Three Essays on the Economics of Traders and Agents

by

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[1]This study uses statistical data from His Majesty's Revenue and Customs (HMRC) which is Crown Copyright. The research data sets used may not exactly reproduce HMRC aggregates. The use of HMRC statistical data in this study does not imply the endorsement of HMRC in relation to the interpretation or analysis of the information. HMRC agrees that the figures and descriptions of results in the attached document may be published.This does not imply HMRC's acceptance of the validity of the methods used to obtain these figures, or of any analysis of the results.

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Abstract

This thesis consists of three chapters on traders and agents.

The first chapter analyzes the characteristics of the UK agent market, particularly focusing on their strategic behavior, survival, and growth patterns. The analysis provides several contributions: First, the agents' market structure remains under-explored despite their significant role in handling over 85% of UK export and taking caring of border-related tasks. Our findings reveal a dual market structure, with a small number of dominant agents controlling the majority of the market through expansive operational networks, while numerous smaller agents foster competition by working in their niche markets. Second, qualitative studies fail to capture agents' development and growth. We find that new entrants typically begin with a narrow focus but gradually expand upon survival.

The second chapter studies trader-agent relationships, especially their connection characteristics and dynamics. While the importance of cross-border buyer-seller relationships has been recognized in the literature, the relationships between traders and agents have been largely overlooked. This chapter uses granular UK customs data to document the key features of the trader-agent relationships and provide empirical evidence regarding their dynamics. We find that larger traders generally use multiple agents, while smaller ones have limited connections. Though the relationships are short-lived, those of high value and deep cooperation are more likely to sustain. In addition, we empirically confirm that traders are seeking more established agents in response to the Brexit-induced uncertainty.

The third chapter examines agents within the framework of Mutual Recognition Agreements (MRAs) for trusted traders, which grant them streamlined customs procedures at foreign borders. Despite the widespread use of MRAs, evident in the fact that over 80% of UK exports occur between trade partners with such agreements in place, there is limited understanding of the effectiveness of this trade policy. We find that the majority of firms are indirectly classified as "safe traders" by working with AEO-certified agents. Building on this, we extend the heterogeneous firm model à la Melitz (2003) by incorporating administrative costs and highlighting the role of agents. Using transaction-level UK customs data, we empirically validate our model's predictions, showing that MRAs enhance firms' export participation and increase their export values through the involvement of certified agents.

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Introduction

Moving goods across borders is costly. The growth of international trade has resulted in ever expanding and complicating networks that operate across multiple jurisdictions and link customs authorities and businesses globally (Hummels and Schaur, 2013; Carballo et al., 2018). This increased complexity, however, has introduced higher administrative costs, greater security risks, and more frequent delays in cross-border transactions (Hummels and Schaur, 2013). In response, firms have increasingly relied on specialized agents, primarily customs and freight forwarding firms, to manage border-related activities and navigate customs procedures. Unlike well-documented trade intermediaries such as wholesalers and retailers (e.g. Feenstra and Hanson, 2004; Ahn et al., 2011; Akerman, 2018), these agents specifically focus on customs operations on behalf of firms. In the UK, these agents facilitate over 85% of exports to non-EU countries.[3] Despite their crucial role, the dynamics of agents in international trade and their interactions with firms, remains under explored. This thesis contributes to the limited body of empirical research on specialized agents by analyzing their role in UK exports using granular-level customs data. It focuses on three key areas: The structure of the agent market; the dynamics of trader-agent relationships; and the effectiveness of trade facilitation policies such as Mutual Recognition Agreement (MRA)

[3]Authors' own calculation with HMRC data from 2009 to 2019.

for trusted traders.

The first chapter offers empirical evidence on the structure and development of the agent market, addressing a long-standing lack of quantitative studies. Unlike previous qualitative studies, which have been unable to capture a comprehensive view of the entire agent industry (Murphy et al., 1992; Murphy and Daley, 1995, 2001), this chapter provides a broader and data-driven analysis. We start by investigating the market structure of agents and their operational strategies. Specifically, we examine whether agents tend to specialize or diversify their selection of industries and destinations. Furthermore, we explore the dynamics of agents over time. We are to capture the general trends in agents' development and examine how the characteristics of new entrants' initial clients influence their long-term performance and survival in the market. The findings reveal a dual market structure with dominant agents controlling a significant share, while smaller agents contribute to competition. Larger agents tend to diversify across industries and markets, while smaller ones often specialize in niche areas. In addition, the dynamics of new entrants show that those starting with larger clients tend to enjoy a higher probability of long-term success.

In the second chapter, we extend our analysis of the agent by focusing on the relationships between traders and agents. While much of the existing trade literature has examined cross-border buyer-seller dynamics, particularly interactions between exporters and importers (e.g. Benguria, 2021; Bernard, Bøler and Dhingra, 2018), the domestic relationships between traders and agents have received far less attention. These trader-agent interactions, though under explored, represent a unique form of buyer-seller relationship where firms outsource critical logistics and customs services to specialized agents. Our analysis begins by documenting the key characteristics of these relationships, revealing a highly skewed distribution of relationship values.

A small number of large firms and dominant agents account for a disproportionate share of trade, while most firms maintain limited connections with only a few agents. We find a negative degree assortativity between traders and agents, suggesting that large exporters tend to engage with both well-connected and less-connected agents. Furthermore, we investigate the role of gravity factors and find that larger agents typically handle exports to more distant destinations, whereas smaller agents focus on closer markets. Cultural similarities also play a significant role, with increased agent engagement and higher trade volumes observed in markets with shared cultural ties. Finally, we extend the analysis to investigate how firms adjust their use of agents in response to Brexit-related uncertainty, particularly in anticipation of potential non-tariff trade barriers that may arise as a result of Brexit. The findings indicate that firms have increased their reliance on larger, more established agents, while maintaining a stable number of agent relationships throughout this period of uncertainty.

In the third chapter, we explore the trader-agent relationship within the framework of MRA-AEO, namely the Mutual Recognition Agreement (MRA) for trusted traders and the Authorized Economic Operator (AEO) program. With such a scheme in place, customs authorities and trusted traders participating in the AEO program should expect export declarations also serve as import declarations, and that export controls will be fully acknowledged by the import administration (Aigner, 2010). Despite the fact that over 80% of UK exports to trade partners with an MRA benefit from reduced customs controls, there is limited understanding of how these agreements influence trade.[4] This chapter focuses on the UK-US MRA to assess their impact on trade flows. Our analysis reveals that many firms are indirectly classified as "trusted traders" by utilizing AEO-certified agents. Building on this, we extend the heterogeneous firm model of Melitz (2003) by incorporating administrative costs and the

[4] Author's own calculation with HMRC data from 2009 to 2019.

critical role of agents in facilitating trade. Using transaction-level UK customs data, our empirical findings confirm the model's predictions, demonstrating that MRAs significantly enhance firms' participation in export activities and increase the value of exports handled by certified agents.

Collectively, this thesis contributes to the literature on trade facilitation and the role of intermediaries by offering a comprehensive empirical analysis of the logistics sector, particularly focusing on the UK. The results provide valuable insights for policymakers seeking to enhance trade efficiency and resilience, especially in light of trade shocks such as Brexit. Each chapter builds on existing theoretical frameworks and extends the literature by utilizing detailed customs data to explore the micro-dynamics of agent-based trade facilitation.

The remainder of the thesis is structured as follows. Chapter 1 discusses the structure and evolution of the agent market in the UK. Chapter 2 focuses on the dynamics of trader-agent relationships, examining the factors that drive firms to use agents and the impact of trade shocks on these relationships. Chapter 3 evaluates the policy implications of MRAs for trusted traders, both theoretically and empirically. Finally, the conclusion summarizes the key findings and offers directions for future research.

Chapter 1

The role of agents in the UK: Descriptive evidence

Abstract

Specialized agents, responsible for freight forwarding, customs brokerage, and broader logistics services, play a critical role in international trade. However, their market structure and dynamics remain underexplored. This study utilizes granular UK customs data to analyze the characteristics of the UK agent market, focusing on their strategic behavior, survival, and growth patterns. Our findings reveal a dual market structure, with a small number of dominant agents controlling the majority of the market, while numerous smaller agents foster competition. Larger agents tend to diversify across multiple sectors, whereas smaller agents often specialize in niche markets. New entrants typically begin with a narrow focus, but their long-term success depends on diversifying their client base, with the characteristics of their initial clients playing a crucial role in their survival. A deeper understanding of these strategies and development patterns can inform policymakers in designing industry regulations that encourage competition, support agent survival, and mitigate the impact of trade shocks.

1.1 Introduction

The increasing reliance on freight forwarding and other logistics services, such as inventory management and distribution, is a well-established feature of international trade. For example, *Kuehne+Nagel*, the largest UK freight forwarder, acts as a crucial intermediary to coordinate shipments by arranging transportation and managing the necessary documentation to ensure smooth transit across borders.[1] On the other hand, customs brokers focus more on regulatory compliance. For instance, *ChamberCustoms* provides an HMRC-compliant service, with direct connections to all major UK air, sea, and land port terminals.[2] There are also some logistics providers, such as *DHL Supply Chain*, offer more integrated services including warehousing, inventory control, and distribution to ensure efficient movement of goods.

These service providers are commonly referred to as third-party logistics (TPL) (e.g. Lieb, 1992; Murphy and Poist, 1998; Berglund et al., 1999) or as part of logistics alliances (e.g. Bagchi and Virum, 1998; Van Laarhoven and Sharman, 1994). This study, however, refers to them as "agents" to align with the data source.[3] Despite their vital role in facilitating international trade, there is a surprising lack of quantitative research exploring the structure and dynamics of this sector. This gap is particularly notable given the increasing complexity of global trade networks, which rely heavily on these intermediaries to ensure the efficient movement of goods (Murphy et al., 1992).

To our knowledge, this is the first paper to provide an overview of the entire agent market using granular-level data. The analysis is centered around two main research questions. First, we seek to understand the market structure of agents and their basic

[1] See "CILT(UK) reveals the Top 30 Logistics Service Providers in the UK for 2024" at `https://ciltuk.org.uk/News/Latest-News/ArtMID/6887/ArticleID/37647/CILTUK-reveals-the-Top-30-Logistics-Service-Providers-in-the-UK-for-2024`, *CILT(UK)*, July 2024.

[2] `https://www.chambercustoms.co.uk/`.

[3] `https://www.gov.uk/guidance/appoint-someone-to-deal-with-customs-on-your-behalf`

characteristics. Specifically, we examine whether agents tend to specialize in a limited number of industries and markets or whether they pursue a diversified strategy. In addition, we investigate the market shares associated with each strategy and explore the relationship between agent size and strategy, asking whether larger agents are more likely to operate across a broader range of industries, markets, and industry-country pairs. The second research question is to explore the dynamics of agents. We aim to capture the general trends in agents' development and examine how the characteristics of new entrants' initial clients influence their long-term performance and survival in the market.

This study makes two key contributions. First, it provides quantitative evidence for the previous qualitative studies, moving beyond survey and interview-based approaches to leverage the universe of UK exports. This data-driven approach avoids the biases associated with limited responses and self-reporting issues inherent in surveys (Murphy et al., 1992; Murphy and Daley, 1995, 2001). Second, this study offers an empirical analysis of agent development, addressing a significant gap in the literature where such analysis has been limited due to the unavailability of data tracking agents over time (Murphy et al., 1992). We analyze the strategies adopted by new entrants, track their growth trajectories, and investigate the impact of their initial client base on their future success.

The study finds a dual market structure where a few dominant agents control a substantial portion of the market, while a large number of smaller agents foster competition. This duality is evidenced by a low Herfindahl-Hirschman Index (HHI) and the observation that the top 100 agents consistently capture between 75% and 80% of the market. Over time, the number of agents has increased, particularly after 2011, indicating a growing and potentially more competitive market. However, despite this growth, market concentration remains high, with the leading agents maintaining their dominant position.

The operational strategies of agents reveal a tendency towards diversification across multiple industries and markets, which can be perceived as a necessary response to the broad scope of their client base. On average, an agent operates in approximately 4.60 sectors and 18.27 industries, reflecting a significant breadth of activities. This diversification is consistent with the broader trends in the logistics sector, where agents increasingly offer value-added services beyond traditional freight forwarding (Skiba and Karas, 2022; Lai and Cheng, 2004). Nevertheless, substantial variation exists, with some agents adopting a more specialized focus. Notably, larger agents are more likely to diversify across industries, markets, and transport modes, while smaller agents tend to concentrate on niche markets (Murphy et al., 1992).

Motivated by the above stylized facts, our research investigates the survival and growth strategies of new agents. Unlike previous studies, which often rely on survey data, our use of customs data provides a more comprehensive and objective view of market dynamics. The data reveals that new entrants typically begin with a narrow focus but tend to diversify over time. Nearly half of new entrants exit the market within their first year, but those that survive significantly increase their market share. Our empirical analysis shows that the characteristics of an agent's initial clients are crucial to their long-term success. Specifically, agents that start with larger, more diversified clients are more likely to survive and expand, although the influence of initial client size diminishes over time.

This paper is organized as follows. In Section 2, an extensive literature review is carried out in the first part regarding the definition, services provided, and evolution of agents. The following section introduces the data source as well as the strength and weakness of using it. The summary statistics and stylized facts are presented in Section 4, motivating the dynamics and empirical analysis regarding agents development and survival in Section 5. Section 6 closes the paper by offering conclusions and an attempt to provide some perspectives on future research.

1.2 Literature review

The role of agents in global trade can be traced back to the 15th century, when they emerged in response to the growing complexity of trade routes and the expansion of commodity production. Initially appearing as freight forwarders, agents addressed the increasing need for specialized services in the transport and logistics of goods. As exporters and importers sought to streamline their operations, they began delegating the responsibility of moving goods to dedicated transport companies, allowing them to focus on core business activities. This separation between the ownership of goods and the physical logistics of their distribution laid the foundation for the modern trade agent industry, which continues to play a pivotal role in global commerce today (Ficoń, 2010).

Over time, the services provided by agents have evolved significantly. Freight forwarders are no longer limited to simply arranging transportation: They now participate in various stages of the export process and offer a range of value-added services, including warehousing, inventory management, and customs compliance. Recent studies underscore the increasing influence of logistics on international trade, particularly in the case of time-sensitive products, where efficient logistics operations can determine market access and competitiveness (Gani, 2017). Furthermore, research has highlighted the differentiated effects of logistics services on exports from developing countries, where improvements in logistics can substantially boost trade flows by mitigating infrastructure challenges and reducing transaction costs (Saslavsky and Shepherd, 2014).

Despite the recognized importance of logistics in facilitating international trade, there remains a notable gap in quantitative studies that explore the industry's structure and dynamics in depth. Much of the existing research relies on case studies, interviews, or surveys, leaving a significant opportunity for empirical investigation using broader datasets.

Definition and scope

Freight forwarding is the origin point for modern trade agents, with its roots tracing back to the 15th century, as noted by Ficoń (2010). Initially, freight forwarders emerged in response to the increasing complexity of commodity production and trade. The origins of such transformation lie in the separation of ownership rights from the physical distribution of goods and the increasing involvement of various market participants, such as carriers, suppliers, and shippers. In other words, some logistics functions that have traditionally been performed in house are outsourced to a third party provider (Lieb, 1992). As international trade expanded, the role of freight forwarders grew from simply managing the transportation of goods to providing a broader range of services such as customs handling, warehousing, and logistics management, effectively transitioning into third-party logistics (TPL).

However, defining TPL consistently remains a challenge, as the involvement of such agents can vary significantly across contexts (e.g. Knemeyer and Murphy, 2005*a*,*b*; Murphy and Poist, 1998). Broadly, TPL refers to the use of external companies to perform logistics functions that are traditionally managed within the organization (Van Laarhoven et al., 2000). This broad approach suggests that TPL can either encompass the entire logistics process or focus on specific activities within it. Similarly, Coyle et al. (2003) define TPL as involving an external organization that performs all or part of a company's logistics functions.

In contrast, narrower definitions of TPL distinguish it from "traditional" outsourcing, which often occurs on a transaction-by-transaction basis. Certain criteria must be met for a relationship to be classified as TPL (Marasco, 2008). For example, Berglund et al. (1999) emphasize that the relationship must include some management, analytical, or design activities and last for at least one year to be distinguished from traditional "arm's length" sourcing. Murphy and Poist (1998) further stress the win-win nature of the relationship as well as the customization and broader range of logistics services offered.

A reconciliation between these broader and narrower perspectives on TPL can be found in Bask (2001), who describes TPL as "relationships between interfaces in the supply chains and third-party logistics providers, where logistics services, ranging from basic to customized, are offered in either short-term or long-term relationships, with the goal of achieving effectiveness and efficiency." For this study, we adopt Bask (2001) definition as it aligns with the observed dynamics in the customs data, particularly in terms of the scope and duration of services provided by agents. This approach also corresponds to the definition used by HMRC, which proves useful when the exact nature of the services is not directly observable, ensuring the inclusion of a wide range of logistics activities under the umbrella of TPL.[4]

We classify trade agents as a special form of intermediaries, as they are both related to the real resource costs of exporting and importing (Blum et al., 2018). Intermediaries have arose to more effectively match sellers and buyers (e.g., Rubinstein and Wolinsky, 1987; Spulber, 1996; Feenstra and Hanson, 2004; Blum et al., 2018) and to avoid adverse selection by guaranteeing quality (Spulber, 1996). Agents, on the other hand, have emerged to deal with the administrative tasks involved in interna-

[4]Agents, such as freight forwarders, customs brokers, and fast parcel operators, need to be established in the UK and registered with HMRC to be qualified to deal with customs for firms. Available at `https://www.gov.uk/guidance/appoint-someone-to-deal-with-customs-on-your-behalf`. HMRC internally uses a unique agent ID to identify them.

tional trade, such as customs clearing and shipping solutions. In other words, instead of acquiring and consolidating products on behalf of the manufacturing firms, the specialized agents provide necessary services along the global supply chain.

Evolution of agents

The evolution of freight forwarders and logistics service providers has been largely driven by the growth of international trade, regulatory changes, and technological advancements. For example, studies such as those by Van Laarhoven et al. (2000) and Van Laarhoven and Sharman (1994) trace the development of third-party logistics (TPL) in Europe. They emphasize the concentration of outsourced European distribution centers in Northern Europe, particularly in the Netherlands has been driven by proximity to major markets and infrastructure efficiency.

While many agents were established well before the onset of recent regulatory shifts (e.g. Murphy et al., 1992; Murphy and Daley, 2001), significant policy changes have continued to reshape the industry. A prominent example is China's accession to the World Trade Organization (WTO), which prompted substantial service improvements among third-party logistics providers (3PLs) and freight forwarders, particularly in regions like Hong Kong, as documented by Lai and Cheng (2004). Such policy changes have often led to heightened competition and increased pressure on logistics providers to enhance their service offerings and operational efficiency.

Technological innovation has been another critical driver of change in the TPL industry. The adoption of advanced systems, including Warehouse Management Systems (WMS), Transportation Management Systems (TMS), and real-time tracking technologies, has revolutionized operational processes, improving efficiency and transparency across supply chains (e.g. Min, 2006; Kumar and Shirisha, 2014). These systems enable greater visibility into inventory, more precise delivery scheduling, and streamlined transportation management. In recent years, the integration of smart technologies, such as artificial intelligence, machine learning, and big data, has further transformed logistics and transportation networks (e.g. Winkelhaus and Grosse, 2020; Chung, 2021). These smart technologies create cognitive awareness within systems, supported by information and communication technologies, allowing for more dynamic and efficient logistics processes.

The scope of services provided by logistics agents has also broadened significantly over time. Initially, agents focus primarily on ensuring the efficient movement of goods from one location to another. However, as international trade networks have become more complex, and traditional forwarding businesses face shrinking profit margins (Skiba and Karas, 2022; Lai and Cheng, 2004, e.g.), agents have increasingly expanded their service portfolios to include customs handling, warehousing, and a range of value-added services (e.g. Murphy et al., 1992; Murphy and Daley, 1995, 2001). This shift toward value-added services, such as order fulfillment, kitting, product customization, and after-sales support, has become a hallmark of modern TPL providers.(e.g. Skiba and Karas, 2022; Lai and Cheng, 2004)

1.3 Data

The dataset used in this study is extracted from UK customs data provided by HMRC, a non-ministerial department responsible for tax collection, state support payments, and trade statistics. This dataset offers a detailed view of international trade transactions, including unique trader and agent identifiers, the destination or origin country, transaction date, product classification (through the five-digit Standard International Trade Classification (SITC), the four-digit Harmonized System (HS), and the ten-digit comcode product code), as well as the value (in sterling), mass (in kilograms), and other relevant variables. Crucially, the agent identifier allows us to distinguish agent-handled transactions and analyze the performance of both agents and traders in export-related activities. The focus of this chapter is on non-EU trade between 2009 and 2019. The period between 2009 and 2019 avoids the impacts of the 2008 Financial Crisis and the COVID-19 pandemic in 2020, making the data more reliable for this analysis. Notably, non-EU trade accounts for approximately 50% of the UK's total trade.

This dataset offers several advantages. First, it provides a more comprehensive and objective measure of agent performance compared to previous studies, which have largely relied on surveys or interviews that are subject to self-reporting biases. By using customs data, we capture the actual value of goods handled by agents, offering a more precise reflection of their performance. Second, the dataset allows us to track the development of agents over time, avoiding the issue of non-responses or inconsistent participation that often arises in longitudinal survey-based studies (e.g. Murphy et al., 1992; Murphy and Daley, 1995; Murphy and Poist, 1998). This longitudinal aspect enables us to monitor the emergence and exit of agents, offering valuable insights into their life cycle and development. We acknowledge the existence of several limitations.

First, while the dataset provides reliable transaction-level data, it offers only indirect insights into the internal operations of agents. Second, the data does not reveal the business relationships between traders and agents, meaning we cannot identify cases where agents are established by traders for more efficient shipment. Besides, the exact nature of services provided by agents to each client remains unclear, limiting our understanding of their specific business strategies. Third, the dataset only covers a segment of the agents' operational history, so we lack information on the full life cycle of established agents, such as their founding dates or long-term development patterns.

Notwithstanding these limitations, we are confident in the reliability and robustness of our findings. The strengths of the dataset, including its objective and comprehensive nature, allow us to derive meaningful insights into agent performance and dynamics over time. While the data constraints necessitate caution in interpreting certain aspects, our methodological approach ensures that the key trends and patterns identified are both valid and relevant. Furthermore, the limitations themselves highlight areas for future research, which could build on this study to provide a more granular understanding of agent operations and strategies. Therefore, the conclusions drawn from this analysis remain well-supported and contribute valuable knowledge to the field.

1.4 Summary statistics

1.4.1 General

The use of agents is far more prevalent than we previously thought. The share of exports going through agents has remained high throughout the sample period between 2009 and 2019, roughly between 85 and 90%.[5] However, despite such a high value of trade going through the agents, little finding is made regarding the market structure or their operational strategies for agents, as most of the previous studies are based on surveys and interviews and therefore fail to provide a full picture for the industry. Using the customs data, this study finds that this is a market where a limited number of agents serve numerous firms, industries, and destinations. In other words, most firms work with a very limited number of agents while an agent usually serves a large group of firms.[6] For example, according to Table 1.1, there are 1,728 agents serving 73,911 exporters covering 159 destination markets in 2014, suggesting that an agent has on average 184 clients.

In terms of the market structure, the low Herfindahl–Hirschman Index (HHI) of around 250 indictaes a relatively fragmented market.[7] However, in terms of the market share, the top 10 agents account for around 30-40% of the exports, while the top 100 account for 75-80%, suggesting the existence of agents with substantial market control.[8] In other words, the market has a dual structure with a few dominant agents and many smaller ones as indicated by several studies (for example, Murphy et al.,

[5]We exclude transactions in SITC9 (unspecified goods), transactions without a proper trader ID. We also remove transactions with a negative or zero statistical value or a zero quantity.

[6]The detailed discussions regarding the matching patterns between traders and agents can be found in Chapter 3.

[7]The Herfindahl–Hirschman Index (HHI), the most commonly used market concentration, is the added portion of market attentiveness. It is derived by adding the squares of all the market participants market shares. A higher HHI indicates a higher level of market concentration. A market concentration level of less than 1000 is typically seen as low.

[8]This refers to the agent-handled exports in 2014. Data of other years yield very similar results.

1992; Murphy and Daley, 1995, 2001; Lai and Cheng, 2004). The detailed distribution features documented in Table 1.1 also support the dual structure argument. Specifically, the average number of clients per agent is more than six times greater than the median of 24, which demonstrates the presence of dominant agents with substantial customer bases. Likewise, the mean agent size is nearly 15 times higher than the median, showing that while many agents are small, the mean is significantly impacted by a few larger agents.

