left(\frac{p_D}{P}\right)^{-\sigma} - n_D f_D - f \tag{2.8}$$

costs are homogeneous across firms.

[42]The variety index ω is dropped to ease readability.

Maximization yields the following optimal prices and the condition for optimal proliferation:

$$p_D^* = \frac{\sigma}{\sigma - 1} c_D(\phi) \tag{2.9}$$

$$n_D^* : f_D n_D^* = x(\phi, n_D^*) \epsilon_n c_D(\phi) \tag{2.10}$$

where the elasticity $\epsilon_n \equiv \frac{\partial s(n_D)}{\partial n_D} \frac{n_D}{s(n_D)}$ is a measure for consumers' sensitivity to the number of versions the brand is providing. Firms will increase the number of versions up to the point where the increase in demand due to higher *perceived* quality exactly equals the costs for establishing a new version (equation (2.10)).

Intuitively, optimal proliferation is decreasing in fixed and variable costs of differentiation, f_D and $c_D(\phi)$. More productive firms are offering more versions which increases the *perceived* quality of their variety.[43]

When producing with the differentiation technology, optimal profits can be rewritten as:[44]

$$\pi_D^*(\phi) = x(\phi, n_D^*) c_D(\phi) \left(\frac{1 - \epsilon_n(\sigma - 1)}{\sigma - 1} \right) - f \tag{2.11}$$

Note that $x(\phi, n_D^*)$ describes the demand for the variety of a brand. By symmetry of production costs and constant demand across brands' versions, every version of the variety is supplied at an equal share, $\frac{x(\phi, n_D^*)}{n_D^*}$. This share is decreasing in the number of versions the brand is offering.[45] Note the difference between total output and output per version where a lower level of the latter is a quality signal for the firm. Hence, *mass production* at the version level indicates that the firm offers lower quality.

Firms that are active in the market need to make non-negative profits which is determined by $\pi_D^*(\phi_D^*) \equiv 0$.

$$\pi_D^*(\phi_D^*) = X s(n_D^*)^{\sigma-1} P^\sigma \sigma^{-\sigma} (\sigma - 1)^{\sigma - 1} (\overline{c_D}(\gamma, w))^{1-\sigma} (\phi_D^*)^{\sigma-1} - n_D^* f_D - f \equiv 0 \tag{2.12}$$

The threshold is increasing in wages, w, and the fixed costs, f_D.[46] While more productive firms offer more versions, i.e. $\frac{\partial n_D^*}{\partial \phi} > 0$, the effect of productivity through n_D^* on profits is zero at the optimum.

When the customization technology is adopted there are economies of scope. Upon investment of f_C, the firm can serve the infinitum of versions. This implies $s(n_C \rightarrow$

[43]In Kugler and Verhoogen (2011, p. 322ff.), more capable plants provide products at higher levels of quality.

[44]Thereby, the condition for profits to be non-negative is: $1 > \epsilon_n(\sigma - 1)$.

[45]Formally, the condition for $\partial \frac{x(\phi, n_D^*)}{n_D^*} / \partial n_D^* < 0$ results in $\epsilon_n(\sigma - 1) < 1$ which necessarily needs to hold for equation (2.11) to be above zero.

[46]Note that equation (2.12) cannot be solved explicitly for ϕ_D^* as optimal proliferation, n_D^*, is also a function of ϕ_D^*.

$\infty) = 1$. The profit function is given by

$$\max_{p_C} \pi_C(\phi) = (p_C - c_C(\phi))X\left(\frac{p_C}{P}\right)^{-\sigma} - f_C - f \tag{2.13}$$

Optimal prices are a constant mark-up over marginal costs, $c_C(\phi)$:

$$p_C^* = \frac{\sigma}{\sigma - 1}c_C(\phi) \tag{2.14}$$

The cutoff for the customization technology is given by

$$\phi_C^* = \overline{c_C}(\gamma, \eta, w, r)\left[\frac{(f_C + f)(\sigma - 1)}{XP^\sigma}\left(\frac{\sigma}{\sigma - 1}\right)^\sigma\right]^{\frac{1}{\sigma - 1}} \tag{2.15}$$

Firms choose the technology that yields the highest profits. This is similar to the technology choice in Bustos (2011, p. 310). Her model features a constant and exogenous relation between costs of two technologies.[47] In contrast, here, (part of) total fixed costs for the differentiation technology are determined endogenously induced by consumers who value proliferation. Moreover, a demand side effect of technology is absent in her paper.

Given optimal profits and equal sunk costs, f, the difference between profits from customization and differentiation, $\Delta\pi(\phi) \equiv \pi_C^*(\phi) - \pi_D^*(\phi)$, is given by:[48]

$$\Delta\pi(\phi) = \frac{XP^\sigma\phi^{\sigma-1}}{\sigma^\sigma(\sigma - 1)^{\sigma-1}}\left[\overline{c_C}(\gamma, \eta, w, r)^{1-\sigma} - s(n_D^*)^{\sigma-1}(1 - \epsilon_n(\sigma - 1))\overline{c_D}(\gamma, w)^{1-\sigma}\right] - f_C$$

Firms adopt automation and offer customized goods whenever $\Delta\pi(\phi) > 0$.[49] The term in brackets bears similarity with the expression for cost savings through automation in Koch et al. (2019, p. 13) but there is the additional dependence on quality (proliferation). Koch et al. (2019, p. 12f.) assume that robot adoption implies lower marginal costs as part of the tasks can be automated and $w > r$. If consumers attribute a sufficiently high value to proliferation and fixed costs, f_C, are not too large, firms might adopt the automation technology even if it entails higher marginal costs, $\overline{c_C} > \overline{c_D}$. Ceteris paribus, an increase in w makes automation more attractive. The effect is amplified through a decrease in optimal proliferation and a quality discount through consumers.

There might be different scenarios:

Traditional Technology Only: If the expression in brackets is negative, all firms that are active in the market, i.e. above the productivity level ϕ_D^*, would offer differentiated versions. The rental rate for capital would be too high relative to the wage rate. More

[47] In her paper, the new technology is introduced with higher fixed but lower marginal costs by factors $\eta > 1$, $\frac{1}{\gamma} < 1$, respectively (Bustos 2011, p. 309).

[48] Thereby, $\overline{c_T} = c_T\phi$.

[49] Any active firm needs to pay the sunk costs, f, which also determines the cutoff values, ϕ_T^*, but does not differentially affect technology choice.

productive firms offer more versions, charge lower prices and make higher profits. This case would also happen when the expression in brackets is positive but not sufficient to cover f_C even for the most productive firm, $\Delta\pi(\phi_{max}) < 0$.

Traditional and Customization Technology: The expression in brackets is above zero whenever

$$\left(\frac{\overline{c_D}(w)}{\overline{c_C}(w,r)}\right)^{\sigma-1} > s(n_D^*)^{\sigma-1}(1-\epsilon_n(\sigma-1)) \tag{2.16}$$

Since the first term in equation (2.16) is increasing in ϕ, more productive firms are more likely to be able to cover the higher fixed costs, f_C. When $\phi_D^* \leq \phi_C^*$, there are firms that are productive enough to be active in the market but not able to cover the high fixed costs for automation. All firms within $\phi \in (\phi_D^*, \phi_C^*)$, produce with the traditional technology but offer multiple versions of their variety. The TIC 2018 survey, for instance, reports that adoption rates of 3D printing was higher among larger firms (Insee 2019a).

Customization Technology Only: Finally, whenever $\phi_C^* < \phi_D^*$, all firms offer customized products. Full customization in the entire market implies that the function $s(n(\omega)\infty) = 1$ for all firms. If all firms offer customized products, there is no quality differentiation anymore as maximum quality is bounded to be one. This could be perceived by consumers as brands getting more similar. Relative sales of two firms with productivity levels $\phi_1 > \phi_2$ are larger when all firms produce with the traditional technology than the case of automation only as more productive firms offer more versions.

$$\frac{p_D(\phi_1)x_D(\phi_1)}{p_D(\phi_2)x_D(\phi_2)} = \left(\frac{s(n^*(\phi_1))}{s(n^*(\phi_2))}\right)^{\sigma-1}\left(\frac{\phi_1}{\phi_2}\right)^{\sigma-1} > \left(\frac{\phi_1}{\phi_2}\right)^{\sigma-1} = \frac{p_C(\phi_1)x_C(\phi_1)}{p_C(\phi_2)x_C(\phi_2)} \tag{2.17}$$

The set-up could be extended to model firms' production and location choices in international markets. If fixed and variable costs for exporting are sufficiently high, there is a selection of more productive firms into exporting as in the standard Melitz (2003, p. 1709) model. When f_C is large compared to fixed costs of exporting, the most productive exporters produce with customization technology like most productive exporters use the new technology in Bustos (2011, p. 312) and automation in Koch et al. (2019, p. 14).

Sensitivity to customization on the demand side might vary across countries. When customization requires co-creation or is complementary to fast delivery, firms have an incentive for *nearshoring* and adoption of automation technologies (i.e. *botsourcing*) depending on the location's comparative advantage.

The model is able to allow for mechanisms on the demand and supply side: The sensitivity of consumers to customization could increase optimal proliferation to an extent which makes adoption of automation more attractive or adoption of automation technologies could reduce costs to an extent that makes customization attractive from the supply side.

2.5 Outlook and Discussion

There are several aspects that were not explicitly discussed but would be interesting to consider or study in future research.

The article abstracts from the fact that, for instance, 3D printing allows consumers to develop a model and send it to a 3D printing manufacturer or to potentially even buy a printer and produce their own goods. The latter would require that the costs of printers are low and that the knowledge and abilities of consumers to handle the printer are sufficiently high. Consumers would turn into so-called “prosumers” “who become[...] involved with designing or customizing products for their own need” (Oxford University Press 2021c). While co-creation could actually further increase the value a consumer attributes to a good, if consumers are producing the good themselves, some of the (production) services that traditional producers are currently providing might become obsolete. In the future, this will crucially depend on the role of *branding*, quality, e.g. precision, of printed goods by consumers, and input as well as fixed costs for 3D printers.

When consumers produce their own goods, this might require regulatory responses, rules, and standards to ensure safety, avoid fraud, and protect intellectual property rights (IPRs). The World Intellectual Property Organization (2015, p. 106f.) discusses challenges that come with individuals printing their own goods regarding enforcement and enforceability of IPRs given the mass of potential individuals and IPR violations.

Furthermore, the chapter considers a one-dimensional difference between tailor-made and mass-produced goods. That is, if there is full customization, the model collapses to a standard model of horizontally differentiated firms as in Dixit and Stiglitz (1977) and Melitz (2003). Thereby, it abstracts from the aspect of differences between differentiated and customized products beyond the *perfect* fit. Given that the investment in technology implies different quality levels of the same product, in theory, firms would not adopt both technologies. In reality, though, firms might offer both, differentiated and customized products. Firms might, however, also introduce new varieties to be customized instead of customizing varieties that were previously mass-produced. In fact, the model could be extended to allow firms to offer several varieties. This would imply that firms could have an influence on market aggregates which contrasts the assumption of monopolistic competition in section 2.4.2.

There might be a difference between the *perceived* quality and the *intrinsic* quality of the product. Personalized goods might be perceived as higher quality, e.g. as they are *unique* or reflecting the personality (see sections 2.1 and 2.4). However, depending on the type of 3D printers, the *intrinsic* quality of the good might actually be lower. In order to capture that in the theory, there would be the need for an additional quality dimension on the consumer and producer side.

As mentioned above (see section 2.3), considering patent data might bias results as the tendency for patenting varies across industries. For a broader picture, one would require detailed product-firm level data on differentiated vs. customized products. Another aspect for future research is how automation technologies but in particular 3D printing itself might affect innovative activity. Rapid prototyping should increase the speed of product innovations.

On-demand production reduces waste. In contrast to traditional subtractive manufacturing, additive manufacturing processes do not, by their very name, produce any waste. However, there might be other aspects, e.g. the usage of certain input materials and high energy consumption, that need to be considered. On the other hand, local production shortens delivery routes. The potential of 3D printers to localize production might be especially helpful for countries or regions that are, given their geography or infrastructure, difficult to reach.

Customization and 3D printing could influence market structures in different ways. Section 2.3.1 revealed that most filings were related to ICT. In that sector, there are several high tech firms with significant market positions. If personalizing services provides them with additional market shares, the trend for customization might actually reflect a decrease in competition. A recent report recommends, for instance, how a regulatory response could lower barriers to enter for search engines when they offer personalized results (Bonatti et al. 2021). On the other hand, when 3D printing entails very low fixed costs, also small and niche firms could provide customized goods. If there is full customization, brands become more similar which might increase competition.

2.6 Conclusion

Inventions related to the *Fourth Industrial Revolution* likely affect labor markets and global value chains. This chapter studies trends in customization and additive manufacturing. As there seems to be a link between automation, AI, big data, and customization in patent data, the theory section adapts the model of the previous chapter to include automation of tasks in the production of custom products. ICT and big data provide information and means for communication with consumers that are complementary to offering personalized products.

> “[I]t seems that mass communication and information technology is bringing people together so that they can signal their individuality more easily than ever.”
>
> Foulkes (2018, p. 129)

Chapter 3

Distributed Ledger Technology, Smart Contracts, and International Trade

3.1 Introduction

Financial intermediation plays an important role in global supply chains. Moral hazard, information asymmetries, and search costs are instances of frictions in international transactions that cause costs and inefficiencies. Procedural obstacles and document handling delay time to trade and affect international trade flows, especially in developing countries. There are several mechanisms to secure a trustworthy buyer-seller relationship. Thereby, banks play a central role as intermediaries in source and destination countries. But what if digital databases increase transparency and reduce paperwork? What if decentralized digital networks enable agents to perform and verify immutable transactions instantaneously and independent of location? What if blockchain changes the role of middlemen in international trade relationships?[1]

In order to analyze these questions, this chapter develops a theoretical model. If blockchain adoption reduces delays at the border and strengthens contract enforcement, trade flows increase at the intensive and extensive margin. The size of the platform depends on prevailing information frictions in and distance to destination markets and impacts the welfare benefits from blockchain adoption. If the platform is managed by a single entity, commission rates for network provision could extract the additional surplus.

Blockchain is a so-called distributed ledger technology (DLT):[2] In short, agents' computers -*nodes* - are part of a digital, decentralized network. They can store information,

[1] Or as Maupin et al. (2019)'s title asks: "Blockchain: A World Without Middlemen?"

[2] In the literature, they are often used interchangeably, even though blockchains are, technically, a subset of DLT.

for instance, a payment transaction in a *block*. The latter will be time-stamped and encrypted to prevent modification. The information is added to the network. It becomes part of the *chain* of *blocks* that members of the network can instantaneously verify. In reality, there are several forms of blockchains with varying access rules and permissions concerning the rights to write and read entries. A bitcoin platform is an example of an open, permissionless network where all individuals worldwide could participate, read, and add information. This article focuses on so-called permissioned blockchains where access is restricted which nowadays seems to be the preferred design among companies (PricewaterhouseCoopers (PwC) 2018, p. 10).[3] While there are still barriers to adoption of blockchains, such as legal uncertainty and limited cybersecurity, the impact on international trade could be important. The effect for cross-border trade, as opposed to domestic trade, is expected to be larger as time delays, information asymmetries, mistrust, and paperwork are more severe.

Some call blockchain a “trust machine” (The Economist 2015b): Sellers and buyers can, at any point in time and from any location, keep track of their market transaction whether goods were shipped or arrived at a port, or whether bills were paid. Transparency, accountability, immutability, and instantaneity might be particularly relevant for countries with weak institutional framework and contract enforcement that affect available payment methods. This ultimately influences which firms are able to participate in cross-border activities.

Importers and exporters can agree on different types of contracts for the payment of the transaction: cash-in-advance (CIA), open account (OA), letter of credit (LC), or documentary collection (DC).[4] Antràs and Foley (2015) and Schmidt-Eisenlohr (2013) provide empirical evidence that imports to countries with weak contract enforcement are often paid on preshipment terms. Importers need to provide sufficient funds to cover the bill before sales revenues are realized but limited access to capital in these countries reduces the set of firms that is able to participate in international trade (Antràs and Foley 2015; Foley and Manova 2015). The effect of uncertainty and risk of default are attenuated by longer shipping times (Berman et al. 2012). Demir and Javorcik (2020) report that during the COVID-19 pandemic where uncertainty and risk of default or non-delivery have substantially increased, trade flows with bank intermediated payments reacted less to adverse shocks than those financed through OA or CIA.

Access to trade finance and LC is limited for firms in developing countries, where the number of correspondent bank relationships has decreased after the financial crisis (Demir and Javorcik 2020, p. 407). Blockchains might create the necessary trust to enable or

[3] Note that this is a very simple and general, non-technical description of blockchains. For more details see section 3.2 or Ganne (2018, Annex, p. 113f.) “Blockchain for tech fans”.

[4] CIA is also referred to as importer finance, OA as exporter finance, and LC as bank finance.

intensify international trade.[5] The theoretical model below is analyzing how different payment methods, pre- or postshipment, as well as their relative choice might be affected by the level of information frictions and contract enforcement in a country.

Beyond existing technologies, blockchain also includes non-financial actors, allows instant transparency and verification as well as automation through smart contracts. Smart contracts are programs that automatically trigger an action if a certain condition is met, e.g. transferring a payment upon upload of the bill of lading (Ganne 2018, p. 127).

Cross-border transactions involve significant amounts of paperwork. The administrative burden takes time and is costly (Djankov et al. 2010). According to the data on *Doing Business* provided by the World Bank (2020), time to import reaches a maximum of 402 hours (16.75 days) for *Border compliance* in Tanzania and 15 days for *Documentary compliance* in South Sudan. In the data, mean and median hours for *Border compliance* (*Documentary compliance*) amount to 64.18 and 53 (50.97 and 33).

Moreover, opacity increases the risk of misreporting, manipulation, and fraud which require costly control mechanisms. In a business survey, European exporters report time constraints, administrative burdens, and information and transparency issues as the main procedural obstacles (International Trade Centre and European Commission 2016, p. 20). These obstacles could be tackled by the main economic features of blockchains, i.e. the increase in transparency, trust, and accountability as well as the reduction in paperwork. This affects international trade relationships differently across countries. As DLT ensures traceability and transparency in business relationships, Antràs (2020, p. 21) argues that it can compensate for a country's fragile institutional framework and enable its inclusion in global value chains (GVCs). Given the rise in the share of people having access to mobile phones and internet, some expect blockchain to contribute remarkably to economic growth and trade facilitation in developing countries (United Nations Conference on Trade and Development (UNCTAD) 2020; UNCTAD 2021).

There are recent (micro-)theoretical models of blockchain technologies (e.g. Abadi and Brunnermeier 2018; Catalini and Gans 2016). Ganne (2018) provides a broad descriptive discussion on the potential of blockchain technologies for supply chain management and international trade. Patel and Ganne (2020, p. 12f.) set up a "Periodic table of DLT projects". This chapter aims to proxy the spread of DLT across time and space through an analysis of patent data: The data section reports an increase in patent filings over the past decade. Text analysis of patent abstracts serves as an indicator for applications of the new technology to financial intermediation, cross-border activities, and document handling.

The chapter provides a partial equilibrium model of trade finance choices. Firms differ in productivity as in Melitz (2003). A monopolistic intermediary offers blockchain partici-

[5] DLT is also applied in development aid as discussed in the report by Maupin et al. (2019).

pation to some firms. This increases the extensive margin as firms at lower productivity levels find it profitable to start exporting. The active intermediary increases aggregate trade flows but extracts all additional surplus. The set-up of direct and intermediated trade in a world with information frictions is an extension of the theoretical model by Petropoulou (2008b, 2011). Relaxing the assumption of identical firms and constant surplus in her baseline model as well as considering trade finance specifically allow to gain further insights on the impact of information frictions on trade flows.

There is literature on information frictions and (historical) innovations in information and communication technologies (ICT) (e.g. Allen 2014; Steinwender 2018). It seems, however, that the impact of ICT on trade intermediation, in general, and financial intermediation, in particular, is widely unexplored.

Note that limited (cyber)security, restricted access to internet, and energy consumption might reduce benefits of DLT. There might be additional risk associated with permissionless platforms such as bitcoin. While these aspects will be briefly discussed in the outlook, a more in depth analysis goes beyond the scope of this article. Furthermore, the focus is on the (main) economic mechanisms of a blockchain in international trade. The chapter is general on technical information technology (IT) related aspects of blockchains such as computing power or specific technical requirements for encryption.

The next section (section 3.2) provides a brief introduction in blockchain technology and the related literature. The subsequent section 3.3 provides the results of the analysis of patent data. Section 3.4 presents the theoretical model followed by the discussion (section 3.5). Section 3.6 concludes.

3.2 Blockchain, Smart Contracts, and International Trade

3.2.1 Definitions and Examples

Recent business surveys among executives suggest that more than 80% of companies are (in any way) involved with blockchain technology (PwC 2018, p. 1). Moreover, mainstream adoption of the technology is expected in the future (Deloitte 2020, p. 5). The ICC Global Survey 2018 reports that 46% of responding banks indicate "[e]merging technology, such as Digital Ledgers" as "priority area" for trade finance in the "next 3-5 years" (International Chamber of Commerce (ICC) 2021).[6]

In contrast to traditional ledgers that are kept at one location such as books, centralized databases or servers, distributed ledger technologies (DLT) decentralize the storage of information. All participants (nodes) can instantaneously access information which in-

[6] Shares are lower for "in the next 1-3 years" (38%) and "in the next 12 months" (17%) (ICC 2021).

creases transparency and traceability among business partners.
As mentioned above, blockchains vary in terms of the degree of decentralization and access rules. There are numerous forms and hybrid formats of these platforms. In terms of user management and authentication, most of them can be classified as either public, consortium, or private. Concerning rights to write and validate transactions, they are usually classified as either permissioned or permissionless.
Fully decentralized public blockchains are not managed by a single party, any user can anonymously participate. If it is a permissionless public blockchain such as bitcoin, any agent has equal rights to read, write, and validate transactions. The mechanisms for validation is determined in a so-called consensus protocol. In permissioned blockchains, the right to validate transactions is connected to certain conditions. Private and consortium blockchains are provided by a single or several entities, respectively, that manage user authentication and the right to read, write, and validate information. A public permissionless blockchain needs to ensure a high level of cybersecurity and faces intense technical requirements in terms of computing power (Ganne 2018, p. 12). On the other hand, a private permissioned platform risks to hamper transparency and decentralization benefits.
The growing relevance of the technology in general is mirrored by an increase in patent filings related to DLT (see section 3.3). There are several applications of permissioned consortium blockchains in international trade. Patel and Ganne (2020, p. 12) provide a “Periodic table of DLT projects” with applications in “Trade Finance”, “Know Your Customer (KYC)”, “DLT digitization of trade documents”, and “Shipping & Logistics/Supply Chain”. For this chapter and the theoretical model below, the focus lies on blockchains related to financial intermediation. Examples include *komgo*, *Marco Polo* or *we.trade*.[7] The platform *komgo*, for instance, offers participants to handle trade finance related services such as digital letters of credit, to track associated trade flows, and KYC services. It is reported to have processed more than 20.000 digital letters of credits in the past six years and to demand a subscription fee (Patel and Ganne 2020, p. 27f.).
When a trade transaction is based on letter of credit (LC), the importer’s bank is guaranteeing payment for the importer: The importer’s bank is issuing an LC to the exporter’s bank. Upon shipment, necessary documents are transferred from the exporter through the exporter’s bank to the importer’s bank. When documentation is complete and the agreed conditions are met, payments will be executed. Even though document exchange has already been digitized over the past years, manual LCs usually still involve significant amounts of paper based documents interchanged between several parties. In contrast, the digital LC on a blockchain ensures that all involved parties can register information on

[7]Note that these examples of consortium blockchains are named in the “Periodic table” Patel and Ganne (2020, p. 12). It is difficult to get a complete, up-to-date sample of active projects and their relevance for international trade flows.

the platform. Moreover, they have always access to the same information on the status of the trade. Beyond decreasing time and costs for manual document handling, there is a significant increase in transparency. Combined with a smart contract, part of the procedure can even be automated.[8] For the theory part, adoption of blockchain implies usage of digital LCs.

The combination of services on a platform, e.g. financial intermediation as well as search and identification of customers, is also captured by the theoretical model. The mentioned platforms go beyond proof of concept. But as buyer and seller or the intermediaries need to be part of the same network, only a minority of international transactions is (yet) likely to be handled through a blockchain. *TradeLens* is a platform that includes companies along the entire supply chain: from port authorities, over third party logistics to "five of the six largest ocean carriers" (TradeLens 2019). In July 2021, it reports to have tracked more than 2 billion events, handled more than 20 million documents, and processed more than 44 million containers over time (TradeLens 2021).[9]

Finally, the mentioned platforms are often applying smart contracts, for instance, to trigger payment as soon as the arrival of the shipment is registered. There are several applications of smart contracts in international trade and supply chain logistics. To minimize delays related to paperwork and uncertainty on border compliance after Brexit, French customs apply electronic data interchange (EDI) and a "frontière intelligente" ("smart border") at the Channel Tunnel. It is scanning the vehicles' number plates, verifying and checking information and then signaling only those vehicles to stop where further checks are needed (Douane française 2021).[10] The combination of smart contracts and blockchain ensures increased enforcement and time efficiency through automation. In the theoretical model, this is captured by a complete elimination of any delays related to information frictions and paperwork.

3.2.2 Related Literature

Beyond the technological aspects, the current analysis is related to several strands of research: First, it is related to the literature on trade finance such as Antràs and Foley (2015) and Schmidt-Eisenlohr (2013). However, it extends Berman et al. (2012) to include delays due to administrative barriers beyond shipping time and it studies how ICT might affect the choice of the payment method. Second, the article is related to discussions on the impact of administrative procedures on international trade on country

[8]The exact procedure depends on the technology and platform (see also Ganne (2018, p. 23)).

[9]Information as of July 18, 2021 on `https://www.tradelens.com/platform`. For a comparison, the Port of Rotterdam reports to have processed more than 8 million containers (incoming and outgoing) in 2020 (Port of Rotterdam 2021, p. 3).

[10]This is an example of a smart contract that is not necessarily linked to blockchain technology (see e.g. Buyse 2021; Williamson 2021).

level (Amiti and Weinstein 2011; Djankov et al. 2010; Hummels and Schaur 2013) but also on the firm level (Fontagné et al. 2020; Maggi et al. 2018). Moreover, the analysis connects to research on ICT innovations and international trade (Allen 2014; Steinwender 2018) as well as on trade intermediation (Ahn et al. 2011).[11] Innovations in ICT such as blockchain, internet or telephone reduce information frictions between firms and financial institutions.

There is a growing literature on trade finance in international trade relationships.[12] Trade finance is the more general term for different contract agreements between importers, exporters, and potential intermediaries such as banks (Foley and Manova 2015, p. 133). Trade credit is often used specifically for open account or cash-in-advance agreements between firms (Committee on the Global Financial System (CGFS), p. 4).

Schmidt-Eisenlohr (2013) develops a theoretical model for the choice of the payment contract - CIA, OA or LC - depending on the institutional quality in the trading countries, i.e. contract enforcement and the share of entrepreneurs who will fulfill the contract. The relative choice of the payment method depends on the conditions in both, importing and exporting countries. CIA (OA) is likely to be used when importing countries are riskier (safer) (Schmidt-Eisenlohr 2013, p. 98).

These results are consistent with the findings in Antràs and Foley (2015, p. 854f.): The majority of transactions does not involve LC but CIA and OA, the latter (former) when contract enforcement in the destination country is strong (weak). Intuitively, problems to enforce contracts are increasing in distance (Antràs and Foley 2015, p. 869). The model below yields consistent results but includes the explicit dependence of contract enforcement on the level of information frictions. Smart contracts can automate payments. Thereby, blockchains could eliminate delays and the risk of non-payment after delivery. The scope for enforcing production is limited.[13] Ceteris paribus, the introduction of blockchain technology is therefore likely to increase the relative occurrence of postshipment agreements in all countries.

Bronzini and D'Ignazio (2017) find that prior existence of local bank branches in the destination country increases the probability of Italian firms to start exporting.[14] Relying on *Doing Business* data of the World Bank to measure "intangible barriers, involving [...]

[11] How trade itself affects innovation and the usage of information technology is analyzed by Bloom et al. (2016). There is also a growing literature on the role of ICT for multinational firms and sourcing decisions (see Fort (2017) and Gumpert (2018)).

[12] See, for instance, Foley and Manova (2015) for a detailed review article.

[13] Transparency, immutability, and accountability might reduce time to contact local courts but, in the end, production - unlike payment - cannot be automatically triggered.

[14] Literature and data on matching between firms and banks seem relatively scarce. Amiti and Weinstein (2011) have information on banks providing loans to Japanese firms. While Amiti and Weinstein (2011, p. 1870) discuss potential reverse causality issues when exporters choose banks with better financial health, they do not provide detailed stylized facts on firm-bank matching.

cultural and institutional aspects" (Bronzini and D'Ignazio 2017, p. 482), the authors argue that local branches facilitate exporting through better information about the importing country. The existence of bank affiliates has a larger effect on the probability to start exporting for countries where barriers are higher. Concerning banks' presence in the importing country, Bronzini and D'Ignazio (2017, p. 491) admit that effects of trade finance and information are difficult to separate but they state that their regression results reflect information as the main driver. These findings highlight that trade intermediation by banks matters beyond the provision of loans and guarantees but as a provider of knowledge about destination markets. With the introduction of blockchains, the "information channel" (Bronzini and D'Ignazio 2017, p. 491) gets even more important but potentially also more complementary to the provision of bank loans (see section 3.5).

The importance of contacts and networks as sources for information on destination countries are also discussed and structurally estimated in Chaney (2014). Firms can search for future customers "directly" or "remotely" (Chaney 2014, p. 3601), i.e. through their established "network" of customers. He finds that the probability that a firm starts exporting to a country increases with the amount of countries and the closeness to markets that the firm is already serving (Chaney 2014, p. 3607). This underlines the importance of networks for international trade.[15]

The previously mentioned papers focus mainly on differences across countries and representative firm types. However, financial constraints (Chaney 2016; Manova 2013) and administrative barriers (Fontagné et al. 2020; Maggi et al. 2018) have differential effects across heterogeneous firms. There is an ongoing discussion on whether small or large firms gain relatively more from trade facilitation agreement (TFA). Maggi et al. (2018, p. 1) analyze "Red-Tape Barriers (RTB)".[16] The authors highlight the extensive margin effect but also that trade liberalization might induce governments to raise RTB which dampens benefits from trade (Maggi et al. 2018, p. 6).

Based on survey answers, Djankov et al. (2010, p. 168) report descriptive statistics for the time to export: there is inter- and intra-regional variation, however, the highest minimum (39 days) and maximum time (116 days) for exporting are reported for African countries and the Middle East. The share in delays due to managing administrative requirements amounts to 75% (Djankov et al. 2010, p. 171, fn. 12). In the context of the financial crisis, Berman et al. (2012, p. 3) discuss that longer shipping times increase the probability of default as financial conditions might deteriorate during transit. As a result, exporters will demand higher prices and trade volumes will reduce. In the model below, the effect

[15]Unlike Chaney (2014), in the model below every exporter has a single matching trading partner in a given country. But the network effects in Chaney (2014) are likely to be present when the size of the blockchain expands and covers the entire supply chain.

[16]Maggi et al. (2018, p. 1) specify RTB as "policy-induced trade barriers that do not generate revenue or rents".

of information frictions on the extensive margin is also magnified by distance.
Allen (2014) studies the effect of information frictions on international trade flows. Using data for trade within the Philippines and comparing regions with and without mobile phone access, he finds that access to mobile phones increases transmission of price shocks as well as the share of farmers that is trading (Allen 2014, p. 2052, 2054). On the other hand, Steinwender (2018) focuses on the introduction of the transatlantic telegraph and its effect on price differences and trade flows. Similar effects might be related to the spread of telephones and the internet. Accominotti and Ugolini (2019) are reviewing the history of trade finance from the Middle Ages up until today. The authors are focusing more on the structure of trade finance, i.e. whether it is intermediated by local agents (banks) or going through centralized financial hubs such as London or New York. However, beyond mentioning that among other things the telegraph facilitated control of capital (Accominotti and Ugolini 2019, p. 15), there is no reference to the role of ICT innovations.
There are papers on the possibility for banks to use a screening technology (e.g. Ahn 2011) but not specifically whether and, if so, how ICT affects screening precision. Ahn (2011, p. 5) argues that there is less precision in screening of foreign as compared to domestic firms which results in a finance premium for foreign transactions. But Boot et al. (2020, p. 9) argue that information technology improves the ability to screen and monitor, the availability of non-financial data and the potential to exploit it, while communication technologies render in-person contacts less important. The theoretical model in section 3.4 does not distinguish between screening costs of foreign or domestic firms.[17] Boot et al. (2020, p. 23) highlight implications of monopolistic digital platforms that arise through network effects. The model below features a monopolistic bank which makes *take-it-or-leave-it* offers and thereby extracts all additional surplus.
The article focuses on permissioned blockchains and does not discuss the role of permissionless blockchains, cryptocurrency, and initial coin offerings (ICOs) for international trade and trade finance. This has several reasons: Central banks and supervisory authorities raise concerns due to, for instance, missing liability in a completely decentralized network, the missing legal framework and related uncertainty in some countries or the highly volatile prices also reflecting speculative investments.[18] Given the legal and regulatory uncertainty as well as cybersecurity concerns, most applications of DLT for global supply chain management and trade finance seem to rely on some sort of permissioned blockchain by a consortium of banks or firms. However, there is an ongoing discussion

[17]Digitization reduces the role of (geographical) distance but does probably not completely eliminate it. The assumption of symmetric monitoring costs is also for tractability.