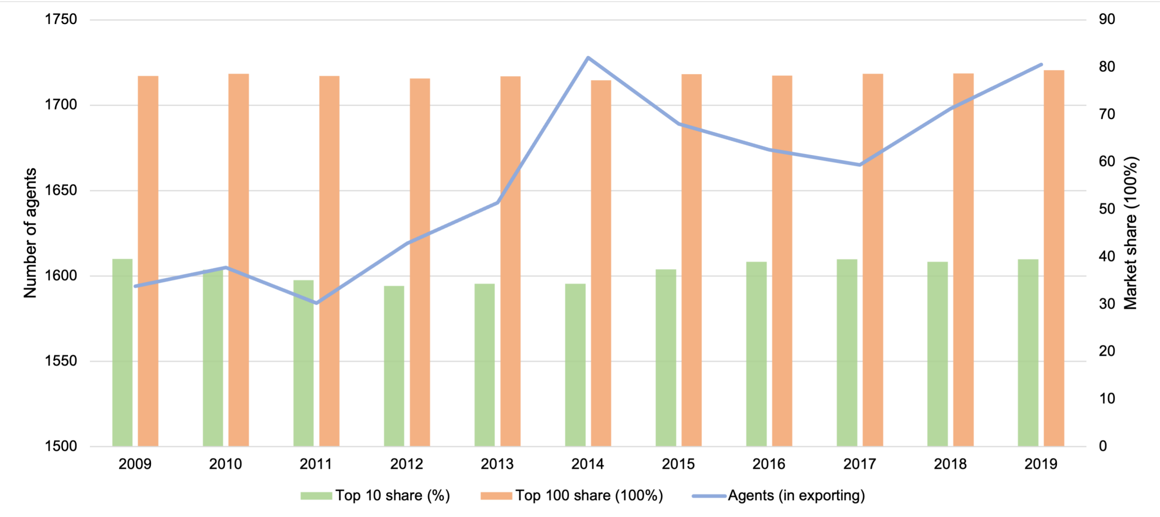
We further plot the number of active agents and the trade shares handled by the top 10 and 100 agents in Figure 1.1. Over this period, the number of agents (for exporting) has gradually increased, especially significant from 2011 onwards, reflecting a growing and possibly more competitive market. Despite such growth in the number of agents, the market remains highly concentrated, where the top 100 agents are consistently controlling 75% to 80% of the market share. Interestingly, the top 10 agents hold a relatively stable market share of around 30-40%, suggesting that while the market is becoming more competitive, the leading firms maintain a significant portion of the trade. The patterns presented in Figure 1.1 highlight the dual nature of the market's expansion and concentration. Specifically, new entrants can coexist with dominant players, while significant market power is retained by the largest agents.

Table 1.1: Summary statistics: All and top 5 destinations

Variables	(1) *All*	(2) *U.S.*	(3) *China*	(4) *U.A.E.*	(5) *H.K.*	(6) *Singapore*
Total value (in billion GBP)	114.30	32.53	7.71	4.99	4.11	3.39
# Exporters	73,911	32,472	10,077	13,819	11,696	10,257
# Agents	1,728	1,054	848	942	808	800
Mean size (in million GBP)	66.10	105.00	123.00	113.00	127.00	129.00
Median size (in million GBP)	4.26	12.50	17.30	14.60	17.30	14.60
Mean exporter per agent	184	63.02	23.75	31.25	25.19	24.33
Median exporter per agent	24	7	4	4	4	3
Mean agent per exporter	4.13	2.05	2.08	2.13	1.74	1.90
Median agent per exporter	2	1	1	1	1	1
Mean sectors per agent	4.60	3.27	3.00	3.01	3.71	2.72
Median sectors per agent	5	3	3	3	2	2
Mean industries per agent	18.27	9.59	7.53	8.03	6.80	6.69
Median industries per agent	14	5	4	4	3	3
Mean transport modes per agent	1.60	1.51	1.45	1.45	1.44	1.44
Median transport modes per agent	1	1	1	1	1	1

Note: We include the UK exports to non-EU countries in 2014 to show the distribution features. Data from other years have produced very similar results.

Figure 1.1: Agent number and market concentration



Note: The primary (left) vertical axis refers to the number of agents involved in exporting, and the secondary (right) vertical axis refers to the market shares by the top agents. The market shares refer to the agent-handled exports.

1.4.2 Agent strategy: Specialization vs diversification

Another key question regarding the agents is how they operate. As indicated in Section 1.4.1, such a small number of agents serve the entire exporting industry, and hence it is reasonable that most agents have to diversify their selection of markets, industries, and transport modes.

According to the operational characteristics of the agents reported in Table 1.1, agents tend to diversify their operations. Specifically, an exemplary agent operates in 4.60 sectors (defined as 1-digit SITC) and 18.27 industries (defined as 2-digit SITC), reflecting a broad scope of its operational activities. The median values of sectors and industries per agent reinforce such diversity, with half of the agents working in more than 5 sectors and 14 industries. Such finding coincides with the literature on service expansion and diversification. Specifically, it has been documented that there is increased diversification in terms of the services provided, that is more value-added services than pure forwarding, and forwarders are becoming more like brokers (e.g., Murphy et al., 1992; Murphy and Daley, 1995, 2001; Lai and Cheng, 2004; Skiba and Karas, 2022). Such service expansion can be attributed to the decreasing profit margins from traditional freight forwarding services due to severe competition as well as the increased transparency in pricing (Lai and Cheng, 2004). Although we cannot observe the exact type of service being provided, the findings in Table 1.1 supplement the literature on agents' choice of destinations and industries.

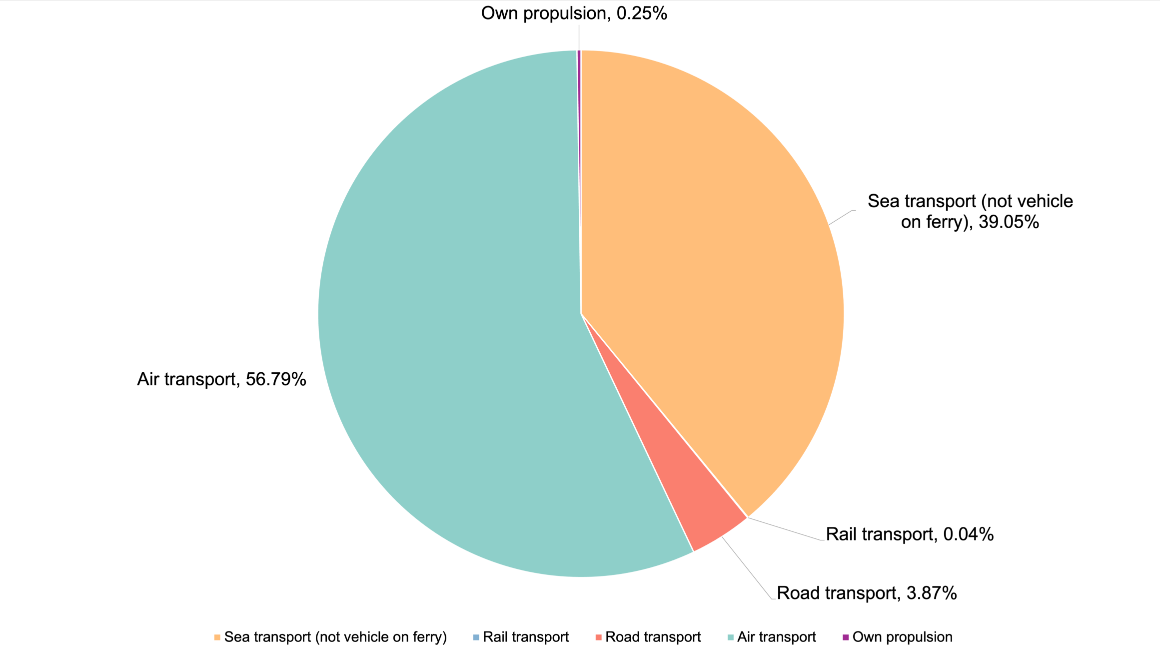
In addition, the statistics for the transport modes aligns with the predominant use of sea and air transport for the UK exports.[9] While the median number of transport modes used is one, the mean value of 1.60 highlights that although many agents

[9]There are nine modes including sea transport, rail transport, road transport, air transport, postal consignment, fixed transport installations, inland waterway transport, and own propulsion.

specialize in a single mode, some agents are capable of leveraging multiple transport modes. The prevalent use of air and sea transport has been well documented in the (e.g. Murphy et al., 1992; Murphy and Daley, 1995, 2001); there is also an increasing use of air shipments, and our latest data reflect this.

The table also reveals several links between the destination market and the agents' operational features as shown in Columns (2)-(6), where we present the agent-related summary statistics for the top 5 destinations for the UK. The total export value to each country is reported in the first row, and the number of exporters and agents serving each market is reported right below it. First, it is clear that a smaller market usually hosts fewer exporters, agents, and industries. Specifically, the US, accounting for nearly 30% of the UK exports, attracts almost half of the exporters and two thirds of the agents. Besides, the top five destinations have considerably larger agent sizes, suggesting that leading agents are more likely to operate in these locations. Second, agents still diversify within a given market, and agents in bigger markets usually operate in more industries. For example, an agent exporting to the US operates in 3.27 sectors and 9.59 industries on average, while its counterpart exporting to Singapore covers 2.72 sectors and 6.69 industries. When compared with the whole sample, agents in each destination exhibit much lower degree of diversification. For example, the mean industry per agent is 18.27 for the entire sample, while it is halved to 9.59 for the US and even lower for the rest of the markets. Thirdly, the indicators related to transport modes exhibit similar values for the whole sample and the individual destination. According to Figure 1.2, there is not much room in the choice of transport modes considering the fact that sea and air transportation accounts for over 95% of the UK exports.

Figure 1.2: Transport mode shares in the UK exports



Note: We include the UK exports to non-EU countries in 2014. Data of other years have produced very similar results.

Table 1.2 further decouples the agents' operational strategies. The results reveal that large variation exists among agents. Notably, while some agents stick with their diversification strategy, others tend to specialize within a given industry or destination. Specifically, an agent on average manages around 115 industry-market pairs, 25 markets and 18 industries, reflecting agents' broad engagement across multiple markets and industries. However, the large standard deviations and high p90 values, particularly for industry-market pairs, reveal significant disparities among agents. The lower percentiles (p10) suggest that some agents remain highly focused, often dealing with just one market or industry. One possible explanation can be found in the qualitative studies carried out by Murphy et al. (1992) that while many agents diversify to mitigate risk, a few continue to specialize, prioritizing depth and efficiency in specific areas. In addition, agents tend to broadly spread their operation network and serve markets that are far away from each other. Agents serve around four areas on average, and over half of the agents serve more than five areas out of the total six.[10] Moreover, when we fix destination or industry, diversification still exists but to a milder degree. For a given destination market, an agent on average operates in around 5 industries, while it sends products in a given industry to around 6 destination markets. At the same time, the smaller median values (i.e. two for both) for these two indicators also confirm that nearly half of the agents become more specialized within a given destination or industry. The number of transport modes for a given market, industry and market-industry pair is always around one, and the standard deviations are small.

Table 1.2: Diversification: Per-agent level

Variables	Mean	sd	p10	p50	p90
Destination markets	24.77	16.27	1	14	43
Industries	18.27	16.27	1	14	43
Industry-market pairs	115.51	278.53	1	31	280
Industry per given market	4.66	6.97	1	2	12
Market per given industry	6.32	11.42	1	2	16
Transport mode per given market	1.29	0.48	1	1	2
Transport mode per given industry	1.39	0.56	1	1	2
Transport mode per given market-industry	1.18	0.39	1	1	2

Note: We include the UK exports to non-EU countries in 2014 to show the distribution features. Data from other years have produced very similar results.

Following the findings in Table 1.2, we proceed to document whether agents have a dominant market, industry, market-industry as presented in Table 1.3. Dominance is defined as the case when more than half of the agent's trade value is from a single market, industry, or industry-market pair. Around a thousand agents have a dominant market focus, and a similar number of agents have a dominant industry focus. However, such agents only account for one third of the trade value, suggesting that

[10]Observations are categorized into six areas, which are *South and Southeast Asia*, *the US*, *other Americas*, *China*, *excl. European Committee*, and *All other countries.*

it is the smaller agents that are more likely to focus on a single market or industry. Fewer agents, only 665, have an industry-market focus and account for less than one fifth of the total exports.

Table 1.3: Dominance: Per-agent level

	Yes		No	
Dominance	Number	Share (%)	Number	Share (%)
Market	959	31.46	769	68.54
Industry	965	36.48	763	63.52
Market-industry pair	665	17.18	1063	82.82

Note: We include the UK exports to non-EU countries in 2014. There are 1,728 agents in that year. Data from other years have produced very similar results.

Table 1.3 reveals that there is a possible relationship between agent size and its strategy: Bigger agents are more likely to diversify their operations into different industries and countries. The differences in operational strategies between small and big agents have been well documented in the literature. For example, Murphy et al. (1992) find that larger agents may enjoy size economics that smaller ones do not, while smaller agents can thrive in distinct market niches such as specialization in a particular commodity or destination country. We further plot the relationship between agent operational strategy and agent size in Figure 1.3. In the left panel 1.3a, we categorize agents into four quartiles according to their number of markets.[11] Each box shows the 75^{th} (upper whisker) and 25^{th} (lower whisker) percentiles, and the line within the box identifies the median. We can clearly see a positive relationship between the agent size and the number of destination markets it has. Agents in the lowest quartile exhibit the broadest interquartile range (IQR), which reflects significant variability in

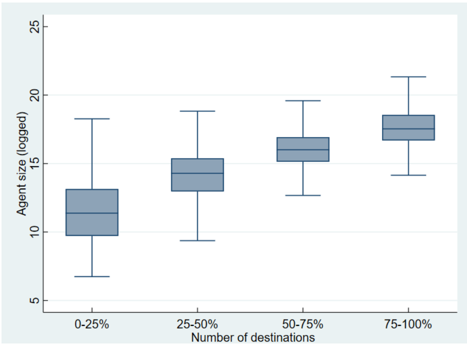
[11] Agents in the first quartile have fewer (or equal to) 3 destinations; Agents in the second quartile have a number of destinations between 3 and 14 (included); Agents in the third quartile have a number of destinations between 14 and 37 (included); Agents in the last quartile have more than 37 destinations.

the agent size. The higher quartiles have relatively narrower IQR implying that only bigger agents are capable of extending their operational networks into more markets. The middle panel 1.3b shows a positive relationship between agent size and its diversification across industries. Similar to panel 1.3a, we again categorize agents into four quartiles according to their number of industries.[12] Similar to the pattern found in 1.3a, the first quartile in 1.3b also has the broadest IQR suggesting significant variation in the agent size, while the highest quartile has the narrowest IQR implying that only larger agents are capable of diversifying their selection of industries. Besides, we also find a positive relationship between the number of transport modes and agent size as shown in the right panel 1.3c. The first quartile possesses the broadest IQR, which is in line with the fact that most agents, regardless of their size, manage only one type of mode. The remaining three quartiles see much concentrated agent size, and notably agents operate more than one mode are generally bigger.

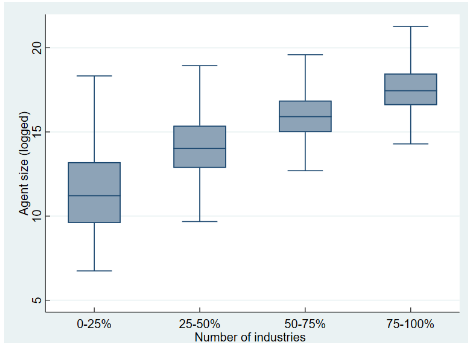
Following previous descriptive evidence, Figure 1.4 illustrates the dynamics in the average number of destinations, industries, and industry-country pairs per agent from 2009 to 2019. The primary (left) vertical axis represents the number of destinations (blue bars) and industries (orange bars), and the secondary (right) vertical axis indicates the number of country-industry pairs. Over this period, agents maintained a relatively stable number of destination markets and industries, while the number of industry-country pairs (red line) shows a noticeable fluctuation, peaking around 2017 before declining. The fluctuations may reflect agents' regular response to market dynamics. For example, there is a sudden drop between 2013 and 2014, which coincides with the rising number of new entrants. Strong competition brought by the new entrants may have forced some agents to refine their selection of destinations

[12] Agents in the first quartile have fewer (or equal to) 3 industries; Agents in the second quartile have a number of industries between 3 and 14 (included); Agents in the third quartile have a number of industries between 14 and 31 (included); Agents in the last quartile have more than 31 industries.

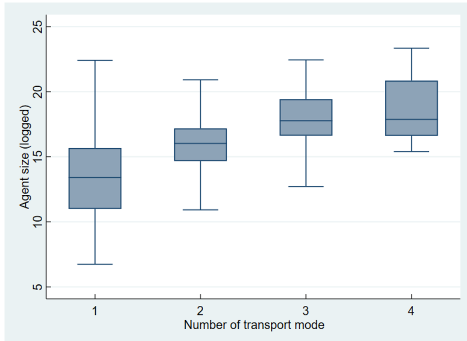
Figure 1.3: Diversification and agent size



(a) Number of markets



(b) Number of industries

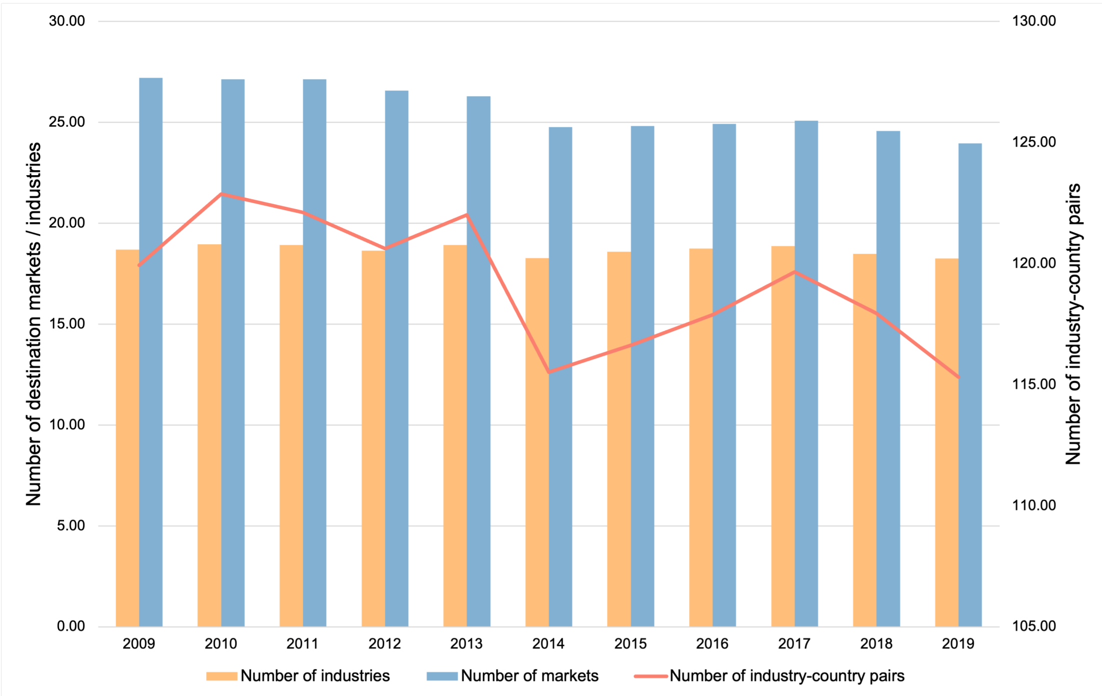


(c) Number of transport modes

Note: We include the UK exports to non-EU countries in 2014. Data from other years have produced very similar results. We have removed outliers according to the disclosure requirements, and this does not change our result viability.

and industries, only keeping the most lucrative combinations. Interestingly, another significant drop happens around 2017, which can be attributed to agents' efforts to mitigate risks amid rising trade policy uncertainty due to Brexit.[13] Specifically, agents are more likely to become cautious and reassess their selection of destinations and industries when facing deteriorating trade environment and therefore end up focusing on more stable or profitable markets, leading to a decline in industry-country pairs.

Figure 1.4: Change in agents' strategies



Note: The primary (left) vertical axis shows the average number of destination markets or industries agents operate in. The secondary (right) vertical axis shows the number of industry-country pairs an agent has on average.

Overall, the above findings illustrate the dual nature of the agent market and the strategic flexibility agents employ in a dynamic trade environment. The agent market is characterized by both concentration and diversity. While a few dominant agents control a large share of trade, the presence of numerous smaller agents fosters com-

[13]In Chapter 3, we discuss how Brexit affects firms' use of agents, and we find that traders switch to bigger agents and narrow down their operational scope.

petition. The analysis shows that despite a steady increase in the number of agents, market concentration has remained stable, with the top 100 agents consistently handling the majority of exports. Agents generally adopt diverse operational strategies, spanning multiple sectors and industries, though some focus on specific markets or services.

1.5 Agent dynamics

1.5.1 Survive and develop

While section 1.4 describes the basic features of agents, a major question is how agents develop. Several studies on freight forwarders have argued that agents may employ different strategies as they develop, but so far, quantitative evidence has been precluded. For example, Murphy et al. (1992) argue that agents may become more diversified (in terms of the services provided) when their clients seek a single-source of suppliers of intermediary services. Another theory is that agents are pushed by their clients' needs and the competitive nature of the industry (Lai and Cheng, 2004). For example, Schramm (2015), based on the Austrian logistics service providers, find that agents are pushed (by their clients) to obtain certain certificates.

The lack of empirical evidence can be partly due to the non-responses bias in surveys. For example, in Murphy et al. (1992), Lai and Cheng (2004) and Murphy and Daley (2001), the effective response rate are all below 30%. In addition, the usable responses usually come from forwarders with a relatively long history of operation. For example, over 30% of the usable responses are from forwarders with over 30 years experience (Murphy and Daley, 2001). In other words, new entrants may be reluctant to respond to surveys. Contrary to the literature, our study, based on the universal customs data, avoids such bias and finds relatively active entry/exit activities and confirms the existence of relatively young agents. The data used ensures we have a more precise picture of the dynamics of the agents. As shown in Figure 1.4, agents' strategies remain relatively stable through the sample period. New agents turn out to be a more suitable subject to study the agent dynamics as we can observe how they develop. Specifically, we start with whether the new agents' strategies differ from what we have observed from the entire sample and investigate how they survive and develop.

First, we define the new agents if they have no export recorded in the previous three years. Figure 1.5 illustrates the annual dynamics of the new market entrants from 2012 to 2019, as measured by their absolute numbers and their respective shares of total exports.[14] The primary (left) vertical axis represents the number of new agents, while the secondary (right) vertical axis indicates their trade shares. A notable observation is the substantial spike in both the number and share of new entrants in 2018, with new agents accounting for 3.1% of the exports, a stark contrast to the preceding and succeeding years. The fluctuation in new agent number does not consistently align with changes in market share, suggesting that the impact of new agents on trade value is not solely dependent on their numerical presence but possibly on the strategic positioning and market conditions during their entry.

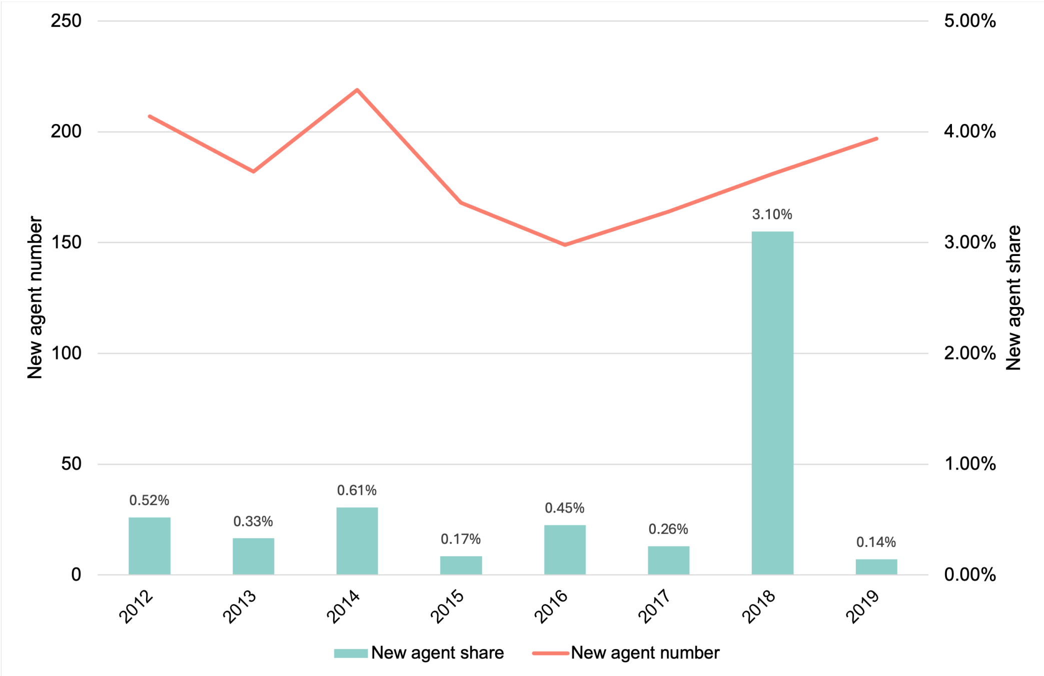
To further understand the new entrants' characteristics, we present the summary statistics for the new entrants only in Table 1.4. When comparing the entire sample and the new entrants, distinct differences in their operational characteristics become apparent. The new entrants, on average, have a mean size of 0.24 million GBP, which is significantly smaller compared to the broader agent population. Such discrepancy is underscored by the fact that the 10^{th} percentile for new entrants is effectively zero, reflecting the presence of numerous small-scale operators within the new entrants.

Furthermore, new entrants tend to operate in fewer markets and industries, with averages of 4.86 markets and 5.18 industries per agent, compared to higher averages observed in the broader sample as shown in Table 1.1. This suggests that new agents are more likely to focus their initial operations narrowly, potentially as a strategy

[14] The sample of new agents starts from the year 2012 as we lose observations for the years between 2009 and 2011 due to lags.

to mitigate risks and establish a foothold in specific areas before expanding. The variability in industry-market pairs is also more pronounced among new entrants, with a mean of 10.95 pairs and a standard deviation of 25.87, indicating that while some new agents are highly diversified, many are still quite specialized. In contrast, the broader sample may exhibit a more consistent level of diversification across agents. Besides, the lower averages for the number of industries per given market (2.25) and markets per given industry (2.11) for new entrants reflect a more concentrated approach in their market strategies, in contrast to the more expansive reach observed in the more established agents within the whole sample. These comparisons highlight that new entrants typically start with a narrower focus and smaller scale, potentially reflecting strategic caution or limited resources, whereas more established agents in the entire sample display broader market and industry engagement, likely driven by accumulated experience and resources.

Figure 1.5: New entrants: Numbers and shares



Note: The primary (left) vertical axis represents the number of new agents, while the secondary (right) vertical axis indicates their trade shares. The data between 2009 and 2011 will be dropped as new entrants should have zero exports recorded for the past three years.

Table 1.4: Summary statistics: New agents

Variables	Mean	sd	p10	p50	p90
Size (in million GBP)	0.24	1.79	0.00	0.03	0.22
Exporter per agent	11.95	30.42	1	1	27
Markets per agent	4.86	9.24	1	1	12
Industries per agent	5.18	7.66	1	1	15
Industry-market pairs	10.95	25.87	1	2	25
Industry per given market	2.25	3.48	1	1	1
Market per given industry	2.11	3.51	1	1	4

Note: We use the new agents in 2014 as an example to show the distribution features. Data from other years have produced very similar results. The 10 percentile for *Size* is 3183.3 and rounded to 0.00.

As the new entrants tend to start with a narrower focus and smaller scale, a critical question to follow is whether they survive and how they develop. Specifically, we am to investigate whether the new entrants expand their network scale and expand their operational focus conditional on successful survival. In Figure 1.6, we use the new entrants in 2014 as an example and track their survival rates and the corresponding trade shares over time. The orange curve tracks the number of new agents that remain operational after their initial entry, over 1, 3, and 5 years.[15] Initially, 219 agents entered the market, accounting for 0.66% of the total market share. After one year, nearly half of the new entrants stop operating, but those remaining tripled their market share to 1.77%. Such trend continues at the three-year mark, where despite a further but slight reduction in the number of the surviving agents, their collective market share rises again, to 2.47%. By the fifth year, the number of the surviving agents stabilizes, and their market share drops from its peak value but remains three times above its starting value. Most exits happen during the first year, while the number of surviving agents tend to stabilize in the long run. The declining number of the surviving agents suggests that many new entrants struggle to sustain operations in the long term. However, the initial increase in the market share despite the declining number of agents indicates that those who do survive are likely consolidating their positions.

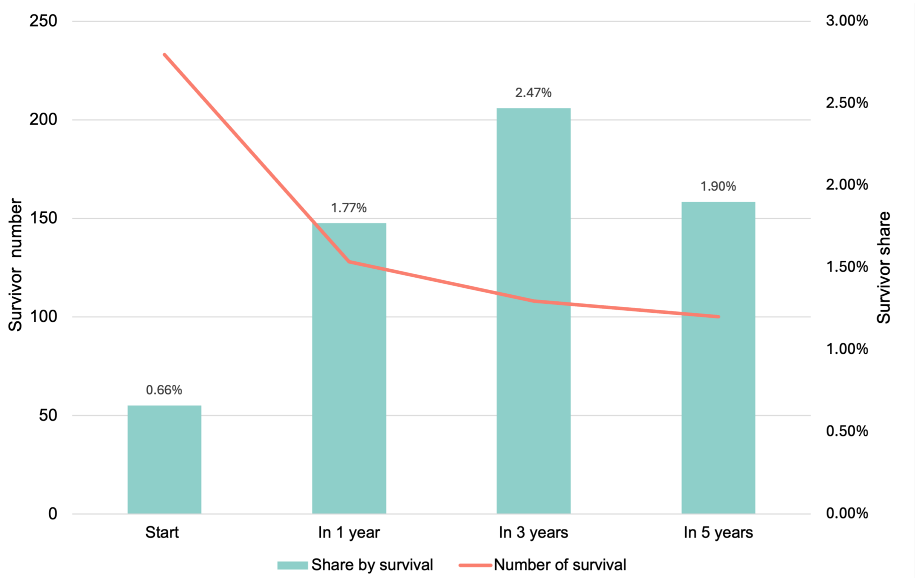
Figure 1.7 presents how the new entrants' strategies develop after their entry (conditional on their survival). The primary (left) vertical axis measures the number of destination markets and industries, while the secondary (right) vertical axis tracks the number of industry-country pairs. At the point of entry in 2014, new agents typically target an average of about 4.5 destination markets and industries, indicating a relatively focused approach, especially when compared with the broader sample as shown in Table 1.1. Over the subsequent years, there is a clear trend of expansion. Only

[15] As we are to track how many agents remain active after a given period, we define "exit" in the case when an agent has no export recorded for a specific year. We allow for re-entry.

in one year (2015), the number of destination markets and industries both increase significantly, signaling the agents' strategy to diversify their operations early on. This expansion trend continues steadily over the five-year period, with both metrics nearly doubling by 2019. Simultaneously, the number of industry-country pairs, represented by the red line, shows a consistent upward trajectory. This indicates that new entrants are actively diversifying their portfolio. By 2019, the number of industry-country pairs has more than quadrupled compared to the start year.

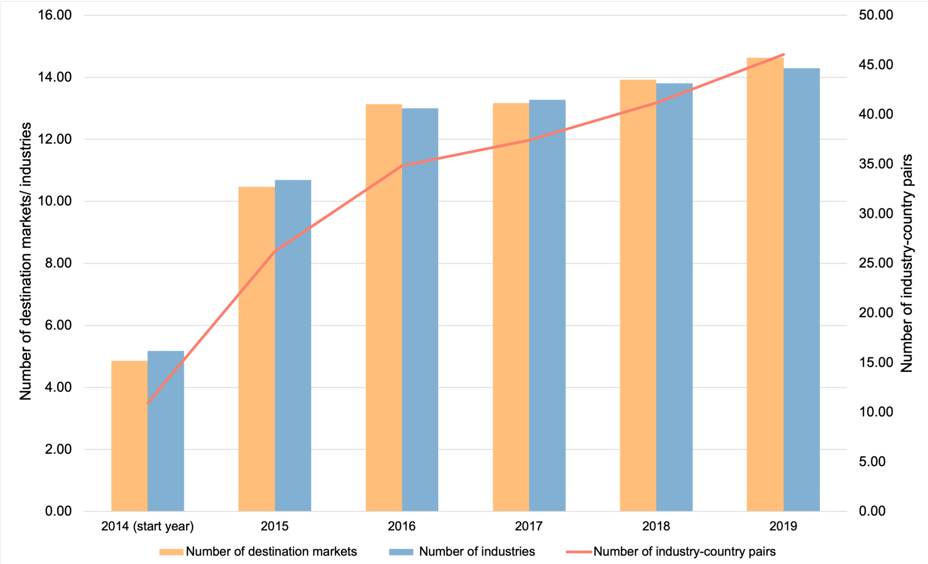
In summary, the analysis of new market entrants reveals that agents typically begin with a smaller, more focused scope but expand their operations if they survive beyond the initial volatile period. Nearly half of new entrants exit within the first year, yet those who remain significantly increase their market share, indicating successful consolidation. Survivors tend to diversify both their industry and market reach, with the number of industry-market pairs nearly quadrupling within five years.

Figure 1.6: New entrants: Survival in 1, 3, and 5 years



Note: The primary (left) vertical axis represents the number of surviving agents, while the secondary (right) vertical axis indicates the corresponding trade shares. This figure is based on the new entrants in 2014. Data of other years have produced very similar results. The number of survivors in each period is 219, 128, 108, and 100 respectively.

Figure 1.7: New entrants: Change in strategies



Note: The primary (left) vertical axis measures the number of destination markets and industries, while the secondary (right) vertical axis tracks the number of industry-country pairs. The figure is based on the new entrants in 2014. Data of other years have produced very similar results. The three indicators are the sample averages for the surviving agents.

1.5.2 Initial match

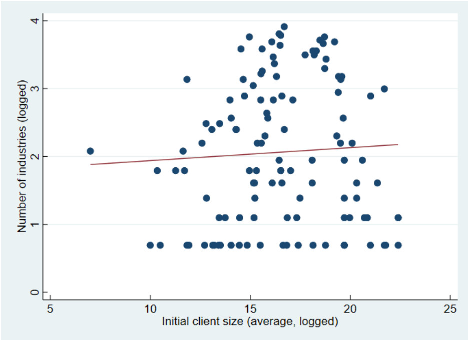
In this section, we explore the development of agents by utilizing a sample of new entrants. As indicated in the literature, a large number of agents have been established for a very long time (e.g. Murphy et al., 1992; Murphy and Daley, 1995, 2001). As we do not have information regarding these agents' age or history, and the length of our sample period is significantly shorter than their existence, we cannot precisely capture their development. Our data, however, can reliably identify new agents and their activities. Furthermore, new agents are currently missing from the literature due to non-response biases. Empirical analysis based on them can fill in a long-existing research gap. Given the fact that only export activities can be observed from the data, it is reasonable to differentiate agents by their initial match characteristics. In other words, we consider clients needs a major driving force of agents' development and have an impact on new entrants' future strategies. Specifically, we are to investigate whether the size, connectiveness, and diversification degree of their clients have an impact on the new entrants' development strategies. For example, are new entrants pairing with larger clients more likely to survive and diversify?

Before presenting the analytical results, we first illustrate the relationship between the initial match and the agents' future development. Figure 1.8 uses the new entrants between 2012 and 2014. We choose the *Initial Client Size* as the primary factor to study as it reflects more about traders' capabilities and productivity (Benguria, 2021). Given the fact that agents usually have multiple clients, the *Initial Client Size* is calculated as the (logged) average size of all the clients an agent has within the year of entry and presented on the horizontal axis in all the panels from 1.8a to 1.8i. We measure agents' development in terms of its (logged) size, number of destinations, and number of industry-country (jc) pairs. We depict the above three indicators' relationships with *Initial Client Size* in 1, 3, and 5 years after they entering the market. The three sets of plots 1.8a - 1.8c, 1.8d - 1.8f, and 1.8g - 1.8i present the relationships between the *Initial Client Size* and the number of industries, destination countries, and jc pairs respectively.[16]. All the relationships tend to start as a positive but weak one, suggesting that agents with larger initial clients may diversify slightly more early on. By the fifth year, the trend either becomes either relatively flat as shown in Plot 1.8f and 1.8i or reverses slightly as shown in 1.8c. These varying patterns suggest that the *Initial Client Size* might influence early diversification but does not consistently drive long-term strategies. The above illustrative example highlights the complex nature embedded in agents' development and needs for further empirical analysis.

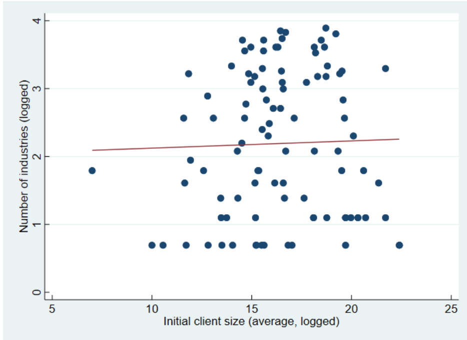
As indicated in Section 1.5.1, new entrants are defined when there are at least

[16]Each dot in the scatter plots represents a new entrant. The dots become less dense as time goes by, which is in line with Table 1.6.

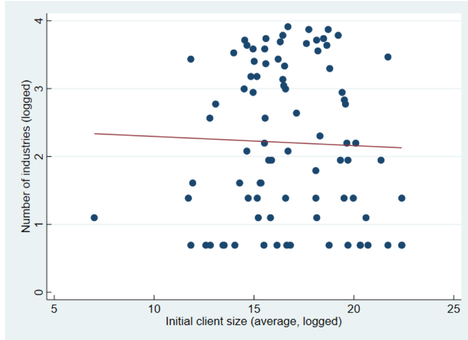
Figure 1.8: Initial client size and diversification: 1, 3, and 5 years



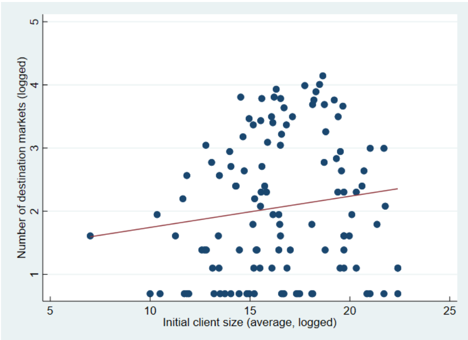
(a) Initial client size and number of industries: 1 year



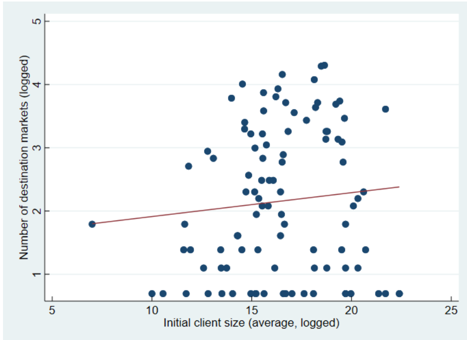
(b) Initial client size and number of industries: 3 years



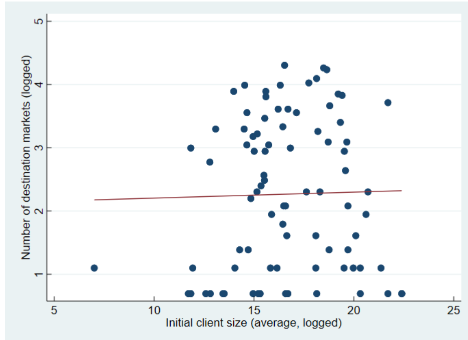
(c) Initial client size and number of industries: 5 years



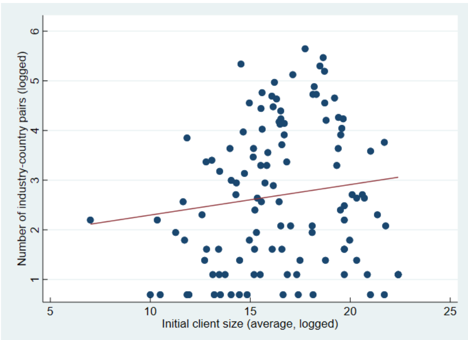
(d) Initial client size and number of markets: 1 year



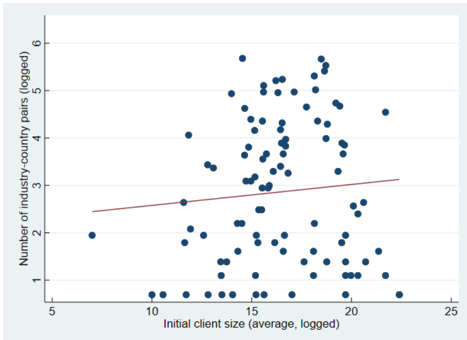
(e) Initial client size and number of markets: 3 years



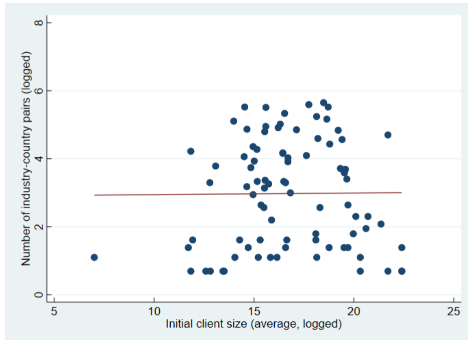
(f) Initial client size and number of markets: 5 years



(g) Initial client size and number of *jc* pairs: 1 year



(h) Initial client size and number of *jc* pairs: 3 years



(i) Initial client size and number of *jc* pairs: 5 years

Note: There are 608 new entrants in total between 2012 and 2014. Given that some agents exit, there are 344, 282, 247 agents left in 1, 3, and 5 years respectively. Specifically, plots 1.8a, 1.8d, and 1.8g have 344 observations; plots 1.8b, 1.8e, and 1.8h have 282 observations; plots 1.8c, 1.8f, and 1.8i have 247 observations.

three consecutive years recorded of zero export.[17] To study agents' development, we choose 1, 3, and 5 years after their entering the market to observe their strategy changes. As indicated by Figure 1.6 that new entrants are likely to experience more ups and downs in the first three years (for example, more exits happen within a shorter time). We therefore include all the new entrants between 2012 and 2014. Due to the frequent exits of new entrants, there are 344, 282, and 247 agents left within 1, 3, and 5 years respectively. In terms of the variable choice, we are interested in the following initial match characteristics per specific new entrant: The initial match size, $Size_i^{Match}$, proxied by the average size of all the clients within in the first year, the initial match diversification degree, jc_i^{Match}, measured by the average number of jc pairs its clients have, and the connectiveness, which is the average number of agents their clients have, $Agents_i^{Match}$.[18] We estimate the following specification using OLS to investigate the impact of the initial match:

$$y_{it} = \alpha_0 + \alpha_1 Size_i^{Match} + \alpha_2 jc_i^{Match} + \alpha_3 Agents_i^{Match} + \delta_{entry\ year} + \epsilon_{it} \tag{1.1}$$

where the subscripts i and t stand respectively for (new) agent and time. Time t refers to the time period after the market entry, that is 1, 3, and 5 years. On the right-hand side, we include the initial match characteristics, $Size_i^{Match}$, jc_i^{Match}, and $Agents_i^{Match}$, as defined above. We also include $\delta_{entry\ year}$ to control for entry-year fixed effects. In terms of the new entrants' performance and development, three aspects are of interest, that is, survival, diversification and size. We therefore incorporate three dependent variables into a generalized dependent variable y_{it}: (i) a dummy variable,

[17] We define new entrants in 2012 when there are exactly three consecutive years of zero export.
[18] More on the trader-agent connectiveness and assortativity please see Chapter 2.

D_{it}^{Exit}, takes on the value of 1 if the new entrant i exits within time t; (ii) for the surviving entrants, n_{it}^{jc} denotes the (logged) number of jc pair it has at time t; (iii) for the surviving entrants, $Size_{it}$ is the logged export value for the entrant i at time t.

For the baseline analysis, we include three time periods: 1, 3, and 5 years after entering market and present the corresponding results in Table 1.5. The initial match size, $Size_i^{Match}$, appears to play a vital role in affecting the survival of new entrants. According to Columns (1), (4), and (7), $Size_i^{Match}$ is negatively and significantly correlated with the likelihood of exit across all time frames. Specifically, 1% increase in the average client size decreases the new entrants probability of exit by 1.57% within the first year of entry. The other two indicators, jc_i^{Match} and $Agents_i^{Match}$, exhibit little impact on entrants' survival.

For the new entrants' diversification strategies, as shown in Table 1.5 Columns (2), (5), and (8), $Size_i^{Match}$ again exhibits a strong early impact, which fades in importance over time. The diversification degree of the initial match shows a surprisingly insignificant relationship with the number of jc pairs a new entrant can develop. In other words, pairing with a trader that exports in a large number of jc pairs does not necessarily lead to the new entrants' diversification. One possible explanation is that new entrants are likely to be assigned a limited number of industries (and destination countries), but those pairing with bigger traders enjoy the spillover of their clients' high productivity and can later enter into more industries and destination countries. $Agents_i^{Match}$ may negatively influence agents' diversification strategies, but such impact remains insignificant.

The size of the new entrants is strongly correlated with the initial match size as shown in Table 1.5 Columns (3), (6), and (9). Specifically, 1% increase in the average client size will result in 0.85% increase in the new entrant's size within the first year. $Size_i^{Match}$ has a persistent impact on the new entrant's size but with a diminishing annual margin. Notably, the average number of agents its clients have, $Agents_i^{Match}$, turns to negatively affect a new entrant size, especially in longer terms. For example, as shown in Column (6), 1% increase in $Agents_i^{Match}$ will result in an almost 1% drop in the agent size over three years. This finding suggests that while traders usually hire multiple agents to handle their goods, fierce competition exists among these agents. In other words, securing a big client may help a new entrant expand, but the embedded competition can impair its growth potential.

In the robustness checks as presented in Table 1.6, the three independent variables, $Size_i^{Match}$, jc_i^{Match}, and $Agent_i^{Match}$, take on their previous values from one year before the match to mitigate the potential bias that the matching process could influence both the trader and the agent simultaneously. The results remain largely consistent with those in Table 1.5. Notably, the impact of $Size_i^{Match}$ remains significant, although its magnitude is slightly reduced. For instance, a 1% increase in the average client size is associated with a 2.6% decrease in the probability of new entrants exiting within a one-year period. Meanwhile, the other two variables, jc_i^{Match} and $Agent_i^{Match}$, continue to show minimal impact on the survival of new entrants.

The initial match size, $Size_i^{Match}$, is found to have an overall significant and positive impact on all measures of the new entrants' development. These results suggest that the larger the initial client an agent serves, the more likely the agent is to experience growth in terms of industries and destination markets served. However, the findings also reveal the competitive dynamics among agents: Serving a well-connected client may hinder a new entrant's ability to expand into additional industries and destination countries, possibly due to the client's existing network of preferred service providers or the agent becoming too dependent on a single, large client.

Despite these insights, the results should be interpreted cautiously and considered indicative rather than conclusive. First, we are unable to capture the potential pre-existing connections between traders and agents. For instance, traders and agents may have pre-established relationships, with an agent potentially being a subsidiary or spin-off of an existing firm. In such cases, the agent may have immediate access to a broader range of industries and destination markets from the outset, giving it an advantage that is not directly observable in the data. Second, we lack detailed information regarding the types of services provided by agents. Moreover, other factors could influence the growth trajectories of new agents, including their initial productivity levels or whether they emerge from mergers and acquisitions.

The development strategies employed by new entrants are also likely to vary over time, as indicated by Figure 1.6. Specifically, while many new agents successfully navigate the initial challenges of market entry, a substantial number struggle to maintain long-term survival. The slight decline in the number of surviving agents after five years, coupled with a relatively stable market share among those that remain, suggests that while some agents do exit the market, those that endure are able to solidify their positions. These surviving agents maintain, or in some cases enhance, their market presence, indicating a consolidation of market power among the strongest players.

Table 1.5: Initial match and performance

	In 1 year			In 3 year			In 5 years		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(8)
Initial match	D_i^{Exit}	n_i^{jc}	$Size_i$	D_i^{Exit}	n_i^{jc}	$Size_i$	D_i^{Exit}	n_i^{jc}	$Size_i$
Trader size	−0.055***	0.237***	0.847***	−0.059***	0.194**	0.715	−0.052***	0.149	0.533***
	(0.0143)	(0.0561)	(0.1037)	(0.0143)	(0.0729)	(0.1289)	(0.0143)	(0.0805)	(0.1491)
Number of jc pairs	−0.058	0.034	−0.079	−0.022	−0.084	−0.276	−0.002	0.008	0.119
	(0.0457)	(0.1629)	(0.3013)	(0.0465)	(0.2144)	(0.3793)	(0.0458)	(0.2343)	(0.4340)
Number of agents	0.124*	−0.432*	−1.330	0.124*	−0.204	−0.935*	0.059	−0.343	−1.192*
	(0.0508)	(0.1746)	(0.3229)	(0.0508)	(0.2279)	(0.4032)	(0.0509)	(0.2487)	(0.4607)
Entry year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	608	344	344	608	282	282	608	247	247
R^2	0.059	0.067	0.211	0.039	0.020	0.111	0.037	0.010	0.065

Notes: There are 608 new entrants in total between 2012 and 2014. Given that some agents exit, there are 344, 282, 247 agents left in 1, 3, and 5 years respectively.
***, **, and * denote 0.1%, 1% and 5% significance level respectively.