[18]See, for instance, Balz and Paulick (2019) and Wuermeling (2019). Supervisory authorities also issued warnings and advice related to ICOs (e.g. European Securities and Markets Authority (ESMA) 2019).

on so-called *stablecoins* and digital currencies (see also section 3.5).[19]
The next section provides an empirical analysis of patent data related to DLT. The data should offer some idea of their (future) usage, application, and the geographical distribution as there is scarcity of data that go beyond business surveys (e.g. PwC 2018; ICC 2021) or collection of projects as in Patel and Ganne (2020). Section 3.3 presents stylized facts. The recent advent of blockchain, limited (knowledge on) adoption rates on firm but also on country level impede identification and measurement of (potential) effects of blockchain on international trade.

3.3 Blockchain and Patent Data

Due to its relative newness, information on adoption and usage of blockchain technology, in general, and at a global scale, in particular, are scarce. Hence, data that looks at research and innovations in DLT can serve as a proxy for its - intended - usage. Given the benefits of patent data such as timely availability and the breadth of information (Organisation for Economic Co-operation and Development (OECD) 2009, p. 27), the following analysis relies on data of the PATSTAT Online 2020 Autumn Edition.
There are no specific technical classifications, International Patent Classification (IPC) or Cooperative Patent Classification (CPC) codes, for distributed ledger technologies. The classification of patents as related to DLT in general relies on a combination of keywords and technical classifications based on Jordan and Bitton (2019) provided by the European Patent Office (EPO).[20]
One major caveat is that developers might provide open source solutions instead of patents (The Economist 2017). Looking at patent data might therefore bias the results in terms of applicants, application authorities, and coverage of the patent. Permissionless blockchains are probably more likely open source while agents providing permissioned consortium (or private) blockchains might be more likely to file a patent. The same might be true for applications intended for developing and developed countries.[21] One should also keep in mind that existence and scope of a legal framework for DLT vary across countries. Hence, this analysis should be seen as a motivation for the growing relevance of distributed ledger technologies but it is not intended to provide conclusive results.
Table 3.1 lists the number of distinctive inventions (priorities of DOCDB patent families),

[19]On July 14, 2021, the Governing Council of the European Central Bank (ECB) (2021) announced to initiate "the investigation phase of a digital euro project" (see `https://www.ecb.europa.eu/press/pr/date/2021/html/ecb.pr210714~d99198ea23.en.html` (July 17, 2021)).

[20]Further information on the keywords are provided in the appendix in table C.6. For data retrieval, the language is not restricted to English as the technical terms are used in several languages.

[21]The Kreditanstalt für Wiederaufbau (KfW) (2019), for instance, offers *TruBudget* as an open source solution which is targeted to support developing aid, see `https://www.kfw.de/KfW-Konzern/Newsroom/Aktuelles/Pressemitteilungen-Details_515008.html` (April 16, 2021).

application filings, and the share of granted applications from 2008 to 2018.[22] The year refers to the filing of the application or the earliest filing for DOCDB patent families. There is a rapid increase in filings and inventions in the past years: The number of priority filings more than tripled from 2017 to 2018. Given the time intensive process of patent grant or refusal, this does not reveal any information on the quality of patents, though. The observable rise in applications might reflect accelerating innovative activity but, given the discussion above, there could potentially also be a shift in the patenting behavior (as opposed to open source solutions) related to blockchain technology and the types of applicants. Still, as there are costs associated with patent filings, table 3.1 suggests that agents attribute growing economic value to DLTs.

In the following, the analysis is based on patent filings from 2008 onward. While there was research related to DLT before, 2008 is the year where the white paper on bitcoin was published. This is often referred to as a breakthrough in the development of blockchain technology. This is consistent with the data where only around 5% of total applications where filed between 1990 and 2007. The results refer to *all* applications independent of grant status of the patent. This comes with the risk of comparing filings with very dif-

Table 3.1: DOCDB Patent Families and Applications by Earliest Application filing Year

Year	DOCDB Families	Applications	Granted [%]
2018	6409	9521	11.78
2017	1801	3329	25.71
2016	798	1505	35.95
2015	174	432	47.69
2014	102	263	42.97
2013	76	182	54.40
2012	66	165	57.58
2011	47	183	51.37
2010	47	174	49.43
2009	90	199	47.74
2008	123	213	46.01

Data Source: PATSTAT Online 2020 Autumn Edition; DOCDB patent families refer to year of first filing (priority); Cumulative sum over the years 1990 to 2018: 28.150 applications, 16.479 DOCDB patent families.

[22]There are time lags between filing and visibility in PATSTAT Online (around 18 months). The process of grant or refusal of a patent varies across patent authorities but can take between 2-8 years (OECD 2009, p. 19) which could at least partly explain the drop in the share of granted applications for recent years in table 3.1 but could also bias the results, e.g. concerning application authorities.

ferent quality. Given that time lags of publication do vary across application authorities, results might be biased to specific locations. However, as only 15.5% of patents in the data set are granted, the sample size would reduce tremendously and would not capture very recent trends in filings.
Table 3.2 shows that the majority of applications are filed in China (CN) followed by the

Table 3.2: Application Per Application Authority

Application authority	Share of all applications [%]
CN	57.49
US	23.76
EP	5.38
KR	3.97
TW	1.74
AU	1.65
CA	1.49
JP	0.94

Data Source: PATSTAT Online 2020 Autumn Edition; Only applications in national or regional phase considered; Share of all applications since 2008 (23.098). See table C.1 for data including PCT applications.

United States (US) and applications filed as European patents (EPs).[23]
Following Coelli et al. (2020, p. 4), patent applications can be seen as an indicator for expected (future) market potential. Figure C.1 shows that over the last decades, filings related to DLT have increased in China (a trend which is observable for other technologies as well). Filings at the United States Patent and Trademark Office (USPTO) make up at least 15% of filings worldwide over the time period considered. Applicants search protection for their DLT especially in large markets and mostly in developed countries. However, as discussed above, open source might be more relevant in smaller and especially less wealthy jurisdictions.
Data on service exports shows that China and the United States were also among the ten leading exporters of ICT in 2018 measured in current US$ (see table C.2). There is few variation in application authorities: Over the time period, patents were filed at 36 different authorities which limits the possibility for identification. Still, simple Pearson's product moment correlation suggests a positive significant correlation between patent filings related to DLT and ICT exports. This hints towards a relation between the existing ICT level in a country and adoption of blockchain technology.
In order to proxy application areas of the blockchain technology, the abstracts of priority

[23] An application for a European patent (EP) can be extended to the contracting states (EPO 2020).

filings are analyzed. To ensure linguistic consistency, the focus is on abstracts published in English. This covers more than 99% of priority filings in the data set. The wordcloud in figure C.2 reports keywords related to the typical functioning of a blockchain such as node, system, transaction, record, or account. Note that the keywords to identify patents where as broad as to capture any DLT related patents. Figure C.2 suggests that many patents rely on blockchains. Moreover, the word(stem)s "smart" and "contract" appear in the wordcloud which could be an indicator for the combination of blockchains with smart contracts. A keyword search summarized in table 3.3 reveals that more than 80% of applications name blockchain. Around 10% of inventions refer to smart contracts or document handling. 15% of priorities contain words that might be related to international activities.

Interestingly, conditioning on these priorities - classified as international in table 3.3 - results in comparable shares of applications naming blockchain, smart contracts or private. The latter term might hint to private blockchains. However, references to financial activities and document handling become more important. This would be consistent with the examples in the previous section: Platforms such as *TradeLens* are targeted to include the entire supply chain for document handling. *Marco Polo*, *we.trade*, or *komgo* include financial institutions. It might also point towards a complementarity between ICT innovations and financial service provision (Boot et al. 2020; Bronzini and D'Ignazio 2017; United Nations Conference on Trade and Development 2015). Both aspects will be considered in the theoretical section: The introduction of a blockchain eliminates delays and ensures perfect contract enforcement through intermediation by a financial institution, improved document handling, and automation through smart contracts.

The analysis shows that countries where many DLT patents are filed are also among the main exporters of ICT services, in general. Some of them are, in addition, supplying an important share of world trade in financial services and financial intermediation (see tables C.3 and C.5).

In section 3.4, delays due to manual document handling and contract enforcement are modeled to be influenced by the level of ICT in the *importing* country. This is backed up by data: Countries with higher indexes for *E-Government*, *E-Participation*, *Online Service and Telecommunication Infrastructure* in 2018 (United Nations (UN) 2021) have higher scores for *Enforcing Contracts* and *Trading across Borders* in the *Doing Business* data by the World Bank (2021).[24] This is a correlation, an empirical identification would need to address (potential) endogeneity problems such as gross domestic product (GDP) per capita as omitted variable. The following section develops a theoretical model that

[24]Correlations for *Time to import* and *Cost to import* are not significant. Analyzing trade facilitation measures, Carballo et al. (2017, p. 20) point out that identifying their effects on firms' trade performance is difficult due to available aggregated country level data and the need for firm level data that covers the time of the policy change.

Table 3.3: Keyword Match of English Abstracts (15 836 applications)

(a) All priorities

Concept	Share of Inventions [%]
blockchain	86.45
smart contract	10.14
private	9.35
finance	12.96
document handling	9.89
international	14.99

(b) Conditional on "international"

Concept	Share of Inventions [%]
blockchain	86.24
smart contract	9.54
private	10.00
finance	17.86
document handling	12.54

captures the complementarity between blockchain technology and financial services as reflected in table 3.3.

3.4 Theory

The model considers firm-level trade between two countries. The exporting country is denoted by the index X, the importing country by IM. Active firms in IM trade with firms in X: they are importing goods and are selling these goods to consumers in their local market. Introduction of blockchain technology affects contract enforcement, eliminates delays, and introduces network effects.

The representative consumer in the importing country has a constant elasticity of substitution (CES) utility function over a continuum of goods. Utility function and price index are defined as in Melitz (2003, p. 1698ff.):[25]

$$U = \left[\int_{\omega \in \Omega} x(\omega)^{\rho} d\omega\right]^{\frac{1}{\rho}} \tag{3.1}$$

$$P = \left[\int_{\omega \in \Omega} p(\omega)^{1-\sigma} d\omega\right]^{\frac{1}{1-\sigma}} \tag{3.2}$$

[25]Note that utility, price index, and resulting aggregate consumption depend on the conditions in the *destination* country. The subscript $_{IM}$ is dropped to ease readability.

where Ω is defined as the set of all available varieties, $\rho \in (0, 1)$, and the elasticity of substitution is $\sigma = \frac{1}{1-\rho} > 1$.

Let $M_X = M_{IM} = M$ be the mass of active firms in the domestic market with a given productivity level, ϕ. The number of risk-neutral firms is fixed, there is no entry of firms.[26] Ex-ante all firms are potential traders.

For a given country pair, every firm in IM matches with exactly one firm in X. However, given information frictions, trading partners might not be able to match and trade. The intensity of information frictions is given by $i \in [0, 1]$. Innovations in ICT are equivalent to a decrease in i (Petropoulou 2008b, p. 4). The probability of a match is given by $q(i)$ where $q(0) = 1, q'(i) < 0, q(1) \to 0$, i.e. if there are no frictions to the information flow, trade partners match with probability one.[27] In contrast, when costs are prohibitively high, the probability of a direct match converges to but is strictly above zero. Intuitively, ICT innovations such as telegraph, telephone or internet lower the costs to get information on potential trading partners in foreign countries. It is assumed that ICT affects the probability of the one perfect match but that the matching probability is independent of other firm characteristics.[28]

Production requires labor as the only input. The wage rate is taken as numeraire. After paying sunk costs, f_e, firms draw a productivity level, ϕ, as in the standard Melitz (2003) model where $g(\phi), G(\phi), \phi \in (0, \phi_{max})$ are the probability density function, the cumulative distribution function, and the support of ϕ, respectively. ϕ determines firms' labor productivity. There are fixed costs, f, associated with production in the domestic market. The cutoff productivity level for firms, ϕ^*, is determined by the zero profit condition, $\pi(\phi^*) \equiv 0$. Importers are all equally efficient in selling the goods in the destination market.[29]

Given the probability for a direct match, agents might decide on the bilateral payment method, $MP = \{CIA, OA\}$. Or, they might consult an intermediary which might offer a network such as a permissioned, consortium blockchain. Network members can verify whether their matching trading partner is also part of the (same) network. If not, there

[26] For the Melitz (2003) type model below this is equivalent to assuming that the cutoff for domestically active firms is fixed and, in particular, independent of the level of information frictions. This is a simplifying assumption. However, the aim is here to analyze its impact on *international* markets.

[27] For consistency, the variables' notation is mostly identical to the notation in Petropoulou (2008b, 2011). Moreover the term "direct trade" is taken from Petropoulou (2008b, p. 4).

[28] Note the difference to an assumption of a change in the *quality* of a match. This is mainly to keep the model simple as with probability $1 - q(i)$ direct trade yields surplus zero.

[29] Modeling heterogeneity on the importer side goes beyond the scope of this analysis. This would require further assumptions on importer-exporter matching. Recent papers discuss that positive assortative matching might not be prevalent for many-to-many matching in international production networks (Bernard et al. 2018, p. 10; Bernard and Moxnes 2018, p. 11) but for one-to-one matching (Benguria 2021).

is still the possibility for direct trade where the risk of non-matching remains as before.[30] Depending on the legal and institutional system in a country, contract enforcement might be imperfect. Exporter or importer might not fulfill the contract, either by choice or because they default. Following Antràs and Foley (2015) and Schmidt-Eisenlohr (2013), there is a positive probability, $c_n \in (0, 1]$, that a contract settled in $t = 0$ is fulfilled. With probability $(1 - c_n)$, there is the need to go to a local court to enforce the contract.[31] Time and effort to enforce the contract reduces revenues of the agent by $(1 - \delta_n)$. In the baseline model, it is assumed that - with probability $(1 - c_n)$ - revenues are entirely lost: $\delta_n = 1$.

While contract enforcement is static in Antràs and Foley (2015) and Schmidt-Eisenlohr (2013), this article introduces dependency of contract enforcement in the destination country on the level of information frictions, i, where $c'_{IM}(i) < 0, c_{IM}(0) = 1, c_{IM}(1) \to 0$. $c_{IM} = 1, \forall i$ encompasses the idea of blockchain technology and the application of smart contracts: As soon as the arrival of the goods is registered to the blockchain, the transfer of the payment is automatically triggered.

Intuitively, the effect of information frictions on contract enforcement seems to be stronger on the importing than on the exporting side: When agents agree on preshipment terms, enforcement concerns *production* while for post-shipment terms, it is about enforcing *payment*. For simplicity, assume that $c_X(i) = c_X \perp i$.[32] Given this assumption, i can be interpreted as the level of information frictions which affects matching probabilities, delays, and contract enforcement in the *importing* country. The chapter is therefore related to the analysis in Fontagné et al. (2020, p. 567) on the impact of procedural obstacles in the *importing* country on firms' exporting decisions.

3.4.1 Structure of the Game

The general set-up and the structure of the game follow Petropoulou (2008b, 2011) who (theoretically) analyzes the effect of information frictions on the choice of direct versus intermediated trade.[33] Her model features a monopolistic intermediary where information frictions affect the matching probability between importers and exporters where the surplus is fixed. The baseline model is adapted in several aspects in order to study the impact of blockchain technology: Petropoulou (2011)'s general model is extended to specifically model the payment method (MP) that trading partners optimally choose

[30] Blockchains such as *we.trade* allow members to search for participants in the network or include KYC services (e.g. *komgo*).

[31] Glady and Potin (2011, p. 7) motivate that the share $1 - C_n$ of agents is well connected to local authorities.

[32] When $c_X(i) \not\perp i$, the results would depend on the relative magnitude of $c'_X(i)$ vis-à-vis $c'_{IM}(i)$.

[33] She does not mention financial intermediation but generally analyzes "the matching role of intermediaries" (Petropoulou 2011, p. 4) when there is imperfect information.

given prevailing information frictions. That is, information frictions affect the choice between bilateral agreements, $MP = \{CIA, OA\}$, and intermediated trade. The modeling of the payment methods follows Antràs and Foley (2015) and Schmidt-Eisenlohr (2013). Moreover, the extended model includes shipping time as in Berman et al. (2012) and delays related to document handling. Finally, the assumption of identical producers is relaxed to allow for exporting firms that differ in productivity. The latter two features make surplus depend on information frictions. As mentioned above, effects might be similar for innovations such as the internet, telephone, and the telegraph. However, there are some distinguished features of blockchains which are highlighted in the following.
The stages of the game are therefore adapted and extended from Petropoulou (2008b, p. 5f.) and Petropoulou (2011, p. 9):

> **Stage 1:** The intermediary sets up a network. There is only one risk-neutral intermediary with monopoly power that provides the blockchain. It decides on the size of the network, i.e. the share of agents who are offered a contract and screened.

One could either think of a single entity, e.g. a bank, managing a private permissioned blockchain or a single permissioned consortium blockchain which combines financial institutions and firms such as *komgo* or *TradeLens* (see section 3.2). Boot et al. (2020, p. 2) argue that network providers might act as intermediary between banks and customers and thereby gain monopoly power over data and information. The assumption of a monopoly is a limit case. However, Bronzini and D'Ignazio (2017, p. 480) find that cross-border financial activities seem to be concentrated among few banks. Letter of credits are likely to be handled by a bank's local branch offices or correspondent banks. A network of (heterogeneous) banks as an additional layer would further complicate the model and would require assumptions on the matching of firms to banks and banks to consortium networks.[34] In the following, intermediary, platform, or bank are used interchangeably to refer to the monopolist who sets up the network.

> **Stage 2:** The bank offers a contract to (some) importers and exporters specifying a commission rate.

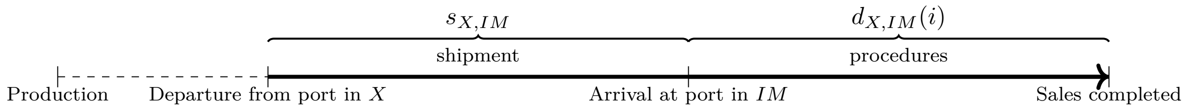
> **Stage 3:** Importers and exporters decide whether to accept the contracts and become part of the network or whether to handle payment directly through an CIA or OA agreement.

[34] In a model with perfect competition between banks and resulting zero profits, networks would not arise.

Stage 4: When trade is handled through the blockchain, participants learn whether the matching trading partner is part of the network. If not, there is still the possibility of a direct trade which is successful with probability $q(i)$. Goods are produced.

After production, goods are carried to a port and shipped from X to IM. Total time between production and arrival at the importer's firm consists of shipping time and the time from the factory gate to the ship and vice versa.

Figure 3.1: Timeline $T(s,i) = s_{X,IM} + d_{X,IM}(i)$



In order to keep the model tractable, it is assumed that production and transport to the *exporting* port are instantaneous as illustrated in figure 3.1. Shipping between the importing and exporting country takes time, $s_{X,IM}$. Additionally, there might be delays due to administrative barriers such as document handling. These delays are denoted by $d_{X,IM}(i)$. As described above, i captures the level of information frictions in the *importing* country. Strictly speaking, $d_{X,IM}(i)$ therefore abstracts from delays caused by administrative obstacles in the *exporting* country. It is a function of the information costs i where $d'_{X,IM}(i) > 0, d_{X,IM}(0) = 0, d_{X,IM}(1) = \overline{d}$.
In the further analysis, it will be crucial to distinguish between those two types of time frames: While $s_{X,IM}$ is given exogenously by the geographical distance between countries, delays due to document handling can be reduced or even eliminated with innovations in ICT such as the introduction of a blockchain and smart contracts.[35] Shipping time can be empirically proxied by the (symmetric) geographical distance between countries. The time for shipment itself seems less insecure. Obviously, factors such as weather conditions can cause unexpected delays. However, given that ships are already easily traceable, transparency for all business partners seems not a major issue.[36]
Moreover, traceability of products depends on the service of the respective ocean carrier

[35]There might also be potential investments that reduce shipping times between ports/countries. However, it seems reasonable to assume that these investments have medium-term (or long-term) impacts on the shipping time. Carballo et al. (2016, p. 10) model time to clear the ship at the *importing* port as random.

[36]There are also several economic papers on shipping data based on AIS (automatic identification system) data (see e.g. Heiland et al. 2019, p. 6; Ganapati et al. 2020).

but not so much on the technology level in the *destination* country. On the contrary, the administrative barriers related to importing are endogenous to a country's institutional and regulatory framework. An empirical proxy would be the non-tariff measures provided by the World Bank's data on *Doing Business* and Trading across borders that consider "documentary compliance, border compliance and domestic transport" (World Bank 2021). Djankov et al. (2010, p. 171) find significant effects of delays in the time to export: an increase in the time from factory gate to ship by one day equals an increase in the distance by 1%. For the time being, delays related to document handling and administrative barriers, $d_{X,IM}(i)$, are country-pair specific. Data on *Doing Business* (World Bank 2021) suggests that time (costs) to import and export are almost perfectly correlated. It holds that $d_{X,IM}, s_{X,IM} \in \mathbb{Z}^{0+}, \forall X, IM$. Hence, total transit time can be written as $T(s,i) \equiv s_{X,IM} + d_{X,IM}(i), T_i'(s,i) > 0$.

> **Stage 5:** Upon arrival, goods are instantaneously sold to the market and payments are potentially made. Agents learn whether their direct trade was successful.

The model is solved recursively. The equilibrium is subgame perfect if network size, commission rate, and the trading partners' decision at **Stage 3** are maximizing their respective profits (Petropoulou 2011, p. 10). The following subsections discuss the different method of payments. Buyer and seller interact only once.[37]

3.4.2 Direct Trade: Open Account or Cash-in-Advance

Importer and exporter might agree on pre- or post-shipment terms. In the former case, it is the importer who bears the risk that the exporter (in)voluntarily defaults or ships goods that deviate from the agreement, e.g. shipping goods at lower quality. The importer also needs to cover the working capital during transit. The interest rate in the destination country is denoted, r_{IM}. In contrast, the exporter takes all risk when agents agree on post-shipment terms. The exporter needs to cover working capital until sales are realized in the destination market. The discount rate is r_X. Financing costs are assumed to be exogenous.

Exporters make a *take-it-or-leave-it* offer to the importers. The case of varying bargaining power would be an interesting extension but even if the agents (unequally) share the surplus, they both have an interest in maximizing it. Hence, unless bargaining power

[37] Multiple interactions similar to Antràs and Foley (2015, p. 875ff.) would be an interesting path for future research.

varies across payment methods their preferences should be aligned.

$$\pi_{s,i}^{CIA}(\phi) = \frac{c_X p(\phi)\tau(s)x(\phi)}{(1+r_{IM})^{T(s,i)}}q(i) - \frac{\tau(s)x(\phi)}{\phi} - f_{IM} \tag{3.3}$$

$$\pi_{s,i}^{OA}(\phi) = \frac{c_{IM}(i)p(\phi)\tau(s)x(\phi)}{(1+r_X)^{T(s,i)}}q(i) - \frac{\tau(s)x(\phi)}{\phi} - f_{IM} \tag{3.4}$$

where $d_{X,IM}(i) \equiv d(i), s_{X,IM} \equiv s$. There are iceberg trade costs such that $\tau(s)$ units need to be shipped for one unit to arrive. It is assumed that these iceberg trade costs depend on distance only, i.e. $\tau(s) \perp i$: Hornok and Koren (2015, p. S111) argue that administrative costs are incurred per-shipment and result in inventory and infrequent, larger shipments. Here, importers and exporters interact and ship only once.[38] Revenues are realized only when trading partners perfectly match. Iceberg trade costs and fixed costs need to be paid in either case.

$$p_{s,i}^{MP}(\phi) = \frac{\sigma}{\sigma-1}\frac{1}{\phi}\frac{(1+r_n)^{T(s,i)}}{c_{\overline{n}}(i)q(i)} \tag{3.5}$$

$$x_{s,i}^{MP}(\phi) = XP^{\sigma}\left[\frac{\sigma}{\sigma-1}\frac{\tau(s)}{\phi}\frac{(1+r_n)^{T(s,i)}}{c_{\overline{n}}(i)q(i)}\right]^{-\sigma} \tag{3.6}$$

for $MP = \{CIA; OA\}$: $n = \{IM; X\}$, $\overline{n} = \{X; IM\}$.[39] More information frictions lead to higher prices and lower export quantities. These effects are increasing in the distance to the destination market and the discount rate.

Since fixed costs are independent of the contract agreement, the profit maximizing choice depends only on revenues. The agents prefer postshipment over preshipment terms when

$$\left[\frac{1+r_{IM}}{1+r_X}\right]^{T(s,i)} \geq \frac{c_X}{c_{IM}(i)} \tag{3.7}$$

The condition is independent of productivity as information frictions, contract enforcement, and discount rates are country(-pair) specific. Moreover, the direct matching probability does not affect the decision. A change in information frictions affects the choice of the payment method: When information frictions increase, contract enforcement in the destination country reduces, $c'_{IM}(i) < 0$. Moreover, there are more delays associated with a longer transit time. When $r_X > r_{IM}$, the left hand side of equation (3.7) decreases in i which makes OA less likely. Ceteris paribus, a higher r_X reduces the present value of the transaction under OA. This effect is stronger when transit time increases as exporters need to finance working capital for a longer time. Given the conditions in the exporting country (c_X), more information frictions increase the occurrence of CIA agreements. Note the difference between the impact of a change in $q(i)$ and $c_n(i)$: The matching probability affects profits of both payment methods, $q(i)$. Contract enforcement, $c_n(i)$, is particularly

[38] If firms wait to ship in order to exploit economies of scale in shipping (see Hornok and Koren 2015), delays would be even more severe.

[39] $q(i) \in (0, 1]$ and $c_n \in (0, 1]$ such that the fraction is always properly defined.

relevant for their relative choice. Proposition 3.1 summarizes the condition under which preshipment terms are chosen for high values of information frictions:

Proposition 3.1 *A reduction in information frictions makes post-shipment (OA) agreements more likely whenever*

$$\epsilon_{d,i} d(i)(r_X - r_{IM}) \frac{(1+r_{IM})^{T(s,i)}}{c_X} > \epsilon_{c_{IM},i} \frac{(1+r_X)^{T(s,i)}}{c_{IM}(i)} \tag{3.8}$$

where $\epsilon_{d,i}, \epsilon_{c_{IM},i}$ are the elasticities of delays and contract enforcement with respect to information frictions.

For $r_X > r_{IM}$ the condition in proposition 3.1 is always fulfilled: More information frictions decreases contract enforcement (right hand side of equation (3.8)). Moreover, high values of i and resulting long delays increase the relative attractiveness of CIA. On the other hand, if $r_X < r_{IM}$, the differential negative impact of delays needs to be smaller than the effect on contract enforcement.[40]
The cutoff depends on the payment method:

$$\phi^{*MP}_{s,i} = \left(\frac{f_{IM}}{\sigma^{-\sigma}(\sigma-1)^{\sigma-1} X P^{\sigma}} \right)^{\frac{1}{\sigma-1}} \tau(s) \left[\frac{(1+r_n)^{T(s,i)}}{c_{\overline{n}}(i) q(i)} \right] \tag{3.9}$$

for $MP = \{CIA; OA\}$, $n = \{IM; X\}$, $\overline{n} = \{X; IM\}$. Intuitively, the payment method that maximizes surplus is associated with a lower productivity cutoff. Note that a potential dependence of fixed costs on information frictions would not alter the relative choice of the payment method but would tighten the cutoff productivity in equation (3.9). If information frictions decrease, for instance, through trade facilitation measures, the cutoff reduces. The extensive margin effects of RTB are also discussed in Maggi et al. (2018). The impact is reinforced by the geographical distance, s (similar to the effect of shipping time in Berman et al. (2012, p. 9)), and the discount rate, r_n:

$$\frac{\partial \phi^{*MP}_{s,i}}{\partial i} > 0 \quad \frac{\partial^2 \phi^{*MP}_{s,i}}{\partial i \partial s} > 0 \quad \frac{\partial^2 \phi^{*OA}_{s,i}}{\partial i \partial r_X} > 0 \quad \frac{\partial^2 \phi^{*CIA}_{s,i}}{\partial i \partial r_{IM}} > 0$$

Aggregate exports are then given by

$$X^{*MP}_{s,i} = \int_{\phi^{MP}_{s,i}}^{\phi_{max}} p^{*MP}_{s,i} x^{*MP}_{s,i} dG(\phi) = \int_{\phi^{*MP}_{s,i}}^{\phi_{max}} X \left(\frac{P}{\tau_s}\right)^{\sigma} \left[\frac{\sigma}{\sigma-1} \frac{(1+r_n)^{T(s,i)}}{c_{\overline{n}}(i) q(i) \phi} \right]^{1-\sigma} dG(\phi) \tag{3.10}$$

The impact of information frictions on aggregate trade flows mirrors the results on the productivity cutoff. A reduction in i increases the intensive and extensive margin.

$$\frac{\partial X^{*MP}_{s,i}}{\partial i} < 0 \quad \frac{\partial^2 X^{*MP}_{s,i}}{\partial i \partial s} < 0 \quad \frac{\partial^2 X^{*MP}_{s,i}}{\partial i \partial r_X} > 0 \quad \frac{\partial^2 X^{*MP}_{s,i}}{\partial i \partial r_{IM}} > 0$$

[40] Note that $ln(1+r_X) - ln(1+r_{IM}) \approx r_X - r_{IM}$ for small values of $r_n, n = \{X, IM\}$ is exploited.

Let $\Pi^D_{s,i}(\phi) \equiv \max\{\mathbb{E}(\pi^{CIA}_{s,i}(\phi)), \mathbb{E}(\pi^{OA}_{s,i}(\phi))\}$. In the following, it is assumed that proposition 3.1 holds such that OA is more likely chosen for low values of information frictions.[41]

3.4.3 Intermediated Trade: Permissioned Blockchain

It is assumed that bank intermediation eliminates voluntary default, i.e. $c_{IM}(i) = 1, \forall i$, as in Schmidt-Eisenlohr (2013, p. 101). Additionally, improved document handling and automation through smart contracts ensure that payment is instantaneous, $d(i) = 0, \forall i$. Bank intermediation through blockchain is modeled as facilitating post-shipment agreements by offering digital (standby) letter of credits. The effect of blockchain on pre-shipment agreements seems less important (see discussion above). Hence, as part of a blockchain (N), expected profits of the exporter are

$$\pi^N_s(\phi) = \frac{p(\phi)\tau(s)x(\phi)}{(1+r_X)^{T(s)}} - \frac{\tau(s)x(\phi)}{\phi} - f_{IM} \tag{3.11}$$

There is no direct dependence of the surplus on the level of information frictions. Prices, quantities, and the productivity cutoff are

$$p^N_s(\phi) = \frac{\sigma}{\sigma-1}\frac{1}{\phi}(1+r_X)^{T(s)} \tag{3.12}$$

$$x^N_s(\phi) = XP^\sigma \left[\frac{\sigma}{\sigma-1}\frac{\tau(s)}{\phi}(1+r_X)^{T(s)}\right]^{-\sigma} \tag{3.13}$$

$$\phi^{*N}_s = \left(\frac{f_{IM}}{\sigma^{-\sigma}(\sigma-1)^{\sigma-1}XP^\sigma}\right)^{\frac{1}{\sigma-1}} \tau(s)(1+r_X)^{T(s)} \tag{3.14}$$

With perfect contract enforcement and elimination of delays in payment, optimal profits are higher and the productivity cutoff, ϕ^{*N}_s, is lower than under bilateral OA. The difference between the two cutoffs, $\phi^{*N}_s - \phi^{*OA}_{s,i}$, is increasing in the geographical distance to the destination market.