Table 1.6: Initial match and performance: Robustness

	In 1 year			In 3 year			In 5 years		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(8)
Initial match	D_i^{Exit}	n_i^{jc}	$Size_i$	D_i^{Exit}	n_i^{jc}	$Size_i$	D_i^{Exit}	n_i^{jc}	$Size_i$
Previous trader size	-0.026^{**}	0.172^{***}	0.318^{***}	-0.059^{***}	0.126^{**}	0.299^{***}	-0.052^{***}	0.107^{*}	0.420^{***}
	(0.0078)	(0.0300)	(0.0717)	(0.0145)	(0.0395)	(0.0812)	(0.0143)	(0.0437)	(0.0575)
Previous number of jc pairs	−0.041	0.056	0.240	0.022	0.013	0.716	−0.002	0.201	0.465
	(0.0485)	(0.1691)	(0.4086)	(0.0465)	(0.2251)	(0.4780)	(0.0458)	(0.2573)	(0.3239)
Previous number of agents	0.072	-0.447^{*}	−1.088	0.103^{*}	−0.285	-1.682^{**}	0.059	−0.566	-1.510^{***}
	(0.0568)	(0.1933)	(0.4720)	(0.0517)	(0.2600)	(0.5550)	(0.0509)	(0.2987)	(0.3702)
Entry year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	608	344	344	608	282	282	608	247	247
R^2	0.043	0.105	0.076	0.039	0.031	0.074	0.037	0.026	0.189

Notes: There are 608 new entrants in total between 2012 and 2014. Given that some agents exit, there are 344, 282, 247 agents left in 1, 3, and 5 years respectively. ***, **, and * denote 0.1%, 1% and 5% significance level respectively.

1.6 Conclusion

Our study provides a broad picture of the UK agent market using granular-level customs data, offering important insights into the market structure, strategies, and development patterns of agents in UK trade. Our findings reveal a dual market structure characterized by a small number of dominant agents controlling the majority of the market, while a large pool of smaller agents fosters competition.

The operational strategies of agents highlight the importance of diversification. Our analysis shows that agents operate in an average of 4.60 sectors and 18.27 industries, reflecting significant operational breadth. We also find that larger agents tend to operate across a wider range of industries, markets, and transport modes, while smaller agents are more likely to thrive in niche markets. This diversification strategy appears to be a necessary response to the complex and competitive nature of global trade.

We also examine the survival and growth trajectories of new entrants, finding that nearly half of new agents exit the market within the first year. However, those that survive significantly increase their market share and tend to extend their operational scope over time. The initial characteristics of an agent's clients play a crucial role in their long-term success, with larger and more diversified clients providing a strong foundation for future growth. This finding underscores the competitive advantage enjoyed by agents with a diversified and established client portfolio, though the influence of initial client size diminishes as agents mature.

Notwithstanding some data weaknesses, our findings offer important implications for policymakers and industry stakeholders. First, the dual structure of the agent market suggests that policies designed to support smaller agents could enhance competition and market dynamism. Furthermore, encouraging diversification among agents could lead to a more resilient logistics sector, better equipped to handle trade shocks and changes in the global trade environment. The concentration of market power among a few dominant agents highlights the need for policies that promote competition and prevent monopolistic practices.

Chapter 2

The matching and sorting between traders and agents

Abstract

More than 85% of UK trade is facilitated through specialized agents who are experts in logistics and dealing with customs controls. However, the nature of the engagement with agents and why remains largely unknown. Using comprehensive UK Customs data from HM Customs and Revenue, we examine the factors influencing firms' decisions to employ agents and provide novel insights into trader-agent matching mechanisms and the evolving nature of these relationships. In addition, we investigate how Brexit-induced uncertainty has shaped the use of agents. Our analysis reveals a highly skewed distribution, where the median relationship value is 30 times higher than the median. Firm size emerges as a key determinant of agent utilization: a 1% increase in firm size correlates with a 0.21% increase in the number of agents and an almost 1% increase in the average relationship value. Relationships are dynamic. Nearly 75% of our sampled relationships dissolve within three years, with younger and lower-value relationships being the most vulnerable. A 1% increase in relationship value and experience (measured by historical transactions) reduces the likelihood of dissolution by 3% and 10%, respectively. Furthermore, we find that firms respond to Brexit-induced uncertainty by engaging with a greater number of agents and larger agents. Understanding

the trader-agent relationship can help policymakers design trade policy, support small and medium enterprises, and develop strategies to foster a more inclusive and resilient global trade landscape.

2.1 Introduction

In recent years, the scale and significance of administrative trade barriers have gained considerable attention, particularly in the context of Brexit. These developments underscore the critical importance of timely and cost-effective goods movement as a key determinant of success for exporters. The expansion of international trade has given rise to complex networks that span multiple jurisdictions, connecting customs authorities and economic entities worldwide (Hummels and Schaur, 2013; Carballo et al., 2018). However, this growing complexity has led to higher administrative costs, increased security risks, and more frequent delays in cross-border trade (Hummels and Schaur, 2013). To address these challenges, firms have increasingly relied on specialized agents, mostly third-party logistics (3PL) providers and freight forwarding firms, to manage border-related tasks. In the UK, more than 85% of exports to non-EU countries are facilitated by such agents. Despite their widespread use, the nature of the interaction between firms and these agents has remained largely underexplored in the existing literature.

While much of the literature on trade relationships has concentrated on the cross-border interactions between exporters and importers, as highlighted by Benguria (2021) and Bernard, Bøler and Dhingra (2018), the relationships between traders and agents have been largely overlooked. The trader-agent relationships, though less examined, represent a specialized form of buyer-seller interaction, where firms outsource logistics and customs services. Given the critical role that agents play in facilitating the movement of goods across borders, this gap in the literature is notable. The significant involvement of intermediaries in ensuring the smooth transit of goods underscores the need for a deeper understanding of these domestic interactions, particularly as they contribute to the overall efficiency of international trade.

Building on this literature gap, this is the first paper to examine the trader-agent relationship at a granular level. This paper focuses on addressing two key sets of research questions. The first research question is to understand the nature of the connections between firms and agents. Specifically, we seek to identify the factors that influence a firm's decision to use an agent. For example, do larger firms tend to engage more agents and send a higher volume of goods (in terms of trade value) through these entities? Furthermore, we explore the concept of assortativity within these relationships. In other words, we are interested in whether well-connected firms are more likely to work exclusively with well-connected agents? The second research question investigates the matching dynamics between firms and agents, focusing on the temporal and geographic dimensions of these relationships. We examine how relationships evolve over time, considering whether certain partnerships are more prone to dissolution. In addition, we analyze whether the use of agents exhibits features akin to gravity models in trade, where the likelihood of engaging a specific type of agent depends on geographic proximity, trade volume and other geopolitical factors. Building upon the above two sets of research questions, we extend our inquiry to examine how uncertainty impacts the use of agents, with a particular focus on the Brexit Referendum in 2016 and its influence on the trader-agent relationship.

We focus on UK exports to non-EU countries between 2009 and 2019 and use the detailed customs data provided by His Majesty's Revenue and Customs. We start our analysis by documenting the key features of the trader-agent relationships. We find that the relationship distributions in terms of value are highly-skewed, with a small number of large firms and dominant agents accounting for a significant portion of trade. In 2014, for example, the mean relationship value is nearly 30 times the median, highlighting the prevalence of high-value relationships.[1] Furthermore, we observe that while a few (large) firms use multiple agents, most firms maintain limited connections. We observe a negative degree assortativity between traders and agents, suggesting that large exporters tend to work with both well-connected and less-connected agents. Our analysis of matching patterns reinforces the previous finding that large, well-connected exporters and agents dominate UK trade. Firms with multiple agents account for nearly 90% of trader-agent relationships (in terms of counts) and 96% of the agent-handled exports. Larger exporters are more likely to employ multiple agents, with a strong positive correlation between firm size and the number of agents hired. Furthermore, trade relationships are highly concentrated, with the largest exporters and agents managing the bulk of trade flows, as confirmed by both the Sankey diagram and heat map. Furthermore, the relationships are surprisingly short-lived, with a substantial turnover of agents over time. Firms tend to drop younger and lower-value relationships while retaining those with higher trade values and deeper cooperation. Lastly, we explore the role of gravity factors, showing that larger agents typically handle exports to more remote destinations, while smaller agents serve closer markets. Cultural similarities also influence the use of agents, with more agents and higher trade volumes observed in markets with shared cultural ties.

Our research is related to at least three strands of literature. Firstly, the importance of relationships has been well recognized (e.g. Macchiavello and Morjaria, 2015; Benguria, 2021; Bernard, Bøler and Dhingra, 2018). The trader-agent relationships, though in the domestic territory, can be deemed as a special seller-buyer relationship where firms buy logistics and customs services. The second one is related to the prominence of intermediaries. The role of intermediaries, mostly whole-

[1] The relationship value is calculated as the annual export value going through a specific trader-agent combination.

salers and retailers, has been well documented in previous studies (Ahn et al., 2011, Tang and Zhang, 2012; Akerman, 2018; Boehm et al., 2023). Our study complements the existing literature by focusing on specialized agents, which handle border-related tasks on behalf of traders. The third strand relates to the emerging literature of supply chain. Most of the current research qualitatively evaluates the roles played by intermediaries along the supply chain (e.g., Utar, 2017; Fung et al., 2007; Cole and Aitken, 2020). Our work complements the existing literature by focusing on agents, which are widely used for customs procedures and logistics purposes, and we investigate their relationships with their clients, the traders. While the utilization of such agents may involve certain similar cost considerations to the selection of intermediaries, it's crucial to emphasize that various other factors can vary. Our data analysis has revealed that firms may employ different agents for various products and even for different port locations.

Our research also has significant policy implications. First, understanding the circumstances under which agents are engaged is vital in recognize the trade barriers encountered by exporters. For example, if firms are more inclined to utilize agents for specific products and destinations, further investigation is warranted to pinpoint potential trade barriers. Second, our study contributes to understanding how agents assist firms in thriving within a competitive market, thus informing the design of future policies, particularly for small and medium-sized enterprises. Our findings will provide insights into devising remedies for trade disruptions during periods of tumultuous trade shocks.

The remainder of the paper is structured as follows: Section 2.2 introduces the data source. In Section 2.3, we examine the key characteristics of trader-agent relationships, while Section 2.4 focuses on the dynamics of these relationships.

2.2 Data

This study utilizes a unique dataset extracted from UK Customs data provided by His Majesty's Revenue and Customs (HMRC), a non-ministerial department of the UK Government responsible for tax collection, state support payments, and the compilation of trade statistics. The data offers a detailed view of UK trade. We specifically focus on transactions related to non-EU exports between 2009 and 2019. This time frame allows for the exclusion of the 2008 Financial Crisis and the disruptions caused by the COVID-19 pandemic in 2020, ensuring the analysis captures stable periods of trade activity.

For each transaction, the dataset includes several key variables: a unique trader identifier, the country of destination, the transaction date, the five-digit Standard International Trade Classification (SITC) code, the four-digit Harmonized System (HS) code, and the ten-digit Comcode product code, which corresponds to the eight-digit HS code. Additionally, the data contains the transaction's value (in sterling), mass (in kilograms), and, most importantly, an agent identifier. The inclusion of both trader and agent identifiers enables us to precisely identify trader-agent relationships and track their development through our sample period.

The focus on non-EU trade is critical for our study, as prior to Brexit, EU trade data is collected on a voluntary basis rather than through compulsory declaration, which makes non-EU trade data more reliable and comprehensive for this analysis. Non-EU trade represents approximately 50% of total UK trade during the study period, making it a significant portion of the dataset.

This dataset offers several distinct advantages over previous studies, particularly those relying on surveys and interviews. First, customs data provides an objective and comprehensive view of trade activities, avoiding the self-reporting biases and non-response issues often encountered in surveys. For example, this dataset allows for a more accurate assessment of the trader-agent relationship features such as the relationship value and length. Furthermore, the ability to track the emergence, exit, and development of trader-agent relationships over time provides a dynamic view of this specific type of firm-to-firm connections.

2.3 Initial observations

We start by documenting the basic and static trader-agent relationship features. We first describe the connections between traders and agents, answering questions such as whether an exporter has multiple agents and how much each relationship is worth. We then investigate the assortativity patterns between traders and agents. Specifically, we try to confirm whether well-connected traders will exclusively use well-connected agents. In the final part of this section, we calculate the relationship length to inform later empirical analysis.

2.3.1 Connections

First, the characteristics of trader-agent relationships in UK exports are significantly shaped by large and dominant firms and agents. For example, in 2014, there are 314,081 active trader-agent relationships in UK exports to non-EU countries, involving 73,911 exporters and 1,728 agents. As demonstrated in Table 2.1, the distribution of relationship values is notably skewed, with the mean relationship value (£363.89k) being nearly 30 times larger than the median (£12.96k). This indicates the presence of a few high-value relationships that dominate the distribution. A similar pattern emerges in the distributions of exporters per agent and agents per exporter. On average, exporters engage with approximately four agents, while the median exporter works with only two. The mean agent, however, handles 184 exporters, which is almost six times higher than the median value of 24.

Table 2.1: Summary statistics: All and top 5 destinations

Variables	(1) *All*	(2) *US*	(3) *China*	(4) *UAE*	(5) *HK*	(6) *Singapore*
Total value (in billion GBP)	114.30	32.53	7.71	4.99	4.11	3.39
# Exporters	73,911	32,472	10,077	13,819	11,696	10,257
# Agents	1,728	1,054	848	942	808	800
# Relationships	314,081	66,419	20,991	29,436	20,352	19,464
Mean value per relationship (£'000s)	363.89	489.81	367.32	169.56	202.02	174.08
Median value per relationship (£'000s)	12.96	12.52	14.25	8.91	8.83	8.78
Mean exporter per agent	184	63.02	23.75	31.25	25.19	24.33
Median exporter per agent	24	7	4	4	4	3
Mean agent per exporter	4.13	2.05	2.08	2.13	1.74	1.90
Median agent per exporter	2	1	1	1	1	1

Note: We include UK exports to non-EU countries in 2014 to show the distribution features. Data from other years have produced very similar results.

These pronounced discrepancies underscore the role of a small number of large trading firms and dominant agents in shaping the market structure. The prominence of large firms in international trade is well-recognised in the literature (e.g. Bernard, Moxnes and Ulltveit-Moe, 2018; Bernard, Jensen, Redding and Schott, 2018; Mayer and Ottaviano, 2008). The findings presented here reinforce this perspective and extend it by emphasizing the pivotal role played by the logistics sector, particularly through the influence of large agents in facilitating trade relationships.

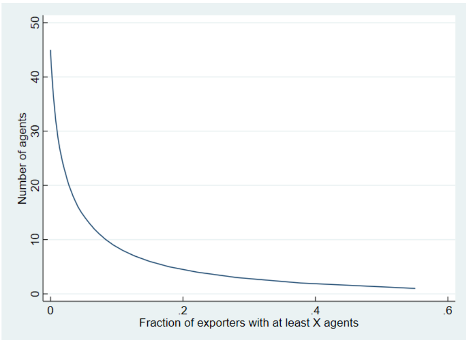
Next, we examine the role played by different destination markets, expecting that trader-agent relationships may vary across these markets. Columns (2) through (6) in Table 2.1 present key relationship features for the top five non-EU destinations. These columns include data on total export value, as well as the number of exporters, agents, and trader-agent relationships for each destination. The US stands out as the largest non-EU destination for UK exports, accounting for nearly 30% of the total export value and 20% of the total number of trader-agent relationships. Nearly half of UK exporters list the US among their export destinations. In contrast, China, the second-largest destination, attracts only 10,077 UK exporters, which is approximately one-third of the number of exporters to the US.

However, the number of agents serving each market does not fluctuate as dramatically as the number of exporters. For example, while exports to China are only a quarter of those to the US, the number of agents serving China is only marginally lower. Interestingly, larger markets tend to not only attract more relationships but also experience higher values per relationship. For example, the average value per relationship in the UAE is approximately one-third of that in the US and half of that in China, suggesting that relationships in larger markets, like the US and China, tend to be more valuable.

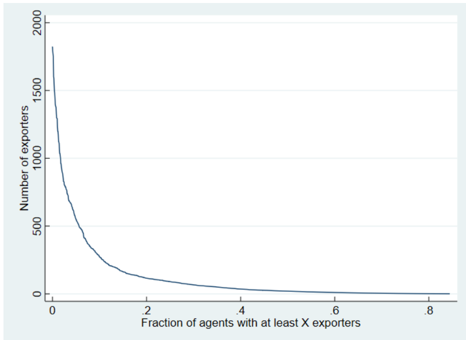
In terms of firm-agent connections, the US exhibits the highest ratios of exporters per agent and agents per exporter, indicating a dense network of well-connected firms exporting to the US In contrast, the other four destinations do not display such pronounced differences. Notably, the exporter-to-agent ratio is significantly higher when considering the overall sample. This finding reaffirms the presence of a few well-connected agents who manage a disproportionately large number of clients, particularly in major export markets.

To further examine the distributional characteristics of trader-agent relationships, we explore the number of exporters per agent and agents per exporter, as depicted in Figure 2.1. These figures illustrate the log-distributions of these relationships. Specifically, the plot 2.1a shows the number of exporters per agent plotted against the cumulative fraction of UK exporters with at least X agents, while another plot 2.1b shows the number of agents per exporter. In both figures, the distributions closely follow a power-law pattern, where a long tail is observed on the right-hand side, indicating the majority of agents or exporters with only a few connections. On the right-hand side, we observe a small number of agents or exporters with a disproportionately large number of connections.

Figure 2.1: Relationship distribution: Firm and agent



(a) Fraction: agent numbers



(b) Fraction: trader numbers

Note: We include UK exports to non-EU countries in 2014. Data from other years have produced very similar results.

These distributions highlight the highly concentrated nature of relationships within the trader-agent network. The findings suggest that while a small number of exporters maintain relationships with a large number of agents, the vast majority of firms rely on only one or two agents in a given year. A similar pattern is evident on the agent side, where a few dominant agents serve a large number of clients, while the majority of agents maintain relationships with only a limited number of exporters.

2.3.2 Assortativity

In this section, we begin by presenting key features of the agent market structure and then examine the assortativity patterns between exporters and agents. The results from Table 2.1 and Figure 2.1 highlight the presence of large agents that serve a substantial number of exporters, prompting a closer examination of this dominance.

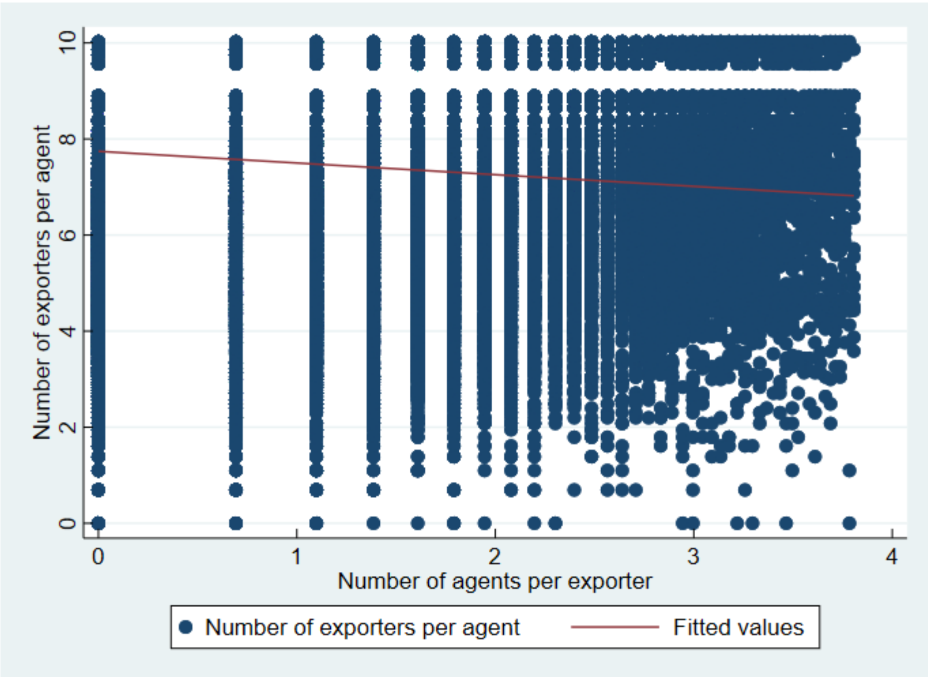
To describe the relationship between exporters and agents, we borrow the concept of assortativity from social network theory (Bernard, Bøler and Dhingra, 2018). In social networks, individuals with a high number of connections are more likely to connect with others who are similarly well-connected, exhibiting positive assortativity. However, research on exporter-importer relationships has often found evidence of negative assortativity. This means that exporters with many connections tend to be linked to importers with fewer connections, and vice versa (Bernard, Bøler and Dhingra, 2018; Bernard, Moxnes and Ulltveit-Moe, 2018).

To investigate this pattern, we analyze a sample of 73,557 relationships from 2014, where each relationship represents an exporter paired with its most dominant agent (in terms of trade value).[2] Figure 2.2 plots the logged number of agents per UK exporter on the x-axis and the logged number of exporters per agent on the y-axis. The fitted line suggests a negative degree assortativity, indicating that well-connected exporters are likely to use less-connected agents. It is important to note, however, that this does not imply that well-connected exporters exclusively use less-connected agents. Rather, large exporters engage with agents across a broad spectrum, ranging from small to large, while smaller exporters tend to rely on more well-connected agents. Similar findings of negative assortativity between buyers and sellers are well documented: for example, Bernard, Moxnes and Ulltveit-Moe (2018) in their study of Norwegian export data, Bernard, Bøler and Dhingra (2018) for Colombian data, and Bernard et al. (2019) using Japanese data. It is suggested that small firms are less likely to match profitably with other small firms, whereas large firms can engage with partners

[2]For data quality purposes, exporters with more than 45 agents are excluded, which explains the vertical boundary on the right side of the graph.

of all sizes. Another possible explanation is that bigger firms are able to sample more times and have higher probability of matching with a smaller partner (Bernard and Zi, 2022). However, considerable dispersion exists across observations, and our results should be interpreted as indicative.

Figure 2.2: Assortativity between exporters and agents



Note: We include UK exports to non-EU countries in 2014. Data from other years have produced very similar results. The axes are in logs. A relationship represents an exporter and its dominant agent. There are 73,557 relationships in the figure. The vertical right edge is due to data censoring and does not affect our conclusion.

2.3.3 Relationship length

To capture the dynamics of the trader-agent relationship, we first assess the duration for which firms remain active in the sample, ensuring the accurate measurement of the length of these relationships. As shown in Table 2.2, exporters are present in the sample for an average of 8.79 years out of a possible 12 years, with over half of them maintaining consistent activity throughout the period.

According to Table 2.2 nearly half of the trader-agent combinations exist for only one year. Only 1% of the relationships last for 12 years. To avoid biases brought by the exits of firms, we look at firms that export in at least six years, and the same pattern holds. Furthermore, we develop a measurement for relationship longevity by dividing the active relationship length (i.e. how long this specific relationship lasts) by the number of a firm's active years. We find that, on average, a relationship exists for around 30% of the firm's active time. For example, if a firm have exported for ten years, then this specific agent has been involved for three years. Over half of the trader-agent relationships last less than half of the firm's active time.

Table 2.2: How long can a trader-agent relationship last

	Mean	sd	p25	p50	p75
Number of years a firm exports	8.79	3.83	6	11	12
Number of years an agent is used	2.31	2.26	1	1	3

Note: We include all relationships appearing between 2009 and 2019.

2.4 Matching

2.4.1 Matching patterns

The previous analysis highlights that most UK exporters are associated with only a few agents, while a smaller number of exporters are connected to many agents. To further explore these patterns, we categorize the relationships and trade values based on the number of agents per firm. In Table 2.3, we classify exporters and agents into two groups: those with a single partner and those with multiple partners.

Table 2.3 underscores the critical role that large and well-connected firms play in driving international trade flows. Exporters with more than one agent (i.e., many-

1 and many-many) dominate the trader-agent landscape, accounting for the overwhelming majority of UK exports, contributing to 95.98% of the total export value. Notably, the many-many category, where both exporters and agents have multiple partners—accounts for 95.15% of total UK exports. This indicates that large, highly interconnected exporters and agents play a dominant role in facilitating trade.

Table 2.3: Match types

Trader-agent	*2009*		*2014*		*2019*	
	Count	*Value*	*Count*	*Value*	*Count*	*Value*
1-1	20	0.01	34	0.03	30	0.07
1-many	33,525	3.89	32,954	3.99	38,566	8.41
many-1	195	0.57	231	0.83	268	0.58
many-many	271,819	95.53	280,862	95.15	277,890	90.94
Total	305,559	100%	314,081	100%	316,754	100%

Note: We have selected UK exports to non-EU countries in 2009, 2014, and 2019 to show the changes in the match types. Data from other years have produced very similar results.

The relationship between firm size and agent use is further illustrated in Figure 2.3. The vertical axis represents the number of agents employed by an exporter, while the horizontal axis shows the logged total exports of each firm. The data include 70,171 firms exporting to non-EU destinations in 2014.[3] The fitted line in Figure 2.4 demonstrates a strong positive relationship between the number of agents and total firm exports. Larger exporters are more likely to engage multiple agents, reflecting their ability to distribute their export volume across a wider network of intermediaries. The dense clustering along the $y = 1$ line highlights the prevalence of 1-many relationships, where one agent serves multiple exporters, which is in line with the pattern observed in Table 2.3.

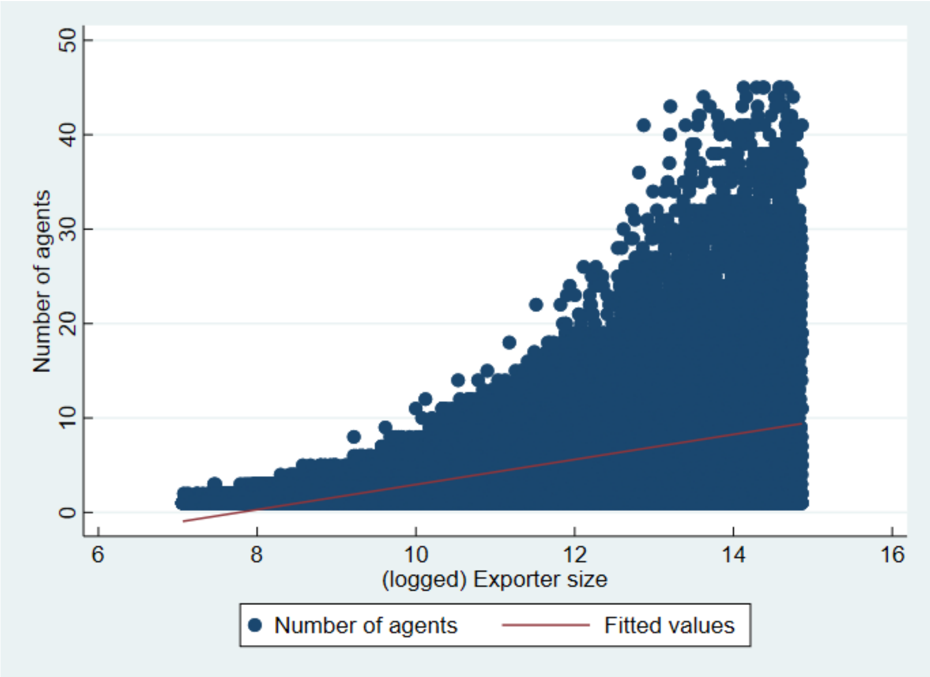
In Figure 2.4, we investigate whether larger exporters tend to use agents more

[3]To protect disclosure, firms in the top and bottom 5% of size distribution and those with more than 45 agents are excluded. These modifications do not alter the conclusions drawn from the analysis, although they explain the vertical right boundary in Figure 2.3.

intensively. The y-axis represents the average per-agent export value, while the x-axis segments firms into quartiles based on their size. The quartiles are arranged from 0-25% (smallest firms) to 75-100% (largest firms). The box plot clearly shows that as firm size increases, the average value of exports managed by each of its agents rises significantly. Firms in the top quartile (75-100%) exhibit a median relationship value well above the other groups. This result indicates that larger firms not only tend to use more agents, as we demonstrated in previous sections, but also ship exports of higher value through these agents. The spread of the data in the upper quartiles further suggests that some large firms are heavily reliant on a small number of highly valuable agent relationships, while others maintain a more diversified agent portfolio.

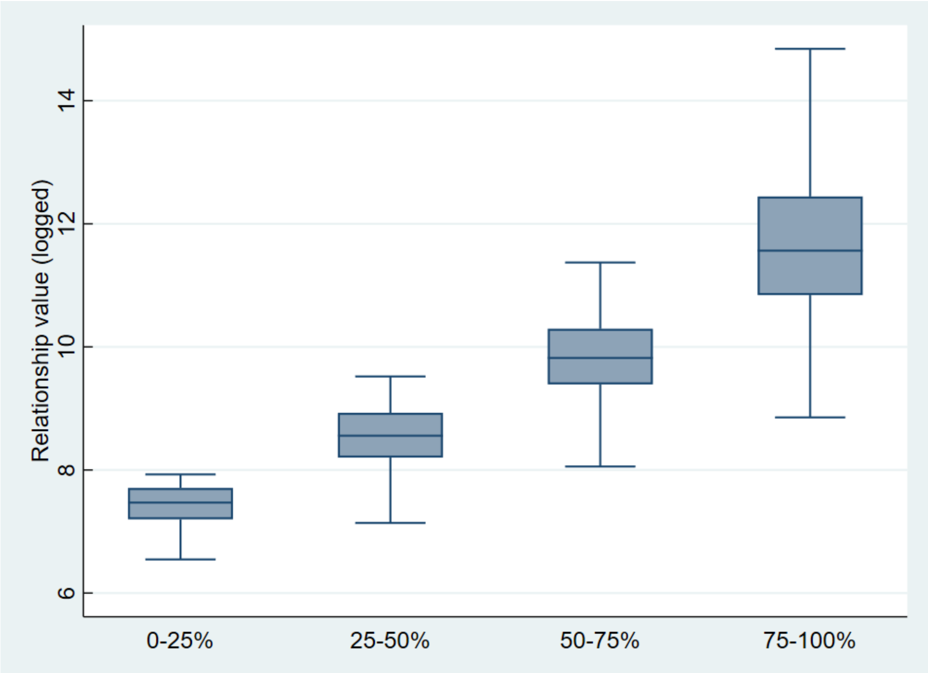
This finding complements the earlier analysis, where we observed that larger exporters are connected to a higher number of agents. As exporters increase in size, their export volumes rise, and so does the intensity of their agent relationships. This suggests that larger firms may achieve economies of scale through their use of agents, managing more extensive and valuable transactions per agent (Murphy et al., 1992). Additionally, the dense concentration of smaller firms in the lower quartiles supports the notion of smaller firms operating with fewer, less intensive agent relationships, often limiting the scale of their agent-mediated exports.

Figure 2.3: Log exports and the number of agents



Note: We include firms exporting to non-EU destinations in 2014. Data of other years yield very similar patterns. There are 70,171 firms included in the figure. The vertical right edge is due to data censoring and does not affect our conclusion.

Figure 2.4: Log exports and the relationship value



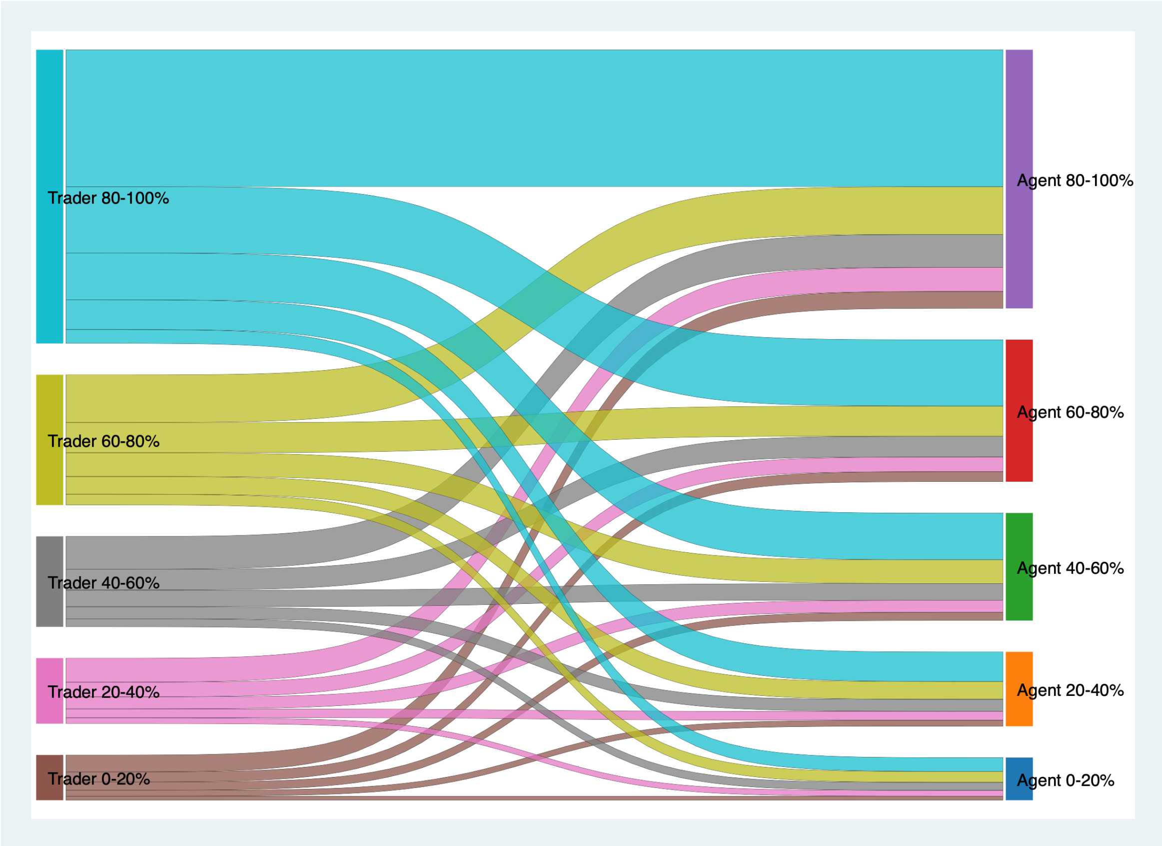
Note: We include firms exporting to non-EU destinations in 2014. Data of other years yield very similar patterns. The number of observations (that is, individual firm) in each group is 13,044, 16,268, 15,183, and 14,338 respectively. We remove outliers, and this should not change our results.

To further illustrate the trade dynamics between exporters and agents, we present a Sankey diagram in Figure 2.5. In this diagram, both exporters and agents are divided into five groups based on their total trade value, with each band representing the flow of trade between these groups. The size of each band corresponds to the volume of trade, and both the entity sizes and trade flows are presented on a logarithmic scale. The diagram reveals that while exporters distribute their trade across all agent groups, a strong concentration of trade is observed among large exporters and agents. The largest share of trade originates from exporters in the top 80-100% range, with a substantial portion flowing to agents in the same 80-100% tier. In contrast, traders in the lower quartiles (0-20% and 20-40%) tend to distribute their trade more evenly across all agent groups, with no single group of agents receiving a dominant share of their trade flows. The Sankey diagram also offers insight into the market structure for agents. Although the top 20% of agents receive the largest share of trade, agents in the middle ranges (60-80% and 40-60%) also handle a substantial amount of trade, albeit less than the top-tier agents. This distribution highlights the role of mid-sized agents in facilitating a notable portion of trade, despite the dominance of the largest players.

The heat map in Figure 2.6 complements Figure 2.5 by proving a more granular view of the trade values between different sizes of traders and agents. The value in each cell represents the mean trade value for the corresponding pair of trader size (on the x axis) and agent size (on the y axis). A clear pattern emerges from this visualization: larger traders (towards the right of the x-axis) tend to engage with larger agents (towards the top of the y-axis). The highest mean trade values are concentrated in the bottom-right corner, specifically in cell (10,10), which reflects the relationships between the largest traders and agents. This reinforces the notion that the most significant trade volumes are concentrated between the largest participants on both sides of the market.

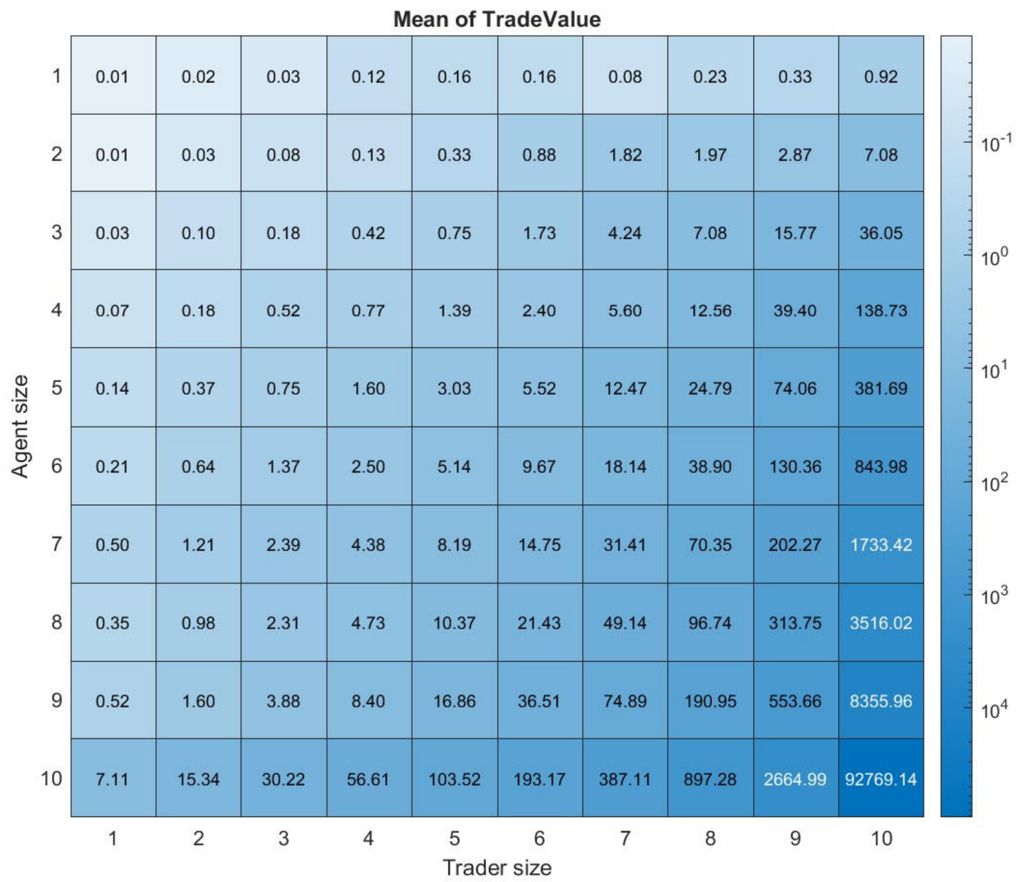
Both the Sankey diagram and the heat map underscore the dominance of high-volume trading relationships between the largest players in the market. While mid-sized agents and traders contribute meaningfully to trade flows, the largest entities drive the majority of the total trade value, consolidating their influence within the market.

Figure 2.5: Sankey diagram: Trade flows between exporters and agents



Note: We include UK exports to non-EU countries in 2014. Data from other years have produced very similar results.

Figure 2.6: Heat map: Trade flows between exporters and agents



Note: We include UK exports to non-EU countries in 2014 to show the assortativity. Data from other years have produced very similar results. Exporters and agents are categorized into ten groups based on their total export value. The trade value are in million GBP. Each cell represents the (logged) mean trade value for the corresponding pair of trader size (on the x-axis) and agent size (on the y-axis).

Empirical confirmation

Building on the preceding discussion on the relationship between firm size and the use of agents, we now turn to empirically confirm these findings. For this purpose, we utilize all the active trader-agent relationships between 2009 and 2019. As observed in Tables 2.1 and 2.3, firms frequently work with multiple agents simultaneously. However, for estimation purposes, we focus on the relationships with the dominant agent, defined as the agent handling the largest share of a firm's export. This allows us to more accurately capture the core dynamics between firm size and agent usage. We estimate the following equation at relationship level ia:

$$y_{iat} = \alpha_0 + \alpha_1 FirmSize_{it} + \delta_t + \delta_{ia} + \epsilon_{iat} \tag{2.1}$$

where i, a, and t stand for firm, agent, and year respectively. y_{iat} is a generalized dependent variable: (i) $NumAgent_{it}$ is the logged number of agents that a firm engages with at time t; (ii) $RValue_{iat}$ is the logged average relationship value, reflecting the average export value managed by a firm's agents at time t; (iii) $AgentSize_{iat}$ represents the logged average size of agents, which is calculated by subtracting the actual trade value between firm i and agent a from the agent's total revenue, following the method outlined by Benguria (2021). Firm and agent size are proxied by their logged revenue, given the absence of balance sheet data.[4] Time fixed effects δ_t and relationship-level fixed effects δ_{ia} are also included to control for potential unobserved heterogeneity.

Table 2.4 presents the results of our empirical analysis, which confirms several key patterns observed earlier. Column (1) supports the finding from Figure 2.3, showing that a 1% increase in firm size leads to a 0.21% increase in the number of agents that a firm engages with in a given year. While the effect is statistically significant, the magnitude is relatively small, indicating that only the largest firms exhibit a noticeable increase in the number of agents they use. This is again in line with the finding of Figure 2.1a that only a handful of firms have a large number of agents. In Column

[4]The use of export values as a proxy for firm size is well-documented in the literature (e.g. Ahn et al., 2011; Fontagné et al., 2015).

Table 2.4: Firm size and the use of agents

	Dominant relationships			All relationships		
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	$NumAgent_{it}$	$RValue_{iat}$	$AgentSize_{iat}$	$NumAgent_{it}$	$RValue_{iat}$	$AgentSize_{iat}$
$FirmSize_{it}$	0.207***	0.960***	0.012***	0.242***	0.526***	0.002***
	(0.0004)	(0.0004)	(0.0007)	(0.0002)	(0.0003)	(0.0010)
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm-level fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm-agent fixed effects	No	Yes	Yes	No	Yes	Yes
Observations	902,610	902,610	902,610	3,179,325	3,179,325	3,179,325
R^2	0.840	0.936	0.974	0.945	0.707	0.973

Note: We include the dominant relationships between 2009 and 2019. Data of any single year yield very similar results. ***, **, and * denote 0.1%, 1% and 5% significance level respectively.

(2), we observe that the relationship value increases proportionally with firm size. Specifically, a 1% increase in firm size translates almost fully into a corresponding increase in the relationship value. This is potentially due to that most firms have only one or a limited number of agents as suggested in Table 2.1, and since we are proxying sizes using trade value, any growth in their size is directly reflected in the value of their relationships. In Column (3), we find a positive but trivial relationship between traders' size and their agents' size. Specifically, 1% increase in firm size will lead to 0.01% increase in the average agent size. One possible explanation is that as firms grow bigger, they may export more intensively through the existing relationships, but at the same time they may be hiring more agents as suggested in Column (1).

In Columns (4)–(6), we expand the analysis by relaxing the constraint on dominant relationships and including all active trader-agent relationships as a robustness check. The results for $NumAgent_{it}$ and $AgentSize_{iat}$, as shown in Columns (4) and (6), remain consistent with the baseline findings in Columns (1) and (3). However, the results in Column (5) reveal an important difference when all active relationships are included. A 1% increase in firm size now leads to a 0.53% increase in the relationship value, compared to the near 1:1 relationship seen in the baseline analysis. This indicates that as firms grow, they tend to hire additional agents, which in turn dilutes the trade share of each individual agent. In other words, while larger firms do continue to strengthen their relationships with their existing agents, the distribution of their trade across a larger number of agents results in a less direct increase in the relationship value per agent.

The results presented in Table 2.4 provide valuable insights, but they should be interpreted as indicative. For example, it is possible that firms working with larger agents may experience productivity gains through knowledge transfer or learning, which could artificially bias the results toward stronger positive correlations. As such, these findings offer suggestive evidence of the relationship between firm size and agent use, but they should be approached with caution, recognizing the potential for confounding factors.

2.4.2 Relationship dynamics

As evidenced in Table 2.2, the majority of trader-agent relationships are relatively short-lived, with nearly 75% of these relationships lasting fewer than three years. Despite this transience, firms demonstrate active management of their agent portfolios. On average, firms in our sample maintain export activities for nine years, collaborating with approximately two agents per year. In this section, we provide a detailed analysis of the evolving dynamics in firms' use of agents over time.

Table 2.5 presents the dynamics of firms' decisions to add or drop agents over various time intervals. For each period, we report the number of firms involved in these changes and the corresponding share of trade value. The trade share for agents dropped (*Drop*) is calculated using the trade value in 2014, while that of agents added (*Add*) is calculated using the trade values in 2015, 2017, and 2019. To minimize potential biases from firms exiting the market, we restrict the sample to firms that continuously exported between 2009 and 2019, designating 2014 as t_0, and we include all matching types.

At t_0, 73,439 exporters maintained a total of 232,983 active relationships with agents. Within just one year, nearly one-third of these firms terminated approximately 100,000 relationships. Although this represents over 40% of the total number of relationships, these dropped relationships accounted for only 7.36% of the 2014 trade value, suggesting that smaller-scale relationships are more likely to be discontinued.

As the observation period extends, we see further changes in relationships. After three years, over half of the original relationships from 2014 had ended, representing around 20% of the trade value. By the five-year mark, approximately 70% of these relationships had dissolved, yet the trade value associated with them amounted to only 30%, indicating that larger, more valuable relationships tend to persist longer.

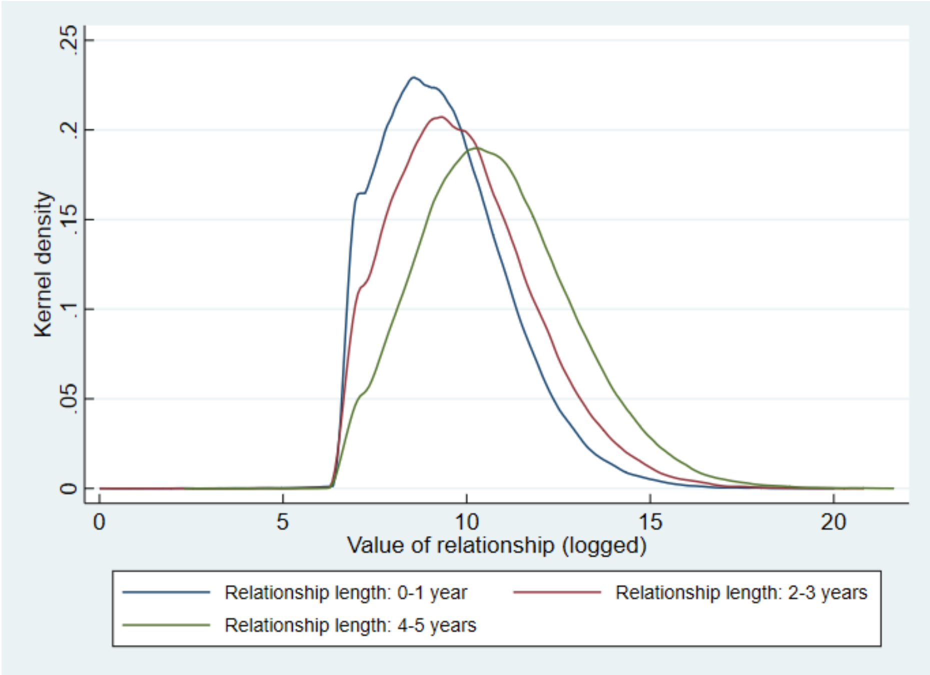
The pattern for adding new agents closely mirrors that of dropped relationships. For example, within one year, firms establish 98,470 new relationships, almost matching the 99,721 relationships that are dropped during the same period. The number of firms adding new agents (25,332) is also nearly identical to those that dropped agents (25,159), further underscoring the dynamic management of agent relationships over time.

Table 2.5: Relationship dynamics: Adding and dropping of agents

Period	*Die within 1 year*		*Die within 3 years*		*Die within 5 years*	
	Drop	*Add*	*Drop*	*Add*	*Drop*	*Add*
Number of relationships	99,721	98,470	132,409	134,860	156,604	153,442
Number of firms involved	25,159	25,332	27,478	27,684	29,904	29,500
Trade value share (%)	7.36	7.86	20.77	21.12	32.47	33.57

We include firms with positive exports in all years between 2009 and 2019. We set the year 2014 as t_0 and capture the dynamics of the relationships during 1-year, 3-year, and 5-year intervals.

Figure 2.7: Relationship value and relationship length



Note: We include firm-agent combinations with positive exports to non-EU destinations in 2014. Firms included have positive exports in all years between 2014 and 2019 so that relationships are not dropped due to firm exits. There are 70,171 firms included in the figure. The number of relationships in each curve is in Table 2.5. Data of other years yield very similar results.

Figure 2.7 further checks the relationship between relationship value and length. We group relationships according to their length: less than 1 year (included), less than 3 years (included), and less than 5 years (included). As seen in the figure, the average relationship value increases as the relationship lengthens, with the density curves shifting to the right as the relationship duration extends. This indicates that longer-lasting relationships tend to be associated with higher trade values.[5]

Empirical analysis

Building on the insights from Table 2.5 and Figure 2.7, we argue that firms are

[5]The relatively steep slope on the left-hand side of the figure reflects the substantial variation in relationship values. The average relationship value in 2014 was GBP 435,799, with a standard deviation exceeding 1.13×10^7.

more likely to drop relationships that are both younger and of lower trade value (i.e., "cheaper" relationships). To empirically validate this hypothesis, we analyze all active relationships between 2009 and 2019. Additionally, to avoid biases brought by firm exits, we include firms with active exports in all years.