Exporters accept intermediation whenever $\pi^{N*}_s(\phi) \geq \pi^{CIA*}_{s,i}(\phi)$ which results in

$$\frac{(1+r_{IM})^{T(s,i)}}{c_X q(i)} \geq (1+r_X)^{T(s)} \tag{3.15}$$

Contract enforcement in the exporting country is imperfect and there is the risk of non-matching when trading bilaterally, $c_X q(i) < 1$. Moreover, there are delays $T(s, i > 0)$. The left hand side of equation (3.15) is increasing in the level of information frictions. For preshipment terms to be preferred over bank intermediated trade the discount rate in the exporting country would need to be sufficiently high (and necessarily larger than

[41] More precisely, whenever proposition 3.1 is true, OA is chosen for $i \in (0, \min\{i_D, 1\})$ and CIA for $i \in (\max\{0, i_D\}, 1)$ where $\pi^{CIA}(i_D) \equiv \pi^{OA}(i_D)$. When i_D is above (below) 1 (0), OA (CIA) would be chosen for all values of i.

r_{IM}).[42]
The bank needs to decide on the size of the network but does not observe the firm's productivity before screening.[43] It decides on the shares of exporters and importers to be screened which are denoted by S_X, S_{IM}, respectively.
A priori, in a given country, every firm is equally likely to be screened, independent of the productivity level. Moreover, the probabilities are independent across countries such that expected matching $Prob(S_X \bigcap S_{IM}) = S_X S_{IM}$. Screening costs $\chi(i, S_X, S_{IM})$ are positively correlated with the level of information frictions and convex in the size of the network. For simplicity, screening costs are identical for importing and exporting countries.[44] Establishing a network (blockchain) also requires sunk costs, F^N.
The structure of fixed and variable costs follows Petropoulou (2011, p. 8, 17) with the exception of the integration over firms' productivity levels:

$$C^N = F^N + \int_{\phi^*}^{\phi_{max}} \chi(i, S_X, S_{IM})(S_X + S_{IM})dG(\phi) \tag{3.16}$$

$$\chi(i, S_X, S_{IM}) = \gamma i^\alpha S^\beta \quad \alpha \geq 1, \beta > 1, \gamma > 0 \tag{3.17}$$

The bank will ask a commission rate $\alpha_B \in [0, 1]$ that is proportional to the surplus.[45]
Information in Patel and Ganne (2020) suggests that blockchain providers often demand a mixture of subscription and transaction fees that are based on volume or value. Sunk costs, F_N, result in economies of scale in network size. For a successful trade, importer and exporter need to be part of the same network. Given symmetry on the cost side, the bank will screen the same amount of importers and exporters, $S_X = S_{IM} \equiv S$.[46]
When the exporter agreed to join the network at **Stage 3**, i.e. $x \in S_X$, expected profits are:

$$\mathbb{E}(\pi_X^N(\phi)|x \in S_X) = S(1 - \alpha_B)\pi_s^N(\phi) + (1 - S)\Pi_{s,i}^D(\phi) \tag{3.18}$$

where α_B is the commission rate charged by the bank and $(1 - S)$ is the probability that the matching importer is *not* part of the blockchain. In the latter case, trade would

[42] If so, this would also imply that equation (3.7) cannot hold and that agents prefer CIA for all $i \in (0, 1)$.

[43] The model in Feenstra et al. (2014) also features a monopolistic bank which cannot observe firms' productivity. It designs loan contracts such that firms honestly state their productivity (Feenstra et al. 2014, p. 731). In contrast to the latter paper, here the bank invests in screening to learn about the firm and extracts additional surplus through a commission rate tailored to the productivity level.

[44] Ahn (2011, p. 17) discusses that banks screen foreign firms less precisely than firms in the domestic market. Here, the model is kept general, the bank's "home" country is not defined. Boot et al. (2020, p. 5) argue that "in-person interaction" becomes less important for financial intermediation. It is unlikely that geographical proximity becomes completely irrelevant, though.

[45] This is similar to the modeling of LC in Schmidt-Eisenlohr (2013, p. 100) or Glady and Potin (2011, p. 10) where fees are proportional to transaction volumes.

[46] Maximizing expected trade, i.e. the probability that matching trading partners are both part of the network, subject to equation (3.16), results in $S_X = S_{IM} \equiv S$ (Petropoulou 2008b, p. 7).

still need to be handled bilaterally. In order to make sure that the exporter accepts the contract at **Stage 2**, the bank needs to set the commission rate sufficiently low to make exporters at least indifferent between joining the network and direct trade. Indifference implies joining the network or network membership yields profits that are higher by "ϵ" (Petropoulou 2011, p. 12, fn.12):

$$\mathbb{E}(\pi_X^N(\phi)|x \in S_X) \geq \mathbb{E}(\Pi_{s,i}^D(\phi)) \iff S(1-\alpha_B)\pi_s^N(\phi) + (1-S)\Pi_{s,i}^D(\phi) \geq \Pi_{s,i}^D(\phi)$$
$$\alpha_B \leq \frac{\pi_s^N(\phi) - \Pi_{s,i}^D(\phi)}{\pi_s^N(\phi)} \tag{3.19}$$

The bank sets α_B such that equation (3.19) holds with equality. Ex-ante, expected profits of being in the network exactly equals the expected profits of a bilateral agreement. The agents are indifferent.

$$\mathbb{E}(\pi_{X|s,i}^N(\phi)) = (1-S^2)\Pi_{s,i}^D(\phi) + S^2\left(1 - \frac{\pi_s^N(\phi) - \Pi_{s,i}^D(\phi)}{\pi_s^N(\phi)}\right)\pi_s^N(\phi) = \Pi_{s,i}^D(\phi) \tag{3.20}$$

where

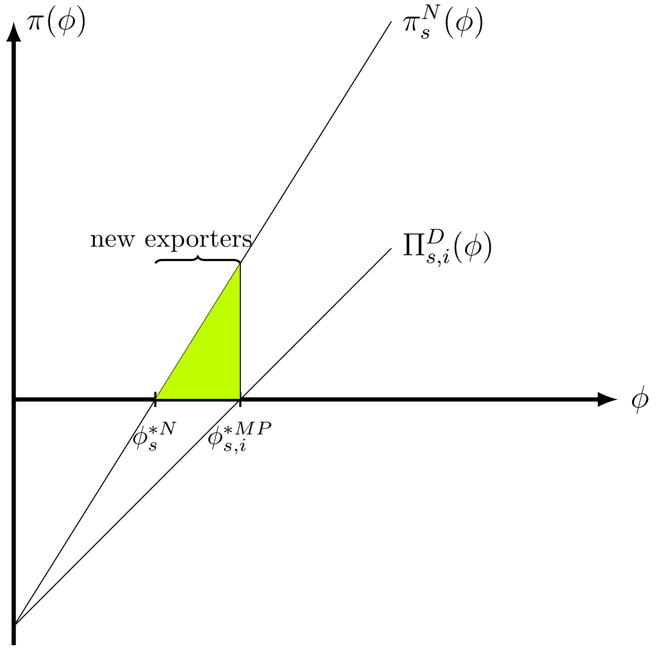
$$\Pi_{s,i}^D(\phi) = \begin{cases} \max\{\mathbb{E}(\pi_{s,i}^{CIA}(\phi)), \mathbb{E}(\pi_{s,i}^{OA}(\phi))\} & \forall \phi \geq \phi_{s,i}^{*MP} \\ 0 & \forall \phi < \phi_{s,i}^{*MP} \end{cases}$$

The surplus the intermediary can extract is restricted to the outside option of zero profits for all firms that would make negative profits with bilateral trade. In fact, without this conditions for equation (3.20), the model would assume that firms are willing to pay in order to participate in international trade. The assumption for firms with $\phi < \phi_{s,i}^{*MP}$ is important for the comparative static results for optimal network size.
A priori, firms' productivity is unobservable. However, after screening the bank knows the firm's productivity. It will therefore demand a commission rate that depends on ϕ. Firms that are below the productivity cutoff for direct trade, $\phi_{s,i}^{*MP}$ in equation (3.9), would not export without an intermediary, $\Pi_{s,i}^D(\phi \leq \phi_{s,i}^{*MP}) = 0$. Within the network, firms with productivity above ϕ_s^{*N} can realize positive profits. This increases the extensive margin of trade. However, given equation (3.19), the monopolist charges a commission rate that extracts all generated surplus of the new entrants. This is illustrated as the green shaded area in figure 3.2.
Bank's expected profits can be written as

$$\mathbb{E}(\Pi_{B|s,i}^N) = \left(\underbrace{\int_{\phi_s^{*N}}^{\phi_{s,i}^{*D}} \pi_s^N(\phi)dG(\phi)}_{\text{new exporters}} + \int_{\phi_{s,i}^{*D}}^{\phi_{max}} (\pi_s^N(\phi) - \Pi_{s,i}^D(\phi))dG(\phi)\right) S^2 - C^N \tag{3.21}$$

$$\text{where} \quad C^N = F^N + 2\int_{\phi^*}^{\phi_{max}} \chi(i,S)SdG(\phi) \tag{3.22}$$

Figure 3.2: Effect of Trade Intermediation on Exporting Cutoff (simplified graphical representation)



The likelihood to be screened is constant across productivity levels and equals S. Costs are aggregated over the set of active firms in the domestic market even though only those above ϕ_s^{*N} are offered a contract in the end. This is an important difference to the baseline model of Petropoulou (2008b, 2011). Optimal network size, $S_{s,i}^*$, is determined by maximizing bank's expected profits. It is a precondition for the monopolist to be active that fixed costs, F^N, are covered. The first order condition yields:

$$S_{s,i}^* = \left(\frac{\int_{\phi_s^{N*}}^{\phi_{max}} \pi_s^N(\phi)dG(\phi) - \int_{\phi_{s,i}^{D*}}^{\phi_{max}} \Pi_{s,i}^D(\phi)dG(\phi)}{i^\alpha \gamma(\beta+1)(G(\phi_{max}) - G(\phi^*))} \right)^{\frac{1}{\beta-1}} \tag{3.23}$$

The denominator captures the increase in marginal costs due to a larger network. The more elastic marginal costs react to an increase in information frictions, α, or network size, β, the lower is the optimal share of firms to be contacted. If the domestic cutoff productivity is low but information frictions lead to a high minimum productivity for exporting, the bank will screen many potential exporters who are not offered a contract, i.e. those where $\phi \in [\phi^*, \phi_s^{N*})$ and consequently $\pi_s^N(\phi) < 0$. The nominator in equation (3.23) represents the surplus that the bank receives through the commission rate. It needs to consider the outside option of direct bilateral trade for all firms above $\phi_{s,i}^{D*}$.
The optimal share depends on the distance and the level of information frictions in the destination country.

Proposition 3.2 *Network size is decreasing in geographical distance when the optimal bilateral payment method is open account.*

Geographical distance implies longer shipping times. When the optimal bilateral payment method is OA, a marginal increase in shipping time reduces profits from intermediated trade relatively more than from bilateral trade. This causes the commission rate to decline for all productivity levels. The reduction in the monopolist's revenues leads to a lower optimal network size. If the outside option for bilateral trade is based on pre-shipment terms, the condition is more sophisticated and depends on the spread between discount rates in the two countries.[47] In this case, the decrease in bilateral profits, $\pi^{*CIA}_{s,i}$, dominates the reduction in π^{*N}_{s} such that the intermediary's rent increases.
Applied to a permissioned blockchain and keeping the level of information frictions fixed, one would expect larger platforms for markets that are geographically closer when business partners would otherwise agree on open account transactions. However, for markets where information frictions are high such that agents are more likely to rely on CIA (see proposition 3.1), network size can be increasing under certain conditions.
The (negative) link between network size and geographical distance resembles findings from applications of gravity models to international trade flows (see e.g. Anderson and Van Wincoop 2003; Head and Mayer 2014; Yotov 2012; Yotov et al. 2016). These models are likewise applied to financial flows between countries (see e.g. Brei and Peter 2018; Buch and Goldberg 2020; Portes and Rey 2005).
Apart from distance, the level of ICT innovations affects the commission rate: An increase in i reduces profits from bilateral trade as the matching probability decreases, $q'(i) < 0$, there is an increase in delays, $d'(i) > 0$, and - if the outside option is OA - contract enforcement worsens, $c'_{IM}(i) < 0$.[48] Bilateral trade becomes less attractive which increases the commission rate that the monopolist can charge (see equation (3.19)). The graph $\Pi^D_{s,i}(\phi)$ in figure 3.2 gets flatter, the area between the two graphs increases. On the other hand, the rise in i increases the marginal costs of screening.

Proposition 3.3 *Network size is increasing in the level of information frictions in the destination country if*

$$-\int_{\phi^{D*}_{s,i}}^{\phi_{max}} \underbrace{\frac{\partial}{\partial i}\Pi^D_{s,i}(\phi)}_{<0}\, dG(\phi)) > \left(\int_{\phi^{N*}_{s}}^{\phi_{max}} \pi^N_s(\phi)dG(\phi) - \int_{\phi^{D*}_{s,i}}^{\phi_{max}} \Pi^D_{s,i}(\phi)dG(\phi)\right)\frac{\alpha}{i} \tag{3.24}$$

Proposition 3.3 formalizes the intuitive results that networks are larger when the intermediary's screening costs react less to information frictions and when i has a large impact on $\Pi^D_{s,i}$.[49] When equation (3.24) is not true, the rise in screening costs dominates the increase in the monopolist's revenues.

[47]For the precise condition see appendix C.2. Under mild conditions, network size should still be decreasing in shipping time.

[48]Finally, also the cutoff productivity, $\phi^{*MP}_{s,i}$, increases but - when applying Leibniz integral rule - for marginal changes evaluated at the cutoff productivity, profits are zero, $\Pi^D(\phi^{*MP}_{s,i}) = 0$.

[49]For the derivations see appendix C.2.

Note that, taking propositions 3.2 and 3.3 together, it might be the case that network size is decreasing in geographical distance and increasing in the level of information frictions, e.g. when equation (3.24) holds and the optimal bilateral payment method is OA. For network size, information frictions and distance would then act as substitutes: Given the level of ICT, one would expect larger blockchain platforms for markets that are either closer to the exporter or, holding shipping time fixed, where information frictions are high (conditional on equation (3.24)). Currently, there are platforms that are limited to regional markets, e.g. among European countries, which could support the former result. The latter highlights that DLT could compensate for a weak institutional framework alongside the argument in the literature (e.g. Antràs 2020, p. 21; Ganne 2018; Maupin et al. 2019). Finally, when proposition 3.3 does not hold but proposition 3.2 is true, network size is decreasing in the level of ICT: Ceteris paribus, platforms are larger in both, closer and more technologically advanced countries which would counter the expectation of DLT as fostering participation of developing countries in GVCs.[50]

With intermediated trade aggregate exports amount to

$$X_{s,i}^{N} = \int_{\phi_s^N}^{\phi_{max}} p_s^N(\phi)x_s^N(\phi)dG(\phi)(S_{s,i}^*)^2 + \underbrace{\int_{\phi_{s,i}^{*MP}}^{\phi_{max}} p_{s,i}^{*MP}(\phi)x_{s,i}^{*MP}(\phi)dG(\phi)}_{X_{s,i}^{*MP}}[1-(S_{s,i}^*)^2] \quad (3.25)$$

A comparison of equation (3.25) and equation (3.10) reveals that when the monopolist is active in the market, $S_{s,i}^* > 0$, aggregate trade flows are necessarily larger than under bilateral trade. This is a similar argument as in the baseline model (Petropoulou 2011, p. 14).

The level of ICT in the destination country affects aggregate trade flows through its effect on the share of intermediated trade, $S_{s,i}^*$, as well as through its effect on aggregate trade flows of bilateral trade. The latter effect is negatively correlated with information frictions, $\frac{\partial X_{s,i}^{*MP}}{\partial i} < 0$: delays, imperfect contract enforcement, and lower matching probabilities increase prices, reduce quantities and ultimately firms' revenues. If network size were decreasing in i, aggregate trade flows would also decrease in a regime with an active monopolist, $\frac{\partial X_{s,i}^{N}}{\partial i} < 0$. On the other hand, if proposition 3.3 holds and more frictions result in a larger network, the impact on network size and bilateral trade flows have opposing signs.

As long as network size is decreasing in geographical distance - which will always be the case when OA is the outside option - aggregate exports are decreasing in distance.

Finally, Petropoulou (2011, p. 14f.) shows that welfare in the economy is higher when the monopolist is active. The results can be extended to the setting with heterogeneous firms: Given equation (3.20), the monopolist ensures that the agents are indifferent be-

[50]Note that Petropoulou (2011) assumes specific functional forms for $q(i)$. Due to the extensions in this chapter, conditions are more complex. Furthermore, it is intended to keep generality.

tween direct trade and intermediation. Their profits are identical in either regime. On the other hand, the intermediary enables trade for some firms with productivity levels in $[\phi_s^{*N}, \phi_{s,i}^{*D}]$ but extracts all their profits. When the bank offers intermediation, i.e. its revenues are larger than screening and fixed costs, aggregate profits in the economy are higher than under bilateral trade. As the monopolist covers all additional profits, this points, however, to a discussion on the distributions of the gains (see section 3.5).
In the baseline model, the intermediary cannot observe the productivity of firms before offering the contract. The commission rate the bank can earn is increasing in firms' productivity level (see equation (3.19)). As long as screening and monitoring costs are independent of productivity, i.e. $\chi(i, S_X, S_{IM}) \perp \phi$, the intermediary would only offer contracts to the most productive firms. In this case, there is only an intensive margin effect as the cutoff productivity, $\phi_{s,i}^{*MP}$, is binding for all remaining firms. In contrast, when screening costs are not convex but linear in network size, there is no interior solution for the intermediary's maximization problem: either none or all firms are offered a contract.[51]
Possible extensions, limitations, and potential policy implications are discussed in the following.

3.5 Outlook and Discussion

One of the main obstacles for adoption and applications of DLT is limited interoperability between different technology systems. Currently, there are several blockchains in the field of international trade and supply chain management (see Patel and Ganne (2020)). As platform participation is not mutually exclusive, firms and banks can be - and some actually are - active on several networks.[52] Unless platforms are fully compatible and connectable, there are economic network effects. Agents want to be part of the largest network to increase the likelihood that matching trading partners are active on the same platform. Hence, in the medium to long run, there could be consolidation in the market of DLT.
While the model in this chapter extends the monopoly version of Petropoulou (2008b, 2011), Petropoulou (2008a) extends her baseline model where two intermediaries compete for customers. Which of the multiple equilibria with either monopolistic or fragmented duopolistic intermediation arises, depends on the assumption whether costs are linear or convex in network size (Petropoulou 2008a, p. 28). The aspect of market structure on the level of platform providers for financial intermediation in international trade is an interesting path for future research but goes beyond the scope of this analysis. The model

[51] See the baseline model in Petropoulou (2008b, p. 9ff.).
[52] The set of financial institutions partly overlaps across the platforms mentioned in section 3.2.

above yields positive trade creation effects which benefits the monopolist who extracts all additional surplus. For future theoretical and empirical work, it would be interesting to consider market structure and distributional consequences of DLT within and across industries and countries.

The fact that entry of record-keepers is free in a permissionless but restricted for permissioned blockchains determines the ability to extract rents and the gains for participants (Abadi and Brunnermeier 2018, p. 46). Boot et al. (2020, p. 5) expect that network providers will take up financial services and gain market power such that banks could be "relegate[d] [...] to upstream providers of maturity transformation services" (Boot et al. 2020, p. 5). The monopolist in the model offers digital (standby) letters of credit as (financial) intermediation. Whether DLT will lead to a shift of former bank services to other market players and to what extent there will be policy or regulatory responses are interesting questions for the future.

In the model, financing costs are assumed to be exogenous. Antràs and Foley (2015, p. 871ff.) endogenize the costs to finance working capital during transit. Banks charge higher interest rates in countries with weak contract enforcement. The latter is likely to be affected by information frictions as well. Note, however, that this concerns the financing costs in the *destination* country, in the case of CIA, and in the *exporting* country for OA agreements. Endogenous financing costs could be captured by including levels of information frictions for both countries, e.g. through an interaction term as in Antràs and Foley (2015, p. 872).

Given uncertainty, CIA can serve as a quality signal for firms (Eck et al. 2015) and can be complementary to bank credits (Engemann et al. 2014). Some of the blockchain systems mentioned above offer digital letters of credit but also credit services. Improved monitoring should then also reduce effective financing costs. In order to exploit efficiency gains, it is likely that all financial services are handled through the platform. However, especially for early adoptions, some services might still be offered offline.

Time and delays are known to have important effects on international trade (Berman et al. 2012; Djankov et al. 2010; Hummels and Schaur 2013). But depending on the durability of a product, efficiency gains of digital document handling and automation can be larger. Moreover, the type of the financing mode could vary across products: Trade in poultry in Antràs and Foley (2015, p. 861) is mostly based on bilateral agreements. It is not surprising that several blockchains are applied for agricultural products specifically (see example in section 3.3 which is targeted to agricultural products). Another example is *IBM Food Trust*, a permissioned blockchain claiming to make the food supply chain "smarter, safer, [and] more sustainable" (IBM 2021).[53] A participating retailer reports that purchases of agricultural products where consumers could verify the product's sup-

[53] See `https://www.ibm.com/blockchain/solutions/food-trust` (April 24, 2021).

ply chain have increased (Thomasson 2019). Beyond the supply side effects, transparency on and traceability of a product's origins and quality could therefore also affect demand. In the theoretical set-up information frictions affect the variable costs. If fixed costs for exporting depended on i, the cut-off for exporting would be higher (see equation (3.9)). For the effect on intermediation, one would need further assumptions on how fixed costs of exporting within the blockchain are affected. Furthermore, the fixed costs are assumed to be identical across bilateral payment methods, OA and CIA. Hence, there is no differential selection of more or less productive firms in one of the two types in contrast to Melitz (2003) type models on transport mode (Coşar and Demir 2018, p. 337) or technology adoption (Bustos 2011, p. 311).

Ahn et al. (2011, p. 75) also incorporate trade intermediation in a Melitz (2003) type model: Competitive intermediaries offer to buy goods from firms to sell them in destination markets. Intermediation entails lower fixed costs but goods are sold at higher prices in the destination market such that low productivity firms self-select into intermediated trade (Ahn et al. 2011, p. 75). Even absent this selection effect, the results that intermediaries enable trade for low productivity firms and that this is especially important for countries that are more difficult to reach are consistent with the theoretical outcomes in this chapter.[54]

The answer to the question "Blockchain: A World Without Middlemen?" (Maupin et al. 2019) will likely depend on the main purpose and type of blockchains. Ganne (2018, p. 84f.) names examples of platforms in developing countries that allow small and medium-sized enterprises to establish trade relationships without traditional intermediaries, e.g. financial services are provided by fintechs instead of banks. While this might facilitate the access to financial means, there is still intermediation and possible rent extraction. When the purpose is the mere information about potential business partners (such as buyers of agricultural goods in Kenya (Ganne 2018, p. 85)) and especially for permissionless blockchains, the relevance and thereby also the rents of middlemen could decrease. In any case, the technology per se does not guarantee quality of the "offline" data that is entered (Maupin et al. 2019, p. 64).

In addition, one needs to reflect on the (potentially) high energy consumption of blockchains (Ganne 2018, p. 92f.). The technology's climate impact will depend on possible solutions to reduce the level of energy needed for validation, especially when adoption and network sizes are growing. High energy consumption also limits scalability (Ganne 2018, p. 90), affects the cost side of and ultimately countries' and firms' access to DLT.

One aspect that has not been analyzed so far, is the (potential) effect of a digital currency or cryptocurrency on trade finance and trade flows. There are very recent debates

[54]This is related to a literature on wholesalers and retailers in international trade. Here, the intermediary provides trust in form of guaranteeing payments. It is not about selling the goods in the destination market.

on central bank digital currencies (see e.g. ECB (2020, 2021)). Digital currencies on a blockchain could lead to an additional reduction in transaction times.
The above mentioned discussions show that the economic impact that DLT might have depends crucially on conditions in terms of information technology, cybersecurity, market structure, and the political and legal framework. Concerning the latter, there might be two countervailing effects: On the one hand, the promise of better contract enforcement through the technical features of DLT but, on the other hand, legal uncertainty related to its application and validity. Hence, policy measures should be targeted to provide a secure technical and legal framework.

3.6 Conclusion

Distributed ledger technologies are expected to affect international trade. The data section of this chapter found an increase in patenting related to blockchain and distributed ledger technologies. Patent abstracts refer to financial intermediation, smart contracts, and document handling, especially when conditioning on keywords related to cross-border activities. The theoretical model is an attempt to formalize effects of information frictions on the choice of the payment method and on the spread and size of intermediated trade through a digital platform. The trade creation effects through a reduction in information frictions and increased efficiency through digitization and automation are more important for countries where information frictions are high and contract enforcement is low. There is still uncertainty about adoption rates, regulatory responses, and technological innovations, but "by offering a way of setting the past and present in cryptographic stone, [...] [blockchains] could make the future a very different place" (The Economist 2015a).

Appendices

A Appendix to Chapter 1

A.1 Additional Figures

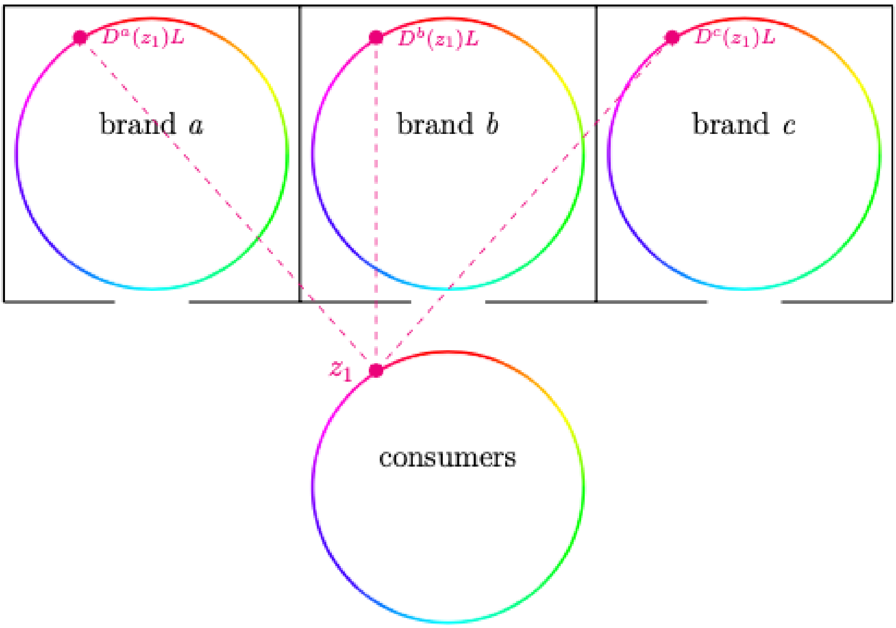


Figure A.1: Illustration: Demand Share at a given Location

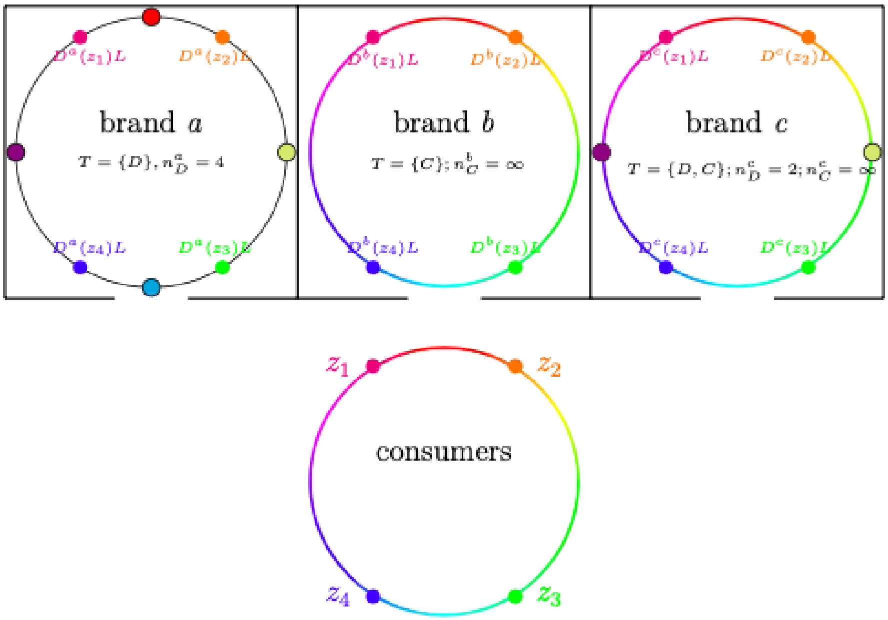


Figure A.2: Illustration Exact Location Based Purchase Decision

A.2 Derivations

Derivations: Price Differences Across Differentiated Versions

The idea of an indifferent consumer between two differentiated versions of a brand follows Eaton and Wooders (1985, p. 286) and Hadfield (1991, p. 533) where individuals are indifferent between firms or retailing outlets.
Let the indifferent consumer between version $i-1$ at z_{i-1} and i at z_i be located at $x \in [0,1]$. Accordingly, the consumer indifferent between version i and $i+1$ at z_{i+1} is located at $y \in [0,1]$. The two indifference conditions for $\alpha = 2$ are:[1]

$$p_i + \bar{t}(z_i - x)^2 = p_{i-1} + \bar{t}(x - z_{i-1})^2 \tag{26}$$
$$p_i + \bar{t}(y - z_i)^2 = p_{i+1} + \bar{t}(z_{i+1} - y)^2 \tag{27}$$

Manipulating the two equations yields

$$p_i + \bar{t}z_i^2 - 2\bar{t}z_i x + \bar{t}x^2 = p_{i-1} + \bar{t}x^2 - 2\bar{t}z_{i-1}x + \bar{t}z_{i-1}^2$$
$$p_i + \bar{t}y^2 - 2\bar{t}z_i y + \bar{t}z_i^2 = p_{i+1} + \bar{t}z_{i+1}^2 - 2\bar{t}z_{i+1}y + \bar{t}y^2$$

Solving for x yields

$$p_i + \bar{t}z_i^2 - 2\bar{t}z_i x + \bar{t}x^2 = p_{i-1} + \bar{t}x^2 - 2\bar{t}z_{i-1}x + \bar{t}z_{i-1}^2$$
$$-2\bar{t}x\underbrace{(z_i - z_{i-1})}_{\frac{1}{n_D^b}} = p_{i-1} - p_i - \bar{t}z_i^2 + \bar{t}z_{i-1}^2$$
$$x = \frac{p_i - p_{i-1} + \bar{t}(z_i^2 - z_{i-1}^2)}{2\bar{t}\frac{1}{n_D^b}}$$

Analogously, solving for y yields

$$y = \frac{p_{i+1} - p_i + \bar{t}(z_{i+1}^2 - z_i^2)}{2\bar{t}\frac{1}{n_D^b}}$$

[1] To ease notation the brand index b is dropped.

Since $y > x$, the market area of version i is given by

$$
\begin{aligned}
y - x &= \frac{p_{i+1} - p_i + \bar{t}\,\overbrace{(z_{i+1} - z_i)}^{\frac{1}{n_D^b}}(z_{i+1} + z_i)}{2\bar{t}\frac{1}{n_D^b}} - \frac{p_i - p_{i-1} + \bar{t}\,\overbrace{(z_i - z_{i-1})}^{\frac{1}{n_D^b}}(z_i + z_{i-1})}{2\bar{t}\frac{1}{n_D^b}} \\
&= \frac{p_{i+1} + p_{i-1} - 2p_i + \bar{t}(z_{i+1} + z_i - z_i - z_{i-1})\frac{1}{n_D^b}}{2\bar{t}\frac{1}{n_D^b}} \\
&= \frac{p_{i+1} + p_{i-1} - 2p_i + \bar{t}(\overbrace{z_{i+1} - z_i}^{\frac{1}{n_D^b}} + \overbrace{z_i - z_{i-1}}^{\frac{1}{n_D^b}})\frac{1}{n_D^b}}{2\bar{t}\frac{1}{n_D^b}} \\
&= \frac{p_{i+1} + p_{i-1} - 2p_i}{2\bar{t}\frac{1}{n_D^b}} + \frac{1}{n_D^b}
\end{aligned}
$$

See graphical illustration below.

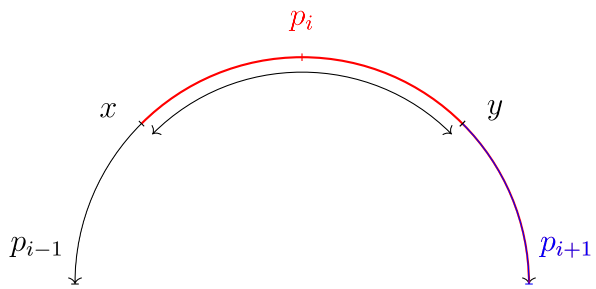


Figure A.3: Localized Competition between Differentiated Varieties $i-1, i, i+1$, of a brand b, priced at p_{i-1}, p_i, p_{i+1}.

Derivations: Expectation Based Purchase Decision

Notes on Expectation Formation and Ex-Post Evaluation

When evaluating the *delivered* price, considering the expectation of "$\hat{z}$ to the power of α" leads to a *delivered* price that is in expectation equal to the mill price.
For notational convenience, the case of symmetric brands will be discussed, i.e. $n_D^b = n_D, \forall b \in \mathcal{M}$. Consumers of mass L are uniformly distributed. When it is assumed that products are allocated equispaced along the unit circle, consumers might be located at distances 0, i.e. exactly at the differentiated product, or on both sides of the product, at the maximum distance of $\frac{1}{2n_D}$. In the expectation based purchase decision, it is assumed that consumers do not observe their distance vis-à-vis the next closest differentiated version. Hence, they form an expectation based on the number of differentiated versions a brand offers where $n_C = \infty$. Let's denote the distance by $\hat{z}$ such that $\hat{z} \sim U[0, \frac{1}{2n_D}]$.[2] The expected distance is $\mathbb{E}[\hat{z}] = \frac{1}{2}[0 + \frac{1}{2n_D}] = \frac{1}{4n_D}$. However, to keep the model general and allow dependence on the degree of convexity, α, indirect utility is

$$
\begin{aligned}
\tilde{V}^b_{j|\hat{z}} &= \tilde{u}_{\hat{z}} + \mu\epsilon^b_{j|\hat{z}} = y - p^b_D - t(\hat{z})^\alpha + \mu\epsilon^b_{j|\hat{z}}, \quad \hat{z} \sim U[0, \frac{1}{2n_D}], \hat{z} \perp \epsilon_b \\
V \equiv \mathbb{E}_{\hat{z}}[\tilde{V}] &= y - p^b_D - t\mathbb{E}_{\hat{z}}[(\hat{z})^\alpha] + \mu\epsilon^b_{j|\hat{z}} \\
\mathbb{E}_{\hat{z}}[(\hat{z})^\alpha] &= \int_0^{\frac{1}{2n_D}} \hat{z}^\alpha f(\hat{z})d\hat{z}; \quad f(\hat{z}) = 2n_D \text{ as } \hat{z} \sim U[0, \frac{1}{2n_D}] \\
&= \frac{1}{\alpha+1}\left[\hat{z}^{\alpha+1}\right]_0^{\frac{1}{2n_D}} 2n_D \\
V &= y - p^b_D - \bar{t}\left(\frac{1}{2n_D}\right)^\alpha + \mu\epsilon^b_{j|\hat{z}} \\
&= y - p^b_D - \bar{t}\overline{x}(n_D) + \mu\epsilon^b_{j|\hat{z}}
\end{aligned}
$$

where

$$
\begin{aligned}
\overline{x}(n_D) \equiv (2n_D)^{-\alpha} &\qquad \frac{\partial\overline{x}(n_D)}{\partial n_D} = -\alpha\frac{(2n_D)^{-\alpha}}{n_D} = -\alpha\frac{\overline{x}(n_D)}{n_D} \\
\bar{t} \equiv \left(\frac{1}{\alpha+1}\right)t < t &\quad t \in (0,1), \alpha > 0
\end{aligned}
$$

Consequently, the expectation of the deviation between the expected *delivered* and actual *delivered* price, or, put differently, the deviation between expected and actual indirect utility is zero, i.e.

$$\mathbb{E}_{\hat{z}}[\tilde{V}_{\hat{z}} - V] = \mathbb{E}_{\hat{z}}[\tilde{V}_{\hat{z}}] - V = 0$$

[2]Note that when $z \sim U[0,1]$ with $f(z) = 1, F(z) = z$ and the circle can be cut into $2n_D$ segments with equal length $\frac{1}{2n_D}$, then $\hat{z}$ is a transformation of the random variable $z \sim U[0,1]$ (multiplication with a scalar). When $\hat{z} \sim U[0, \frac{1}{2n_D}]$, then $f(\hat{z}) = 2n_D$ and $F(\hat{z}) = 2n_D\hat{z}$.

First Order and Second Order Conditions

If consumers form expectation based purchase decisions, demand at any $z \in [0,1]$ is independent of the location.

$$\max_{n_D^b, p_D^b} \Pi_D^b = (p_D^b - c_D^b) D^b L - n_D^b f_D \tag{28}$$

$$\frac{\partial \Pi_D^b}{\partial p_D^b} = D^b L + (p_D^b - c_D^b) \frac{\partial D^b}{\partial p_D^b} L = 0 \tag{29}$$

$$\frac{\partial \Pi_D^b}{\partial n_D^b} = (p_D^b - c_D^b) \frac{\partial D^b}{\partial n_D^b} L - f_D = 0 \tag{30}$$

Intuitively, equation (30) shows that the benefits of a marginal increase in the number of differentiated products (increasing perceived quality, decreasing the expected *delivered* price) through the *inter*-brand dimension equals the fixed costs of establishing an additional variety, f_D.

$$\frac{\partial D^b}{\partial p_D^b} = -\frac{1}{\mu} D^b = -\frac{1}{\mu} \frac{e^{-\frac{p_D^b + \bar{t}\bar{x}(n_D^b)}{\mu}}}{\sum_{\tilde{b}=1}^{\mathcal{M}} e^{-\frac{\tilde{p}_T^{\tilde{b}}}{\mu}}}$$

$$\begin{aligned}
\frac{\partial D^b}{\partial n_D^b} &= \frac{1}{\mu} \alpha \bar{t}\bar{x}(n_D^b) \frac{D^b}{n_D^b} \\
&= \frac{\alpha}{\mu} \bar{t} \frac{\bar{x}(n_D^b)}{n_D^b} \frac{e^{-\frac{p_D^b + \bar{t}\bar{x}(n_D^b)}{\mu}}}{\sum_{\tilde{b}=1}^{\mathcal{M}} e^{-\frac{\tilde{p}_T^{\tilde{b}}}{\mu}}}
\end{aligned}$$

The first order conditions simplify to

$$1 - (p_D^b - c_D^b) \frac{1}{\mu} = 0 \quad \Longleftrightarrow \quad p_D^{b^*} = \mu + c_D^b \tag{31}$$

$$\underbrace{(p_D^{b^*} - c_D^b)}_{\mu} \frac{\alpha}{\mu} \bar{t}\bar{x}(n_D^b) \frac{D^b}{n_D^b} L = f_D \tag{32}$$

For completeness, derivations of the second order conditions show that profits are concave in prices, the number of differentiated products and that the extrema are maxima.

$$\begin{aligned}
\frac{\partial^2 \Pi_D^b}{\partial (p_D^b)^2} &= \frac{\partial D^b}{\partial p_D^b} L + \frac{\partial D^b}{\partial p_D^b} L + (p_D^b - c_D^b) \frac{\partial^2 D^b}{\partial (p^b)^2} L \\
&= -2 \frac{1}{\mu} D^b L + \mu (-\frac{1}{\mu}) \frac{\partial D^b}{\partial p_D^b} L \\
&= -\frac{2}{\mu} D^b L + \frac{1}{\mu} D^b L = -\frac{1}{\mu} D^b L < 0
\end{aligned} \tag{33}$$

$$\begin{aligned}
\frac{\partial^2 \Pi_D^b}{\partial (n_D^b)^2} &= (p_D^b - c_D^b)\frac{\partial^2 D^b}{\partial (n_D^b)^2}L \\
&= \mu L\left[-\frac{\alpha}{\mu}\bar{t}\frac{\overline{x}(n_D^b)}{(n_D^b)^2}D^b - \frac{(\alpha)^2}{\mu}\bar{t}\frac{\overline{x}(n_D)}{n_D^2}D^b + \frac{(\alpha)^2}{\mu^2}\bar{t}^2\frac{\overline{x}(n_D)^2}{(n_D^b)^2}D^b\right] \\
&= \underbrace{LD^b\bar{t}\frac{\alpha}{(n_D^b)^2}\overline{x}(n_D)}_{>0}\left[-1-\alpha+\frac{\alpha}{\mu}\bar{t}\overline{x}(n_D)\right] \qquad (34)
\end{aligned}$$

where

$$\begin{aligned}
\frac{\partial^2 \Pi_D^b}{\partial (n_D^b)^2} < 0 \quad &\iff \\
\left[-1-\alpha+\frac{\alpha}{\mu}\bar{t}\overline{x}(n_D)\right] &< 0 \\
\bar{t}(2n_D^b)^{-(\alpha)} &< \frac{(1+\alpha)^2}{\alpha}\mu \\
\bar{t} &< \frac{(1+\alpha)^2}{\alpha}2^{\alpha}\mu
\end{aligned}$$

where the last row follows from assuming that f_D and L is such that $n_D^b \geq 1$ and calculating the most restrictive version, i.e. $n_D^b = 1$. When $\alpha \geq 1$, then the condition $\mu > t$ is sufficient to guarantee concavity of the profit function with respect to n_D^b. Finally, the cross derivative at the optimum is zero. The extrema are maxima (necessary and sufficient conditions are fulfilled).

$$\begin{aligned}
\frac{\partial^2 \Pi_D^b}{\partial p_D^b \partial n_D^b} &= \frac{\partial D^b}{\partial n_D^b}L + (p_D^b - c_D^b)\frac{\partial^2 D^b}{\partial p_D^b \partial n_D^b}L \\
&= \frac{\partial D^b}{\partial n_D^b}L + \underbrace{(p_D^b - c_D^b)}_{(p_D^{b*}-c_D^b)=\mu}(-\frac{1}{\mu})\frac{\partial D^b}{\partial n_D^b}L \\
&= \frac{\partial D^b}{\partial n_D^b}(1-1) = 0 \\
\frac{\partial^2 \Pi_D^b}{\partial p_D^b \partial n_D^b} &= \frac{\partial^2 \Pi_D^b}{\partial n_D^b \partial p_D^b} = 0 \\
(\frac{\partial^2 \Pi_D^b}{\partial (p_D^b)^2})(\frac{\partial^2 \Pi_D^b}{\partial (n_D^b)^2}) - \frac{\partial^2 \Pi_D^b}{\partial n_D^b \partial p_D^b} &> 0
\end{aligned}$$

The profit function for the customization technology is

$$\begin{aligned}
\max_{p_C^b} \Pi_C^b &= (p_C^b - c_C^b)D^b L - f_C \\
\frac{\partial \Pi_C^b}{\partial p_C^b} &= D^b L + (p_C^b - c_C^b)\frac{\partial D^b}{\partial p_C^b}L = 0 \\
\text{where} \quad \frac{\partial D^b}{\partial p_C^b} &= -\frac{1}{\mu}D^b \\
p_C^{b*} &= \mu + c_C^b \qquad (35)
\end{aligned}$$

Symmetry across brands - short run - partial equilibrium

Technology Choice

Assuming symmetry across (and within) brands, demand for any brand $b \in 1, \ldots, \mathcal{M}$ is given by $D^b L = L^b = \frac{L}{\mathcal{M}}$. Hence, equation (32) simplifies to

$$\begin{aligned}
\alpha 2^{-\alpha}\bar{t}(n_D)^{-(\alpha+1)}\frac{L}{\mathcal{M}} &= f_D \\
n_D^{-(\alpha+1)} &= \frac{2^\alpha}{\alpha}\frac{1}{\bar{t}}f_D\frac{\mathcal{M}}{L} \\
n_D^* &= \left(\frac{\alpha\bar{t}L}{2^\alpha\mathcal{M}f_D}\right)^{\frac{1}{1+\alpha}} = \left(\frac{\alpha}{1+\alpha}\frac{tL}{2^\alpha\mathcal{M}f_D}\right)^{\frac{1}{1+\alpha}}
\end{aligned}$$

How does optimal proliferation respond to changes in the parameters?

$$\begin{aligned}
\frac{\partial n_D^*}{\partial L} &= \frac{1}{1+\alpha}\frac{n_D^*}{L} > 0 \quad , \quad \frac{\partial^2 n_D^*}{\partial L^2} = -\frac{\alpha}{(1+\alpha)^2}\frac{n_D^*}{L^2} < 0 \\
\frac{\partial n_D^*}{\partial \mathcal{M}} &= -\frac{1}{1+\alpha}\frac{n_D^*}{\mathcal{M}} < 0 \quad , \quad \frac{\partial^2 n_D^*}{\partial \mathcal{M}^2} = \frac{2+\alpha}{(1+\alpha)^2}\frac{n_D^*}{\mathcal{M}^2} > 0 \\
\frac{\partial n_D^*}{\partial \bar{t}} &= \frac{1}{1+\alpha}\frac{n_D^*}{\bar{t}} > 0 \quad , \quad \frac{\partial^2 n_D^*}{\partial \bar{t}^2} = -\frac{\alpha}{(1+\alpha)^2}\frac{n_D^*}{\bar{t}^2} < 0 \\
\frac{\partial n_D^*}{\partial f_D} &= -\frac{1}{1+\alpha}\frac{n_D^*}{f_D} < 0 \quad , \quad \frac{\partial^2 n_D^*}{\partial f_D^2} = \frac{2+\alpha}{(1+\alpha)^2}\frac{n_D^*}{f_D^2} > 0
\end{aligned}$$

Intuitively, optimal proliferation is increasing in the size of the market, L, and sensitivity to *fit costs*, $\bar{t}$. A larger number of competitors, $\mathcal{M}$, and higher fixed costs, f_D, decrease n_D^*. These marginal effects are at a decreasing rate.
Calculations of elasticities yield

$$\begin{aligned}
\frac{\partial ln(n_D^*)}{\partial ln(L)} &= \frac{1}{1+\alpha} \in (0,1) \quad \forall \alpha > 0 \\
\frac{\partial ln(n_D^*)}{\partial ln(\mathcal{M})} &= \frac{\partial ln(n_D^*)}{\partial ln(f_D)} = -\frac{1}{1+\alpha} \in (0,-1) \quad \forall \alpha > 0
\end{aligned}$$

The optimal profits are given by[3]

$$\begin{aligned}
\Pi_D^* &= \mu\frac{L}{\mathcal{M}} - \left(\frac{\alpha\bar{t}L}{2^\alpha\mathcal{M}f_D}\right)^{\frac{1}{1+\alpha}} f_D \\
&= \frac{L}{\mathcal{M}}\left(\mu - \left(\frac{\alpha\bar{t}\mathcal{M}^\alpha f_D^\alpha}{2^\alpha L^\alpha}\right)^{\frac{1}{\alpha+1}}\right) \\
&= L^b\left(\mu - (\alpha\bar{t})^{\frac{1}{1+\alpha}}\left(\frac{f_D}{2L^b}\right)^{\frac{\alpha}{\alpha+1}}\right)
\end{aligned}$$

$$L^{\frac{1}{1+\alpha}} = L^{\frac{1+\alpha}{1+\alpha}-\frac{\alpha}{1+\alpha}} = L * L^{-\frac{\alpha}{1+\alpha}}$$

[3]Due to symmetry, superscript b can be ignored.

If the customization technology is adopted there is only maximization with respect to the price which is analogous to equation (35).
The optimal profit for customization in the case of symmetry across firms is simply

$$\Pi_C^* = \mu \frac{L}{\mathcal{M}} - f_C$$

The representative brand compares the optimal short-run profits (number of competitors, $\mathcal{M}$ fixed). The customization technology is adopted if and only if

$$\begin{aligned} &\Pi_C^* \geq \Pi_D^* \\ &\frac{f_C}{f_D} \leq \left(\frac{\alpha \bar{t} L}{2^\alpha \mathcal{M} f_D}\right)^{\frac{1}{1+\alpha}} = n_D^* \end{aligned} \tag{36}$$

Equation (36) also shows that the ratio of fixed costs for adoption of the customization technology and establishing one differentiated variety needs to be smaller than the optimal number of differentiated products.
This is intuitive as the revenues are symmetric with the constant *margin* of μ for both technologies and the number of active competitors is fixed in the short run. Therefore, only the comparison of the fixed costs matter for the decision which technology will be adopted. If $T = C$, these costs simply amount to f_C while in the case of $T = D$, fixed costs are $f_D n_D^*$.
The difference in profits is

$$\Pi_C^* - \Pi_D^* = \left(\frac{\alpha \bar{t} L}{2^\alpha \mathcal{M} f_D}\right)^{\frac{1}{1+\alpha}} f_D - f_C$$

An increase in L (or equivalently in $\overline{L} = \frac{L}{\mathcal{M}}$)[4] leads to an increase in the optimal differentiation n_D^*. Proliferation means that firms need to invest more fixed costs (per version). This reduces, ceteris paribus, optimal profits of differentiation.

$$\begin{aligned} \exists \quad \overline{L} : \Pi_C^*(\overline{L}) - \Pi_D^*(\overline{L}) &\equiv 0 \\ \overline{L} &= \frac{2^\alpha \mathcal{M} f_C^{(1+\alpha)}}{\alpha \bar{t} f_D^\alpha}. \end{aligned}$$

$$\overline{\left(\frac{L}{\mathcal{M}}\right)} \equiv \overline{L^b} = \frac{2^\alpha}{\alpha \bar{t}} \left(\frac{f_C}{f_D}\right)^\alpha f_C$$

The limit depends negatively on the sensitivity to *fit costs*, $\bar{t}$, as the latter increase optimal proliferation.

[4] $\mathcal{M}$ is the number of competitors which is assumed fixed in the short run. An increase in L^b can be caused by either an increase in the mass of consumers or a decrease in the number of competitors.

$$
\begin{aligned}
\frac{\partial(\Pi_C^* - \Pi_D^*)}{\partial L} &= \frac{1}{1+\alpha}\left(\frac{\alpha \bar{t} L}{2^\alpha \mathcal{M} f_D}\right)^{-\frac{\alpha}{1+\alpha}}\left(\frac{\alpha \bar{t}}{2^\alpha \mathcal{M} f_D}\right) f_D \\
&= \frac{1}{1+\alpha}\left(\frac{\alpha \bar{t}}{2^\alpha \mathcal{M} f_D}\right)^{\frac{1}{1+\alpha}} f_D L^{-\frac{\alpha}{1+\alpha}} \\
\frac{\partial^2(\Pi_C^* - \Pi_D^*)}{\partial L^2} &= -\frac{\alpha}{(1+\alpha)^2}\left(\frac{\alpha \bar{t}}{2^\alpha \mathcal{M} f_D}\right)^{\frac{1}{1+\alpha}} f_D L^{\frac{-2\alpha-1}{1+\alpha}}
\end{aligned}
$$

A rise in L increases the difference in optimal profits. However, at a decreasing rate because the increase in n_D^* caused by an expansion in market size is underproportionate (see discussion on elasticities above).

$$
\begin{aligned}
\frac{\partial(\Pi_C^* - \Pi_D^*)}{\partial \bar{t}} &= \frac{1}{1+\alpha}\frac{n_D^*}{\bar{t}} > 0 \\
\frac{\partial(\Pi_C^* - \Pi_D^*)}{\partial f_D} &= -\frac{1}{1+\alpha}\frac{n_D^*}{f_D} f_D + n_D^* \\
&= \frac{\alpha}{1+\alpha} n_D^* > 0 \\
\frac{\partial(\Pi_C^* - \Pi_D^*)}{\partial f_C} &= -1 < 0
\end{aligned}
$$

Note that in general it was assumed that consumers consume at least and at most one unit. The latter assumption is at the core of a discrete choice problem. However, the last version could even be relaxed: At any z the share of

$$
\left[1 - e^{-\sum_{b=1}^{\mathcal{M}} e^{\frac{(y-\tilde{p}_T^b)}{\mu}}}\right]
$$

will buy the good.[5] This is important when variation in μ and resulting changes in prices are analyzed as they might affect the decision whether some consumers buy the differentiated version at all, i.e. the share of consumers.

[5] See Besanko et al. (1990, p. 402).

Heterogeneous Brands: Comparative Statics

Derivations for optimal pricing is analogous to equation (35) and equation (31) and results in

$$p_T^{b^*} = \mu + c_T^b \quad \forall b \in 1, \ldots, \mathcal{M}; T = \{D, C\}$$

If brands differ in marginal costs c_D^b and c_C^b, there is no closed form solution for the optimal number of differentiated products $n_D^{b^*}$.
When the *delivered* price index is defined by

$$\mathcal{P} = \left[\sum_{\tilde{b}=1}^{\mathcal{M}} e^{-\frac{p_T^{\tilde{b}}}{\mu}} \right]^{-1}$$

and expected demand by

$$D^b = e^{-\frac{p_D^b + \bar{t}(\frac{1}{2n_D^b})^\alpha}{\mu}} \mathcal{P}$$

Then, the first order condition equation (32) simplifies to

$$F(\cdot) \equiv \frac{\partial \Pi_D^b}{\partial n_D^b} = \alpha \bar{t} \overline{x}(n_D^{b^*}) \frac{D^b}{n_D^{b*}} L - f_D \tag{37}$$

$$\alpha \bar{t} \overline{x}(n_D^{b^*}) \frac{D^b}{n_D^{b*}} L - f_D = 0$$

$$(n_D^{b^*})^{-(\alpha+1)} e^{-\frac{p_D^{b^*} + \bar{t}(\frac{1}{2n_D^{b^*}})^\alpha}{\mu}} = \frac{2^\alpha f_D}{\bar{t} \mathcal{P} L}$$

Inserting the optimal price $p_D^{b^*} = \mu + c_D^b$ and rearranging yields

$$(n_D^{b^*})^{-(\alpha+1)} e^{-\frac{\bar{t}}{\mu}(\frac{1}{2n_D^{b^*}})^\alpha} = \frac{2^\alpha f_D}{\bar{t} \mathcal{P} L} e^{\frac{\mu + c_D^b}{\mu}} \tag{38}$$

Since equation (38) is not explicitly solvable for the optimal number of differentiated products the implicit function theorem is applied for comparative static analyses.
Since $F(n^{b^*}, \cdot)$ defines a profit maximum (see equation (34)),

$$F_{n_D^b}(\cdot) = \frac{\partial F(\cdot)}{\partial n_D^b} = L D^b \bar{t} \frac{\alpha}{(n_D^b)^2} \overline{x}(n_D^b) \left[-1 - \alpha + \frac{\alpha}{\mu} \bar{t} \overline{x}(n_D^b) \right] < 0$$

The direction of the effect is therefore completely determined by the derivative of $F(\cdot)$ with respect to the variable x considered.[6]

[6] As usual, this derivative will be denoted by $F_x \equiv \frac{\partial F(\cdot)}{\partial x}$.

$$\begin{aligned}
\frac{\partial n_D^{b^*}}{\partial L} &= -\frac{F_L}{F_{n_D^b}} = \frac{\alpha \bar{t}\overline{x}(n_D^{b^*})\frac{D^b}{n_D^{b*}}}{LD^b\bar{t}\frac{\alpha}{(n_D^b)^2}\overline{x}(n_D^b)\left[1+\alpha-\frac{\alpha}{\mu}\bar{t}\overline{x}(n_D^b)\right]} > 0 \\
&= \frac{n_D^{b*}}{L\left[1+\alpha-\frac{\alpha}{\mu}\bar{t}\overline{x}(n_D^{b*})\right]} \qquad (39)\\
F_L &= \alpha\bar{t}\overline{x}(n_D^{b^*})\frac{D^b}{n_D^{b*}} > 0
\end{aligned}$$

Deriving the cross derivative with respect to the marginal costs c_D^b yields

$$\begin{aligned}
\frac{\partial n_D^{b^*}}{\partial L} &= \frac{n_D^{b*}}{L\left[1+\alpha-\frac{\alpha}{\mu}\bar{t}\overline{x}(n_D^{b*})\right]} > 0 \\
\frac{\frac{\partial n_D^{b^*}}{\partial L}}{\partial c_D^b} &= \frac{\partial n_D^{b^*}}{\partial L \partial c_D^b} = \frac{\frac{\partial n_D^{b*}}{\partial c_D^b}L\left[1+\alpha-\frac{\alpha}{\mu}\bar{t}\overline{x}(n_D^{b*})\right]+L\frac{\alpha^2}{\mu}\bar{t}\overline{x}(n_D^{b*})\frac{\partial n_D^{b*}}{\partial c_D^b}n_D^{b*}}{\left(L\left[1+\alpha-\frac{\alpha}{\mu}\bar{t}\overline{x}(n_D^{b*})\right]\right)^2} < 0 \qquad (40)\\
&\text{where} \quad 1+\alpha+\frac{\alpha}{\mu}\bar{t}\overline{x}(n_D^{b*})\underbrace{(\alpha n_D^{b*}-1)}_{>0} \qquad (41)
\end{aligned}$$

since $\frac{\partial n_D^{b^*}}{\partial c_D^b} < 0$ (see below).
An increase in the marginal costs for producing the differentiated versions has a reducing effect on product differentiation. That is,

$$\begin{aligned}
\frac{\partial n_D^{b^*}}{\partial c_D^b} &= -\frac{F_{c_D^b}}{F_{n_D^b}} < 0 \\
F_{c_D^b} &= \alpha\bar{t}\frac{\overline{x}(n_D^{b^*})}{n_D^{b*}}\frac{\partial D^b}{\partial c_D^b}L < 0
\end{aligned}$$

As

$$\frac{\partial D^b}{\partial c_D^b} = (-\frac{1}{\mu})D^b < 0$$

$$\begin{aligned}
\frac{\partial n_D^{b^*}}{\partial \bar{t}} &= -\frac{F_{\bar{t}}}{F_{n_D^b}} > 0 \\
F_{\bar{t}} &= \alpha\frac{\overline{x}(n_D^{b^*})}{n_D^{b*}}D^bL + \alpha\bar{t}\frac{\overline{x}(n_D^{b^*})}{n_D^{b*}}\frac{\partial D^b}{\partial \bar{t}}L \\
&= \alpha\frac{\overline{x}(n_D^{b^*})}{n_D^{b*}}D^bL(1-\frac{\bar{t}}{\mu}\overline{x}(n_D^{b*})) > 0 \qquad \Longleftrightarrow \qquad \bar{t}\overline{x}(n_D^{b*}) < \mu
\end{aligned}$$

$$\begin{aligned}
\frac{\partial n_D^{b^*}}{\partial f_D} &= -\frac{F_{f_D}}{F_{n_D^b}} < 0 \\
F_{f_D} &= -1
\end{aligned}$$

Heterogeneity allows $\mathcal{P}$ and μ to have an effect on the choice of differentiation (see equation (38)). Note that the optimal price depends on μ but not on the optimal number of differentiated products.

$$\frac{\partial n_D^{b^*}}{\partial \mathcal{P}} = -\frac{F_{\mathcal{P}}}{F_{n_D^b}} > 0$$
$$F_{\mathcal{P}} = \alpha \bar{t} \frac{\overline{x}(n_D^{b^*})}{n_D^{b*}} L e^{-\frac{p_D^{b^*} + \bar{t}\overline{x}(n_D^{b*})}{\mu}} L > 0$$

The direction of the effect of an increase in μ depends on the productivity of the brand. It is determined by the sign of the effect of μ on the brand's demand, D^b.

$$\frac{\partial n_D^{b^*}}{\partial \mu} = -\frac{F_\mu}{F_{n_D^b}} \gtreqless ? \quad 0$$
$$F_\mu = \alpha \bar{t} \frac{\overline{x}(n_D^{b^*})}{n_D^{b*}} L \frac{\partial D^b}{\partial \mu}$$
$$= \alpha \bar{t} \frac{\overline{x}(n_D^{b^*})}{n_D^{b*}} L \left[\frac{\partial e^{-\frac{p_D^{b^*} + \bar{t}\overline{x}(n_D^{b*})}{\mu}}}{\mu} \mathcal{P} + \frac{\partial \mathcal{P}}{\partial \mu} e^{-\frac{p_D^{b^*} + \bar{t}\overline{x}(n_D^{b*})}{\mu}} \right] \tag{42}$$

where

$$\frac{\partial e^{-\frac{p_D^{b^*} + \bar{t}\overline{x}(n_D^{b*})}{\mu}}}{\partial \mu} = -[\frac{\mu - (c_D^b + \mu + \bar{t}\overline{x}(n_D^{b*})}{\mu^2}] e^{-\frac{p_D^{b^*} + \bar{t}\overline{x}(n_D^{b*})}{\mu}}$$
$$= \frac{c_D^b + \bar{t}\overline{x}(n_D^{b*})}{\mu^2} e^{-\frac{p_D^{b^*} + \bar{t}\overline{x}(n_D^{b*})}{\mu}} > 0$$
$$\frac{\partial \mathcal{P}}{\partial \mu} = -\left[\sum_{\tilde{b}=1}^{\mathcal{M}} e^{-\frac{\tilde{p}_T^{\tilde{b}}}{\mu}}\right]^{-2} \left[\sum_{\tilde{b}=1}^{\mathcal{M}} (\frac{c_T^{\tilde{b}} + \bar{t}\overline{x}(n_D^{\tilde{b}^*})}{\mu^2}) e^{-\frac{\tilde{p}_T^{\tilde{b}}}{\mu}}\right] < 0$$

Hence, the term in the brackets in equation (42) is positive and consequently $\frac{\partial n_D^{b^*}}{\partial \mu} > 0$ if and only if

$$\left[\frac{\partial e^{-\frac{p_D^{b^*} + \bar{t}\overline{x}(n_D^{b*})}{\mu}}}{\mu} \mathcal{P} + \frac{\partial \mathcal{P}}{\partial \mu} e^{-\frac{p_D^{b^*} + \bar{t}\overline{x}(n_D^{b*})}{\mu}} \right] > 0$$
$$\frac{c_D^b + \bar{t}\overline{x}(n_D^{b*})}{\mu^2} D^b > \left[\sum_{\tilde{b}=1}^{\mathcal{M}} e^{-\frac{\tilde{p}_T^{\tilde{b}}}{\mu}}\right]^{-1} \left[\sum_{\tilde{b}=1}^{\mathcal{M}} (\frac{c_T^{\tilde{b}} + \bar{t}\overline{x}(n_D^{\tilde{b}*})}{\mu^2}) e^{-\frac{\tilde{p}_T^{\tilde{b}}}{\mu}}\right] D^b$$
$$\frac{c_D^b + \bar{t}\overline{x}(n_D^{b*})}{\mu^2} > \sum_{\tilde{b}=1}^{\mathcal{M}} (\frac{c_T^{\tilde{b}} + \bar{t}\overline{x}(n_D^{\tilde{b}*})}{\mu^2}) e^{-\frac{\tilde{p}_T^{\tilde{b}}}{\mu}} \mathcal{P}$$
$$c_D^b + \bar{t}\overline{x}(n_D^{b*}) > \sum_{\tilde{b}=1}^{\mathcal{M}} \left(c_T^{\tilde{b}} + \bar{t}\overline{x}(n_D^{\tilde{b}*})\right) D^{\tilde{b}} \quad | + \mu = +\mu \sum_{\tilde{b}=1}^{\mathcal{M}} D^{\tilde{b}}$$
$$\tilde{p}_D^{b^*} > \sum_{\tilde{b}=1}^{\mathcal{M}} \tilde{p}_T^{\tilde{b}^*} D^{\tilde{b}} \tag{43}$$

Equation (43) shows that the effect of μ on the demand of brand b is positive if and only if the optimal *delivered* price is larger than the demand weighted average *delivered* price.[7] The term

$$\left[\sum_{\tilde{b}=1}^{\mathcal{M}}\left(\frac{c_T^{\tilde{b}}+\bar{t}\bar{x}(n_D^{b*})}{\mu^2}\right)e^{-\frac{\tilde{p}_T^{\tilde{b}}}{\mu}}\right]$$

takes the optimal pricing of all competing brands into account. If one does not take into account that the optimal pricing for all brands is $p_D^{b^*}=c_D^b+\mu, \forall b\in 1,\ldots,\mathcal{M}$ (and therefore depends on μ), the term equals

$$\left[\sum_{\tilde{b}=1}^{\mathcal{M}}\left(\frac{\tilde{p}_T^b}{\mu^2}\right)e^{-\frac{\tilde{p}_T^{\tilde{b}}}{\mu}}\right]$$

The condition for $\frac{\partial n_D^{b^*}}{\partial\mu}>0$ would be

$$\tilde{p}_D^{b^*}-\sum_{\tilde{b}=1}^{\mathcal{M}}(\tilde{p}_D^b)D^{\tilde{b}}>\mu$$

The difference between the optimal *delivered* price and the average demand weighted *delivered* price needs to be larger than μ (the optimal *margin*). Note that, as $\mu>0$, this condition is more restrictive than equation (43).

[7] See also Anderson et al. (1992, p. 347) for a more general discussion and derivations.