To account for firms' prior experience with agents, we use data from the five years preceding t_0 (2009–2013). Although the duration of a relationship, defined as the number of years with positive exports, is the most intuitive measure of relationship length, this metric presents several limitations that could affect the robustness of our analysis. First, collinearity prevents us from controlling for time-fixed effects. Second, this measure fails to capture the intensity of the relationship, as it does not differentiate between relationships with frequent transactions and those with sporadic interactions. To address these concerns, we follow the approach of Macchiavello and Morjaria (2015) and use the number of previous transactions as a proxy for relationship length. This alternative measure better reflects the depth of collaboration, as the number of transactions is not necessarily linear with the duration of the relationship but effectively captures the degree of involvement. We hence estimate the below regression at relationship level:

$$Drop_{ia} = \beta_0 + \beta_1 RValue_{ia} + \beta_2 RLength_{ia} + \beta_3 FirmSize_i + \delta_a + \epsilon_{ia} \tag{2.2}$$

where the subscripts i and a stand for firm and agent respectively. is a binary indicator that takes the value of 1 if the firm-agent relationship ia is dropped. Our key explanatory variables are the logged export value of the relationship, $RValue_ia$, and the (logged) number of transactions between 2009 and 2013, $RLength_{ia}$.[6] We control for firm size $FirmSize_i$, which is the (logged) firm export value at t_0, and agent-level fixed effects δ_a.[7]

The results presented in Table 2.6 provide empirical evidence supporting the hypothesis that both the value and depth of a relationship significantly influence the likelihood of an agent being dropped. Over a one-year period, a 1% increase in the value of a relationship reduces the probability of termination by approximately 3%, while a 1% increase in the number of previous transactions decreases the probability of ending the relationship by over 10%. These findings suggest that both higher-value and deeper relationships are less likely to be dissolved in the short term. However, the impact of relationship value diminishes over time. For example, over three years, a 1% increase in relationship value decreases the likelihood of termination by 1.9%, and by only 1.2% over a five-year period. Despite this decline, the effect of relationship depth remains a significant factor, though it too shows a diminishing effect over time. This suggests that while relationship characteristics are important in the short term, other factors may become more influential in determining relationship longevity over longer periods. Firm size appears to play a relatively minor role in the decision to maintain or drop an agent. Its coefficient is small and does not substantially influence the likelihood of relationship termination across the different time frames considered. Additionally, to account for firm heterogeneity, we also replace $FirmSize_i$ with firm-level fixed effects δ_i, and the results are in Table A.1.

A potential concern with the baseline analysis is that some of the observed terminations might reflect temporary matches between traders and agents, as firms often

[6] We also replace $RLength_{ia}$ using the actual number of years a firm uses a specific agent. The results are consistent.

[7] Replace firm size with firm-level fixed effects does not significantly change our results.

Table 2.6: Dropping agents: Over 1, 3, and 5 years

	All relationships			Dominant relationships		
	(1)	(2)	(3)	(4)	(5)	(6)
$Drop_{ia}$	*Over 1 year*	*Over 3 years*	*Over 5 years*	*Over 1 year*	*Over 3 years*	*Over 5 years*
$RValue_{ia}$	-0.031^{***}	-0.019^{***}	-0.012^{***}	-0.359^{***}	-0.327^{***}	-0.228^{***}
	(0.0006)	(0.0006)	(0.0006)	(0.0108)	(0.0116)	(0.0109)
$RLength_{ia}$	-0.119^{***}	-0.106^{***}	-0.085^{***}	-0.0401^{***}	-0.049^{***}	-0.037^{***}
	(0.0008)	(0.0008)	(0.0008)	(0.0049)	(0.0053)	(0.0049)
$FirmSize_i$	0.010^{***}	0.001^{**}	-0.003^{***}	0.340^{***}	0.321^{***}	0.224^{***}
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0003)	(0.0004)
Agent-level fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	232,983	232,983	232,983	9,318	9,318	9,318
R^2	0.263	0.294	0.291	0.164	0.185	0.260

Note: The year 2014 is t_0. ***, **, and * denote 0.1%, 1% and 5% significance level respectively.

engage in active agent searches, as suggested by Table 2.2. Dominant agents, however, are likely to be treated more seriously by firms and retained for longer periods (Macchiavello and Morjaria, 2015). We hence narrow our sample to include only dominant relationships and present the corresponding findings in Columns (4)–(6) of Table 2.6. The results show that relationship value exerts a much stronger influence on the likelihood of relationship termination for dominant relationships. Specifically, a 1% increase in relationship value reduces the probability of termination over a one-year period by 35.9%, compared to the 3.1% reduction observed in Column (1). Similarly, the effect of previous cooperation is more pronounced in dominant relationships: a 1% increase in the number of prior transactions leads to a 4% decrease in the probability of termination. As with the baseline results, we observe a diminishing effect of both relationship value and length over longer periods, though the decline is milder. For example, over a five-year period, a 1% increase in relationship value still reduces the likelihood of termination by 22.8%, demonstrating that higher-value relationships are more resilient over time, even as the impact weakens. Additionally, in the case of dominant relationships, we also observe a significant impact of firm size on the likelihood of relationship termination. As shown in Column (4), a 1% increase in firm size leads to a 34% increase in the probability of relationship termination. This finding suggests that larger firms may have more resources and flexibility to explore new partnerships and revise their agent portfolios, even when dealing with high-value, dominant relationships.

2.4.3 Matching and gravity

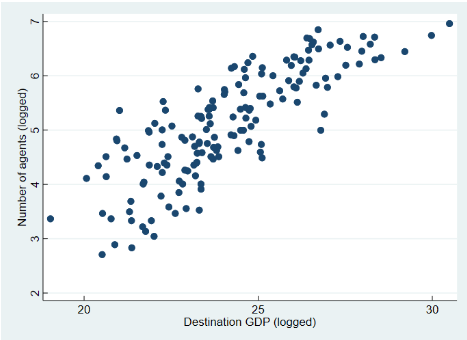
Table 2.1 highlights the connections between destination characteristics and the use of agents in international trade. For example, we observe that relationships exporting to larger markets tend to have higher values, with relationship values in countries such as the US and China significantly exceeding those of other destinations. However, the link between destination size and the number of agents is less clear. Aside from the US, the number of agents and relationships across other major destinations appears relatively similar. While the significance of distance and market size in shaping international trade flows is well-documented in the literature (Head and Mayer, 2014), the specific role of gravity factors in the use of agents remains largely unexplored. To address this gap, we first illustrate the gravity patterns influencing agent utilization and then proceed to empirically test these findings at both the country and firm level

In Figure 2.8, we examine how key gravity model features, particularly market size and distance, influence the utilization of agents, including the total number of agents, their average size, and the average number of agents per firm within a market. The data focus on UK exports to 145 non-EU destinations in 2014.[8] Market size is represented by the logged GDP of the destination countries along the x-axis in plots 2.8a-2.8c. The results show a generally positive relationship between market size and both the total number of agents and the average number of agents per firm. However, the average size of agents exhibits an inverse relationship with market size. This suggests that smaller agents are more likely to engage in larger markets, while larger agents appear indifferent, serving both large and small markets. In plots 2.8d-2.8f, we depict the relationship between market distance and agent use, where distance is plotted on the x-axis. No clear patterns emerge in these plots, indicating that distance

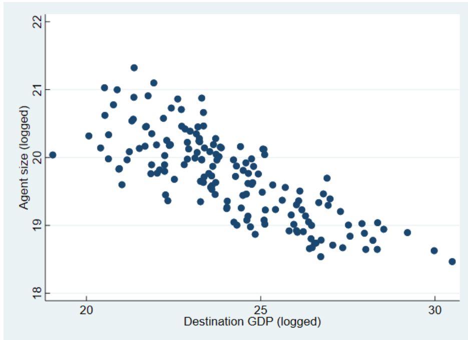
[8]Destinations with insufficient observations have been removed due to disclosure requirements. Despite this, over 90% of the sample remains intact.

does not appear to significantly affect the total number, average size, or number of agents per firm in a destination market.

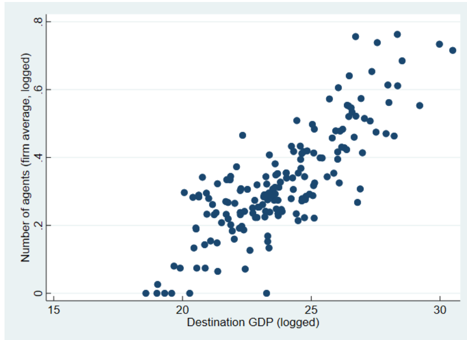
Figure 2.8: Gravity and the use of agents



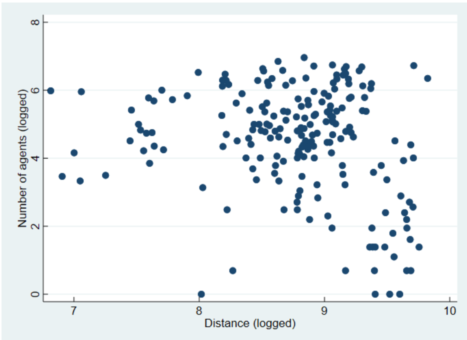
(a) Number of agents and market size



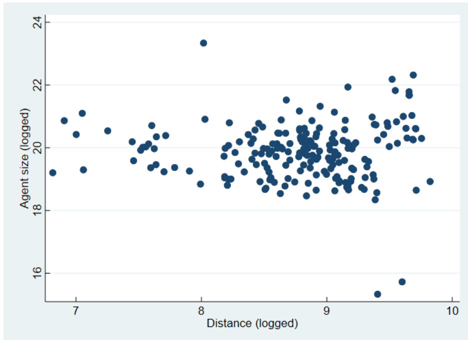
(b) Size of agents and market size



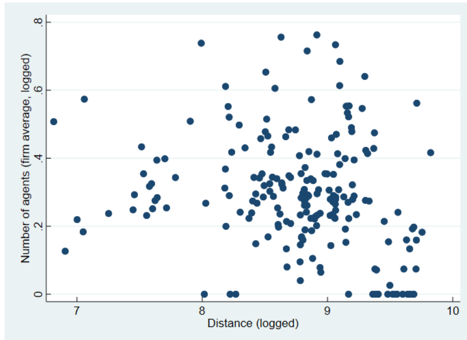
(c) Average number of agents per trader and market size



(d) Number of agents and distance



(e) Size of agents and distance



(f) Average number of agents per trader and distance

Note: We include UK exports to non-EU countries in 2014 in this figure. Data from other years have produced very similar results.

Empirical analysis

We further investigate how country-specific characteristics influence the use of agents. Specifically, we aim to determine whether larger agents predominantly manage exports to smaller and more distant markets, while a larger number of smaller agents operate in more accessible destinations. We estimate the following gravity model at both country and firm-country level using trade data in 2014 given by:

$$y_{ic} = \gamma_0 + \gamma_1 X_c + \delta_i + \epsilon_{ic} \tag{2.3}$$

where the subscripts i and c denote firm and country respectively. The generalized dependent variable y_{ic} is analogous to that in Specification 2.1: (i) $NumAgent_{ic}$ represents the (logged) number of agents a firm employs in country c; (ii) $RValue_{ic}$ denotes the relationship value, calculated as the (logged) average export value handled by firm i's all agents in country c; (iii) $AgentSize_{ic}$ refers to the (logged) average agent size firm i uses to export to country c. We control for firm-level fixed effects δ_i. The independent variables consist of a vector of country-specific gravity indicators X_c, which include geographical, macroeconomics, and cultural aspects.[9] At country level, we utilize aggregated dependent variables y_c: $AgentSize_c$ and $RValue_c$ represent the country-level averages while $NumAgent_c$ reflects the total number of agents serving a given market as the average number of agents employed by each firm is similar across destinations as shown in Table 2.1.

The country-level regression results are presented in Columns (1)-(3) of Table 2.7.

[9]These variables include market size (proxied by destination country GDP), population, GDP per capita, common language, and colonial ties. The data is sourced from the Dynamic Gravity Dataset (Version 2.1) by the United States International Trade Commission, available at `https://www.usitc.gov/data/gravity/dgd.htm`.

Table 2.7: Gravity and agents

	Country level			Firm-country level		
	(1) $NumAgent_c$	(2) $RValue_c$	(3) $AgentSize_c$	(4) $NumAgent_{ic}$	(5) $RValue_{ic}$	(6) $AgentSize_{ic}$
$Distance_c$	−0.027	−0.625***	0.074	−0.035***	−0.048	0.031
	(0.0148)	(0.1241)	(0.0552)	(0.0090)	(0.0308)	(0.0312)
$MarketSize_c$	0.336*	1.485	−1.404*	0.397	0.978	−0.934
	(0.1728)	(1.4475)	(0.6442)	(0.2132)	(0.5628)	(0.641)
$Population_c$	−0.284	−0.976	1.175	-0.346	−0.791	1.013
	(0.1730)	(1.4491)	(0.6449)	(0.2137)	(0.5630)	(0.6384)
$GDPpercap_c$	−0.285	−0.751	1.185	0.324	−0.727	1.176
	(0.1736)	(1.4540)	(0.6470)	(0.214)	(0.5645)	(0.6426)
$CommonLanguage_c$	0.022	−0.127	−0.271***	0.010	−0.055	−0.009
	(0.0176)	(0.1471)	(0.0643)	(0.0146)	(0.0349)	(0.0600)
$Colony_c$	0.048***	0.325*	−0.256***	0.166***	0.166***	0.103***
	(0.0172)	(0.1444)	(0.0643)	(0.0192)	(0.0517)	(0.0608)
Firm-level fixed effects	No	No	No	Yes	Yes	Yes
Observations	145	145	145	320,974	320,974	320,97
R^2	0.652	0.767	0.739	0.102	0.373	0.368

Note: Standard errors clustered at country level for firm-country level regressions. We include active relationships in 2014. Data of other years yield very similar results ***, **, and * denote 0.1%, 1% and 5% significance level respectively.

The findings indicate that larger markets are primarily served by a greater number of smaller agents. 1% increase in the market size leads to 0.34% increase in the total number of agents serving it. However, market size does not appear to significantly influence the average relationship value. Besides, neither population nor GDP per capita has a substantial impact on the use of agents across the examined destinations. Distance, on the other hand, exhibits a differentiated impact. A 1% increase in distance results in a significant reduction of 62.5% in the average relationship value, while having no statistically significant effect on the number of agents or their size. Cultural factors, however, play a notable role in shaping agent size. Specifically, countries that share a common language or have historical colonial ties with the UK are associated with smaller agents. In particular, speaking the same language reduces agent size by 31.13%, while colonial ties decrease agent size by 29.18%. This suggests that smaller agents are more likely to serve culturally similar markets, whereas culturally distant markets tend to rely on larger agents. However, the number of effective observations at country level is relatively small, and the country-level results should be interpreted suggestive evidence.

The firm-country level regression results, presented in Columns (4)-(6) provide insight into how distance and cultural factors affect the use of agents. Most gravity features exhibit little significance at firm-country level. Colonial ties exceptionally play a significant role in shaping the use of agents at the firm-country level. When exporting to a previous British colony, firms tend to use more and bigger agents and export more intensively through each agent.

In summary, our analysis highlights the significant role of gravity model factors, such as market size, distance, and cultural ties, in shaping the use of agents in international trade. Notably, the results demonstrate that larger markets attract a greater number of smaller agents, while culturally similar markets tend to engage smaller agents as well. Conversely, exports to culturally and geographically distant markets rely on larger agents, underscoring the complexity of managing trade relationships in such environments. While distance has a notable impact on the value of trade relationships, its effect on the number of agents or agent size is relatively minor, suggesting that firms primarily adjust relationship intensity rather than the scale of agents in response to geographical barriers. Market size remains a key determinant, not only influencing the number of agents and the relationship value but also shaping the overall size of agents firms employ. Cultural factors, particularly shared language and colonial history, play a distinct role, with opposite effects on relationship value and agent size, reflecting the nuanced ways in which historical and linguistic ties facilitate or complicate international trade. Through our empirical investigation, we bridge the gap in the literature on the use of agents, offering valuable insights into how firms strategically adjust their agent usage based on destination-specific characteristics. These findings contribute to a more comprehensive understanding of the intersection between gravity features and the intermediary structures firms employ in global markets.

2.5 Conclusion

This study has provided a detailed examination of the trader-agent relationship in the context of UK exports to non-EU countries. We first seek to understand the nature of connections between firms and agents, specifically the factors influencing a firm's decision to use an agent and whether well-connected firms tend to work exclusively with well-connected agents. We then further investigate the dynamics of these relationships over time and across destination.

The findings reveal a highly concentrated agent market, dominated by a few key players, but with significant fragmentation as smaller agents play a crucial role in supporting smaller exporters. Firm size is a major determinant in the decision to engage agents, with larger firms employing more agents and managing higher trade volumes. Interestingly, we observed negative assortativity in trader-agent relationships, where well-connected exporters collaborate with both large and small agents, reflecting the complexity and diversity of the network. In terms of relationship dynamics, firms frequently adjust their agent portfolios, with most relationships being short-lived. However, high-value relationships tend to persist, especially for larger firms, which benefit from longer, more valuable partnerships, underscoring the role of economies of scale in trade performance. The study also highlights the impact of Brexit-related uncertainty, with firms, especially smaller ones, turning to more established agents to navigate the complexities of post-Brexit trade, particularly in new or distant markets.

Our research has important policy implications. Understanding the matching patterns between traders and agents is crucial for identifying the trade barriers exporters face. Additionally, our study enhances the understanding of how agents help firms succeed in competitive markets, offering valuable insights for shaping future policies, particularly those aimed at supporting small and medium-sized enterprises. Finally, we demonstrate the link between trader-agent relationships and trade resilience, providing key insights that can guide strategies to mitigate trade disruptions during periods of significant economic shocks.

There are some limitations to this study, particularly the lack of balance sheet data, which prevents us from capturing a complete view of trader-agent relationships. Future research should explore whether firms continue to adjust their behavior following the formal implementation of Brexit and the introduction of the Trade and Cooperation Agreement (TCA). In addition, as exports to European countries now require compulsory customs reporting post-Brexit, future studies could utilize UK-EU trade data to provide a more precise assessment of Brexit's impact on trade dynamics.

Chapter 3

Breaking down barriers: The effectiveness of Mutual Recognition Agreements for trusted traders[1]

Abstract

The value of UK exports between trade partners that are subject to a Mutual Recognition Agreement (MRA) for trusted traders and are subject to reduced customs controls, is over eighty percent. However, little is known about the impact of MRAs as a form of trade policy. In this paper we examine the UK-US MRA and the most widely used trusted trader scheme, the Authorized Economic Operator (AEO) to better understand how MRAs and AEO schemes impact trade flows. Our analysis shows that the majority of firms are indirectly considered “safe traders" by using AEO certified agents and hence we extend the heterogeneous firm model à la Melitz (2003) by incorporating administrative costs and the role of agents. Our empirical results, using transaction-level UK customs data, confirm the predictions of the model and show that an MRA improves firms’ participation in exporting

[1]This chapter is based on joint work with Dr. Wanyu Chung, Prof. Robert Elliott, and Dr. Antonio Navas.

and increased the value of exports through the use of certified agents.

3.1 Introduction

The efficient transportation of goods is crucial for exporters to be successful but involves navigating an intricate web of diverse jurisdictions and customs bureaus with the associated administrative costs, security risks, and time delays. Customs authorities attempt to mitigate these challenges by designating certain firms as trusted traders, granting them benefits like simplified procedures, express processing, and reduced customs checks. The most widely-used trusted trader scheme, the Authorized Economic Operator (AEO) program, was developed in 2008 under the World Customs Organization's (WCO) SAFE Framework of Standards to Secure and Facilitate Global Trade (WCO SAFE Framework of Standards to Secure and Facilitate Global Trade, 2007). Up to 2016, nearly half of the UK exports (to non-EU countries) have been handled through the AEO scheme.

The aforementioned benefits extend beyond domestic borders when customs administrations agree to reciprocate privileges for each other's trusted traders by signing Mutual Recognition Agreements (MRAs). These agreements ensure that export declarations can also serve as import declarations, and that export controls are acknowledged by the importing administration (Aigner, 2010). Such alignment reduces the need for redundant controls, resulting in faster clearance of goods at borders and greater trade predictability. These improvements enhance the competitiveness of certified exporters (Carballo et al., 2016). The significance of MRAs is evident in trade patterns as over 80% of UK exports occur with countries holding MRAs with the UK.

The UK-US MRA and the focus of this paper was signed in 2012.[2]

The impact of MRAs extends far beyond mere trade facilitation. They catalyze trust within global supply chains by recognizing the AEO status of traders across jurisdictions, thereby transforming individual trust partnerships into expansive, interconnected networks. This enhanced trust mitigates security risks and promotes smoother trade flows. For instance, under the agreement between New Zealand's Secure Export Scheme and the US Customs-Trade Partnership Against Terrorism (C-TPAT), certified traders' goods are 3.5 times less likely to face delays at US ports (Widdowson, 2016). Furthermore, MRAs provide significant competitive advantages by granting AEOs access to global supply chains, a benefit particularly crucial for developing economies. Widdowson (2016), citing UNCTAD (2008), highlights how mutual recognition levels the playing field for traders from these regions, enabling them to participate in international trade on equal terms. Additionally, MRAs streamline verification processes, eliminating redundant inspections by different administrations (ICC, 2009), which reduces administrative burdens and enhances supply chain efficiency. They also empower customs authorities to manage risks beyond their borders through "pushing borders out," a strategy that relies on trusted foreign AEOs to ensure compliance with security standards before cargo enters the destination country (Altemoller, 2016). Moreover, MRAs enable the integration of advanced technologies like blockchain, which enhances data security and could potentially eliminate the need for import declarations, as observed by Bowering (2017). Despite these benefits, the broader effectiveness of MRAs, particularly their impact on bilateral trade and exports, remains underexplored.

The purpose of this paper is to theoretically and empirically evaluate the effec-

[2]The UK established an MRA with the EU under the EU–UK Trade and Cooperation Agreement (TCA) and inherits the EU MRAs with Switzerland (1st July 2009), Norway (1st July 2009), Japan (24th May 2011), the US (1st July 2012), and China (3rd November 2015). After Brexit, the UK has signed MRAs with Singapore (14th June 2022) and New Zealand (2nd July 2022).

tiveness of MRAs for trusted traders. More specifically, we first develop a theoretical framework that provides a number of testable hypotheses on the possible impact of MRAs for trusted traders on exports and second, we document changes in export patterns as a result of the signing of the 2012 UK-US MRA using data from the transaction-level UK export data. The UK-US MRA was originally part of the EU-US MRA, which was implemented from 1st July 2012. The UK currently operates under the AEO program which allows us to identify in our transaction data which goods were traded through trusted traders.[3]

The trade facilitation benefits entitled to AEO license holders, however, come at a high price. Though there is no fee for applying to HMRC for AEO accreditation [4], firms have to meet and maintain a high level of security and safety standards and are subject to exhaustive auditing process to prove their financial solvency, all of which incur extra costs. Some estimated costs of obtaining an AEO license range from 5,000 US dollars to more than one million US dollars (Carballo et al., 2016; Martincus, 2016). Moreover, the waiting can be overwhelming given the fact that application preparation and submission typically take between 3 to 12 months, followed by 120 days for customs to assess your submission, including site visits.[5]. While this may limit the number of firms that directly benefit from the AEO program and the subsequent MRAs, a closer examination of the data reveals that most firms are indirectly deemed as "trusted" when they use AEO certified agents.[6] À la Melitz (2003), our theoretical framework highlights a trade cost technology that allows us to incorporate the policy

[3]Before 1st January 2021, the UK operated under the EU AEO scheme. After leaving the EU, the UK operates started its own AEO program and mutually recognises the EU program under the EU-UK Trade and Cooperation Agreement (TCA).

[4]AEO: what is it and could your business benefit? All your questions answered here. Institute of Exports and International Trade, July 2020. Available on: `https://www.export.org.uk/news/320338/AEO--what-is-it-and-could-your-business-benefit`

[5]See footnote 4

[6]However, selection may exist as only certain agents can get accredited.

benefits of an MRA and a possibility for a firm to choose from direct exporting and indirect exporting through the use of an agent. These theoretical extensions provide a mechanism by which less efficient firms are able to access the benefits of an MRA through the use of AEO agents, even if they are not accredited by the AEO scheme themselves. Our theoretical framework predicts that an MRA should increase the probability of exporting to the new MRA trade partner as well as increasing the level of exports for a firm that uses an AEO agent compared to a firm that uses a non-AEO agent.