Heterogeneous Brands: Technology Choice

The brand will adopt the customization technology if the inequality in equation (1.19) holds, in case of $\Pi_C^{b*} = \Pi_D^{b*}$, the firm is indifferent between the technologies. $\Pi_C^{b*} > 0$ if $e^{-\frac{c_C^b}{\mu}} > \frac{f_C}{\mu L \mathcal{P}} e$.
Define the difference in profits by

$$\Pi_C^{b*} - \Pi_D^{b*} = \mu \left[D^b(p_C^{b*}) - D^b(p_D^{b*}, n_D^{b*}) \right] L + n_D^{b*} f_D - f_C$$

Differential effect of an increase in L:

$$\begin{aligned}
\frac{\partial(\Pi_C^{b*} - \Pi_D^{b*})}{\partial L} &= \mu \left[D^b(p_C^{b*}) - D^b(p_D^{b*}, n_D^{b*}) \right] - \mu L \left[\frac{\partial D^b(p_D^{b*}, n_D^{b*})}{\partial n_D^{b*}} \frac{\partial n_D^{b*}}{\partial L} \right] + f_D \frac{\partial n_D^{b*}}{\partial L} \\
&= \mu \left[D^b(p_C^{b*}) - D^b(p_D^{b*}, n_D^{b*}) \right] - \frac{\partial n_D^{b*}}{\partial L} \underbrace{\left(\mu L \frac{D^b(p_D^{b*}, n_D^{b*})}{\partial n_D^{b*}} - f_D \right)}_{\frac{\Pi_D^b(p_D^{b*})}{\partial n_D^b} \equiv 0 \quad \text{at optimum, see equation (32)}}
\end{aligned}$$

At the optimal differentiation, the increase in revenue needs to exactly equal the fixed costs. Therefore, in the following, only the direct effect of the variables matters (the effect through n_D^{b*} on demand and on the fixed costs are compensating each other at the optimum).
The first term in brackets is positive if the price for the customized version is lower than the *delivered* price for differentiation.

$$\begin{aligned}
& e^{-\frac{c_C^b + \mu}{\mu}} - e^{-\frac{c_D^b + \mu + \bar{t}\bar{x}(n_D^{b*})}{\mu}} > 0 \\
\iff \quad & c_C^b - c_D^b < \bar{t}\bar{x}(n_D^{b*})
\end{aligned}$$

$$\begin{aligned}
\frac{\partial(\Pi_C^{b*} - \Pi_D^{b*})}{\partial \bar{t}} &= -\mu \frac{\partial D^b(p_D^{b*}, n_D^{b*})}{\partial \bar{t}} L + f_D \frac{\partial n_D^{b*}}{\partial \bar{t}} \\
&= -\mu \frac{\partial D^b(p_D^{b*}, n_D^{b*})}{\partial \bar{t}} L - \mu L \frac{\partial D^b(p_D^{b*}, n_D^{b*})}{\partial n_D^{b*}} \frac{\partial n_D^{b*}}{\partial \bar{t}} + f_D \frac{\partial n_D^{b*}}{\partial \bar{t}} \\
&= -\mu \frac{\partial D^b(p_D^{b*}, n_D^{b*})}{\partial \bar{t}} L - \frac{\partial n_D^{b*}}{\partial \bar{t}} \underbrace{\left(\mu L \frac{D^b(p_D^{b*}, n_D^{b*})}{\partial n_D^{b*}} - f_D \right)}_{\frac{\Pi_D^b(p_D^{b*})}{\partial n_D^b} \equiv 0 \quad \text{at optimum, see equation (32)}}
\end{aligned}$$

$$= -\mu \frac{\partial D^b(p_D^{b*}, n_D^{b*})}{\partial \bar{t}} L > 0$$

where

$$\frac{\partial D^b(p_D^{b*}, n_D^{b*})}{\partial \bar{t}} = -\bar{x}(n_D^{b*}) \frac{1}{\mu} < 0$$

The effect of an increase in μ:

$$\begin{aligned}\frac{\partial(\Pi_C^{b*}-\Pi_D^{b*})}{\partial\mu} &= \left[D^b(p_C^{b*})-D^b(p_D^{b*},n_D^{b*})\right]L+\mu\left[\frac{\partial D^{b*}(p_C^{b*})}{\partial\mu}-\frac{\partial D^{b*}(p_D^{b*},n_D^{b*})}{\partial\mu}\right]L\\ &-\frac{\partial n_D^{b*}}{\partial\mu}\underbrace{\left(\mu L\frac{D^b(p_D^{b*},n_D^{b*})}{\partial n_D^{b*}}-f_D\right)}_{\frac{\Pi_D^b(p_D^{b*})}{\partial n_D^b}\equiv 0\quad\text{at optimum, see equation (32)}}\\ &= \left[D^b(p_C^{b*})-D^b(p_D^{b*},n_D^{b*})\right]L+\mu\left[\frac{\partial D^{b*}(p_C^{b*})}{\partial\mu}-\frac{\partial D^{b*}(p_D^{b*},n_D^{b*})}{\partial\mu}\right]L\\ &= \left[D^b(p_C^{b*})-D^b(p_D^{b*},n_D^{b*})\right]L+\mu\left[\frac{\partial D^{b*}(p_C^{b*})}{\partial\mu}-\frac{\partial D^{b*}(p_D^{b*},n_D^{b*})}{\partial\mu}\right]L\end{aligned}$$

The first term in brackets is positive if

$$\begin{aligned} c_C^b-c_D^b &< \bar{t}\bar{x}(n_D^{b*})\\ (\tilde{p}_C^{b*}-\tilde{p}_D^{b*}) &< 0 \end{aligned}\tag{44}$$

Manipulating the second term yields

$$\left[\frac{\partial D^{b*}(p_C^{b*})}{\partial\mu}-\frac{\partial D^{b*}(p_D^{b*},n_D^{b*})}{\partial\mu}\right]=\left(\frac{c_C^b}{\mu^2}D^b(p_C^{b*})+\frac{\partial\mathcal{P}}{\partial\mu}e^{-\frac{p_C^{b*}}{\mu}}-\frac{c_D^b+\bar{t}\bar{x}(n_D^{b*})}{\mu^2}D^b(p_D^{b*},n_D^{b*})-\frac{\partial\mathcal{P}}{\partial\mu}e^{-\frac{p_D^{b*}}{\mu}}\right)$$
$$=\frac{1}{\mu^2}\left[D^b(p_C^{b*})\left[c_C^b-\sum_{\tilde{b}=1}^{\mathcal{M}}(\tilde{p}_T^{b*}-\mu)D^{\tilde{b}}\right]-D^b(p_D^{b*},n_D^{b*})\left[c_D^b+\bar{t}\bar{x}(n_D^{b*})-\sum_{\tilde{b}=1}^{\mathcal{M}}(\tilde{p}_T^{b*}-\mu)D^{\tilde{b}}\right]\right]$$

which is positive if

$$D^b(p_C^{b*})\left[\tilde{p}_C^{b*}-\sum_{\tilde{b}=1}^{\mathcal{M}}(\tilde{p}_T^{b*})D^{\tilde{b}}\right]>D^b(p_D^{b*},n_D^{b*})\left[\tilde{p}_D^{b*}-\sum_{\tilde{b}=1}^{\mathcal{M}}(\tilde{p}_T^{b*})D^{\tilde{b}}\right]\tag{45}$$

1. If $\tilde{p}_C^{b*}<\tilde{p}_D^{b*}$: $D(p_C^{b*})>D(p_D^{b*},n_D^{b*})\ \ldots$

There is a positive "*within-brand-revenue-effect*" because, given the respective market shares, the lower price of customization allows to generate higher revenues. For the *across-brand-market-share-effect*, the ordering of the *delivered* price relative to the demand weighted average price matters.
Note that by construction $D(p_C^{b*}),D(p_D^{b*},n_D^{b*})>0$.

a.) $\tilde{p}_C^{b*}<\tilde{p}_D^{b*}<\sum_{\tilde{b}=1}^{\mathcal{M}}(\tilde{p}_T^{b*})D^{\tilde{b}}$

Manipulating equation (45) when $\left[\tilde{p}_C^{b^*} - \sum_{\tilde{b}=1}^{\mathcal{M}}(\tilde{p}_T^{b^*})D^{\tilde{b}}\right] < 0$

$$\overbrace{\frac{D^b(p_C^{b^*})}{D^b(p_D^{b^*}, n_D^{b^*})}}^{>1 \text{ since } \tilde{p}_C^{b^*} < \tilde{p}_D^{b^*}} < \frac{\overbrace{\tilde{p}_D^{b^*} - \sum_{\tilde{b}=1}^{\mathcal{M}}(\tilde{p}_T^{b^*})D^{\tilde{b}}}^{<0}}{\underbrace{\tilde{p}_C^{b^*} - \sum_{\tilde{b}=1}^{\mathcal{M}}(\tilde{p}_T^{b^*})D^{\tilde{b}}}_{<0}} \in (0,1)$$

Since $\tilde{p}_C^{b^*} < \tilde{p}_D^{b^*}$, the fraction on the right hand side is between $(0,1)$. But this contradicts $\frac{D(p_C^{b^*})}{D(p_D^{b^*}, n_D^{b^*})} > 1$. Hence, there cannot be a positive *across-brand-market-share-effect* on the difference $\Pi_C^{b^*} - \Pi_D^{b^*}$: the increase in μ reduces market shares since the brand has marginal costs that are associated with below average demand weighted *delivered* prices. The reduction in demand shares of customized versions is stronger.
$\rightarrow$ *within-brand-revenue-effect* (+) and *across-brand-market-share-effect* (-) go in opposite directions!

b.) $\tilde{p}_C^{b^*} < \sum_{\tilde{b}=1}^{\mathcal{M}}(\tilde{p}_T^{b^*})D^{\tilde{b}} < \tilde{p}_D^{b^*}$

$$\overbrace{\frac{D^b(p_C^{b^*})}{D^b(p_D^{b^*}, n_D^{b^*})}}^{>1 \text{ since } \tilde{p}_C^{b^*} < \tilde{p}_D^{b^*}} < \frac{\overbrace{\tilde{p}_D^{b^*} - \sum_{\tilde{b}=1}^{\mathcal{M}}(\tilde{p}_T^{b^*})D^{\tilde{b}}}^{>0}}{\underbrace{\tilde{p}_C^{b^*} - \sum_{\tilde{b}=1}^{\mathcal{M}}(\tilde{p}_T^{b^*})D^{\tilde{b}}}_{<0}} < 0$$

The fraction on the right hand side is below zero. But this contradicts $\frac{D(p_C^{b^*})}{D(p_D^{b^*}, n_D^{b^*})} > 1$. Hence, there cannot be a positive *across-brand-market-share-effect*. This is similar to (a.).
$\rightarrow$ *within-brand-revenue-effect* (+) and *across-brand-market-share-effect* (-) go in opposite directions!

c.) $\sum_{\tilde{b}=1}^{\mathcal{M}}(\tilde{p}_T^{b^*})D^{\tilde{b}} < \tilde{p}_C^{b^*} < \tilde{p}_D^{b^*}$

$$\overbrace{\frac{D^b(p_C^{b^*})}{D^b(p_D^{b^*}, n_D^{b^*})}}^{>1 \text{ since } \tilde{p}_C^{b^*} < \tilde{p}_D^{b^*}} > \frac{\overbrace{\tilde{p}_D^{b^*} - \sum_{\tilde{b}=1}^{\mathcal{M}}(\tilde{p}_T^{b^*})D^{\tilde{b}}}^{>0}}{\underbrace{\tilde{p}_C^{b^*} - \sum_{\tilde{b}=1}^{\mathcal{M}}(\tilde{p}_T^{b^*})D^{\tilde{b}}}_{>0}}$$

The fraction on the right hand side is above one. It depends on whether the ratio of demand shares is larger than the ratio of the deviation from the *delivered* prices from the

demand weighted average.
$\rightarrow$ *within-brand-revenue-effect* (+) and *across-brand-market-share-effect* (+/-).

2. If $\tilde{p}_C^{b^*} > \tilde{p}_D^{b^*}$: $D(p_C^{b^*}) < D(p_D^{b^*}, n_D^{b^*}) \ldots$

There is a negative "*within-brand-revenue-effect*" because, given the respective market shares, the lower price of differentiation allows to generate higher revenues. For the *across-brand-market-share-effect*, the ordering of the *delivered* price relative to the demand weighted average price matters.
Note that by construction $D(p_C^{b^*}), D(p_D^{b^*}, n_D^{b^*}) > 0$.

a.) $\tilde{p}_C^{b^*} > \tilde{p}_D^{b^*} > \sum_{\tilde{b}=1}^{\mathcal{M}}(\tilde{p}_T^{b^*})D^{\tilde{b}}$

From equation (45), the *across-brand-market-share-effect* is positive if

$$\overbrace{\frac{D^b(p_C^{b^*})}{D^b(p_D^{b^*}, n_D^{b^*})}}^{\in(0,1) \text{ since } \tilde{p}_C^{b^*} > \tilde{p}_D^{b^*}} > \frac{\overbrace{\tilde{p}_D^{b^*} - \sum_{\tilde{b}=1}^{\mathcal{M}}(\tilde{p}_T^{b^*})D^{\tilde{b}}}^{>0}}{\underbrace{\tilde{p}_C^{b^*} - \sum_{\tilde{b}=1}^{\mathcal{M}}(\tilde{p}_T^{b^*})D^{\tilde{b}}}_{>0}} \in (0,1)$$

The denominator is larger than the nominator.
$\rightarrow$ *within-brand-revenue-effect* (-) and *across-brand-market-share-effect* (+/-).

b.) $\tilde{p}_D^{b^*} < \sum_{\tilde{b}=1}^{\mathcal{M}}(\tilde{p}_T^{b^*})D^{\tilde{b}} < \tilde{p}_C^{b^*}$

$$\overbrace{\frac{D^b(p_C^{b^*})}{D^b(p_D^{b^*}, n_D^{b^*})}}^{\in(0,1) \text{ since } \tilde{p}_C^{b^*} > \tilde{p}_D^{b^*}} > \frac{\overbrace{\tilde{p}_D^{b^*} - \sum_{\tilde{b}=1}^{\mathcal{M}}(\tilde{p}_T^{b^*})D^{\tilde{b}}}^{<0}}{\underbrace{\tilde{p}_C^{b^*} - \sum_{\tilde{b}=1}^{\mathcal{M}}(\tilde{p}_T^{b^*})D^{\tilde{b}}}_{>0}} < 0$$

The fraction on the right hand side is below zero. But $\frac{D(p_C^{b^*})}{D(p_D^{b^*}, n_D^{b^*})} \in (0,1)$. The *across-brand-market-share-effect* is clearly positive.
$\rightarrow$ *within-brand-revenue-effect* (-) and *across-brand-market-share-effect* (+) go in opposite directions!

c.) $\tilde{p}_D^{b*} < \tilde{p}_C^{b*} < \sum_{\tilde{b}=1}^{\mathcal{M}}(\tilde{p}_T^{b*})D^{\tilde{b}}$

$$\overbrace{\frac{D^b(p_C^{b*})}{D^b(p_D^{b*}, n_D^{b*})}}^{\in(0,1) \text{ since } \tilde{p}_C^{b*} > \tilde{p}_D^{b*}} < \frac{\overbrace{\tilde{p}_D^{b*} - \sum_{\tilde{b}=1}^{\mathcal{M}}(\tilde{p}_T^{b*})D^{\tilde{b}}}^{<0}}{\underbrace{\tilde{p}_C^{b*} - \sum_{\tilde{b}=1}^{\mathcal{M}}(\tilde{p}_T^{b*})D^{\tilde{b}}}_{<0}} \in (0,1)$$

The denominator is larger than the nominator.
$\rightarrow$ *within-brand-revenue-effect* (-) and *across-brand-market-share-effect* (+/-).

When it is not considered that competitors also increase their mill prices when μ increases, the differences are $\tilde{p}_T^{b*} - \mu$. This more restrictive version implies that the total effect, *within-brand-revenue* and *across-brand-market-share* effects, is positive if

$$0 < D^b(p_C^{b*}) - D^b(p_D^{b*}, n_D^{b*}) + \frac{1}{\mu}\left(D^b(p_C^{b*})\left[\tilde{p}_C^{b*} - \sum_{\tilde{b}=1}^{\mathcal{M}}(\tilde{p}_T^{b*})D^{\tilde{b}} - \mu\right] - D^b(p_D^{b*}, n_D^{b*})\left[\tilde{p}_D^{b*} - \sum_{\tilde{b}=1}^{\mathcal{M}}(\tilde{p}_T^{b*})D^{\tilde{b}} - \mu\right]\right)$$

$$D^b(p_C^{b*})\left[\tilde{p}_C^{b*} - \sum_{\tilde{b}=1}^{\mathcal{M}}(\tilde{p}_T^{b*})D^{\tilde{b}}\right] > D^b(p_D^{b*}, n_D^{b*})\left[\tilde{p}_D^{b*} - \sum_{\tilde{b}=1}^{\mathcal{M}}(\tilde{p}_T^{b*})D^{\tilde{b}}\right]$$

The table below gives an overview on the total effect.

	$\tilde{p}_C^{b*} < \tilde{p}_D^{b*}$	$\tilde{p}_C^{b*} > \tilde{p}_D^{b*}$
$\tilde{p}_C^{b*} < \sum_{\tilde{b}=1}^{\mathcal{M}}(\tilde{p}_T^{b*})D^{\tilde{b}}$	+ *within-brand-revenue-effect* - *across-brand-market-share-effect* $\frac{\partial(\Pi_C^{b*} - \Pi_D^{b*})}{\partial\mu} < 0$	$-$ *within-brand-revenue-effect* $+/-$ *across-brand-market-share-effect* $\frac{\partial(\Pi_C^{b*} - \Pi_D^{b*})}{\partial\mu} > 0 \iff \frac{D^b(p_C^{b*})}{D^b(p_D^{b*}, n_D^{b*})} < \frac{\tilde{p}_D^{b*} - \sum_{\tilde{b}=1}^{\mathcal{M}}(\tilde{p}_T^{b*})D^{\tilde{b}}}{\tilde{p}_C^{b*} - \sum_{\tilde{b}=1}^{\mathcal{M}}(\tilde{p}_T^{b*})D^{\tilde{b}}}$
$\tilde{p}_C^{b*} > \sum_{\tilde{b}=1}^{\mathcal{M}}(\tilde{p}_T^{b*})D^{\tilde{b}}$	+ *within-brand-revenue-effect* $+/-$ *across-brand-market-share-effect* $\frac{\partial(\Pi_C^{b*} - \Pi_D^{b*})}{\partial\mu} > 0 \iff \frac{D^b(p_C^{b*})}{D^b(p_D^{b*}, n_D^{b*})} > \frac{\tilde{p}_D^{b*} - \sum_{\tilde{b}=1}^{\mathcal{M}}(\tilde{p}_T^{b*})D^{\tilde{b}}}{\tilde{p}_C^{b*} - \sum_{\tilde{b}=1}^{\mathcal{M}}(\tilde{p}_T^{b*})D^{\tilde{b}}}$	- *within-brand-revenue-effect* + *across-brand-market-share-effect* $\frac{\partial(\Pi_C^{b*} - \Pi_D^{b*})}{\partial\mu} > 0$

Table A.1: Effect of a Change in the Heterogeneity in Preferences, μ

What is the effect of a change in the marginal costs? Assume that $c_C^b(c_D^b)$, $\frac{\partial c_C^b(c_D^b)}{\partial c_D^b} \geq 0$, $\frac{\partial^2 c^b(c_D^b)}{\partial (c_D^b)^2} \leq 0$: There is a positive mapping between the marginal costs for both technologies.

$$\frac{\partial(\Pi_C^{b*} - \Pi_D^{b*})}{\partial c_D^b} = \mu \left[\frac{\partial D^b(p_C^{b*})}{\partial p_C^{b*}} \frac{\partial p_C^{b*}}{\partial c_D^b} \frac{\partial c_C^b}{\partial c_D^b} - \frac{\partial D^b(p_D^{b*}, n_D^{b*})}{\partial p_D^{b*}} \frac{\partial p_D^{b*}}{\partial c_D^b} \right] L$$

$$= -[D^b(p_C^{b*}) \frac{\partial c_C^b}{\partial c_D^b} - D^b(p_D^{b*}, n_D^{b*})] L$$

where

$$\frac{\partial(\Pi_C^{b*} - \Pi_D^{b*})}{\partial c_D^b} < 0$$

if

$$[D^b(p_C^{b*}) \frac{\partial c_C^b}{\partial c_D^b} - D^b(p_D^{b*}, n_D^{b*})] > 0 \tag{46}$$

$$\frac{\partial c_C^b}{\partial c_D^b} > \frac{D^b(p_D^{b*}, n_D^{b*})}{D^b(p_C^{b*})} = e^{-\frac{c_D^b + \bar{t}\bar{x}(n_D^{b*}) - c_C^b}{\mu}} \tag{47}$$

Note that if $\Delta(\tilde{p}_C^{b*} - \tilde{p}_D^{b*}) < 0$

$$\frac{D^b(p_D^{b*}, n_D^{b*})}{D^b(p_C^{b*})} < 1 \tag{48}$$

If the marginal costs of $c_C^b \perp c_D^b$, it necessarily holds that:

$$\frac{\partial(\Pi_C^{b*} - \Pi_D^{b*})}{\partial c_D^b} > 0$$

$$\frac{\partial(\Pi_C^{b*} - \Pi_D^{b*})}{\partial c_C^b} < 0$$

Finally, consider the cross derivative with respect to the size of the market. This can be expressed as

$$\frac{\partial^2(\Pi_C^{b*} - \Pi_D^{b*})}{\partial L \partial c_D^b} = \frac{\mu}{L} \frac{\partial(\Pi_C^{b*} - \Pi_D^{b*})}{\partial c_D^b} \overbrace{-\mu \underbrace{\frac{D^b(p_D^{b*}, n_D^{b*})}{\partial n_D^{b*}}}_{>0} \underbrace{\frac{\partial n_D^{b*}}{\partial c_D^b}}_{<0}}^{>0}$$

$$= \frac{\mu}{L} \left[\frac{\partial(\Pi_C^{b*} - \Pi_D^{b*})}{\partial c_D^b} - \frac{\partial D^b(p_D^{b*}, n_D^{b*})}{\partial n_D^{b*}} \frac{\partial n_D^{b*}}{\partial c_D^b} L \right]$$

If $c_C^b \perp c_D^b$: Then, the first term is clearly positive. The higher marginal costs for the production of differentiated versions increases the difference in the profits. The incentives to adopt the customization technology as a response to larger markets is increasing in the marginal costs of the firm.
If $c_C^b \not\perp c_D^b$: The first term might be negative. Assume it is (see discussion above). The incentives to adopt the customization technology as a response to larger markets is then increasing in the productivity of a brand if the increase in the difference of the profits is larger than the increase in demand due to a higher degree of differentiation.

Exact Location Based Purchase Decision

Derivations: Differentiated Versions - Optimal Prices and Number of Versions

The profit function is:

$$\max_{p_D^b, n_D^b} \Pi_D^b(p_D^b, n_D^b) = 2n_D^b(p_D^b - c_D^b) \int_0^{\frac{1}{2n_D^b}} Le^{-\frac{p_D^b + \bar{t}(\hat{z}^b)^\alpha}{\mu}} \tilde{\mathcal{P}}_{\hat{z}^b} d\hat{z}^b - n_D^b f_D$$

The first order condition (FOC) with respect to prices yields:
(The brand is small with respect to the market, therefore, it does not consider the effect of a change in its price on the aggregate price index - market aggregates are taken as given.)

$$\begin{aligned}
\frac{\partial \Pi_D^b}{\partial p_D^b} &= 0 \\
0 &= 2n_D^b \int_0^{\frac{1}{2n_D^b}} Le^{-\frac{p_D^b + \bar{t}(\hat{z}^b)^\alpha}{\mu}} \tilde{\mathcal{P}}_{z^b} d\hat{z}^b + 2n_D^b(p_D^b - c_D^b) \int_0^{\frac{1}{2n_D^b}} L(-\frac{1}{\mu}) e^{-\frac{p_D^b + \bar{t}(\hat{z}^b)^\alpha}{\mu}} \tilde{\mathcal{P}}_{z^b} d\hat{z}^b \\
0 &= 1 - \frac{1}{\mu}(p_D^b - c_D^b) \\
p_D^{b^*} &= \mu + c_D^b
\end{aligned}$$

Note that the second order condition with respect to p_D^b is

$$\begin{aligned}
\frac{\partial^2 \Pi_D^b}{\partial (p_D^b)^2} = & \, 2n_D^b \int_0^{\frac{1}{2n_D^b}} L(-\frac{1}{\mu}) e^{-\frac{p_D^b + t(\hat{z}^b)^\alpha}{\mu}} \tilde{\mathcal{P}}_{z^b} d\hat{z}^b \\
& + 2n_D^b \int_0^{\frac{1}{2n_D^b}} L(-\frac{1}{\mu}) e^{-\frac{p_D^b + t(\hat{z}^b)^\alpha}{\mu}} \tilde{\mathcal{P}}_{z^b} d\hat{z}^b \\
& + 2n_D^b(p_D^b - c_D^b) \int_0^{\frac{1}{2n_D^b}} L(\frac{1}{\mu^2}) e^{-\frac{p_D^b + t(\hat{z}^b)^\alpha}{\mu}} \tilde{\mathcal{P}}_{z^b} d\hat{z}^b
\end{aligned}$$

Evaluated at $p_D^{b^*} = \mu + c_D^b$

$$F_{p_D^b p_D^b}(p_D^{b^*}) = -2n_D^b \int_0^{\frac{1}{2n_D^b}} L(\frac{1}{\mu}) \frac{e^{-\frac{p_D^{b^*} + t(\hat{z}^b)^\alpha}{\mu}}}{\sum_{\tilde{b}=1}^{\mathcal{M}} e^{-\frac{\tilde{p}_D^{\tilde{b}}(\hat{z}^b)}{\mu}}} d\hat{z}^b < 0$$

The optimal number of differentiated versions:

$$\begin{aligned}
\frac{\partial \Pi_D^b}{\partial n_D^b} = 0 \iff \quad f_D = & \, 2(p_D^b - c_D^b) \int_0^{\frac{1}{2n_D^b}} L \frac{e^{-\frac{p_D^{b^*} + t(\hat{z}^b)^\alpha}{\mu}}}{\sum_{\tilde{b}=1}^{\mathcal{M}} e^{-\frac{\tilde{p}_D^{\tilde{b}}(\hat{z}^b)}{\mu}}} d\hat{z}^b + \\
& 2n_D^b(p_D^b - c_D^b)[-\frac{1}{2(n_D^b)^2}] L \frac{e^{-\frac{p_D^{b^*} + t(\frac{1}{2n_D^b})^\alpha}{\mu}}}{\sum_{\tilde{b}=1}^{\mathcal{M}} e^{-\frac{\tilde{p}_D^{\tilde{b}}(\frac{1}{2n_D^b})}{\mu}}} \\
0 = & \, 2 \int_0^{\frac{1}{2n_D^{b^*}}} e^{-\frac{p_D^{b^*} + t(\hat{z}^b)^\alpha}{\mu}} \tilde{\mathcal{P}}_{z^b} d\hat{z}^b - \frac{1}{n_D^{b^*}} e^{-\frac{p_D^b + t(\frac{1}{2n_D^{b^*}})^\alpha}{\mu}} \tilde{\mathcal{P}}_{\frac{1}{2n_D^{b^*}}} - \frac{f_D}{L\mu} \equiv \Omega
\end{aligned}$$

where the second row follows from the Leibniz integral rule.
For a comparative static exercise let's define

$$\Omega_x \equiv \frac{\partial \Omega}{\partial x}$$

Hence,

$$\Omega_{n_D^{b*}} dn^{b^*} + \Omega_L dL = 0$$

where

$$\begin{aligned}
\Omega_{n_D^{b*}} &= -\frac{1}{(n_D^{b*})^2} e^{-\frac{p_D^b + t(\frac{1}{2n_D^{b*}})^\alpha}{\mu}} \tilde{\mathcal{P}}_{\frac{1}{2n_D^{b*}}} \\
&+ \frac{1}{(n_D^{b*})^2} e^{-\frac{p_D^b + t(\frac{1}{2n_D^{b*}})^\alpha}{\mu}} \tilde{\mathcal{P}}_{\frac{1}{2n_D^{b*}}} \\
&- \frac{1}{n_D^{b*}} \left(\frac{\alpha t}{2^\alpha \mu} (n_D^{b*})^{-(\alpha+1)} \right) e^{-\frac{p_D^b + t(\frac{1}{2n_D^{b*}})^\alpha}{\mu}} \tilde{\mathcal{P}}_{\frac{1}{2n_D^{b*}}} \\
&= -\frac{\alpha t}{2^\alpha (n_D^{b*})^\alpha \mu} e^{-\frac{p_D^b + t(\frac{1}{2n_D^{b*}})^\alpha}{\mu}} \tilde{\mathcal{P}}_{\frac{1}{2n_D^{b*}}} = F_{n_D^{b*} n_D^{b*}} < 0 \\
\Omega_L &= \frac{f_D}{L^2 \mu} > 0
\end{aligned}$$

Therefore,

$$\begin{aligned}
\Omega_{n_D^{b*}} dn_D^{b*} + \Omega_L dL = 0 \\
\frac{dn_D^{b*}}{dL} &= -\frac{\Omega_L}{\Omega_{n_D^{b*}}} \\
\frac{dn_D^{b*}}{dL} &= \frac{f_D}{L^2} \frac{2^\alpha (n_D^{b*})^\alpha}{\alpha t \tilde{\mathcal{P}}_{\frac{1}{2n_D^{b*}}}} e^{\frac{p_D^b + t(\frac{1}{2n_D^{b*}})^\alpha}{\mu}} > 0
\end{aligned}$$

The effect of an increase in the marginal costs, c_D^b on the optimal n_D^{b*} is:
(Note that the brand is small with respect to the market such that an increase in the marginal cost will not affect the aggregate price index.)

$$\begin{aligned}
\Omega_{c_D^b} &= 2 \int_0^{\frac{1}{2n_D^{b*}}} (-\frac{1}{\mu}) e^{-\frac{\mu + c_D^b + t(\hat{z}^b)^\alpha}{\mu}} \tilde{\mathcal{P}}_{z^b} d\hat{z}^b \\
&- \frac{1}{n_D^{b*}} (-\frac{1}{\mu}) e^{-\frac{\mu + c_D^b + t(\frac{1}{2n_D^{b*}})^\alpha}{\mu}} \tilde{\mathcal{P}}_{\frac{1}{2n_D^{b*}}} \\
&= -\frac{1}{\mu} (\frac{f_D}{L\mu}) \\
&= -(\frac{f_D}{L\mu^2}) < 0 \\
\frac{dn_D^{b*}}{dc_D^b} &= -\frac{\Omega_{c_D^b}}{\Omega_{n_D^{b*}}} = -\frac{2^\alpha f_D (n_D^{b*})^\alpha}{L\alpha t \mu \tilde{\mathcal{P}}_{\frac{1}{2n_D^{b*}}}} e^{\frac{p_D^b + t(\frac{1}{2n_D^{b*}})^\alpha}{\mu}} < 0
\end{aligned}$$

The cross derivative is

$$\frac{d^2 n_D^{b*}}{dL dc_D^b} = -\frac{\Omega_L}{\Omega_{n_D^{b*}}} \frac{\alpha}{n_D^{b*}} \frac{dn_D^{b*}}{dc_D^b} - \frac{\Omega_L}{\Omega_{n_D^{b*}}} (-\alpha \frac{t}{\mu} 2^{-\alpha} (n_D^{b*})^{-(\alpha+1)}) \frac{dn_D^{b*}}{dc_D^b}$$

$$= \overbrace{\underbrace{-\frac{\Omega_L}{\Omega_{n_D^{b*}}}}_{=\frac{dn_D^{b*}}{dL}>0} \underbrace{\frac{dn_D^{b*}}{dc_D^b}}_{<0}}^{<0} \underbrace{\left[\frac{\alpha}{n_D^{b*}} - \frac{\alpha t}{2^\alpha \mu (n_D^{b*})^{\alpha+1}}\right]}_{>0 \iff (n_D^{b*})^\alpha > \frac{t}{2^\alpha \mu}} < 0$$

Accordingly, the effect of an increase in the fixed costs, f_D:

$$\Omega_{f_D} = -\frac{1}{L\mu} < 0$$

$$\Omega_{n_D^{b*}} dn_D^{b*} + \Omega_{f_D} df_D = 0$$

$$\frac{dn_D^{b*}}{df_D} = -\frac{\Omega_{f_D}}{\Omega_{n_D^{b*}}}$$

$$\frac{dn_D^{b*}}{df_D} = -\frac{1}{L\mu} \frac{2^\alpha (n^{b*})^\alpha}{t \tilde{\mathcal{P}}_{\frac{1}{2n_D^{b*}}}} e^{\frac{p_D^b + t(\frac{1}{2n_D^{b*}})^\alpha}{\mu}} < 0$$