Empirically, we exploit information from the transaction level UK customs data provided by HM Revenue and Customs (HMRC) to verify our model predictions. The advantage of using UK customs data is that it is possible to link the activity of traders with trader-agent relationships (direct or indirect exporting and whether an agent is an AEO or not) at granular level and hence precisely capture the changes in trade patterns following the signing of an MRA. The customs data reveal several stylized facts about the UK-US MRA. Between 2011 and 2013, nearly 30% of UK non-EU exports were to the US, making it the primary export market for the UK.[7] Of the UK-US exports during this time, nearly 90% were handled by agents. We also observe that firms decide their exporting strategies at a very disaggregated level, that is, firms tend to stick with a single type of agent for a specific product, and firms seldom switch between different types of agents (for a given product).

To briefly summarise our results, we find evidence that signing an MRA for trusted traders improves trade in three ways. First, it encourages firms to export new products and export products in new industries. Second, it protects existing trade partnership by reducing firms' withdrawal from a given (product) market, and third, it increases the

[7] Author's calculation using HMRC data.

overall value of exports. In terms of magnitude, our estimates imply that, compared to a firm using a non-AEO agent, a firm exporting through an AEO agent benefits from a 22.80% increase in the probability of exporting a new product and a 5.50% reduced probability that a firm drops a product from its export bundle. The MRA also increased the export value (to the US) for incumbent firm-product combinations using AEO agents relative to those with non-AEO agents by around 9.70% between 2011 and 2013.

The study contributes to the literature in the following ways. First, there is limited research investigating the effectiveness of trade facilitation policies aiming at simplified customs procedures. Carballo et al. (2024) analyze the impact of a transit system upgrading, the adoption of TIM, aimed at improving border processing efficiency in developing countries. Using transaction-level export data from El Salvador alongside unique data identifying export flows processed through the upgraded system, they demonstrate that the system reduced regulatory border costs and led to an increase in exports. While the transit system analyzed by Carballo et al. (2024) primarily represents a form of inter-agency cooperation within and across countries, the AEO-MRA mechanism operates on a fundamentally different foundation. AEO-MRAs are built on public-private partnerships and trust cultivated along the entire supply chain (Campos et al., 2018). Moreover, the benefits of MRAs extend well beyond the streamlined customs procedures typical of transit systems. By reducing physical inspections, simplifying administrative processes, and enhancing security measures, MRAs create a more comprehensive framework for facilitating trade and building robust global supply chains.

In addition, multiple customs authorities have recognized their importance. For example, in 2019 the New Zealand Institute of Economic Research (NZIER) prepared two reports exploring the potential economic benefits of customs arrangements.[8] The extensive use of agents is also missing from the current research, leading to an even greater incomplete understanding of the effectiveness of MRAs. The absence of data on firms' use of agents in most of the available trade datasets makes linking trader activities with agent status challenging. Second, empirical studies assessing the benefits of AEO programs (and other trusted trader programs) are rare. The lack of empirical studies is mainly due to the lack of detailed data on the link between exports and the direct or indirect AEO status of the exporter. The few empirical studies of AEO programs that do exist confirm that gaining AEO certification improves trade is several ways. For example, Carballo et al. (2016) evaluate the Mexican trusted trader program (NEEC) and find that participants increased their exports, while Zheng et al. (2013) find that acquiring an AEO certificate improves export stability for China exporters. Our study examines whether there are additional benefits to AEO membership in the presence of an MRA.

The studies assessing the benefits of the AEO program have remained qualitative. A few focus on firm performance (e.g., Cedilnik, 2013; Miled and Fiore, 2014; Campos et al., 2018; Schramm, 2015) and others on supply chain improvements (e.g., Tweddle, 2008; Park and Park, 2018; Janowska-Bucka, 2008). A few studies have also recognized the critical role played by the AEO-certified logistics firms. For example, Park and Park (2018) find that obtaining AEO certification has a positive impact on the effectiveness and efficiency of logistics firms which are able to provide better service with enhanced security. Schramm (2015), on the other hand, in an Austrian study suggests that clients from the manufacturing sector push their logistics firms (i.e. agents) to become certified AEO holders.

[8] See "The value of MRA" at `https://www.customs.govt.nz/business/export/mutual-recognition-arrangements/`.

Finally, our paper contributes to the growing literature on the prominence of intermediaries in international trade. Specialized agents, namely customs agents and freight forwarding firms, are a special form of intermediaries, which account for an astonishingly high share of international trade. Intermediaries and agents are both related to the real resource costs of exporting and importing (Blum et al., 2018). Intermediaries have arose to more effectively match sellers and buyers (e.g., Rubinstein and Wolinsky, 1987; Spulber, 1996; Feenstra and Hanson, 2004; Blum et al., 2018) and to avoid adverse selection by guaranteeing quality (Spulber, 1996). Agents, on the other hand, have emerged to deal with the administrative tasks involved in international trade, such as customs clearing and shipping solutions. In other words, instead of acquiring and consolidating products on behalf of the manufacturing firms, the specialized agents provide necessary services along the global supply chain. Moreover, the use of agents is more prevalent than intermediaries, covering almost every product and firm. Traditional intermediaries account for roughly 10 to 15 % in exports while agents handle over 80% of those.

Agents' role in a context of trade policy have rarely been studied. The use of specialized agents also provides evidence for productivity sorting (e.g., Melitz, 2003; Eaton et al., 2004; Ahn et al., 2011), where the most productive firms handle the administrative tasks internally and less productive firms outsource such tasks to specialized agents. Agents also help firms (especially SMEs) access foreign markets by lowering the administrative costs to export (Ahn et al., 2011).[9] We also present a number of policy recommendations. We highlight a particular mechanism whereby

[9] There are some qualitative studies assessing the benefits of the AEO program looking at firm performance (e.g., Cedilnik, 2013; Miled and Fiore, 2014; Campos et al., 2018; Schramm, 2015) and others on supply chain improvements (e.g., Tweddle, 2008; Janowska-Bucka, 2008; Park and Park, 2018). Park and Park (2018) also find that obtaining AEO certification has a positive impact on the effectiveness and efficiency of logistics firms which provide better service with enhanced security while Schramm (2015) suggests that clients from the manufacturing sector push their logistics firms (i.e. agents) to become certified AEO holders.

smaller firms are able to enjoy a cheaper exporting option by using AEO-accredited agents. Our findings may help policymakers understand the general impact of the MRA (and AEOs) and form informative policy guidance for future MRA negotiations.

The remaining paper is structured as follows. Section 3.2 introduces our data and presents stylized facts and summary statistics to facilitate the construction of our theoretical framework. Section 3.3 provides a simplified theoretical framework for the MRA (and the AEO program) as well as proposes several testable conjectures that we are to verify with the data. Section 3.4 presents the empirical evidence, followed by an overall conclusion.

3.2 Data and Stylized Facts

3.2.1 Customs Data

The customs data used in our empirical analysis is from the HMRC, which is a non-ministerial department of the UK Government responsible for the collection of taxes, the payment of state support, and the collection of trade statistics. For each export transaction, we have a unique trader identifier, the country of destination, the transaction date, the five-digit Standard International Trade Classification (SITC), the four-digit Harmonized System (HS), the ten-digit comcode product code corresponding to the eight-digit HS, the value (in sterling), the mass (in kilogram), and more importantly, an agent identifier. To identify an agent's AEO status, the customs data are manually matched with the list of AEO holders which is publicly available on the UK government's web page.[10] An agent is only classified as an AEO agent after it has received an AEO certificate, otherwise it is classified as a non-AEO agent.

Between 2009 and 2017, exports to non-EU countries accounted for approximately 50% of the UK's total exports, with nearly 30% of those destined for the United States, making the US the UK's largest export market outside Europe. This paper focuses on the UK-US Mutual Recognition Agreement (MRA) implemented from July 2012, which falls near the midpoint of our sample period.[11] Notably, only around 10% of UK exports are conducted directly by firms, while 90% are facilitated by specialist agents. For the empirical analysis, we focus on the period from 2011 to 2014, which avoids the disruptions caused by the 2008 Financial Crisis while also providing a suitable time

[10] The list, previously available on the European Commission's web page before Brexit, is now published by the UK government. Available on `https://www.gov.uk/government/publications/check-if-a-business-holds-authorised-economic-operator-status`

[11] At the time of the analysis in the HMRC Datalab, the available data covered the period from 2009 to 2017.

frame for studying the impact of the UK-US MRA.[12]

3.2.2 Sample statistics

Matching exports with agent status allows us to observe very detailed trends in exports. We first present the basic trends for indirect exporters. The composition of indirect exporters is shown in Figure 3.1. We have seen a continuous but relatively small increase in the total number of US-exporting firms between 2011 and 2014. The small increase is not surprising for two mature markets like the UK and the US. We do observe interesting changes in the composition of indirect firms when breaking down the firm numbers by status. The number of firms using non-AEO agents stabilized while those using AEO agents moderately grew. We also confirm that the increasing number of firms using AEO agents is not merely a result of the accreditation process. As we do not observe any sudden changes in the number of firms using agents, we argue that most of the matching between firms and agents happened before our sample started in 2011.

[12] In further analysis we study the impact of the China-UK MRA, which was implemented from November 2015.

Figure 3.1: US-exporting firm numbers (2011-2014)

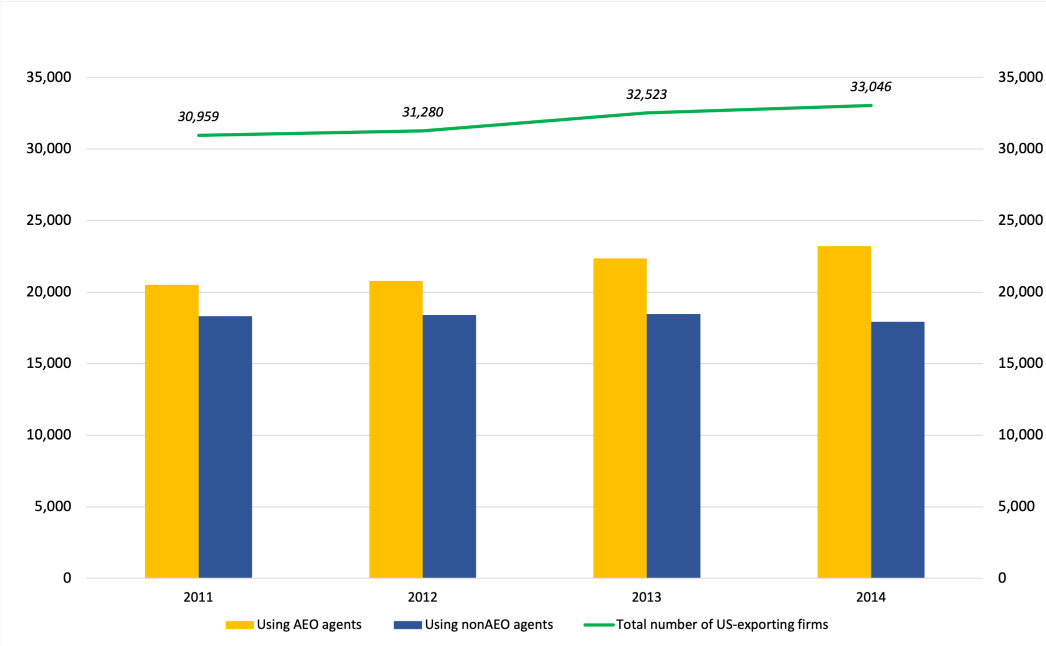


Table 3.1 describes our sample. The total export value is evenly distributed between the two types of agents although we record more observations (export transactions) through the AEO agents (132,821 versus 81,442), implying that shipments that go through AEO agents tend to be a lower value on average. Slightly more firms use AEO agents (21,440 versus 18,394), which is in line with the trend in Figure 3.1. Our sample covers a total of 7,718 products. The total number of products exported by either subgroup is similar.

We report per firm summary statistics to show that firms, except for the type of agents they are using, are similar with regards to their exports to the US. Panels A and B in Table 3.2 present the firm characteristics. A typical firm using an AEO agent exports 1.61 million GBP to the US annually compared with 1.75 million GBP by its counterparts with a non-AEO agent. The smaller annual export value to the US by AEO agents is in line with what we find in Table 3.1 that more shipments are handled by AEO agents but that they tend to be of a smaller value. Annual export value (to the US) are also similar and reveal that firm sizes vary significantly within one group: most firms are fairly small in terms of their export value to the US while only few firms contribute to an extremely high mean annual export value.

Table 3.1: Sample description (2011 and 2013)

	(1) Whole sample	(2) AEO	(3) non-AEO
Trade shares	100%	50.17%	49.83%
Number of observations	214,263	132,821	81,442
Number of firms	43,127	21,440	18,394
Number of products (HS8)	7,178	5,381	5,283
Number of agents	1,282	151	1,131

Notes: In *Number of firms*, a firm is counted as AEO if it uses AEO agents for its exports during the sample period. A firm can use both types of agents at the same time and therefore can appear in both Column (2) and (3). Number of firms and products in Column (2) and (3) do not necessarily add up to the whole sample statistics reported in Column (1).

Table 3.2: Per firm summary statistics (2011 and 2013)

	Panel A: firms use AEO agents				
	Mean	sd	p10	p50	p90
Number of industries (to the US)	1.94	1.83	1	1	4
Number of products (to the US)	3.53	11.11	1	2	7
Annual export value (to the US, in million GBP)	1.61	30.80	0.00	0.02	0.91
Number of markets	10.32	12.36	1	6	26
	Panel B: firms use non-AEO agents				
	Mean	sd	p10	p50	p90
Number of industries (to the US)	1.67	1.46	1	1	3
Number of products (to the US)	2.69	8.67	1	1	5
Annual export value (to the US, in million GBP)	1.75	33.00	0.00	0.03	0.91
Number of markets	9.11	11.68	1	5	23

Notes: When calculating the number of markets, we include all the countries a firm is exporting to. *Number of industries* and *Number of products* are specific for the UK-to-US exports only.

Table 3 presents the trade share distribution by sector at the 1-digit SITC level, comparing the operations of AEO and non-AEO agents across various industries.

While both agent types are active in all sectors, there are clear patterns of specialization. Non-AEO agents dominate in sectors SITC 0–4, including industries such as food and live animals, beverages and tobacco, and crude materials, where they handle between 60% and 86% of trade. In contrast, sectors SITC 5–8, which include chemicals, manufactured goods, machinery, and miscellaneous manufactured articles, show a more balanced distribution of trade between AEO and non-AEO agents, with AEO agents managing just over half of the trade in these sectors.

Table 3.4 provides further insight into the trade share by sector across the entire sample. The data indicate that the vast majority of trade value—nearly 85% – originates from sectors SITC 5–8, which are more manufacturing-focused. In contrast, sectors SITC 0–4 account for less than 15% of the total trade value. This distribution aligns with existing literature, which suggests that AEO certification is more prevalent in export-oriented industries, particularly in the manufacturing sector. Notably, nearly 70% of AEO-managed exports come from manufacturing industries, as shown in Column (2) of Table 3.4.

Table 3.3: Trade share by status (2011 and 2013, %)

Sector	(1) AEO agents	(2) non-AEO agents	(3) Total
SITC0: *Food and live animals*	39.14	60.86	100
SITC1: *Beverage and tobacco*	14.14	85.86	100
SITC2: *Crude materials*	19.12	70.28	100
SITC3: *Mineral fuels*	13.02	86.98	100
SITC4: *Animal and vegetable oils*	14.81	85.19	100
SITC5: *Chemicals*	51.57	48.43	100
SITC6: *Manufactured goods*	51.27	48.73	100
SITC7: *Machinery and transport equipment*	51.81	48.19	100
SITC8: *Miscellaneous manufactured articles*	51.40	48.60	100

Table 3.4: Trade share by sector (2011 and 2013, %)

Sector	(1) Whole sample	(2) AEO	(3) non-AEO
SITC0: *Food and live animals*	1.20	1.40	7.33
SITC1: *Beverage and tobacco*	2.96	0.67	7.33
SITC2: *Crude materials*	0.49	0.45	0.55
SITC3: *Mineral fuels*	11.94	0.06	34.67
SITC4: *Animal and vegetable oils*	0.03	0.03	0.03
SITC5: *Chemicals*	25.37	28.14	20.07
SITC6: *Manufactured goods*	8.83	11.20	4.29
SITC7: *Machinery and transport equipment*	35.73	42.01	23.69
SITC8: *Miscellaneous manufactured articles*	13.47	16.64	8.55
Total	100	100	100

Our data have several advantages. First, we can explicitly identify a treatment group, exports sent through AEO agents, and a control group, exports sent through non-AEO agents. The one-off treatment is the signing of the UK-US MRA. As a reminder, the UK-US MRA (previously the EU-US MRA) was signed on 4th May 2012 and implemented from 1st July 2012. Second, we observe that firms tend to stick with the same type of agents for exports of the same product.[13] We observe that firms rarely switch between different types of agent and such changes account for less than 10% of the sample value. We remove the firm-product combinations that are exported using different types of agents before and after the US MRA.

[13]Here, the same agent's status does not necessarily guarantee that the firm uses the exact same agent.

3.3 A Conceptual Framework of a Trade Facilitating Policy

In order to investigate the role played by the AEO program and the MRA on trade we build a novel theoretical framework based on Melitz (2003) model of trade with heterogeneous firms. We depart from the standard model by introducing two new components: First, we incorporate a trade cost technology that allows us to incorporate the benefits of adhering to the AEO program and benefiting from a MRA agreement, and second we introduce the possibility that firms can choose to export directly, or through the use of an agent, who has the role of dealing with the administrative burden associated with exporting.

The trade cost structure distinguishes between three types of administrative costs: those incurred at the domestic border, in transit, and at the foreign border. This distinction is useful as it allows us to accommodate the benefits of a trade facilitation policy, which is defined as a reduction in the administrative costs that a firm incurs at the domestic border. Moreover, if the countries concerned are part of a previously signed MRA, each of their respective AEO license holders will enjoy a reduction in the administrative costs at the respective foreign border.

Becoming an AEO entails the payment of a fixed cost, which captures the administrative procedures and adaptation costs that the firm needs to incur to obtain an AEO license. The choice of the firm to join the AEO program can be thought of as the decision to incur a higher fixed cost in exchange for a lower variable cost on each export transaction. Note that this framework shares some similarities with early models of technology adoption and heterogeneous firms such as Bustos (2011), in the sense that the decision to become an AEO holder is similar to that one of adopting a more efficient technology. However, our policy differs in three crucial aspects: First, the policy only affects exports, so in that regard, becoming an AEO holder is akin to adopting a more efficient export technology rather than a production technology. Second, the effects of this policy are enhanced by the MRA and third, and probably the most important, less efficient firms are able to access the more efficient export technology by pairing with an already certified AEO agent.

We introduce the use of agents as an external decision of the firm. In particular, a firm can deal with their exports directly, for which an additional fixed cost investment needs to be made to cover the costs of maintaining a dedicated department to process exports or it can use an agent. Agents relieve firms of the need to have a dedicated export department but in exchange firms need to pay for the agents' services. More precisely per each unit shipped an agent will charge λ times their shipping costs. To simplify the model and motivated by our descriptive statistics and empirical strategy, we consider two additional assumptions: First, we leave aside the decision of the agents to become an AEO licence holder by assuming that there is a proportion χ of agents that are AEO licence holders. This is because we observe that most agents were accredited before the US MRA signing date and second, we remove new AEO licence holder observations in our empirical strategy to improve identification.[14] Second, we consider that the matching between firms and agents follows a random process so each firm has the same probability to match with an AEO agent. This is also driven by our descriptive statistics which do show any sharp differences between firms that use AEO agents and firms that use non-AEO agents.

[14]In our sample, the number of new issuance each year is trivial compared to the total number of firms using AEO agents. Specifically, the numbers of issuance in 2012, 2013 and 2014 are 30, 36, and 23, respectively. The trade shares handled by these new AEO holders are negligible at 1.02%, 3.50%, and 0.85%, respectively. A similar trend is also confirmed in the literature that the first large wave of AEO certifications was over by 2011 Schramm (2015).

The theoretical framework provides a rich set of results, especially at the aggregate level and we offer a detailed discussion of the model in the appendix. The AEO program in conjunction with an MRA will increase an industry's total exports at both the extensive and the intensive margin. These are the implications of the model that will be tested in our empirical section. The results at the extensive margin are driven by the fact that less productive exporters have a chance to access indirectly the AEO program through the use of agents. The signing of an MRA will also change the composition of exports within an industry reducing direct exporting and favouring exporting through agents. There will be also standard productivity gains at the industry level associated with selection effects, as the policy is benefiting exporters, which are a subset of the most productive firms in the industry. We focus on evidence at the granular level to quantify the effect of an MRA on the extensive and the intensive margin. In our model we implicitly assume that each firm produces just one product.[15] We summarize this finding as follows.

Conjecture 1. *Conditional on productivity an indirect exporter which uses an AEO agent will export more than an indirect exporter that uses a non-AEO agent.*

Conjecture 2. *An MRA increases the level of exports for a firm that uses an AEO agent compared to a firm that uses a non-AEO agent.*

Conjecture 3. *Conditional on surviving, an MRA increases the probability of a firm exporting to the new MRA trade partner.*

[15] We observe that most firms stick with a single strategy for a specific product, either using an AEO agent or a non-AEO agent. Mixed use of agents with different status' to deal with different product transactions is also rare at the firm level. Therefore, in this paper we leave aside the multi-product dimension of the firm and focus on single-product firms with a single mode of delivery.

3.4 Empirical Analysis

3.4.1 Empirical strategy

We adopt a long difference research design, taking advantage of the changes in exports before and after the 2012 MRA. This approach allows us to focus on the structural changes brought about by the MRA while addressing data limitations. Specifically, the long difference framework compares the difference in exports handled by AEO agents and non-AEO agents between the periods before and after the UK-US MRA. We use UK export data as we do not observe the agent status of an exporter's trade partners. More specifically, when a UK firm imports from the US, whether its imports enjoy the benefits of the MRA depends on the AEO status of the corresponding US exporter.

In defining model specifications, we first consider our sample coverage and the point of time that the UK-US MRA becomes effective. We focus on goods exported through agents to highlight the unique trader-agent mechanisms involved.[16] The sample selection does not lose generality as over 85% of UK-US exports are facilitated through agents, and at the same time the US is a primary export market for the UK.[17] In addition, our sample has a good coverage around the the time of the MRA in 2012.[18] The Japan MRA, signed in 2010 and effective from 2011, was also in operation at the same time but as pointed out above, the export share of exports to Japan are small in comparison.[19] In further analysis we examine the impact of the UK-China MRA

[16]Direct traders constitute a relatively small portion of the dataset. Moreover, we exclude direct traders from the primary empirical analysis to ensure compliance with data protection regulations.

[17]Between 2009 and 2017, nearly 30% of the total UK exports were to the US. In comparison, Japan is around 3% of total UK exports, and China, though the second largest exporting market for the UK is around 7-8% of exports. Total UK exports to the EU are excluded.

[18]The UK-US MRA was signed and effective in the same year. See "EU, US Fully Implement Mutual Recognition Decision" at `https://www.cbp.gov/newsroom/national-media-release/eu-us-fully-implement-mutual-recognition-decision`.

[19]As a robustness check we control for the impact of Japan's MRA with the UK.

(effective in 2015).

Our identification strategy takes into account the disaggregated nature of our data and the type of agent. Given that exporting in different industries and to different markets demands highly distinct knowledge, we argue that the decision to involve an agent is made at a relatively disaggregated level. We hence assess the use of agents at the product level, which is in line with our model settings of single-product firms. This practice should precisely capture the impact of an MRA and the role played by the trader-agent mechanism. We observe that while single-product firms always stick with a single exporting strategy, multi-product firms sometimes use both types of agents for one product. Mixed use of agents is rare in terms of frequency, that is, only 8,681 out of our 214,263 firm-product combinations (around 4.1%) are exported through both types of agents. For these observations, we define their status using a 50% threshold. If we define an agent's type regardless of the market or industry it is involved in, we misclassify trade flow status and generate misleading results. As illustrated in our theory, we further remove the products that are exported through different types of agents before and after the US MRA. Only 7,795 firm-product combinations involve switching, corresponding to 6.6% of our original sample trade value.

Hence, we quantify the impact of the UK-US MRA by estimating the following regression;

$$y_{ip} = \alpha_0 + \alpha_1 D_{ip}^{AEO} + \delta_p + \delta_i + \epsilon_{ip} \tag{3.1}$$

where the subscripts i and p stand respectively for firm and 8-digit HS product. D_{ip}^{AEO} takes on the value of 1 if firm i exports product p through an AEO agent. We incorporate three dependent variables into a generalized dependent variable y_{ip}: (i) a dummy variable, D_{ip}^{entry}, takes on the value of 1 if firm i starts exporting a specific product p to the US after the UK-US MRA; (ii) a dummy variable, D_{ip}^{exit} takes on the value of 1 if firm i stops exporting a specific product p in the end year but having exported it in the start year; (iii) for the incumbent firm-product pairs (i.e. the same product exported by the same firm in both years), Δexp_{ip} denotes the log change of export value in product p for firm i between 2011 and 2013.[20] When estimating the coefficient α_1 for entry D_{ip}^{entry} and exit D_{ip}^{exit}, we ensure the comparability between the observations. Specifically, for entry, we include all the observations with positive exports in the end year; for exit, we include all observations with positive exports in the start year. Despite the dichotomous nature of our independent variable D_{ip}^{AEO}, we rely on a simple linear probability model and hence estimate Equation 3.1 via OLS. This approach should provide simple but direct estimates for the sample average marginal effect of the MRA. We also control for firm-level and product level fixed effects, δ_i and δ_p.