For the effect of μ rewrite the FOC as

$$0 = 2\int_0^{\frac{1}{2n_D^{b*}}} D^b(p_D^{b*}, n_D^{b*})_{\hat{z}^b} d\hat{z}^b - \frac{1}{n_D^{b*}} D^b(p_D^{b*}, n_D^{b*})_{\hat{z}^b = \frac{1}{2n_D^{b*}}} - \frac{f_D}{L\mu} \equiv \Omega$$

$$\begin{aligned}
\Omega_\mu = {} & 2\int_0^{\frac{1}{2n_D^{b*}}} \left[(-\frac{\mu - (\mu + c_D^b + t(\hat{z}^b)^\alpha)}{\mu^2}) - \sum_{\tilde{b}=1}^{\mathcal{M}} (\frac{\tilde{p}^{\tilde{b}}(\hat{z}^b)}{\mu^2}) D_{\hat{z}^b}^{\tilde{b}} \right] D^b(p_D^{b*}, n_D^{b*})_{\hat{z}^b} d\hat{z}^b \\
& - \frac{1}{n_D^{b*}} \left[\frac{c_D^b + t(\frac{1}{2n_D^{b*}})^\alpha}{\mu^2} - \sum_{\tilde{b}=1}^{\mathcal{M}} (\frac{\tilde{p}^{\tilde{b}}(\frac{1}{2n_D^{b*}})}{\mu^2}) D_{\frac{1}{2n_D^{b*}}}^{\tilde{b}} \right] D^b(p_D^{b*}, n_D^{b*})_{\frac{1}{2n_D^{b*}}} + \frac{f_D}{L\mu^2} \\
= {} & \frac{1}{\mu^2} \left[2\int_0^{\frac{1}{2n_D^{b*}}} \left(\tilde{p}_D^{b*}(\hat{z}^b) - \sum_{\tilde{b}=1}^{\mathcal{M}} (\tilde{p}^{\tilde{b}}(\hat{z}^b)) D_{\hat{z}^b}^{\tilde{b}} \right) D^b(p_D^{b*}, n_D^{b*})_{\hat{z}^b} d\hat{z}^b \right. \\
& \left. - \frac{1}{n_D^{b*}} \left(\tilde{p}_D^{b*}(\frac{1}{2n_D^{b*}}) - \sum_{\tilde{b}=1}^{\mathcal{M}} (\tilde{p}^{\tilde{b}}(\frac{1}{2n_D^{b*}})) D_{\frac{1}{2n_D^{b*}}}^{\tilde{b}} \right) D^b(p_D^{b*}, n_D^{b*})_{\frac{1}{2n_D^{b*}}} + \frac{f_D}{L} \right]
\end{aligned}$$

Assume the first term in the last row is negligible (and define $\tilde{\Omega}_\mu$): The deviation at $\hat{z}^b = \frac{1}{2n_D^{b*}}$ is nested in the integral (weighted by 2), whereas in the last row it is weighted by $\frac{1}{n_D^{b^*}}$. If $n_D^{b^*} > 1$ is already large, the term is of minor importance.

$$\begin{aligned}
\tilde{\Omega}_\mu &= \frac{1}{\mu^2}\left[2\int_0^{\frac{1}{2n_D^{b^*}}}\left(\tilde{p}_D^{b^*}(\hat{z}^b) - \sum_{\tilde{b}=1}^{\mathcal{M}}(\tilde{p}^{\tilde{b}}(\hat{z}^b))D_{\hat{z}^b}^{\tilde{b}}\right)D^b(p_D^{b^*}, n_D^{b^*})_{\hat{z}^b}d\hat{z}^b + \frac{f_D}{L}\right] \\
\tilde{\Omega}_\mu &> 0 \iff \\
&0 < 2\int_0^{\frac{1}{2n_D^{b^*}}}\left(\tilde{p}_D^{b^*}(\hat{z}^b) - \sum_{\tilde{b}=1}^{\mathcal{M}}(\tilde{p}^{\tilde{b}}(\hat{z}^b))D_{\hat{z}^b}^{\tilde{b}}\right)D^b(p_D^{b^*}, n_D^{b^*})_{\hat{z}^b}d\hat{z}^b + f_D \\
&0 < 2\int_0^{\frac{1}{2n_D^{b^*}}}\left(\tilde{p}_D^{b^*}(\hat{z}^b) - \sum_{\tilde{b}=1}^{\mathcal{M}}(\tilde{p}^{\tilde{b}}(\hat{z}^b))D_{\hat{z}^b}^{\tilde{b}} + \mu\right)D^b(p_D^{b^*}, n_D^{b^*})_{\hat{z}^b}d\hat{z}^b
\end{aligned}$$

where μ follows from the condition at f_D at the optimum. Hence, when $n_D^{b^*}$ is large enough to neglect the effect at the upper boundary $\frac{1}{2n_D^{b^*}}$, the condition for a positive effect of μ on $n_D^{b^*}$ is

$$\begin{aligned}
&\int_0^{\frac{1}{2n_D^{b^*}}}\left(\tilde{p}_D^{b^*}(\hat{z}^b) - \sum_{\tilde{b}=1}^{\mathcal{M}}(\tilde{p}^{\tilde{b}}(\hat{z}^b))D_{\hat{z}^b}^{\tilde{b}}\right)D^b(p_D^{b^*}, n_D^{b^*})_{\hat{z}^b}d\hat{z}^b > \int_0^{\frac{1}{2n_D^{b^*}}}(-\mu)D^b(p_D^{b^*}, n_D^{b^*})_{\hat{z}^b}d\hat{z}^b \\
&\int_0^{\frac{1}{2n_D^{b^*}}}\left(\sum_{\tilde{b}=1}^{\mathcal{M}}(\tilde{p}^{\tilde{b}}(\hat{z}^b))D_{\hat{z}^b}^{\tilde{b}} - \tilde{p}_D^{b^*}(\hat{z}^b)\right)D^b(p_D^{b^*}, n_D^{b^*})_{\hat{z}^b}d\hat{z}^b < \int_0^{\frac{1}{2n_D^{b^*}}}(-\mu)D^b(p_D^{b^*}, n_D^{b^*})_{\hat{z}^b}d\hat{z}^b
\end{aligned}$$

There is symmetry between all versions $n_D^{b^*}$ of a brand. The left hand side is the aggregated (over all locations $\hat{z}^b \in [0, \frac{1}{2n_D^{b^*}}]$) revenue.

Finally, the effect of an increase in the weight of the *fit costs*, t, on $n_D^{b^*}$ is analyzed. Intuitively, if consumers are more sensitive to the distance, brands should offer more differentiated versions to attract consumers.

$$\begin{aligned}
\Omega_t = &-2\int_0^{\frac{1}{2n_D^{b^*}}}\frac{(\hat{z}^b)^\alpha}{\mu}e^{-\frac{p_D^{b^*}+t(\hat{z}^b)^\alpha}{\mu}}\tilde{\mathcal{P}}_{z^b}d\hat{z}^b + 2\int_0^{\frac{1}{2n_D^{b^*}}}e^{-\frac{p_D^{b^*}+t(\hat{z}^b)^\alpha}{\mu}}\frac{\partial\tilde{\mathcal{P}}_{z^b}}{\partial t}d\hat{z}^b \\
&+\frac{1}{2^\alpha\mu(n_D^{b^*})^{\alpha+1}}e^{-\frac{p_D^b+t(\frac{1}{2n_D^{b^*}})^\alpha}{\mu}}\tilde{\mathcal{P}}_{\frac{1}{2n_D^{b^*}}} - \frac{1}{n_D^{b^*}}e^{-\frac{p_D^{b^*}+t(\frac{1}{2n_D^{b^*}})^\alpha}{\mu}}\frac{\partial\tilde{\mathcal{P}}_{\frac{1}{2n_D^{b^*}}}}{\partial t}
\end{aligned}$$

An increase in the weight for the *fit costs*, increases the aggregate *delivered* price index, i.e.

$$\begin{aligned}
\frac{\partial\tilde{\mathcal{P}}_{z^b}}{\partial t} &= -\left[\sum_{\tilde{b}=1}^{\mathcal{M}}e^{-\frac{\tilde{p}_D^{\tilde{b}}(\hat{z}^b)}{\mu}}\right]^{-2}\sum_{\tilde{b}=1}^{\mathcal{M}}(-\frac{1}{\mu}(\hat{z}^{\tilde{b}}(\hat{z}^b))^\alpha e^{-\frac{\tilde{p}_D^{\tilde{b}}(\hat{z}^b)}{\mu}} \\
&= (\tilde{\mathcal{P}}_{\hat{z}^b})^2\sum_{\tilde{b}=1}^{\mathcal{M}}\frac{1}{\mu}(\hat{z}^{\tilde{b}}(\hat{z}^b))^\alpha e^{-\frac{\tilde{p}_D^{\tilde{b}}(\hat{z}^b)}{\mu}} \\
&= \tilde{\mathcal{P}}_{\hat{z}^b}\sum_{\tilde{b}=1}^{\mathcal{M}}\frac{1}{\mu}(\hat{z}^{\tilde{b}}(\hat{z}^b))^\alpha D^{\tilde{b}}(p_D^{\tilde{b}^*}, n_D^{\tilde{b}^*}) > 0
\end{aligned}$$

such that

$$\Omega_{\bar{t}} = \frac{2}{\mu}\int_0^{\frac{1}{2n_D^{b*}}} D^b(p_D^{b*}, n_D^{b*})_{\hat{z}^b} \left(\sum_{\tilde{b}=1}^{\mathcal{M}} (\hat{z}^{\tilde{b}}(\hat{z}^b))^\alpha D^{\tilde{b}}(p_D^{\tilde{b}*}, n_D^{\tilde{b}*}) - (\hat{z}^b)^\alpha\right) d\hat{z}^b$$

$$- \frac{2}{\mu}\frac{1}{2n_D^{b*}} D^b(p_D^{b*}, n_D^{b*})_{\frac{1}{2n_D^{b*}}} \left(\sum_{\tilde{b}=1}^{\mathcal{M}} (\hat{z}^{\tilde{b}}(\frac{1}{2n_D^{b*}}))^\alpha D^{\tilde{b}}(p_T^{\tilde{b}*}, n_T^{\tilde{b}*}) - \left[\frac{1}{2n_D^{b*}}\right]^\alpha\right) > 0$$

The second row is also part of the integral (upper limit) of the first row. Hence, if $n_D^{b*} > \frac{1}{2}$, the expression is certainly positive.

For optimality, the cross derivative is derived

$$\Omega_{p_D^{b*}} = 2\int_0^{\frac{1}{2n_D^{b*}}} (-\frac{1}{\mu}) e^{-\frac{p^{b*}_D + t(\hat{z}^b)^\alpha}{\mu}} \tilde{\mathcal{P}}_{z^b} d\hat{z}^b + \frac{1}{n^{b^*}\mu} e^{-\frac{p^{b^*} + t(\frac{1}{2n_D^{b*}})^\alpha}{\mu}} \tilde{\mathcal{P}}_{z^b} < 0$$

The second term is also part of the integral. If f $n_D^{b*} > \frac{1}{2}$, the cross derivative is certainly negative.

Hence, the condition for optimality is satisfied.

$$(\frac{\partial^2 \Pi_D^b}{\partial (p_D^b)^2})(\frac{\partial^2 \Pi_D^b}{\partial (n_D^b)^2}) - \frac{\partial^2 \Pi_D^b}{\partial n_D^b \partial p_D^b} > 0$$

Derivations: Customized Versions - Optimal Prices

Maximizing the profit function with respect to prices yields

$$
\begin{aligned}
\max_{p_C^b} \Pi_C^b &= (p_C^b - c_C^b) \int_0^1 \frac{e^{-\frac{p_C^b}{\mu}}}{\sum_{\tilde{b}=1}^{\mathcal{M}} e^{-\frac{\tilde{p}^{\tilde{b}}(z)}{\mu}}} L dz - f_C \\
\frac{\partial \Pi_C^b}{\partial p_C^b} &= \int_0^1 \frac{e^{-\frac{p_C^b}{\mu}}}{\sum_{\tilde{b}=1}^{\mathcal{M}} e^{-\frac{\tilde{p}^{\tilde{b}}(z)}{\mu}}} L dz + (p_C^b - c_C^b)(-\frac{1}{\mu}) \int_0^1 \frac{e^{-\frac{p_C^b}{\mu}}}{\sum_{\tilde{b}=1}^{\mathcal{M}} e^{-\frac{\tilde{p}^{\tilde{b}}(z)}{\mu}}} L dz \equiv 0 \\
p_C^{b^*} &= \mu + c_C^b
\end{aligned}
$$

The SOC is

$$
\frac{\partial^2 \Pi_C^b}{\partial (p_C^b)^2} = -\frac{2}{\mu} \int_0^1 \frac{e^{-\frac{p_C^b}{\mu}}}{\sum_{\tilde{b}=1}^{\mathcal{M}} e^{-\frac{\tilde{p}^{\tilde{b}}(z)}{\mu}}} L dz + (p_C^b - c_C^b)(-\frac{1}{\mu^2}) \int_0^1 \frac{e^{-\frac{p_C^b}{\mu}}}{\sum_{\tilde{b}=1}^{\mathcal{M}} e^{-\frac{\tilde{p}^{\tilde{b}}(z)}{\mu}}} L dz
$$

evaluated at $p_C^{b^*} = \mu + c_C^b$ yields

$$
\frac{\partial^2 \Pi_C^b}{\partial (p_C^b)^2} = -\frac{1}{\mu} \int_0^1 \frac{e^{-\frac{p_C^{b^*}}{\mu}}}{\sum_{\tilde{b}=1}^{\mathcal{M}} e^{-\frac{\tilde{p}^{\tilde{b}}(z)}{\mu}}} L dz < 0
$$

Hence, the extremum is a maximum. In that case optimal profits are

$$
\begin{aligned}
\Pi_C^{b^*} &= \mu \int_0^1 \frac{e^{-\frac{\mu + c_C^b}{\mu}}}{\sum_{\tilde{b}=1}^{\mathcal{M}} e^{-\frac{\tilde{p}^{\tilde{b}}(z)}{\mu}}} L dz - f_C \\
&= \mu e^{-\frac{\mu + c_C^b}{\mu}} \int_0^1 \frac{L}{\sum_{\tilde{b}=1}^{\mathcal{M}} e^{-\frac{\tilde{p}^{\tilde{b}}(z)}{\mu}}} dz - f_C \\
&= \mu e^{-\frac{\mu + c_C^b}{\mu}} L \int_0^1 \tilde{\mathcal{P}}_z dz - f_C
\end{aligned}
$$

Technology Choice

On the other hand, when there is differentiation, optimal profits are

$$\Pi_D^{b*}(p_D^{b*}, n_D^{b*}) = \mu e^{-\frac{\mu+c_D^b}{\mu}} L 2n_D^{b*} \int_0^{\frac{1}{2n_D^{b*}}} \frac{e^{-\frac{t(\hat{z}^b)^\alpha}{\mu}}}{\sum_{\tilde{b}=1}^{\mathcal{M}} e^{-\frac{\tilde{p}^{\tilde{b}}(\hat{z}^b)}{\mu}}} d\hat{z}^b - n_D^{b*} f_D$$

Define the difference between brand b's optimal profits as

$$\begin{aligned}
\Delta^b &= \Pi_C^{b*}(p_C^b) - \Pi_D^{b*}(p_D^{b*}, n_D^{b*}) \\
&= \mu e^{-\frac{\mu+c_C^b}{\mu}} L \int_0^1 \tilde{\mathcal{P}}_z dz - f_C - \mu e^{-\frac{\mu+c_D^b}{\mu}} L 2n_D^{b*} \int_0^{\frac{1}{2n_D^{b*}}} e^{-\frac{t(\hat{z}^b)^\alpha}{\mu}} \tilde{\mathcal{P}}_{\hat{z}^b} d\hat{z}^b + n_D^{b*} f_D
\end{aligned}$$

Whenever $\Delta^b \geq 0$ the brand will offer differentiated versions, while $\Delta^b < 0$ will cause the brand to adopt the customization technology.

$$\begin{aligned}
\frac{\partial \Delta^b}{\partial L} &= \mu \int_0^1 D^b(p_D^{b*})_z dz - \mu 2n_D^{b*} \int_0^{\frac{1}{2n_D^{b*}}} D^b(p_D^{b*}, n_D^{b*})_{\hat{z}^b} d\hat{z}^b \\
&\quad - \frac{dn_D^{b*}}{dL} \underbrace{\left[\frac{\partial (2n_D^{b*} L\mu \int_0^{\frac{1}{2n_D^{b*}}} D^b(p_D^{b*}, n_D^{b*})_{\hat{z}^b} d\hat{z}^b)}{\partial n_D^{b*}} - f_D \right]}_{=0 \quad \text{at optimum}}
\end{aligned}$$

To keep the analysis tractable, assume that changes in the aggregate price index across locations are minor, such that it can be approximated by a constant value, i.e. $\tilde{\mathcal{P}}_z = \tilde{\mathcal{P}}_{\hat{z}^b} = \tilde{\mathcal{P}}$.

$$\frac{\partial \Delta^b}{\partial L} = \frac{\tilde{\mathcal{P}}\mu}{e} \left[e^{-\frac{c_C^b}{\mu}} - 2n_D^{b*} \int_0^{\frac{1}{2n_D^{b*}}} e^{-\frac{c_D^b + t(\hat{z}^b)^\alpha}{\mu}} d\hat{z}^b \right]$$

The effect is positive if

$$\begin{aligned}
\left[e^{-\frac{c_C^b}{\mu}} - 2n_D^{b*} \int_0^{\frac{1}{2n_D^{b*}}} e^{-\frac{c_D^b + t(\hat{z}^b)^\alpha}{\mu}} d\hat{z}^b \right] &> 0 \\
1 &> 2n_D^{b*} \int_0^{\frac{1}{2n_D^{b*}}} e^{-\frac{(c_D^b + t(\hat{z}^b)^\alpha) - c_C^b}{\mu}} d\hat{z}^b \\
2n_D^{b*} \int_0^{\frac{1}{2n_D^{b*}}} e^{-\frac{c_C^b}{\mu}} d\hat{z}^b &> 2n_D^{b*} \int_0^{\frac{1}{2n_D^{b*}}} e^{-\frac{c_D^b + t(\hat{z}^b)^\alpha}{\mu}} d\hat{z}^b \quad | : \tilde{\mathcal{P}} \quad | * \mu \\
2n_D^{b*}\mu \int_0^{\frac{1}{2n_D^{b*}}} D^b(p_C^{b*}) d\hat{z}^b &> 2n_D^{b*}\mu \int_0^{\frac{1}{2n_D^{b*}}} D^b(p_D^{b*}, n_D^{b*})_{\hat{z}^b} d\hat{z}^b
\end{aligned}$$

i.e. the aggregate revenues generated from customization are larger than those from differentiation. Note: At the optimal level of differentiation, the increasing effect of a higher L on n_D^{b*} which reduces maximum *fit costs* and increases D^b is compensated by the increase in the fixed costs. Therefore, the fixed costs do not matter in the differential effect of an increase in L. If $c_C^b < c_D^b$, then even at $\hat{z}^b = 0$ is the *delivered* price lower for the customized version and $D^b(p_C^{b*})$ higher at any $\hat{z}^b$. On the other hand, if $c_C^b \geq c_D^b + t(\frac{1}{4n_D^{b*}})^2$, then, even at the maximum distance would $D^b(p_D^{b*})$ be dominated by demand for differentiation.

$$\frac{\partial^2 \Delta^b}{\partial L \partial c_D^b} = \frac{\tilde{\mathcal{P}}\mu}{e}[-\frac{1}{\mu}e^{-\frac{c_C^b}{\mu}}\frac{\partial c_C^b}{\partial c_D^b} - \underbrace{\frac{dn_D^{b*}}{dc_D^b}}_{<0} \overbrace{\left[2\int_0^{\frac{1}{2n_D^{b*}}} e^{-\frac{c_D^b + t(\hat{z}^b)^\alpha}{\mu}} d\hat{z}^b - \frac{1}{n_D^{b*}} e^{-\frac{c_D^b + t(\hat{z}^b)^\alpha}{\mu}}\right]}^{=\frac{f_D}{L\mu\tilde{\mathcal{P}}}>0}$$

$$+ 2n_D^{b*}\int_0^{\frac{1}{2n_D^{b*}}} \frac{1}{\mu} e^{-\frac{c_D^b + t(\hat{z}^b)^\alpha}{\mu}} d\hat{z}^b]$$

Consistent with the results for heterogeneous firms and expectation based purchase decisions: If $c_C^b \perp c_D^b$: The response is increasing in the marginal costs of a brand.
If $c_C^b \not\perp c_D^b$, then the response is increasing in the productivity of the brand if:

$$-\frac{1}{\mu}e^{-\frac{c_C^b}{\mu}}\frac{\partial c_C^b}{\partial c_D^b} - \frac{dn_D^{b*}}{dc_D^b}\frac{f_D}{L\mu\tilde{\mathcal{P}}} + 2n_D^{b*}\int_0^{\frac{1}{2n_D^{b*}}} \frac{1}{\mu} e^{-\frac{c_D^b + \bar{t}(\hat{z}^b)^\alpha}{\mu}} d\hat{z}^b < 0$$

$$2n_D^{b*}L\mu\int_0^{\frac{1}{2n_D^{b*}}} \left(-\frac{1}{\mu}D^b(p_C^{b*})\frac{\partial c_C^b}{\partial c_D^b} - (-\frac{1}{\mu})D^b(p_D^{b*}, n_D^{b*})_{\hat{z}^b}\right) d\hat{z}^b < \underbrace{\frac{dn_D^{b*}}{dc_D^b}}_{<0} f_D$$

The increase in marginal costs c_D^b has a direct effect on the demand for differentiated versions since $\frac{\partial p_D^{b*}}{\partial c_D^b} = 1 > 0$. The increase in the price decreases demand. However, the higher marginal costs decreases the optimal n_D^{b*} and thereby total fixed costs. An increase in c_D^b (decrease in productivity) might reduce also demand for customized versions if marginal costs across technologies are positively correlated. In that case, the incentives to adopt the customization technology as a response to larger markets is increasing in the productivity of the brand if the differential effect of the increase in c_D^b on the revenue of customization and differentiation is smaller than the reduction in total fixed costs. Effects on demand for both types are negative, so only if there is also a sufficiently strong effect on the marginal costs for customization might the response to larger markets be increasing in the productivity of the brand.
The simple effect of an increase in marginal costs c_D^b on the difference is

$$\begin{aligned}\frac{\partial \Delta^b}{\partial c_D^b} &= -2n_D^{b*}L\int_0^{\frac{1}{2n_D^{b*}}} D^b(p_C^{b*})\frac{\partial c_C^b}{\partial c_D^b} d\hat{z}^b + 2n_D^{b*}L\int_0^{\frac{1}{2n_D^{b*}}} D^b(p_D^{b*}, n_D^{b*})_{\hat{z}^b} d\hat{z}^b \\ &= 2n_D^{b*}L\int_0^{\frac{1}{2n_D^{b*}}} \left(D^b(p_D^{b*}, n_D^{b*})_{\hat{z}^b} - D^b(p_C^{b*})\frac{\partial c_C^b}{\partial c_D^b}\right) d\hat{z}^b\end{aligned}$$

If $c_C^b \perp c_D^b$: the effect is clearly positive. If $c_C^b \not\perp c_D^b$: the effect is positive if the aggregated decrease in demand for differentiation is larger than the decrease in demand for customization.

Finally, consider the effect of μ on the likelihood to adopt the customization technology:

$$\frac{\partial \Delta^b}{\partial \mu} = 2n_D^{b^*} L \int_0^{\frac{1}{2n_D^{b^*}}} (D^b(p_C^{b^*}) - D^b(p_D^{b^*}, n_D^{b^*})_{\hat{z}^b}) d\hat{z}^b$$
$$+ 2\mu n_D^{b^*} L \int_0^{\frac{1}{2n_D^{b^*}}} (\frac{D^b(p_C^{b^*})}{\partial \mu} - \frac{D^b(p_D^{b^*}, n_D^{b^*})_{\hat{z}^b}}{\partial \mu}) d\hat{z}^b$$

See derivations in appendix A.2. $\frac{\partial \Delta^b}{\partial \mu} > 0$ if

$$\int_0^{\frac{1}{2n_D^{b^*}}} D^b(p_C^{b^*}) \left[\tilde{p}_C^{b^*} - \sum_{\tilde{b}=1}^{\mathcal{M}} (\tilde{p}_T^{b^*}) D_{\hat{z}^b}^{\tilde{b}} \right] d\hat{z}^b > \int_0^{\frac{1}{2n_D^{b^*}}} D^b(p_D^{b^*}, n_D^{b^*})_{\hat{z}^b} \left[\tilde{p}_D^{b^*} - \sum_{\tilde{b}=1}^{\mathcal{M}} (\tilde{p}_T^{b^*}) D_{\hat{z}^b}^{\tilde{b}} \right] d\hat{z}^b$$
$$\int_0^{\frac{1}{2n_D^{b^*}}} D^b(p_C^{b^*}) \left[\tilde{p}_C^{b^*} - \sum_{\tilde{b}=1}^{\mathcal{M}} (\tilde{p}_T^{b^*}) D_{\hat{z}^b}^{\tilde{b}} \right] d\hat{z}^b > \int_0^{\frac{1}{2n_D^{b^*}}} D^b(p_D^{b^*}, n_D^{b^*})_{\hat{z}^b} \left[\tilde{p}_D^{b^*} - - \sum_{\tilde{b}=1}^{\mathcal{M}} (\tilde{p}_T^{b^*}) D_{\hat{z}^b}^{\tilde{b}} \right] d\hat{z}^b$$

Technology Mix

If it is possible to adopt both technologies, i.e. choice between $T = \{D, C, DC\}$, the Lagrange function is

$$\mathcal{L} = 2n_D^b L(p_D^b - c_D^b) \int_0^{\left(\frac{p_C^b - p_D^b}{t}\right)^{\frac{1}{\alpha}}} D^b(p_D^b, n_D^b)_{\hat{z}^b} d\hat{z}^b - n_D^b f_D$$
$$+ 2n_D^b L(p_C^b - c_C^b) \int_{\left(\frac{p_C^b - p_D^b}{t}\right)^{\frac{1}{\alpha}}}^{\frac{1}{2n_D^b}} D^b(p_C^b)_{\hat{z}^b} d\hat{z}^b - f_C + \lambda \left(\frac{1}{2n_D^b} - \left(\frac{p_C^b - p_D^b}{t} \right)^{\frac{1}{\alpha}} \right)$$

Maximizing yields

$$\frac{\partial \mathcal{L}}{\partial p_D^b} = 2n_D^b L \int_0^{\left(\frac{p_C^b - p_D^b}{t}\right)^{\frac{1}{\alpha}}} D^b(p_D^b, n_D^b)_{\hat{z}^b} d\hat{z}^b - 2\frac{1}{\mu} n_D^b L(p_D^b - c_D^b) \int_0^{\left(\frac{p_C^b - p_D^b}{t}\right)^{\frac{1}{\alpha}}} D^b(p_D^b, n_D^b)_{\hat{z}^b} d\hat{z}^b$$
$$- \frac{2}{\alpha t} n_D^b L(p_D^b - c_D^b) D^b(p_D^b, n_D^b)_{\left(\frac{p_C^b - p_D^b}{t}\right)^{\frac{1}{\alpha}}} \left(\frac{p_C^b - p_D^b}{t} \right)^{\frac{1}{\alpha} - 1}$$
$$+ \frac{2}{\alpha t} n_D^b L(p_C^b - c_C^b) D^b(p_C^b)_{\left(\frac{p_C^b - p_D^b}{t}\right)^{\frac{1}{\alpha}}} \left(\frac{p_C^b - p_D^b}{t} \right)^{\frac{1}{\alpha} - 1}$$
$$+ \lambda \frac{1}{\alpha t} \left(\frac{p_C^b - p_D^b}{t} \right)^{\frac{1}{\alpha} - 1} = 0$$

$$\frac{\partial \mathcal{L}}{\partial p_C^b} = 2n_D^b L \int_{\left(\frac{p_C^b - p_D^b}{t}\right)^{\frac{1}{\alpha}}}^{\frac{1}{2n_D^b}} D^b(p_C^b)_{\hat{z}^b} d\hat{z}^b - 2n_D^b L(p_C^b - c_C^b) \frac{1}{\mu} \int_{\left(\frac{p_C^b - p_D^b}{t}\right)^{\frac{1}{\alpha}}}^{\frac{1}{2n_D^b}} D^b(p_C^b)_{\hat{z}^b} d\hat{z}^b$$
$$+ \frac{2}{\alpha t} n_D^b L(p_D^b - c_D^b) D^b(p_D^b, n_D^b)_{\left(\frac{p_C^b - p_D^b}{t}\right)^{\frac{1}{\alpha}}} \left(\frac{p_C^b - p_D^b}{t} \right)^{\frac{1}{\alpha} - 1}$$
$$- \frac{2}{\alpha t} n_D^b L(p_C^b - c_C^b) D^b(p_C^b)_{\left(\frac{p_C^b - p_D^b}{t}\right)^{\frac{1}{\alpha}}} \left(\frac{p_C^b - p_D^b}{t} \right)^{\frac{1}{\alpha} - 1}$$
$$- \lambda \frac{1}{t} \left(\frac{p_C^b - p_D^b}{t} \right)^{\frac{1}{\alpha} - 1} = 0$$

Note that at the indifferent consumer $\hat{z}^b = \left(\frac{p_C^b - p_D^b}{t}\right)^{\frac{1}{\alpha}}$: $D^b(p_D^b, n_D^b)_{\hat{z}^b} = D^b(p_C^b)_{\hat{z}^b}$. Hence, the terms cancel when summing over both FOCs, such that

$$\mu \int_0^{\left(\frac{p_C^b - p_D^b}{t}\right)^{\frac{1}{\alpha}}} D^b(p_D^b, n_D^b)_{\hat{z}^b} d\hat{z}^b + \mu \int_{\left(\frac{p_C^b - p_D^b}{t}\right)^{\frac{1}{\alpha}}}^{\frac{1}{2n_D^b}} D^b(p_C^b)_{\hat{z}^b} d\hat{z}^b$$

$$=$$

$$(p_D^b - c_D^b) \int_0^{\left(\frac{p_C^b - p_D^b}{t}\right)^{\frac{1}{\alpha}}} D^b(p_D^b, n_D^b)_{\hat{z}^b} d\hat{z}^b + (p_C^b - c_C^b) \int_{\left(\frac{p_C^b - p_D^b}{t}\right)^{\frac{1}{\alpha}}}^{\frac{1}{2n_D^b}} D^b(p_C^b)_{\hat{z}^b} d\hat{z}^b$$

The ratio of aggregated customized to differentiated sales is

$$\frac{\int_{\left(\frac{p_C^b - p_D^b}{t}\right)^{\frac{1}{\alpha}}}^{\frac{1}{2n_D^b}} D^b(p_C^b)_{\hat{z}^b} d\hat{z}^b}{\int_0^{\left(\frac{p_C^b - p_D^b}{t}\right)^{\frac{1}{\alpha}}} D^b(p_D^b, n_D^b)_{\hat{z}^b} d\hat{z}^b} = \frac{\mu - (p_D^b - c_D^b)}{(p_C^b - c_C^b) - \mu}$$

i.e. the ratio of the deviations from the inverse measure for the correlation among tastes, μ. Given μ, the higher p_D^b (p_C^b), the higher the sales share from customization (differentiation).

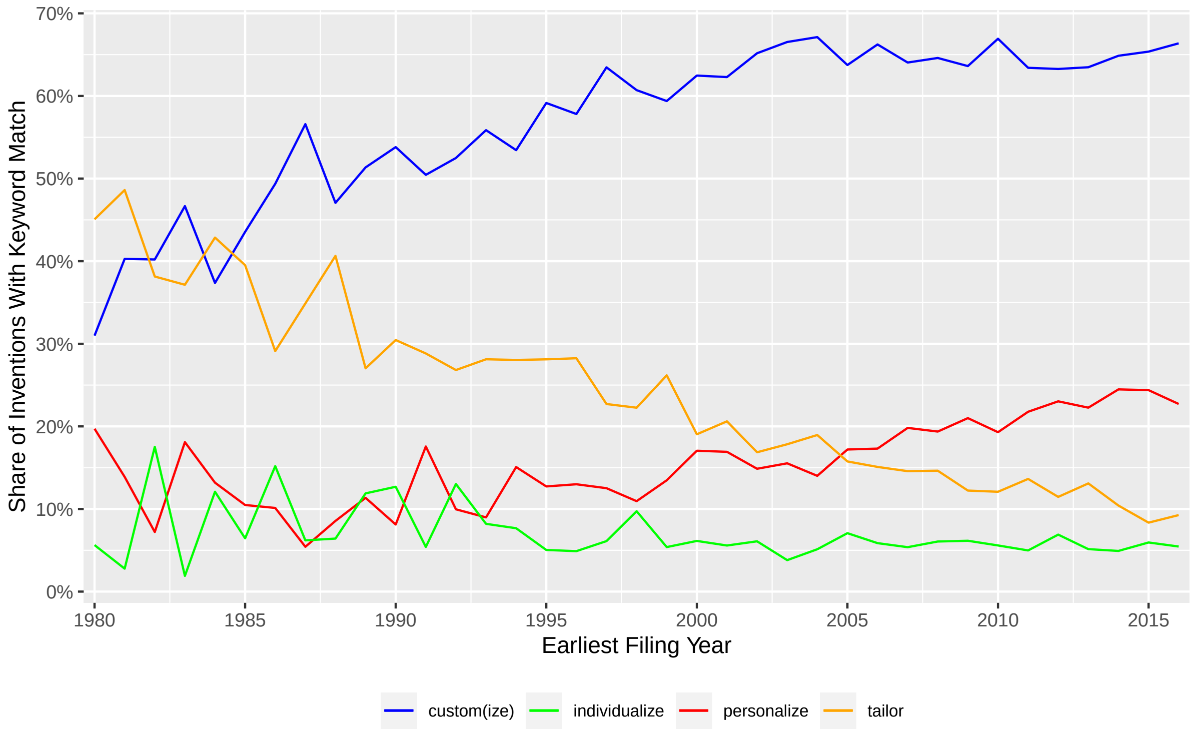
$$\begin{aligned}
\frac{\partial \mathcal{L}}{\partial n_D^b} &= 2L(p_D^b - c_D^b) \int_0^{\left(\frac{p_C^b - p_D^b}{t}\right)^{\frac{1}{\alpha}}} D^b(p_D^b, n_D^b)_{\hat{z}^b} d\hat{z}^b - f_D \\
&+ 2L(p_C^b - c_C^b) \int_{\left(\frac{p_C^b - p_D^b}{t}\right)^{\frac{1}{\alpha}}}^{\frac{1}{2n_D^b}} D^b(p_C^b)_{\hat{z}^b} d\hat{z}^b - 2n_D^b L(p_C^b - c_C^b) \frac{1}{2(n_D^b)^2} D^b(p_C^b)_{\frac{1}{2n_D^b}} \\
&- \lambda \frac{1}{2(n_D^b)^2} = 0
\end{aligned}$$

B Appendix to Chapter 2

B.1 Additional Figures and Tables

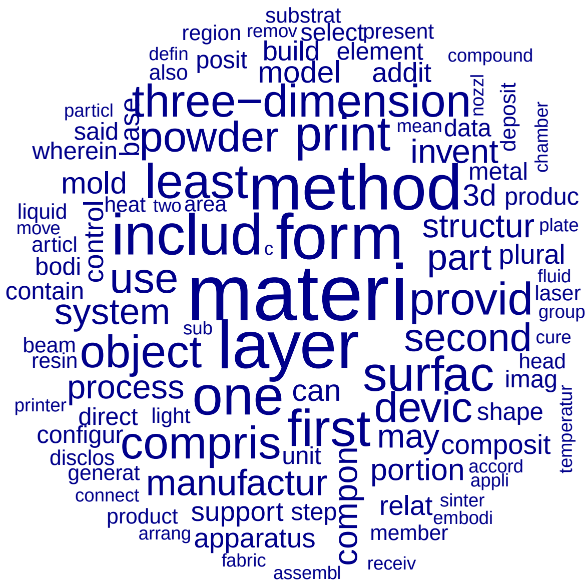
Figures

Figure B.1: Share of Inventions Containing Specific Word(stem)s Over Time



Notes: Data Source: PATSTAT Online 2020 Autumn Edition; Inventions classified as customization inventions as in section 2.3.1.

Figure B.2: Wordcloud of All Abstracts (Additive Manufacturing)



Notes: Data Source: PATSTAT Online 2020 Autumn Edition; Patents classified as AM inventions as in section 2.3.2.

Tables

Table B.1: List of Keywords and Wordstems Used for Analysis of Abstracts

Keywords, Wordstems
tailor—tailor-made—tailor made—custom tailor—custom-tailor
individualis — individualiz (excluding individuality)
personalis — personaliz (excluding personality)
custom (excluding customary—customarily—customer—customs)
customi—custom made—custom-made—custom built—custom-built—custom-tailor—custom tailor
made-to-order—made to order—make-to-order—make to order—made to measure—made-to-measure—make to measure—make-to-measure
built to order—built-to-order—build to order—build-to-order
engineered to order—engineered-to-order—engineer to order—engineer-to-order
bespoke
precision medicine—precision-medicine

For consistency, the term customer is excluded as otherwise, one would need to include synonyms such as client, buyer, purchaser. The terms (customary—customarily—customs) are excluded conditional on the abstract not matching with any of the other entries in the table B.1.

Table B.2: Synonyms for Keyword Search

Verb	Synonyms	Dictionary (Source)
personalize	customize, individualize, give a personal touch to, make distinctive, make to order	OUP, Collins Dictionary
customized	bespoke, custom, custom-made, custom-tailored, made-to-order, tailor-made, tailored	Merriam Webster
custom	bespoke(n), custom-made, custom-tailored, customized, made-to-order, tailor-made, tailored	Merriam Webster
custom-built	handcrafted, handmade, bespoke(n), custom, customized, custom-made, custom-tailored	Merriam Webster
	made-to-order, tailored, tailor-made, particular, special, specialized, made-to-measure	Merriam-Webster
individualized	personalize	Cambridge Dictionary
personalize	bespoke, customized, individualized	Cambridge Dictionary
bespoke	custom-made, tailor-made, tailored	Cambridge Dictionary
tailor-made	custom-made, personalized, customized	Collins Dictionary

Words used for keyword list in table B.1 highlighted in red.

References:

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Table B.3: Distribution across CPC Classes of Customization Inventions

CPC class	Share over all years [%]
G06 Computing, Calculating; Counting	28.68
H04 Electric Communication Technique	16.70
Y10 Technical subjects covered by former USPC	5.4
A61 Medical or Veterinary Science	4.99
H01 Basic Electric Elements	3.41
G01 Measuring; Testing	2.76
Y02 Technologies or applications for mitigation or adaption against climate change	2.27
G07 Checking-devices	1.94
G09 Education; Cryptography; Display; Advertising; Seals	1.65
G16 Information and Communication Technology (ICT) specifically adapted for specific application fields	1.63
A63 Sports; Games; Amusements	1.44
G05 Controlling; Regulating	1.27
B60 Vehicles in general	1.26
A47 Furniture; Domestic Articles or appliances; coffee mills; spice mills; suction cleaners in general	1.14
G02 Optics	1.14
G10 Musical Instruments; Acoustics	1.10
B29 Working of plastics; working of substances in a plastic state in general	1.08
B65 Conveying; Packing; Storing; Handling thin or filamentary material	1.02
H05 Electric techniques not otherwise provided for	0.87

Data Source: PATSTAT Online 2020 Autumn Edition; Inventions from 1980 up until 2016. Assignment of inventions to CPC classes not mutually exclusive and based on aggregation over DOCDB patent families; Classification in customization inventions as in as in section 2.3.1.

Table B.4: Comparison of Matches in Claims and Abstracts: EP full-text search

A≡	ABEN = customiz* OR customis* OR individualis* OR individualiz* OR personalis* OR personaliz* OR tailor* OR custom* OR bespoke*
C≡	CLEN = customiz* OR customis* OR individualis* OR individualiz* OR personalis* OR personaliz* OR tailor* OR custom* OR bespoke*

Set	Reported Document Matches
$C \cup A$	35.622
$C \cap A$	4.881
$C \setminus A$	25.033
$A \setminus C$	5.708

Source: EP full-text search (`https://www.epo.org/searching-for-patents/technical/ep-full-text.html`), version EP AB2021/20, retrieved: May 19, 2021.

B.2 Derivations

Firms' Maximization

Maximization of the profit function yields the first order conditions:

$$
\begin{aligned}
\frac{\partial \pi_D}{\partial p_D} &= X\left(s(n_D)\right)^{\sigma-1}\left(\frac{p_D}{P}\right)^{-\sigma} - \sigma X\left(s(n\right)^{\sigma-1}\left(\frac{p_D}{P}\right)^{-\sigma}\frac{(p_D - c_D(\phi))}{p_D} \equiv 0 \\
p_D &= \frac{\sigma}{\sigma-1}c_D(\phi) \\
\frac{\partial^2 \pi_D}{\partial (p_D)^2} &= -\sigma X\left(s(n_D)\right)^{\sigma-1}\left(\frac{p_D}{P}\right)^{-\sigma}\left(\frac{p_D - \sigma(p_D - c_D(\phi)) + (p_D - c_D(\phi))}{(p_D)^2}\right) < 0 \\
\frac{\partial \pi_D(\phi)}{\partial n_D} &= (\sigma-1)\frac{s'_{n_D}(n_D)}{s(n_D)}X\left(s(n_D)\right)^{\sigma-1}\left(\frac{p_D}{P}\right)^{-\sigma}(p_D - c_D(\phi)) - f_D \equiv 0 \\
\frac{\partial^2 \pi_D(\phi)}{\partial (n_D)^2} &= (\sigma-1)X\left(s(n_D)\right)^{\sigma-1}\left(\frac{p_D}{P}\right)^{-\sigma}(p_D - c_D(\phi))\left[\frac{s''(n_D)s(n_D) - (s'(n_D))^2(1+\sigma)}{s(n_D)^2}\right]
\end{aligned}
$$

$$
\underbrace{\left(\frac{\partial^2 \pi_D(\phi)}{\partial (n_D)^2}\right)\left(\frac{\partial^2 \pi_D}{\partial (p_D)^2}\right)}_{>0 \text{ see comment below on SOC}} - \frac{\partial^2 \pi_D(\phi)}{\partial n_D \partial p_D} > 0
$$

$$
\begin{aligned}
\frac{\partial^2 \pi_D(\phi)}{\partial n_D \partial p_D} &= -\frac{(\sigma-1)\sigma}{p_D}\frac{s'_{n_D}(n_D)}{s(n_D)}X\left(s(n_D)\right)^{\sigma-1}\left(\frac{p_D}{P}\right)^{-\sigma}(p_D - c_D(\phi)) \\
&+ (\sigma-1)\frac{s'_{n_D}(n_D)}{s(n_D)}X\left(s(n_D)\right)^{\sigma-1}\left(\frac{p_D}{P}\right)^{-\sigma} \\
&= (\sigma-1)\frac{s'_{n_D}(n_D)}{s(n_D)}X\left(s(n_D)\right)^{\sigma-1}\left(\frac{p_D}{P}\right)^{-\sigma}(1 - \underbrace{\frac{\sigma(p_D - c_D)}{p_D})}_{=1 \text{ at the optimum}} = 0
\end{aligned}
$$

For the second order condition (SOC) to be negative, $\frac{s''(n_D)s(n_D)}{(s'(n))^2} < 1+\sigma$. If $s''(n_D) < 0$, i.e. if $s(n_D)$ is concave, the condition necessarily holds. For instance, with the functional form $s(n_D) = 1 - n_D^{-\alpha}$, the condition is $-\frac{\alpha+1}{\alpha}(n^\alpha - 1) < (1+\sigma)$. When $n_D \geq 1$, the bracket on the left hand side is positive for all $\alpha > 0$ and therefore smaller than $1+\sigma$. Let $\epsilon_n \equiv \frac{\partial s(n_D)}{\partial n_D}\frac{n_D}{s(n_D)}$ be the elasticity of consumers to the number of versions offered by the brand. The first order condition for optimal proliferation can be rewritten as

$$
\begin{aligned}
n_D^* f_D &= x(\phi, n_D^*)\epsilon_n c_D(\phi) \\
n_D^* &= x(\phi, n_D^*)\epsilon_n \frac{c_D(\phi)}{f_D}
\end{aligned}
$$

Note that $x(\phi, n_D^*)$ depends on optimal proliferation as well. Hence, the implicit function theorem is applied to derive comparative static results for optimal proliferation:

$$F \equiv (\sigma-1)\frac{s'_{n_D}(n_D)}{s(n_D)}X\left(s(n_D)\right)^{\sigma-1}\left(\frac{p_D^*}{P}\right)^{-\sigma}(p_D^*-c_D(\phi))-f_D=0$$

$$\begin{aligned}
F_{n_D^*} &< 0 \quad \text{(maximum)}\\
\frac{d(n_D^*)}{df_D} &= -\frac{F_{n_D^*}}{F_{f_D}} < 0\\
F_{c_D} &= -(\sigma+1)\frac{s'_{n_D}(n_D)}{s(n_D)}X\left(s(n_D)\right)^{\sigma-1}\left(\frac{p_D^*}{P}\right)^{-\sigma} < 0\\
\frac{d(n_D^*)}{dc_D} &= -\frac{F_{n_D^*}}{F_{c_D}} < 0
\end{aligned}$$

$$\begin{aligned}
\frac{\partial\frac{x(\phi,n_D^*)}{n_D^*}}{\partial n_D^*} &= \frac{(\sigma-1)\frac{s'(n_D^*)}{s(n_D^*)}x(\phi,n_D^*)n_D^*-x(\phi,n_D^*)}{(n_D^*)^2}\\
&= \left(\frac{(\sigma-1)\epsilon_n-1}{(n_D^*)^2}\right)x(\phi,n_D^*)
\end{aligned}$$

Comparative static for demand per version:

$$\frac{\partial\frac{x(\phi,n_D^*)}{n_D^*}}{\partial\phi} = \frac{(\frac{\partial x(\phi,n_D^*)}{\partial\phi}+\frac{\partial x(\phi,n_D^*)}{\partial n_D^*}\frac{\partial n_D^*}{\partial\phi})n_D^*-\frac{\partial n_D^*}{\partial\phi}x(\phi,n_D^*)}{(n_D^*)^2}$$

The sign is determined by:

$$\begin{aligned}
\frac{\partial x(\phi)}{\partial\phi} &> \left((\sigma-1)\epsilon_n-1\right)x(\phi,n_D^*)\frac{\partial n_D^*}{\partial\phi}\\
\frac{\sigma x(\phi,n_D^*)}{\phi} &> \left((\sigma-1)\epsilon_n-1\right)x(\phi,n_D^*)\frac{\partial n_D^*}{\partial\phi}
\end{aligned}$$

The cutoff productivity level, ϕ_D^* is determined by:

$$\begin{aligned}
\left[\frac{(n_D^*f_D+f)(\sigma-1)}{XP^\sigma}\left(\frac{\sigma}{\sigma-1}\right)^\sigma\right]^{\frac{1}{1-\sigma}} s(n_D^*) &= \frac{1}{\phi_D^*}\overline{c_D}(\gamma,w)\\
\phi_D^* &= \frac{\overline{c_D}(\gamma,w)}{s(n_D^*)}\left[\frac{(n_D^*f_D+f)(\sigma-1)}{XP^\sigma}\left(\frac{\sigma}{\sigma-1}\right)^\sigma\right]^{\frac{1}{\sigma-1}}
\end{aligned}$$

where $\overline{c_D}(\gamma,w)=[\gamma(N-1,N)w^{1-\sigma}]^{\frac{1}{1-\sigma}}$ and $n_D^*(c_D(\phi))$. The function is not explicitly solvable for the cutoff value. But as argued above, the effect of ϕ through n_D on optimal profits is zero as firms are optimizing proliferation.

Analogously, the cutoff for the customization technology is given by

$$\phi_C^* = \overline{c_C}(\gamma,\eta,w,r)\left[\frac{(f_C+f)(\sigma-1)}{XP^\sigma}\left(\frac{\sigma}{\sigma-1}\right)^\sigma\right]^{\frac{1}{\sigma-1}}$$

Firms choose the profits that are higher and consequently adopt automation and customization whenever

$$\pi_C(\phi)-\pi_D(\phi)>0$$

C Appendix to Chapter 3

C.1 Additional Figures, Graphs, and Tables

Tables

Table C.1: Applications Per Application Authority (including PCT) [%]

Application authority	Share of all applications [%]
CN	49.72
US	20.54
WO	13.53
EP	4.65
KR	3.43
TW	1.51
AU	1.42
CA	1.29

Data Source: PATSTAT Online 2020 Autumn Edition; PCT applications are all in the international phase; Share of all applications filed since 2008 (26.711).

Table C.2: TOP 10 Exporting Countries of Telecommunications, Computer, and Information Services (BPM6) in 2018

Country	Exports to World in billions (current US\$)
IE	102.31
IN	58.19
US	49.65
CN	47.07
DE	42.65
GB	31.97
NL	26.72
FR	20.41
SE	15.15
SG	14.60

Data Source: UNCTADstat, `https://unctadstat.unctad.org/EN/` (April 29, 2021); Services (BPM6): Exports in Telecommunications, computer, and information services; Exports in US dollars at current prices in billions; Missing data for some countries when further subdivided.

Table C.3: TOP 10 Exporting Countries of Financial Services (BPM6) in 2018

Country	Exports to World in billions (current US\$)
US	132.42
GB	84.35
LU	64.80
SG	28.45
DE	24.72
HK	22.21
CH, LI	21.58
IE	18.13
FR	11.78
JP	11.52

Data Source: UNCTADstat, `https://unctadstat.unctad.org/EN/` (April 29, 2021); Services (BPM6): Exports in Financial Services; Exports in US dollars at current prices in billions; Missing data for some countries when further subdivided.

Table C.4: TOP 10 Exporting Countries of Explicitly Charged and other Financial Services (BPM6) in 2018

Country	Exports to World in billions (current US\$)
US	113.68
GB	69.76
LU	61.58
SG	21.16
IE	16.62
HK	16.60
DE	15.89
FR	8.21
IT	5.92
NL	5.72

Data Source: UNCTADstat, `https://unctadstat.unctad.org/EN/` (April 29, 2021); Services (BPM6): Explicitly charged and other financial services; Exports in US dollars at current prices in billions.

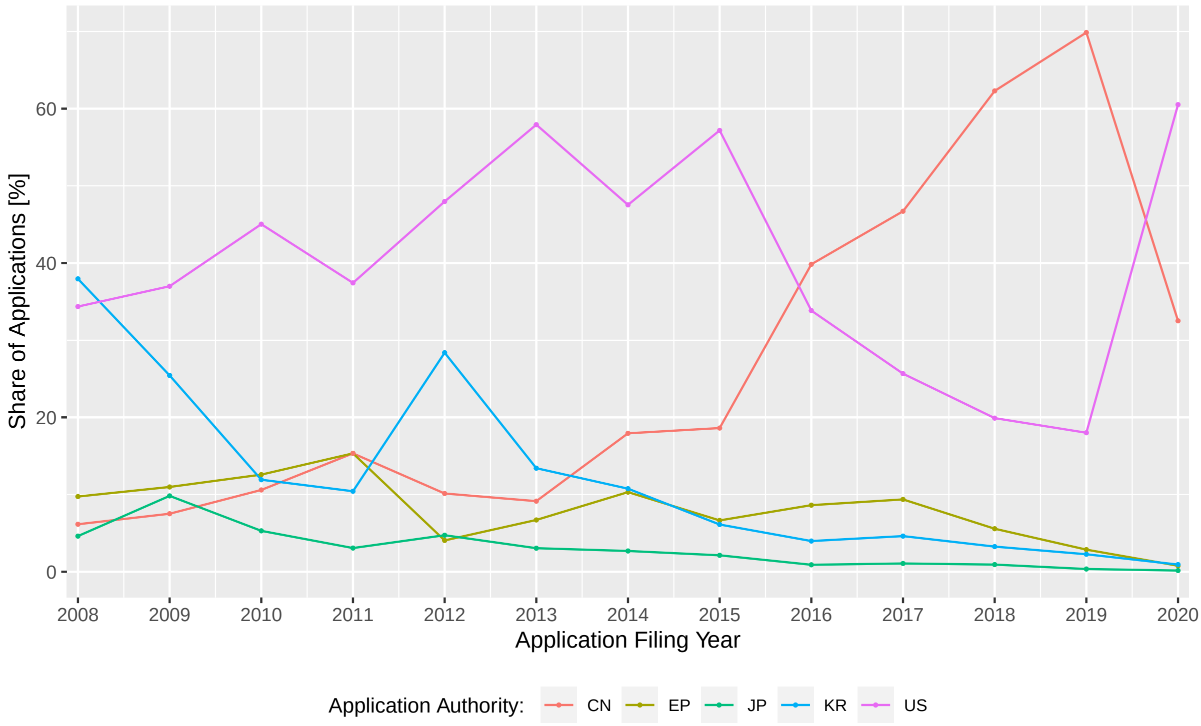
Table C.5: TOP 10 Exporting Countries of Financial Intermediation Services Indirectly Measured (FISIM) in 2018

Country	Exports to World in billions (current US\$)
US	18.74
GB	14.59
DE	8.83
SG	7.29
HK	5.61
CA	3.74
FR	3.57
BE	3.40
LU	3.21
NL	1.83

Data Source: UNCTADstat, `https://unctadstat.unctad.org/EN/` (April 29, 2021); Services (BPM6): Financial intermediation services indirectly measured (FISIM); Exports in US dollars at current prices in billions.

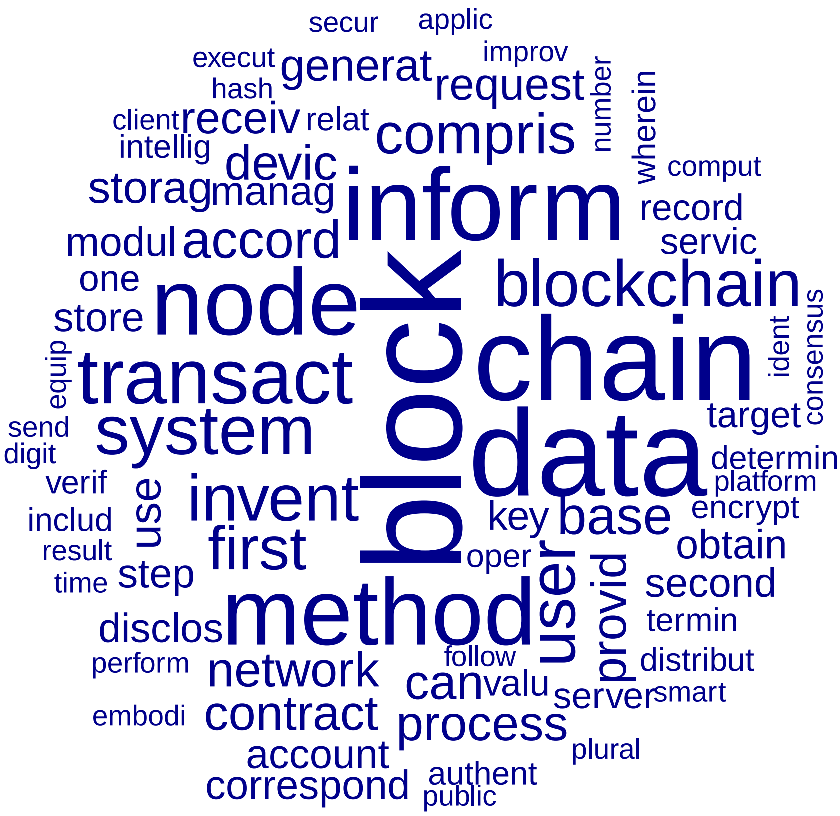
Figures

Figure C.1: Share of Applications at Application Authority



Notes: Data Source: PATSTAT Online 2020 Autumn Edition; Classification of patents as related to DLT as in section 3.3.

Figure C.2: Wordcloud Priority Filings (DLT Patents)



Notes: Data Source: PATSTAT Online 2020 Autumn Edition; Applications classified as related to DLT as in section 3.3.

C.2 Derivations

Utility maximization by the representative consumer results in demand, $x(\omega)$:

$$x(\omega) = X\left[\frac{\tau(s)p(\omega)}{P}\right]^{-\sigma} \tag{1}$$

$$\frac{\partial x(\omega)}{\partial p(\omega)} = -\sigma\frac{x(\omega)}{p(\omega)} \tag{2}$$

where $X \equiv U$.

Bilateral Trade: Open Account or Cash-in-Advance

$$\max_{p(\phi)} \quad \pi^{CIA}(\phi) = \frac{c_X p(\phi)\tau(s)x(\phi)}{(1+r_{IM})^{T(s,i)}}q(i) - \frac{\tau(s)x(\phi)}{\phi} - f_{IM} \tag{3}$$

$$\frac{\partial \pi^{CIA}(\phi)}{\partial p(\phi)} = (1-\sigma)\frac{c_X\tau(s)x(\phi)}{(1+r_{IM})^{T(s,i)}}q(i) + \sigma\frac{\tau(s)x(\phi)}{\phi p(\phi)} \equiv 0 \tag{4}$$

$$p_{s,i}(\phi) = \frac{\sigma}{\sigma-1}\frac{1}{\phi}\frac{(1+r_{IM})^{T(s,i)}}{c_X q(i)} \tag{5}$$

$$x_{s,i}(\phi) = XP^{\sigma}\left[\frac{\sigma}{\sigma-1}\frac{\tau(s)}{\phi}\frac{(1+r_{IM})^{T(s,i)}}{c_X q(i)}\right]^{-\sigma} \tag{6}$$

Demand and prices can be derived accordingly for $MP = OA$:

$$\max_{p(\phi)} \quad \pi^{OA}(\phi) = \frac{c_{IM} p(\phi)\tau(s)x(\phi)}{(1+r_X)^{T(s,i)}}q(i) - \frac{\tau(s)x(\phi)}{\phi} - f_{IM} \tag{7}$$

$$p_{s,i}(\phi) = \frac{\sigma}{\sigma-1}\frac{1}{\phi}\frac{(1+r_X)^{T(s,i)}}{c_{IM} q(i)} \tag{8}$$

$$x_{s,i}(\phi) = XP^{\sigma}\left[\frac{\sigma}{\sigma-1}\frac{\tau(s)}{\phi}\frac{(1+r_X)^{T(s,i)}}{c_{IM} q(i)}\right]^{-\sigma} \tag{9}$$

From equation (3.7) define OA_i as:

$$OA_i \equiv \left[\frac{1+r_{IM}}{1+r_X}\right]^{T(s,i)} - \left[\frac{c_X}{c_{IM}(i)}\right] \tag{10}$$

An increase in OA_i means that the difference between surplus of OA and CIA increases which makes OA more likely.

$$\left[\frac{1+r_{IM}}{1+r_X}\right]^{T(s,i)} = exp\{T(s,i)(ln(1+r_{IM}) - ln(1+r_X))\} \tag{11}$$

$$\begin{aligned}\frac{\partial exp^{T(s,i)(ln(1+r_{IM})-ln(1+r_X))}}{\partial i} &= d'(i)(\underbrace{ln(1+r_{IM})}_{\approx r_{IM}} - \underbrace{ln(1+r_X)}_{\approx r_X}))\left[\frac{1+r_{IM}}{1+r_X}\right]^{T(s,i)} \\ &= d'(i)(r_{IM} - r_X)\left[\frac{1+r_{IM}}{1+r_X}\right]^{T(s,i)}\end{aligned} \tag{12}$$

$$OA_i' = d'(i)(r_{IM} - r_X)\left[\frac{1+r_{IM}}{1+r_X}\right]^{T(s,i)} + \left[\frac{c_X}{c_{IM}(i)}\right]\frac{c_{IM}'(i)}{c_{IM}(i)} \tag{13}$$

As $c_{IM}'(i) < 0$ by assumption, the second term of equation (13) is necessarily negative. Whenever $r_X > r_{IM}$, the first term is negative: ceteris paribus, a larger discount rate in the exporting country reduces the present value of profits under post-shipment terms. Hence, $r_X > r_{IM}$ implies that OA is preferred for lower values of information frictions. OA_i is monotonically decreasing in i ($OA_i' < 0$) only if

$$\begin{aligned} d'(i)(r_X - r_{IM})\left[\frac{1+r_{IM}}{1+r_X}\right]^{T(s,i)} &> \left[\frac{c_X}{c_{IM}(i)}\right]\frac{c_{IM}'(i)}{c_{IM}(i)} \\ \epsilon_{d,i} d(i)(r_X - r_{IM})\frac{(1+r_{IM})^{T(s,i)}}{c_X} &> \epsilon_{c_{IM},i}\frac{(1+r_X)^{T(s,i)}}{c_{IM}(i)} \end{aligned} \tag{14}$$

where $\epsilon_{d,i} \equiv \frac{\partial d(i)}{\partial i}\frac{i}{d(i)} > 0, \epsilon_{c_{IM},i} \equiv \frac{\partial c_{IM}(i)}{\partial i}\frac{i}{c_{IM}(i)} < 0$ are the elasticities of distance and contract enforcement to information frictions. Whenever $r_X > r_{IM}$ equation (14) is fulfilled as $\epsilon_{c_{IM},i} < 0$. However, OA_i is only decreasing in i under $r_X < r_{IM}$ when the impact of i on contract enforcement is larger (more elastic) than the differential effect on delays.

Profits equal

$$\pi^{CIA}(\phi) = \phi^{\sigma-1}\sigma^{-\sigma}(\sigma-1)^{\sigma-1}P^\sigma X\tau^{1-\sigma}\left[\frac{(1+r_{IM})^{T(s,i)}}{c_X q(i)}\right]^{1-\sigma} - f_{IM} \tag{15}$$

$$\pi^{OA}(\phi) = \phi^{\sigma-1}\sigma^{-\sigma}(\sigma-1)^{\sigma-1}P^\sigma X\tau^{1-\sigma}\left[\frac{(1+r_X)^{T(s,i)}}{c_{IM}(i)q(i)}\right]^{1-\sigma} - f_{IM} \tag{16}$$

In order to determine the cutoff value $\phi_{s,i}^{*MP} : \pi_{s,i}^{MP*}(\phi_{s,i}^{*MP}) \equiv 0$:

$$\begin{aligned} \pi^{CIA}(\phi_{s,i}^{*CIA}) \equiv 0 = (\phi_{s,i}^{*CIA})^{\sigma-1}\sigma^{-\sigma}(\sigma-1)^{\sigma-1}P^\sigma X\tau^{1-\sigma}\left[\frac{(1+r_{IM})^{T(s,i)}}{c_X q(i)}\right]^{1-\sigma} - f_{IM} \\ \phi_{s,i}^{*CIA} = \left(\frac{f_{IM}}{\sigma^{-\sigma}(\sigma-1)^{\sigma-1}XP^\sigma}\right)^{\frac{1}{\sigma-1}}\tau(s)\left[\frac{(1+r_{IM})^{T(s,i)}}{c_X q(i)}\right] \end{aligned} \tag{17}$$

$$\begin{aligned} \pi^{OA}(\phi_{s,i}^{*OA}) \equiv 0 = (\phi_{s,i}^{*OA})^{\sigma-1}\sigma^{-\sigma}(\sigma-1)^{\sigma-1}P^\sigma X\tau^{1-\sigma}\left[\frac{(1+r_X)^{T(s,i)}}{c_{IM}(i)q(i)}\right]^{1-\sigma} - f_{IM} \\ \phi_{s,i}^{*OA} = \left(\frac{f_{IM}}{\sigma^{-\sigma}(\sigma-1)^{\sigma-1}XP^\sigma}\right)^{\frac{1}{\sigma-1}}\tau(s)\left[\frac{(1+r_X)^{T(s,i)}}{c_{IM}(i)q(i)}\right] \end{aligned} \tag{18}$$

$$\phi_{s,i}^{*OA} < \phi_{s,i}^{*CIA} \iff \left[\frac{1+r_X}{1+r_{IM}}\right]^{T(s,i)} < \left[\frac{c_{IM}(i)}{c_X}\right] \tag{19}$$

Comparative static (derivations for CIA accordingly, where $c_X \perp i$)

$$\frac{\partial \phi^{*OA}_{s,i}}{\partial i} = \phi^{*OA}_{s,i}\left[d'(i)ln(1+r_X) - \frac{c'_{IM}(i)}{c_{IM}(i)} - \frac{q'(i)}{q(i)}\right] > 0 \tag{20}$$

$$\text{as } d'(i) > 0, c'_{IM}(i) < 0, q'(i) < 0$$

$$\frac{\partial^2 \phi^{*OA}_{s,i}}{\partial i \partial r_X} = \frac{\phi^{*OA}_{s,i}}{\partial r_X}\left[d'(i)ln(1+r_X) - \frac{c'_{IM}(i)}{c_{IM}(i)} - \frac{q'(i)}{q(i)}\right] + \frac{d'(i)}{1+r_X}\phi^{*OA}_{s,i} > 0 \tag{21}$$

$$\frac{\partial \phi^{*OA}_{s,i}}{\partial r_X} = T(s,i)\frac{\phi^{*OA}_{s,i}}{1+r_X} > 0 \tag{22}$$

$$\frac{\partial \phi^{*OA}_{s,i}}{\partial s} = \phi^{*OA}_{s,i}\left[\frac{\tau'(s)}{\tau(s)} + ln(1+r_X)\right] > 0 \tag{23}$$

$$\frac{\partial \phi^{*OA}_{s,i}}{\partial s}\frac{s}{\phi^{*OA}_{s,i}} = s\left[\frac{\tau'(s)}{\tau(s)} + ln(1+r_X)\right] > 0 \tag{24}$$

$$\frac{\partial^2 \phi^{*OA}_{s,i}}{\partial i \partial s} = \phi^{*OA}_{s,i}\left[\frac{\tau'(s)}{\tau(s)} + ln(1+r_X)\right]\left[d'(i)ln(1+r_X) - \frac{c'_{IM}(i)}{c_{IM}(i)} - \frac{q'(i)}{q(i)}\right] > 0 \tag{25}$$

$$\text{as } \tau'(s) > 0$$

$$\frac{\partial \phi^{*CIA}_{s,i}}{\partial i} = \phi^{*CIA}_{s,i}\left[d'(i)ln(1+r_{IM}) - \frac{q'(i)}{q(i)}\right] > 0 \quad \text{as } d'(i) > 0, q'(i) < 0 \tag{26}$$

$$\frac{\partial^2 \phi^{*CIA}_{s,i}}{\partial i \partial r_{IM}} = \frac{\partial \phi^{*CIA}_{s,i}}{\partial r_{IM}}\left[d'(i)ln(1+r_{IM}) - \frac{q'(i)}{q(i)}\right] + \frac{d'(i)}{1+r_{IM}}\phi^{*}_{s,i} > 0 \tag{27}$$

$$\frac{\partial \phi^{*CIA}_{s,i}}{\partial r_{IM}} = T(s,i)\frac{\phi^{*CIA}_{s,i}}{1+r_{IM}} > 0 \tag{28}$$

$$\frac{\partial \phi^{*CIA}_{s,i}}{\partial s} = \phi^{*CIA}_{s,i}\left[\frac{\tau'(s)}{\tau(s)} + ln(1+r_{IM})\right] > 0 \tag{29}$$

$$\frac{\partial \phi^{*CIA}_{s,i}}{\partial s}\frac{s}{\phi^{*CIA}_{s,i}} = s\left[\frac{\tau'(s)}{\tau(s)} + ln(1+r_{IM})\right] > 0 \tag{30}$$

$$\frac{\partial^2 \phi^{*CIA}_{s,i}}{\partial i \partial s} = \phi^{*CIA}_{s,i}\left[\frac{\tau'(s)}{\tau(s)} + ln(1+r_{IM})\right]\left[d'(i)ln(1+r_{IM}) - \frac{q'(i)}{q(i)}\right] > 0 \tag{31}$$

$$\text{as } \tau'(s) > 0$$

Comparative static for aggregate exports:

$$X^{*OA}_{s,i} = \int_{\phi^{*OA}_{s,i}}^{\phi_{max}} X\left(\frac{P}{\tau_s}\right)^{\sigma}\left[\frac{\sigma}{\sigma-1}\frac{(1+r_X)^{T(s,i)}}{c_{IM}(i)q(i)\phi}\right]^{1-\sigma} dG(\phi) \tag{32}$$

$$\begin{aligned}\frac{\partial X^{*OA}_{s,i}}{\partial i} &= \int_{\phi^{*OA}_{s,i}}^{\phi_{max}} X\left(\frac{P}{\tau_s}\right)^{\sigma}\underbrace{(1-\sigma)}_{<0}\left[\frac{\sigma}{\sigma-1}\frac{(1+r_X)^{T(s,i)}}{c_{IM}(i)q(i)\phi}\right]^{1-\sigma} \\ &\quad * \underbrace{\left[d'(i)ln(1+r_X) - \frac{c'_{IM}(i)}{c_{IM}(i)} - \frac{q'(i)}{q(i)}\right]}_{>0} dG(\phi) - \frac{\partial \phi^{*OA}_{s,i}}{\partial i}\sigma^{\sigma} f_{IM}\tau(s) \\ &= \left[d'(i)ln(1+r_X) - \frac{c'_{IM}(i)}{c_{IM}(i)} - \frac{q'(i)}{q(i)}\right]\left[(1-\sigma)X^{*OA}_{s,i} - \sigma^{\sigma} f_{IM}\tau_s \phi^{*OA}_{s,i}\right] < 0\end{aligned} \tag{33}$$

$$\frac{\partial X_{s,i}^{*MP}}{\partial i} < 0 \quad \frac{\partial^2 X_{s,i}^{*MP}}{\partial i \partial s} < 0 \quad \frac{\partial^2 X_{s,i}^{*MP}}{\partial i \partial r_X} > 0 \quad \frac{\partial^2 X_{s,i}^{*MP}}{\partial i \partial r_{IM}} > 0$$

Intermediated Trade: Permissioned Blockchain

When exporters decide to join the blockchain, their optimal profits are

$$\pi_s^{N*}(\phi) = \phi^{\sigma-1}\sigma^{-\sigma}(\sigma-1)^{\sigma-1}P^\sigma X \tau_s^{1-\sigma}\left[(1+r_X)^{T(s)}\right]^{1-\sigma} - f_{IM} \tag{34}$$

$$\phi_s^{*N} = \left(\frac{f_{IM}}{\sigma^{-\sigma}(\sigma-1)^{\sigma-1}XP^\sigma}\right)^{\frac{1}{\sigma-1}} \tau(s)\left[(1+r_X)^{T(s)}\right] < \phi_{s,i}^{*OA} \text{ by construction} \tag{35}$$

Comparative static:

$$\frac{\partial \phi_{s,i}^{*N}}{\partial s} = \phi_{s,i}^{*N}\left[\frac{\tau'(s)}{\tau(s)} + ln(1+r_X)\right] > 0 \tag{36}$$

$$\frac{\partial \phi_{s,i}^{*N}}{\partial s}\frac{s}{\phi_{s,i}^{*N}} = s\left[\frac{\tau'(s)}{\tau(s)} + ln(1+r_X)\right] > 0 \tag{37}$$

Comparing the effect of a change in geographical distance across payment methods reveals that the impact of a marginal change of s on the productivity cutoff of OA is larger. The elasticities are identical. For CIA, it depends on the relative size of the discount rates.

$$\frac{\partial \phi_{s,i}^{*N}}{\partial s} = \phi_{s,i}^{*N}\left[\frac{\tau'(s)}{\tau(s)} + ln(1+r_X)\right] < \frac{\partial \phi_{s,i}^{*OA}}{\partial s} = \phi_{s,i}^{*OA}\left[\frac{\tau'(s)}{\tau(s)} + ln(1+r_X)\right]$$

$$\frac{\partial \phi_{s,i}^{*N}}{\partial s}\frac{s}{\phi_{s,i}^{*N}} = s\left[\frac{\tau'(s)}{\tau(s)} + ln(1+r_X)\right] = \frac{\partial \phi_{s,i}^{*OA}}{\partial s}\frac{s}{\phi_{s,i}^{*OA}}$$

$$\frac{\partial \phi_{s,i}^{*N}}{\partial s} = \phi_{s,i}^{*N}\left[\frac{\tau'(s)}{\tau(s)} + ln(1+r_X)\right], \quad \frac{\partial \phi_{s,i}^{*CIA}}{\partial s} = \phi_{s,i}^{*CIA}\left[\frac{\tau'(s)}{\tau(s)} + ln(1+r_{IM})\right]$$

$$\frac{\partial \phi_{s,i}^{*N}}{\partial s}\frac{s}{\phi_{s,i}^{*N}} = s\left[\frac{\tau'(s)}{\tau(s)} + ln(1+r_X)\right], \quad \frac{\partial \phi_{s,i}^{*CIA}}{\partial s}\frac{s}{\phi_{s,i}^{*CIA}} = s\left[\frac{\tau'(s)}{\tau(s)} + ln(1+r_{IM})\right]$$

By construction

$$\pi^{N*}(\phi) > \pi^{OA*}(\phi) \text{ as } c_{IM}(i) \leq 1, d(i) \geq 0, q(i) \leq 1$$

However, when the optimal choice under direct trade would be CIA, then (note that $1-\sigma < 0$)

$$\pi_s^{N*}(\phi) \geq \pi_{s,i}^{CIA*}(\phi)$$

$$\left[(1+r_X)^{T(s)}\right]^{1-\sigma} \geq \left[\frac{(1+r_{IM})^{T(s,i)}}{c_X q(i)}\right]^{1-\sigma}$$

$$\frac{(1+r_{IM})^{T(s,i)}}{c_X q(i)} \geq (1+r_X)^{T(s)}$$

$$T(s,i)\underbrace{ln(1+r_{IM})}_{\approx r_{IM}} - ln(c_X q(i)) \geq T(s)\underbrace{ln(1+r_X)}_{\approx r_X}$$

Expected profits of an exporter conditional on being contacted is given by:

$$\mathbb{E}(\pi_X^N(\phi)|x \in S_X) = S(1-\alpha_B)\pi_s^N(\phi) + (1-S)\Pi_{s,i}^D(\phi) \tag{38}$$

where α_B is the commission rate. Here, $S_{IM} = S_X = S$, is the probability that the trading partner is also part of the network (and $\pi_s^N(\phi)$) is realized or with probability $(1-S)$, trade needs to be settled bilaterally.

Before joining the network expected profits are:

$$\mathbb{E}(\pi_X^N(\phi)) =$$
$$\underbrace{\left[(1-S)S + S(1-S) + (1-S)^2\right]}_{S-S^2+S-S^2+1-2S+S^2=(1-S^2)}\Pi_{s,i}^D(\phi) + S^2\left(1 - \frac{\pi_s^N(\phi) - \Pi_{s,i}^D(\phi)}{\pi_s^N(\phi)}\right)\pi_s^N(\phi) = \Pi_{s,i}^D(\phi)$$

where the first and second terms in the first bracket capture that the importer is part of the network but the exporter not (or vice-versa). The third term captures the case where neither importer nor exporter are part of the blockchain. Finally, S^2 is the probability that both partners are in the blockchain.

Expected profits of the intermediary is given by:

$$\mathbb{E}(\Pi_{B|s,i}^N)$$
$$= \left(\underbrace{\int_{\phi_{s,i}^{*N}}^{\phi_{s,i}^{*D}} \pi_{s,i}^N(\phi)dG(\phi)}_{\text{new exporters}} + \int_{\phi_{s,i}^{*D}}^{\phi_{max}} (\pi_{s,i}^N(\phi) - \Pi_{s,i}^D(\phi))dG(\phi)\right) S^2 - 2\int_{\phi^*}^{\phi_{max}} \chi(i,S)SdG(\phi) - F$$

$$\frac{\partial \mathbb{E}(\Pi_{B|s,i}^N)}{\partial S}$$
$$= 2\left(\int_{\phi_{s,i}^{*N}}^{\phi_{s,i}^{*D}} \pi_{s,i}^N(\phi)dG(\phi) + \int_{\phi_{s,i}^{*D}}^{\phi_{max}} (\pi_{s,i}^N(\phi) - \Pi_{s,i}^D(\phi))dG(\phi)\right) S - 2\int_{\phi^*}^{\phi_{max}} \chi(i,S)dG(\phi) \equiv 0$$

The optimal share is given by:

$$S_{s,i}^* = \left(\frac{\int_{\phi_s^{N*}}^{\phi_{max}} \pi_s^N(\phi)dG(\phi) - \int_{\phi_{s,i}^{D*}}^{\phi_{max}} \Pi_{s,i}^D(\phi)dG(\phi)}{i^\alpha\gamma(\beta+1)(G(\phi_{max}) - G(\phi^*))}\right)^{\frac{1}{\beta-1}}$$

$$\frac{\partial S_{s,i}^*}{\partial s} = \frac{1}{\beta-1}\left(\frac{\int_{\phi_s^{N*}}^{\phi_{max}} \pi_s^N(\phi)dG(\phi) - \int_{\phi_{s,i}^{D*}}^{\phi_{max}} \Pi_{s,i}^D(\phi)dG(\phi)}{i^\alpha\gamma(\beta+1)(G(\phi_{max}) - G(\phi^*))}\right)^{\frac{1}{\beta-1}-1} *$$
$$\left(\frac{\int_{\phi_s^{N*}}^{\phi_{max}} \frac{\partial\pi_s^N(\phi)}{\partial s}dG(\phi) - \int_{\phi_{s,i}^{D*}}^{\phi_{max}} \frac{\partial\Pi_{s,i}^D(\phi)}{\partial s}dG(\phi)}{i^\alpha\gamma(\beta+1)(G(\phi_{max}) - G(\phi^*))}\right)$$

The sign of the effect is determined by:

(Note that for the Leibniz integral rule, at the respective cutoffs, profits equal zero.):

$$\int_{\phi_s^{N*}}^{\phi_{max}} \frac{\partial \pi_s^N(\phi)}{\partial s} dG(\phi) - \int_{\phi_{s,i}^{D*}}^{\phi_{max}} \frac{\partial \Pi_{s,i}^D(\phi)}{\partial s} dG(\phi)$$

Derive the condition for $\frac{\partial S_{s,i}^*}{\partial s} < 0$:

$$\int_{\phi_s^{N*}}^{\phi_{max}} \frac{\partial \pi_s^N(\phi)}{\partial s} dG(\phi) - \int_{\phi_{s,i}^{D*}}^{\phi_{max}} \frac{\partial \Pi_{s,i}^D(\phi)}{\partial s} dG(\phi) < 0$$

$$\int_{\phi_s^{N*}}^{\phi_{max}} \frac{\partial \pi_s^N(\phi)}{\partial s} dG(\phi) < \int_{\phi_{s,i}^{D*}}^{\phi_{max}} \frac{\partial \Pi_{s,i}^D(\phi)}{\partial s} dG(\phi)$$

$$(1-\sigma)\int_{\phi_s^{N*}}^{\phi_{max}} \phi^{\sigma-1}\sigma^{-\sigma}(\sigma-1)^{\sigma-1}P^\sigma X \tau_s^{1-\sigma}\left[(1+r_X)^{T(s)}\right]^{1-\sigma} dG(\phi)[\frac{\tau'(s)}{\tau(s)} + ln(1+r_X)]$$

$$<$$

$$(1-\sigma)\int_{\phi_{s,i}^{D*}}^{\phi_{max}} \phi^{\sigma-1}\sigma^{-\sigma}(\sigma-1)^{\sigma-1}P^\sigma X \tau_s^{1-\sigma}\left[\frac{(1+r_n)^{T(s,i)}}{c_{\overline{n}}(i)q(i)}\right]^{1-\sigma} dG(\phi)[\frac{\tau'(s)}{\tau(s)} + ln(1+r_n)]$$

If $MP = OA$ (inequality sign changes as $(1-\sigma)<0, \sigma>1$)

$$\int_{\phi_s^{N*}}^{\phi_{max}} \phi^{\sigma-1} dG(\phi) > \int_{\phi_{s,i}^{D*}}^{\phi_{max}} \phi^{\sigma-1}\left[\frac{(1+r_X)^{d(i)}}{c_{IM}(i)q(i)}\right]^{1-\sigma} dG(\phi)$$

$$\int_{\phi_s^{N*}}^{\phi_{max}} \phi^{\overbrace{\sigma-1}^{>0}} dG(\phi) > \int_{\phi_{s,i}^{D*}}^{\phi_{max}} \phi^{\overbrace{\sigma-1}^{>0}} dG(\phi) \underbrace{\left[\overbrace{\frac{\overbrace{(1+r_X)^{d(i)}}^{>1}}{\underbrace{c_{IM}(i)q(i)}_{<1}}}^{>1}\right]^{\overbrace{1-\sigma}^{<0}}}_{<1}$$

As $\phi_s^{N*} < \phi_{s,i}^{D*}$: $\frac{\partial S_{s,i}^*}{\partial s} < 0$ for all values. If $MP = CIA$: $\frac{\partial S_{s,i}^*}{\partial s} < 0$ when:

$$\int_{\phi_s^{N*}}^{\phi_{max}} \phi^{\sigma-1}\left[(1+r_X)^{T(s)}\right]^{1-\sigma} dG(\phi)[\frac{\tau'(s)}{\tau(s)} + ln(1+r_X)]$$

$$> \int_{\phi_{s,i}^{D*}}^{\phi_{max}} \phi^{\sigma-1}\left[\frac{(1+r_{IM})^{T(s,i)}}{c_X q(i)}\right]^{1-\sigma} dG(\phi)[\frac{\tau'(s)}{\tau(s)} + ln(1+r_{IM})]$$

$$\underbrace{\frac{\int_{\phi_s^{N*}}^{\phi_{max}} \phi^{\sigma-1} dG(\phi)}{\int_{\phi_{s,i}^{D*}}^{\phi_{max}} \phi^{\sigma-1} dG(\phi)}}_{>1} > \frac{\frac{\tau'(s)}{\tau(s)} + \overbrace{ln(1+r_{IM})}^{\approx r_{IM}}}{\frac{\tau'(s)}{\tau(s)} + \underbrace{ln(1+r_X)}_{\approx r_X}} \underbrace{\left[\overbrace{\frac{(1+r_X)^{T(s)}}{\frac{(1+r_{IM})^{T(s,i)}}{c_X q(i)}}}^{<1}\right]^{\overbrace{\sigma-1}^{>1}}}_{<1} \tag{39}$$

The left hand side is larger 1, otherwise the monopolist would not be active. The right hand side is decreasing in r_{IM} if:

$$\frac{\partial}{\partial r_{IM}} = \frac{\left[\frac{\frac{(1+r_X)^{T(s)}}{(1+r_{IM})^{T(s,i)}}}{c_X q(i)}\right]^{\sigma-1}}{\frac{\tau'(s)}{\tau(s)} + ln(1+r_X)} \left(\frac{1 - \overbrace{T(s,i)}^{>1}\overbrace{(\sigma-1)}^{>1}(\frac{\tau'(s)}{\tau(s)} + \overbrace{ln(1+r_{IM})}^{>0})}{1+r_{IM}} \right)$$

$\frac{\partial S^*_{s,i}}{\partial s} < 0$, the difference in the discount rates cannot be too large.
Derivation for $\frac{\partial S^*_{s,i}}{\partial i}$:

$$\frac{\partial S^*_{s,i}}{\partial i} = \frac{1}{\beta-1} \left(\frac{\int_{\phi_s^{N*}}^{\phi_{max}} \pi_s^N(\phi)dG(\phi) - \int_{\phi_{s,i}^{D*}}^{\phi_{max}} \Pi_{s,i}^D(\phi)dG(\phi)}{i^\alpha \gamma(\beta+1)(G(\phi_{max}) - G(\phi^*))} \right)^{\frac{1}{\beta-1}-1} *$$

$$(\frac{i^\alpha \gamma(\beta+1)(G(\phi_{max}) - G(\phi^*))(-\frac{\partial}{\partial i}\int_{\phi_{s,i}^{D*}}^{\phi_{max}} \Pi_{s,i}^D(\phi)dG(\phi))}{(i^\alpha \gamma(\beta+1)(G(\phi_{max}) - G(\phi^*)))^2}$$

$$\frac{-(\int_{\phi_s^{N*}}^{\phi_{max}} \pi_s^N(\phi)dG(\phi) - \int_{\phi_{s,i}^{D*}}^{\phi_{max}} \Pi_{s,i}^D(\phi)dG(\phi))\alpha i^{\alpha-1}\gamma(\beta+1)(G(\phi_{max}) - G(\phi^*))}{(i^\alpha \gamma(\beta+1)(G(\phi_{max}) - G(\phi^*)))^2})$$

The first row is larger zero as $\beta > 1$ and $S^*_{s,i} \geq 0$ as the bank would not offer intermediation services when commission rates turn negative. The denominator in the second row is also larger zero. Hence, the direction of the effect is determined by

$$(-\frac{\partial}{\partial i}\int_{\phi_{s,i}^{D*}}^{\phi_{max}} \Pi_{s,i}^D(\phi)dG(\phi)) - (\int_{\phi_s^{N*}}^{\phi_{max}} \pi_s^N(\phi)dG(\phi) - \int_{\phi_{s,i}^{D*}}^{\phi_{max}} \Pi_{s,i}^D(\phi)dG(\phi))\frac{\alpha}{i}$$

Applying Leibniz integral rule:

$$(\underbrace{\Pi_{s,i}^D(\phi_{s,i}^{D*})}_{=0} \underbrace{\frac{\partial \phi_{s,i}^{D*}}{\partial i}}_{>0}$$

$$- \int_{\phi_{s,i}^{D*}}^{\phi_{max}} \underbrace{\frac{\partial}{\partial i}\Pi_{s,i}^D(\phi)}_{<0} dG(\phi)) - (\int_{\phi_s^{N*}}^{\phi_{max}} \pi_s^N(\phi)dG(\phi) - \int_{\phi_{s,i}^{D*}}^{\phi_{max}} \Pi_{s,i}^D(\phi)dG(\phi))\frac{\alpha}{i}$$

Let's assume that agents' outside option is $D = \{OA\}$. Then,

$$\frac{\partial}{\partial i}\Pi_{s,i}^{OA}(\phi) = (1-\sigma)(\phi)^{\sigma-1}\sigma^{-\sigma}(\sigma-1)^{\sigma-1}P^\sigma X \tau^{1-\sigma}\left[\frac{(1+r_X)^{T(s,i)}}{c_{IM}(i)q(i)}\right]^{1-\sigma} *$$

$$\frac{1}{i}(d(i)\epsilon_{d,i} ln(1+r_X) - \epsilon_{c_{IM},i} - \epsilon_{q,i})$$

$$\underbrace{(\Pi^D_{s,i}(\phi^{D*}_{s,i})}_{=0}\underbrace{\frac{\partial \phi^{D*}_{s,i}}{\partial i}}_{>0} - \int_{\phi^{D*}_{s,i}}^{\phi_{max}} \underbrace{\frac{\partial}{\partial i}\Pi^D_{s,i}(\phi)}_{<0}\, dG(\phi)) - (\int_{\phi^{N*}_s}^{\phi_{max}} \pi^N_s(\phi)dG(\phi) - \int_{\phi^{D*}_{s,i}}^{\phi_{max}} \Pi^D_{s,i}(\phi)dG(\phi))\frac{\alpha}{i}$$

$$= \int_{\phi^{D*}_{s,i}}^{\phi_{max}} (\phi)^{\sigma-1}dG(\phi)\sigma^{-\sigma}(\sigma-1)^{\sigma-1}P^{\sigma}X\tau^{1-\sigma}\left[\frac{(1+r_X)^{T(s,i)}}{c_{IM}(i)q(i)}\right]^{1-\sigma} *$$

$$\frac{1}{i}[(\sigma-1)(d(i)\epsilon_{d,i}ln(1+r_X)-\epsilon_{c_{IM},i}-\epsilon_{q,i})+\alpha]$$

$$-\int_{\phi^{N*}_s}^{\phi_{max}} \phi^{\sigma-1}dG(\phi)\sigma^{-\sigma}(\sigma-1)^{\sigma-1}P^{\sigma}X\tau^{1-\sigma}\left[(1+r_X)^{T(s)}\right]^{1-\sigma}\frac{\alpha}{i}$$

$$+ f_{IM}(G(\phi^{D*}_{s,i}) - G(\phi^{N*}_s))\frac{\alpha}{i} > 0$$

$$\int_{\phi^{D*}_{s,i}}^{\phi_{max}} \phi^{\sigma-1}dG(\phi)\overbrace{\left[\frac{(1+r_X)^{d(i)}}{c_{IM}(i)q(i)}\right]^{1-\sigma}}^{<1}[\overbrace{(\sigma-1)}^{>1}(\overbrace{d(i)\epsilon_{d,i}ln(1+r_X)-\epsilon_{c_{IM},i}-\epsilon_{q,i}}^{>0})]$$
$$> \int_{\phi^{N*}_s}^{\phi_{max}} \phi^{\sigma-1}dG(\phi)\alpha - f_{IM}(G(\phi^{D*}_{s,i}) - G(\phi^{N*}_s))\alpha$$

Comparative static for aggregate trade flows:

$$X^N_{s,i} = \int_{\phi^N_s}^{\phi_{max}} p^N_s(\phi)x^N_s(\phi)dG(\phi)(S^*_{s,i})^2 + \underbrace{\int_{\phi^{*MP}_{s,i}}^{\phi_{max}} p^{*MP}_{s,i}(\phi)x^{*MP}_{s,i}(\phi)dG(\phi)}_{X^{*MP}_{s,i}}[1-(S^*_{s,i})^2] \quad (40)$$

$$\frac{\partial X^N_{s,i}}{\partial i} = 2\int_{\phi^N_s}^{\phi_{max}} p^N_s(\phi)x^N_s(\phi)dG(\phi)S^*_{s,i}\frac{\partial S^*_{s,i}}{\partial i} + \frac{\partial X^{*MP}_{s,i}}{\partial i}[1-(S^*_{s,i})^2] - 2X^{*MP}_{s,i}S^*_{s,i}\frac{\partial S^*_{s,i}}{\partial i}$$
$$= 2S^*_{s,i}\frac{\partial S^*_{s,i}}{\partial i}\underbrace{\left[\int_{\phi^N_s}^{\phi_{max}} p^N_s(\phi)x^N_s(\phi)dG(\phi) - X^{*MP}_{s,i}\right]}_{>0} + \underbrace{\frac{\partial X^{*MP}_{s,i}}{\partial i}}_{<0}\underbrace{[1-(S^*_{s,i})^2]}_{>0}$$

whenever $\frac{\partial S^*_{s,i}}{\partial i} < 0$, aggregate trade flows are decreasing. When $\frac{\partial S^*_{s,i}}{\partial i} > 0$, the condition for $\frac{\partial X^N_{s,i}}{\partial i} > 0$ is:

$$\frac{\partial X^N_{s,i}}{\partial i} > 0 \iff$$
$$2S^*_{s,i}\frac{\partial S^*_{s,i}}{\partial i}\underbrace{\left[\int_{\phi^N_s}^{\phi_{max}} p^N_s(\phi)x^N_s(\phi)dG(\phi) - X^{*MP}_{s,i}\right]}_{>0} > -\underbrace{\frac{\partial X^{*MP}_{s,i}}{\partial i}}_{<0}\underbrace{[1-(S^*_{s,i})^2]}_{>0}$$

The effect of shipping time:

$$
\begin{aligned}
\frac{\partial X^N_{s,i}}{\partial s} &= 2S^*_{s,i}\frac{\partial S^*_{s,i}}{\partial s}\underbrace{\left[\int_{\phi^N_s}^{\phi_{max}} p^N_s(\phi)x^N_s(\phi)dG(\phi) - X^{*MP}_{s,i}\right]}_{>0} + \overbrace{\frac{\partial X^{*MP}_{s,i}}{\partial s}}^{<0}[1-(S^*_{s,i})^2] \\
&+ \int_{\phi^N_s}^{\phi_{max}} \underbrace{\frac{\partial}{\partial s}(p^N_s(\phi)x^N_s(\phi))}_{<0} dG(\phi)(S^*_{s,i})^2 \\
&= 2S^*_{s,i}\frac{\partial S^*_{s,i}}{\partial s}\underbrace{\left[\int_{\phi^N_s}^{\phi_{max}} p^N_s(\phi)x^N_s(\phi)dG(\phi) - X^{*MP}_{s,i}\right]}_{>0} \\
&+ (S^*_{s,i})^2\underbrace{(\int_{\phi^N_s}^{\phi_{max}} \frac{\partial}{\partial s}(p^N_s(\phi)x^N_s(\phi))dG(\phi) - \frac{\partial X^{*MP}_{s,i}}{\partial s})}_{<0} + \underbrace{\frac{\partial X^{*MP}_{s,i}}{\partial s}}_{<0}
\end{aligned}
$$

If network size is decreasing in shipping time, i.e. if the outside option is OA, aggregate trade flows are decreasing in distance.

$$
\begin{aligned}
\frac{\partial^2 X^N_{s,i}}{\partial i\partial s} &= 2\frac{S^*_{s,i}}{\partial s}\frac{\partial S^*_{s,i}}{\partial i}\underbrace{\left[\int_{\phi^N_s}^{\phi_{max}} p^N_s(\phi)x^N_s(\phi)dG(\phi) - X^{*MP}_{s,i}\right]}_{>0} \\
&+ 2S^*_{s,i}\frac{\partial^2 S^*_{s,i}}{\partial i\partial s}\underbrace{\left[\int_{\phi^N_s}^{\phi_{max}} p^N_s(\phi)x^N_s(\phi)dG(\phi) - X^{*MP}_{s,i}\right]}_{>0} \\
&+ 2S^*_{s,i}\frac{\partial S^*_{s,i}}{\partial i}\underbrace{\left[\int_{\phi^N_s}^{\phi_{max}} \frac{\partial}{\partial s}p^N_s(\phi)x^N_s(\phi)dG(\phi) - \frac{\partial X^{*MP}_{s,i}}{\partial s}\right]}_{<0} \\
&+ \frac{\partial X^{*MP}_{s,i}}{\partial i\partial s}\underbrace{[1-(S^*_{s,i})^2]}_{>0} - 2S^*_{s,i}\frac{\partial S^*_{s,i}}{\partial s}\frac{\partial X^{*MP}_{s,i}}{\partial i}
\end{aligned}
$$

C.3 Data

Keyword Search

In PATSTAT Online 2020 Autumn Edition, patents where identified as related to DLT based on a keyword match of the abstracts conditional on CPC codes. The list of keywords is taken from Jordan and Bitton (2019) (Search Matters 2019).

Table C.6: WHERE clause in SQL code to identify patents related to DLT: Abstracts taken from TLS203_APPLN_ABSTRACT and CPC codes from TLS224_APPLN_CPC.

CONTAINS(appln_abstract,...) – connected with OR
’“blockchain*”’, ’block-chain’, ’NEAR((block, chain),2)’, ’“bitcoin*”’, ’bit-coin’, ’NEAR((bit, coin),2)’, ’blocksign’,’codius’, ’colored-coin’, ’NEAR((colored, coin),2)’, ’coloured-coin’, ’NEAR((coloured, coin),2)’, ’“cryptocurrenc*”’, ’“crypto-currenc*”’, ’NEAR((crypto, currenc*),2)’, ’NEAR((distributed, ledger),2)’, ’ledger’, ’dogecoin’, ’doge-coin’, ’ethereum’, ’factom’, ’litecoin’, ’lite-coin’, ’NEAR((lite, coin),2)’, ’pay-to-script-hash’, ’P2SH’, ’proof-of-stake’,’NEAR((proof, of, stake),3)’, ’“sidechain*”’, ’smart-contract’, ’NEAR((smart, contract),2)’, ’“smartcontract*”’, ’zerocash’, ’zcash’, ’zero-knowledge’, ’zero-knowledge’, ’NEAR((zero, knowledge),2)’, ’zero-coin’, ’NEAR((zero, coin),2)’, zerocoin’, ’“typecoin*”’, ’“metacoin*”’, ’name-coin’, ’NEAR((name, coin),2)’, ’“namecoin*”’, ’NXT’, ’proof-of-work’, ’NEAR((proof, of, work),3)’, ’hash-cash’, ’NEAR((name, coin),2)’, ’hashcash’, ’rootstock’, ’RSK’, ’ripple’, ’stellar’, ’symbiont’, ’type-coin’, ’NEAR((name, coin),2)’, ’meta-coin’, ’NEAR((meta, coin),2)’, ’merkleroot’, ’merkle-root’, ’NEAR((merkle, root),2)’, ’hashtree’, ’hash-tree’, ’NEAR((hash, tree),2)’, ’merkletree’, ’merkle-tree’, ’NEAR((merkle, tree),2)’, ’lisk’, ’ledger’, ’hawk’, ’forks’, ’forking’, ’ether’, ’digital-currenc’, ’NEAR((digital,currenc),2)’, ’“digitalcurrenc*”’, ’XCP’, ’counterparty’, ’“chaincod*”’
AND (cpc_class_symbol like ...
’G06Q%’ OR cpc_class_symbol like ’H04L%’ OR cpc_class_symbol like ’G06F%’ OR cpc_class_symbol like ’H04W%’ OR cpc_class_symbol like ’G06K%’ OR cpc_class_symbol like ’A61B%5%’)

Table C.7: Word(stem)s for Keyword Match in Table 3.3: Share of Matching Priorities.

<table>
<tr><th>Concept (table 3.3)</th><th>Word(stem)s for keyword match</th><th>Comment</th><th>Share [%]</th></tr>
<tr><td>blockchain</td><td>“blockchain|block-chain|block chain”</td><td></td><td>86.45</td></tr>
<tr><td>smart contract</td><td>“smart contract|smart”</td><td>contract considered too general</td><td>10.14</td></tr>
<tr><td>private</td><td>“private”</td><td></td><td>9.35</td></tr>
<tr><td>permissioned</td><td>“permissioned”</td><td></td><td>0.26</td></tr>
<tr><td>permissionless</td><td>“permissionless”</td><td></td><td>0</td></tr>
<tr><td>finance</td><td>“financ|pay|credit|bank|loan”</td><td></td><td>12.96</td></tr>
<tr><td>insurance</td><td>“insur”</td><td></td><td>0.95</td></tr>
<tr><td>kyc</td><td>“know your customer|
know-your-customer|kyc”</td><td></td><td>0.09</td></tr>
<tr><td>document handling</td><td>“document|upload|up load|up-load|scan”</td><td></td><td>9.89</td></tr>
<tr><td>international</td><td>“international|global|border|supply chain|
supply-chain|logistic|ship|customs|carrier|
authorit|trade|import|export| port”</td><td>exclude “portab”</td><td>14.99</td></tr>
</table>

Notes: Data Source: PATSTAT Online 2020 Autumn Edition; Share of priorities classified as related to DLT as in section 3.3.

Classification: Priorities, DOCDB Patent Families

Data set: PATSTAT Online 2020 Autumn Edition

- Excluding kind codes “T” (translations) and “U” (utility model) (European Patent Office 2020b, p. 101).
- DOCDB families are identified through DOCDB_FAMILY_ID in TLS201_APPLN.
- Year refers to first filing classified as Paris convention priority based on absence in TLS204_APPLN_PRIOR: Paris convention priority and INTERNAT_APPLN_ID == 0 in TLS201_APPLN (European Patent Office 2020b, p. 44) and earliest filing date.
- Wordcloud and analysis of abstracts based on priorities as classified above but restricted to English abstracts.

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