Using such a long difference approach removes any potential bias resulting from unobserved and time-invariant industry and firm characteristics. Our empirical design allows us to control for firm-level, industry-level, and product-level trends. We can eliminate the concern that the results are driven by omitted variables correlated with the AEO status. In other words, by adding fixed effects defined differently from the level of aggregation, we are able to check the robustness of our results.

[20]We have considered that D_{ip}^{entry} and D_{ip}^{exit} may pick up random or seasonal shipping patterns and generate misleading results. We therefore aggregate our data to industry level to mitigate the impact of random shipping. The results are reported alongside the firm-product level results.

3.4.2 Baseline results

Our baseline analysis estimates Equation 3.1 using exports to the US in 2011 and 2013, one year before and after the signing of the UK-US MRA. The choice of start year means we avoid capturing any increasing trade volumes related to the AEO certification process (Schramm, 2015). As a robustness check, we extend the sample period to 2014. We do not include years after 2014 as they may pick up trade diversion caused by the UK-China MRA in 2015.[21]

Results are presented in Table 3.5. Columns (1)-(3) report the results when observations are aggregated at the firm-product level. According to Column (1), after the UK-US MRA, there is a 31.0% increase in the probability that firms using AEO agents start exporting a new product to the US, compared to firms using non-AEO agents. This evidence supports theoretical Conjecture 2.

To fully understand the trade dynamics, we progressively check whether the MRA improves firm US export survival rates. We expect that an MRA will reduce the likelihood of exit from a given (product) market and hence regress D_{ip}^{exit} on D_{ip}^{AEO}. The results in Column (2) suggest that, compared with a firm with a non-AEO agent, that one with an AEO agent is 5.50% less likely to stop exporting a given product to the US following the signing of the MRA. The results it Column (3) further verify Conjecture 3 where we assess the impact of an MRA on the export value regressing Δexp_{ip} on D_{ip}^{AEO} using incumbent firm-product pairs. The results indicate that if an indirect exporter exports through an AEO agent instead of a non-AEO agent, its export value for a given product increased by approximately 10.96% ($(e^{10.4\%}-1)\times 100\% \approx 10.96\%$) over the three years, corresponding to an average annual growth rate of 3.53%.

[21] In further analysis we quantify the impact of the UK-China MRA using a sample period between 2014 and 2016 using a similar estimation process.

However, one concern we might have when observations are aggregated at the firm-product level is that our estimates may be strongly influenced by occasional shipments of certain products. To address this concern we aggregate the observations at firm-industry (2-digit SITC) level and re-estimate Equation 3.1. Instead of the product level fixed effects δ_p, we control for industry level fixed effects δ_j. Table 3.5 Columns (4)-(6) report the industry-level results. Compare the firm-product and firm-industry results, we find that at firm-industry level the impact of an MRA is similarly significant but exhibit different magnitudes.

In terms of entry, firms with AEO agents are 19.7% more likely to expand their operations into a new industry when exporting to the US. The decrease in magnitude (from 31.0% to 19.7%) is expected given exporting a new product is easier then exporting a new product that is part of a new 2-digit industry. Firms that add a new product line may already export other products within the same industry, and, given the fact that these highly disaggregated products tend to be similar in terms of factor content, their knowledge from their previous exporting experience is likely to be transferable. The marginal cost for adding a new product is likely to be lower than starting to export in a completely new industry. When it comes to export survival, the MRA's impact at product and industry level are similar. Columns (2) and (5) show that after the UK-US MRA, an indirect exporting firm with an AEO agent is 16.6% less likely to withdraw from a given product market, higher than the industry-level result of 10.4%.

The impact of the MRA on intensive margins is greater at the industry level. An exporter in a given industry using an AEO agent experiences an increase of 19.12% $((e^{34.7\%} - 1) \times 100\% \approx 41.48\%)$ in export value, equivalent to annual growth rate of 12.26%. The larger impact at industry level can be explained by the higher entry probability at product level shown in Column (1). If a firm decides to add new product lines (within the same industry), these products will be counted as entries at product level but an increase in trade value at the industry level.

Table 3.5: Entry, exit and intensive margin (2011-2013)

	Firm-product level			Firm-industry level		
	(1) Entry	(2) Exit	(3) Intensive margin	(4) Entry	(5) Exit	(6) Intensive margin
	D_{ip}^{entry}	D_{ip}^{exit}	Δexp_{ip}	D_{ij}^{entry}	D_{ij}^{exit}	Δexp_{ij}
D_{ip}^{AEO}	0.310***	−0.104***	0.104***	0.197***	−0.166***	0.347***
	(0.0160)	(0.0087)	(0.1040)	(0.0153)	(0.0126)	(0.0448)
Firm level fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry level fixed effects	No	No	No	Yes	Yes	Yes
Product fixed effects	Yes	Yes	Yes	No	No	No
Observations	172,945	121,657	32,254	84,471	62,730	25,525
R^2	0.279	0.201	0.064	0.224	0.178	0.081

Notes: For firm-industry and firm-product analysis, standard errors are clustered at industry level. Industry is defined as 2-digit SITC. Product is defined as 8-digit HS. ***, **, and * denote 0.1%, 1% and 5% significance level respectively.

We then check whether our results are consistent across sectors by interacting our independent variable D_{ip}^{AEO} with a sector indicator $Sector_p$ and estimate the following specification;

$$y_{ip} = \beta_0 + \beta_1 D_{ip}^{AEO} \times Sector_p + \delta_i + \delta_p + \omega_{ip} \tag{3.2}$$

where the indicator $Sector_p$ denotes to which the 1-digit SITC sector product p belongs. When interpreting the by-sector results, we take into account the trade share of each sector shown in Table 3.6. Sectors SITC 5-8 dominate our sample as they contribute over 80% of the total trade share. Similar patterns are found for the two subgroups: nearly 97% of AEO exports and over 50% of non-AEO exports are from these four sectors. Their dominance still holds in terms of the number of observations where they contribute a total of 208,650 observations, covering 97% of sample. Of the five sectors, SITC 0-4 are dominated by non-AEO agents with a trade share of 80%, and hence the captured impact of an MRA for these sectors may differ from our baseline results. On the other hand, exports for sectors SITC 5-8 are equally handled by the two types of agent. We therefore argue that the impact of an MRA should be mainly captured in the chemical sector (SITC 5) and the manufacturing sectors (SITC 6-8), and, in these four sectors, we should find consistent estimates across entry, exit, and the intensive margin.

Table 3.6 presents the by-sector results where Columns (1)-(3) are for product level and Columns (4)-(6) for industry level. The by-sector results are generally in line with our expectations. Sectors SITC 0-4 have relatively few observations so we need to interpret the coefficients with care although the results are generally similar in terms of entry and intensive margins. The results for sectors SITC 5-8 are however, consistent with our baseline results. Specifically, in Table 3.6 Columns (1)-(2) and (3)-(4), we observe a similar improved probability for entry and a decreasing probability for exit through the use of AEO agents at both firm-product and firm-industry levels and the magnitude of the captured impact is similar to what we observe in Table 3.5 Columns (1)-(2) and (3)-(4). However, the impact on the intensive margins differs across sectors. At product level, we only observe a significant improvement in the intensive margin for the sector SITC 7 while the coefficients are positive and significant for all the manufacturing industries (SITC 6-8) handled by AEO agents at the firm-industry level. The by-sector analysis also highlights that the observed differences between industry-level and product-level results (from Table 3.5) still hold.

Table 3.6: Entry, exit and intensive margin: By sector analysis (2011-2013)

	Firm-product level			Firm-industry level		
	(1) Entry	(2) Exit	(3) Intensive margin	(4) Entry	(5) Exit	(6) Intensive margin
	D_{ip}^{entry}	D_{ip}^{exit}	Δexp_{ip}	D_{ij}^{entry}	D_{ij}^{exit}	Δexp_{ij}
$(SITC = 0, N = 2,386)$	0.123***	0.039	0.235*	0.049***	0.076*	0.305*
Food and live animals	(0.0213)	(0.0329)	(0.1018)	(0.0115)	(0.0291)	(0.1283)
$(SITC = 1, N = 1,103)$	0.105***	−0.001	0.328***	0.033	0.097***	0.116***
Beverages and tobacco	(0.0015)	(0.0054)	(0.0235)	(0.0363)	(0.0086)	(0.0067)
$(SITC = 2, N = 1,638)$	0.120**	0.018	0.692**	0.248***	0.008	0.238*
Crude materials, inedible, except fuels materials	(0.0331)	(0.0165)	(0.2383)	(0.0340)	(0.0377)	(0.01056)
$(SITC = 3, N = 317)$	0.286***	−0.042	−2.547***	0.285***	−0.035	−0.420***
Mineral fuels , lubricants and related materials	(0.0180)	(0.0391)	(0.0023)	(0.0239)	(0.0198)	(0.0128)
$(SITC = 4, N = 169)$	0.104	0.023	2.410***	0.178*	0.048	0.122***
Animal and vegetable oils, fats and waxes	(0.1003)	(0.1220)	(0.0084)	(0.0866)	(0.0866)	(0.0290)
$(SITC = 5, N = 14,289)$	0.115***	−0.055***	0.006	0.116***	−0.048***	0.0424
Chemicals and related products, n.e.s.	(0.0211)	(0.0117)	(0.0520)	(0.0249)	(0.0130)	(0.0356)
$(SITC = 6, N = 34,161)$	0.216***	−0.041***	0.069	0.144***	−0.042**	0.196***
Manufactured goods)	(0.0185)	(0.0044)	(0.0563)	(0.0164)	(0.0126)	(0.0368)
$(SITC = 7, N = 92,931)$	0.257***	−0.064***	0.133**	0.144***	−0.062***	0.221***
Machinery and transport equipment	(0.0206)	(0.0103)	(0.0421)	(0.0216)	(0.0113)	(0.0349)
$(SITC = 8, N = 67,269)$	0.222***	−0.055**	0.072	0.086***	−0.033	0.144***
Miscellaneous manufactured articles	(0.0205)	(0.0181)	(0.0532)	(0.0122)	(0.0270)	(0.0316)
Firm level fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry level fixed effects	No	No	No	Yes	Yes	Yes
Product level fixed effects	Yes	Yes	Yes	No	No	No
Observations	172,965	121,666	32,265	84,471	62,730	25,525
R^2	0.288	0.216	0.260	0.342	0.084	0.357

Notes: Standard error clustered at industry level. Industry is defined as 2-digit SITC. Product is defined as 8-digit HS. SITC9 represents unclassified goods and is removed at the very beginning. ***, **, and * denote 0.1%, 1% and 5% significance level respectively. $Firm\ size_i$ and $\Delta Export\ size_i$ are both included but not reported in the table.

To investigate whether an MRA has heterogeneous effects on exporters of different sizes, we include an interaction term between a firm size indicator and our AEO status indicator. The firm size indicator is a categorical variable and evenly divides the firms into four groups based on their annual export value, $Firm\ size_i$. Heterogeneous firm models (e.g., Melitz, 2003; Melitz and Ottaviano, 2008; Arkolakis, 2010) suggest that the impact of an MRA may depend on the size of firm, provided that size is associated with productivity, and hence with the ability to cope with such a policy change. In other words, the degree of trade costs reduction brought by an MRA may vary depend of firm size.

The results in Table 3.7 show that an MRA has a differential impact on firms by size. Product-level results are resented in Columns (1)-(3) and show that the UK-US MRA increases the probability of exporting a new product (to the US) regardless of the firm size, but the impact is the strongest for the second quartile, that is, firms of a small to medium size. The impact of the MRA on exit differs markedly between big and small firms. We find no significant evidence for firms of less than a median size but stronger than baseline impact for bigger firms. One possible explanation is that bigger firms may have better access to the cost reductions brought by the MRA and therefore enjoy a higher survival rate compared to their smaller counterparts. As for the intensive margin, we find small firms from the first quartile enjoy the highest increase in their trade value growth rate while the other firms only see moderate improvements. Our intensive margin results are in line with the prediction of Arkolakis (2010) that the elasticity of sales with respect to variable trade costs should decline with firm size, and therefore firms previously with low values of trade (i.e. smaller firms) grow more when trade costs decline. This finding suggests that an MRAs may favour small and medium sized firms.

When we aggregate our observations at industry level, as shown in Table 3.7 Columns (4)-(6), we find a similar increased effect for entry. In Column (5), the positive estimated coefficient of D_{ij}^{AEO} implies that small firms using AEO agents are more likely to quit the market although the sample size is small (5,919 out of 24,747). Although the number of exits recorded in each quartile is similar, the small size of AEO users in the first quartile leads to an upward biased probability for leaving the market. For the intensive margin, we observe a positive and significant impact across all firm sizes.

Table 3.7: Entry, exit and intensive margin: By firm size (2011-2013)

	Firm-product level			Firm-industry level		
	(1) Entry	(2) Exit	(3) Intensive margin	(4) Entry	(5) Exit	(6) Intensive margin
	D_{ip}^{entry}	D_{ip}^{exit}	Δexp_{ip}	D_{ij}^{entry}	D_{ij}^{exit}	Δexp_{ij}
$D_{ip}^{AEO} \times (Firm\ Size < 25\%)$	0.193***	0.007	0.197***	0.106***	0.030***	0.146**
	(0.0170)	(0.0060)	(0.0471)	(0.0106)	(0.0068)	(0.0453)
$D_{ip}^{AEO} \times (25\% \leq Firm\ Size < 50\%)$	0.286***	−0.004	0.110*	0.169***	0.003	0.144***
	(0.0188)	(0.0084)	(0.0411)	(0.0208)	(0.0079)	(0.0283)
$D_{ip}^{AEO} \times (50\% \leq Firm\ Size < 75\%)$	0.233***	−0.065***	0.054*	0.132***	−0.062***	0.152***
	(0.0141)	(0.0088)	(0.0236)	(0.0165)	(0.0112)	(0.0214)
$D_{ip}^{AEO} \times (75\% \leq Firm\ Size)$	0.207***	−0.131***	0.087*	0.101***	−0.120***	0.221***
	(0.0160)	(0.0087)	(0.0385)	(0.0159)	(0.0155)	(0.0266)
Firm level fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry level fixed effects	No	No	No	Yes	Yes	Yes
Product level fixed effects	Yes	Yes	Yes	No	No	No
Observations	172,965	121,666	32,265	84,471	62,730	25,525
R^2	0.258	0.178	0.152	0.357	0.304	0.355

Notes: Standard error clustered at industry level. Industry is defined as 2-digit SITC. Product is defined as 8-digit HS. SITC9 represents unclassified goods and is removed at the very beginning. ***, **, and * denote 0.1%, 1% and 5% significance level respectively.

3.4.3 Robustness checks

We hence perform a series of additional checks to verify the robustness of our results. First, we examine the impact of a longer sample period including 2014 which allows a longer period for the MRA to take effect. We re-estimate Equation 3.1 using the new sample period at firm-product and firm-industry level. We expect that the previously captured impact of an MRA should still be in place and of greater magnitude, as more firms learn about the benefits of the MRA. The results in the first row of Panels A and B in Table 3.8 are in line with expectations. For example, in terms of encouraging firm entry, using an AEO agent results in a probability increase of 25.20% at the firm-product level and 20% at firm-industry level over the three years compared with our baseline estimates of 22.80% and 12.50%, respectively. When we interpret the intensive margin as an annual growth rate, we find that our baseline results and robustness checks give similar results: 3.29% versus 4.47% at firm-product level and 6.01% versus 6.53% at firm-industry level.

To eliminate the concern that our results are a result of outliers, we remove the large firms and industries that have few AEO agents. In the second row of Panels A and B in Table 3.8, we remove the top 5% firms in terms of their total trade value. Comparing the results with those from Table 3.5, we find that removing the larger firms had little impact on the results. For example, the firm-product level probability increase for firms using AEO agents is 23.0% compared to 22.8% in Table3.5. This practice again implies that smaller firms can actually benefit from an MRA. The fifth rows of Panels A and B show that our results are not sensitive to removing the observations in SITC 2 and 3.

A possible concern is related to whether we are capturing the exact impact of the UK-US MRA given that multiple MRAs were signed between 2009 and 2016 such that spillovers (trade diversion) from the previous MRAs may contaminate our estimates. Our solution is to remove firms that had previously exported to Japan before 2011 as they may have learnt about the benefits of an MRA and self-selected into exporting to the US after hearing about the new UK-US MRA. Removing these firms doed not significantly change our results for entry and intensive margins as shown in the third rows of Panel A and B in Table 3.8 although the coefficient on exit is now insignificant. One possibility is that the previous Japan MRA meant exporters to Japan have already learnt about their input requirement and given up their less productive product/industry lines. However, given Japan is a much smaller market compared to the US, it is evident that the benefits of an MRA had not been exhausted. The reduced trade costs brought by the new UK-US MRA are lower enough for a critical number of firms to increase their participation in trade (through firm entry and intensive margins).

Although our empirical design attempted to avoid any possible upward bias as a result of the AEO certification process by estimating the intensive margins removing firm-product (industry) combinations that are handled by agents of different statuses, we further remove those agents certified between 2012 and 2013 in the fourth rows of Panel A and B. The results were broadly similar although the firm-industry level estimates for entry and the intensive margin become closer to the firm-product level estimates. A possible explanation is that the recently-accredited agents mainly serve multi-product firms, and when these combinations are removed, the firm-industry estimates come closer to the firm-product results. This is plausible if agents are encouraged to become certified by their clients (Schramm, 2015). There is no significant change to the exit estimates and supports the argument that there exists a large number of single product firms as indicated in Section 3.4.2.

In the baseline specification, we include firm level and product level fixed effects, δ_i and δ_p to eliminate any firm-level and product-level unobserved heterogeneity. We replace firm-level fixed effects using firm-level control variables, initial firm size $Firm\,size_i$ and log change in total exports $\Delta Export\,size_i$. $Firm\,size_i$, proxied by the total export value of firm i as of 2010, as well as the log change in total exports $\Delta Export\,size_i$. The estimated results stay in line with our baseline estimation.[22]

[22]The heterogeneous-firm trade models (e.g., Melitz, 2003; Arkolakis, 2010; Melitz and Ottaviano, 2008) suggest that the effect of an MRA on export performance may depend on the size of a firm assuming that size is associated with productivity (for example) and hence with the ability to overcome the (administrative) costs of exporting. This approach has also been adopted by empirical studies using firm-level data (e.g., Ahn et al., 2011; Fontagné et al., 2015).

Table 3.8: Entry, exit and intensive margin: Robustness checks

	(1) Entry	(2) Exit	(3) Intensive margin
Panel A: firm-product level			
2011-2014	0.252***	−0.064***	0.173***
(*Obs. 177,834; 121,444; 27,791*)	(0.0146)	(0.0070)	(0.0248)
Remove top 5% firms	0.230***	−0.044***	0.097**
(*Obs. 149,407; 105,498; 26,052*)	(0.0164)	(0.2188)	(0.0275)
Remove firms exporting to Japan before 2011	0.212***	−0.019***	0.131**
(*Obs. 82,647; 56,436; 11,967*)	(0.0184)	(0.0066)	(0.0416)
Remove agents certified in 2012 and 2013	0.229***	−0.055***	0.097***
(*Obs. 172,640; 121,666; 32,265*)	(0.0151)	(0.0075)	(0.0268)
Remove sectors SITC 2 and 3	0.229***	−0.056***	0.096**
(*Obs. 171,608; 120,605; 32,064*)	(0.0152)	(0.0075)	(0.0269)
Firm-level control variables	0.228***	−0.55***	0.097*
(*Obs. 172,965; 121,666; 32,265*)	(0.0151)	(0.0075)	(0.0268)
Panel B: firm-industry level			
2011-2014	0.200***	−0.058***	0.253***
(*Obs. 91,418; 62,730; 21,171*)	(0.0145)	(0.0122)	(0.0278)
Remove top 5% firms	0.127***	−0.038***	0.167***
(*Obs. 79,677; 58,929; 23,073*)	(0.0141)	(0.0012)	(0.0245)
Remove firms exporting to Japan before 2011	0.126***	−0.012	0.150***
(*Obs. 51,231; 36,753; 12,269*)	(0.0131)	(0.0114)	(0.0278)
Remove agents certified in 2012 and 2013	0.195***	−0.062***	0.085***
(*Obs. 82,780; 63,105; 29,924*)	(0.0145)	(0.0120)	(0.0207)
Remove sectors SITC 2 and 3	0.123***	−0.046***	0.162***
(*Obs. 83,213; 61,916; 29,824*)	(0.0139)	(0.0112)	(0.0235)
Firm-level control variables	0.125***	−0.045***	0.175***
(*Obs. 84,471; 62,730; 25,525*)	(0.0138)	(0.0110)	(0.0234)

Notes: Standard errors clustered at industry level. We only report estimated coefficients for the variables of interest, D_{ip}^{AEO} and D_{ij}^{AEO}. Industry is defined as 2-digit SITC. Product is defined as 8-digit HS. ***, **, and * denote 0.1%, 1% and 5% significance level respectively. We report sample size in the bracket.

3.4.4 Further analysis: UK-China MRA

To check whether our results can be generalised to other MRAs, we extend our research to the UK-China MRA. China is the second largest market for the UK exports, accounting for 7-8% of the UK non-EU exports, and, compared with the US, is a more remote market, geographically and culturally. The UK-China MRA was effective from

November 2015.[23] Between 2014 and 2016, nearly 65% of the UK-China exporter are indirect, that is to say, facilitated through agents.

We begin by describing our UK-China sample in Table 3.9. The share of export value through the non-AEO agents is slightly higher than that through AEO agents. Contrary to the UK-US sample in Table 3.1, we have more observations of exports through non-AEO agents (29,289 versus 22,9682). Exports to China involve fewer firms, agents and varieties than UK trade with the US. We find a similar pattern in that slightly more firms use AEO agents (7,218 versus 5,826) while the total number of products exported through either type of agent is similar.

We report per firm summary statistics to show that firms, except for the type of agents they are using, are similar in regards of exporting to China. Panels A and B in Table 3.10 present the distribution patterns for firm characteristics. A typical firm using an AEO agent exports 1.58 million GBP to China annually compared with 2.04 million GBP by firms using non-AEO agents. The firms exporting to China have a wider distribution compared to US exporters. As shown in Table 3.9, the standard deviation of the annual export value is nearly double that of UK-US exports while the means in the two samples are similar. Firms exporting to China also access more markets (15 on average) compared to firms exporting to the US (9 on average), suggesting that the more remote market attracts larger firms to operate successfully.

[23]See "Frequently Asked Questions China EU Authorised Economic Operators Mutual Recognition Decision" at `https://taxation-customs.ec.europa.eu/system/files/2020-04/2015-11_aeo_china_faqs.pdf`.

Table 3.9: Sample description (UK-China exports, 2014 and 2016)

	(1) Whole sample	(2) AEO	(3) non-AEO
Trade shares	100%	46.91%	56.09%
Number of observations	52,257	22,968	29,289
Number of firms	10,277	7,218	5,826
Number of products (HS8)	4,800	3,851	3,514
Number of agents	867	146	721

Notes: In *Number of firms*, a firm is counted as an AEO if it uses AEO agents for its exports during the sample period. A firm can use both types of agents at the same time and therefore can appear in both Column (2) and (3). Number of firms and products in Column (2) and (3) do not necessarily add up to the whole sample statistics reported in Column (1).

Table 3.10: Per firm summary statistics (UK-China exports, 2014 and 2016)

	Panel A: firms use AEO agents				
	Mean	sd	p10	p50	p90
Number of industries (to China)	1.73	1.69	1	1	3
Number of products (to China)	3.02	9.17	1	1	6
Annual export value (to China, in million GBP)	1.58	57.30	0.00	0.03	0.81
Number of markets	15.17	14.79	2	11	34
	Panel B: firms use non-AEO agents				
	Mean	sd	p10	p50	p90
Number of industries (to China)	1.47	1.33	1	1	2
Number of products (to China)	2.30	8.59	1	1	4
Annual export value (to China, in million GBP)	2.04	64.40	0.00	0.04	1.12
Number of markets	15.65	15.19	2	11	35

Notes: When calculating the number of markets, we include all the countries a firm is exporting to. *Number of industries* and *Number of products* are specific for the UK-to-China exports only.

To estiamte the impact of the UK-China MRA we follow a similar empirical strategy. We compare the changes in the UK exports to China through AEO agents and non-AEO agents before and after the signing of the MRA. The UK-China MRA was signed in May 2014 but did not enter into force until November 2015.[24] We therefore

[24]See "Frequently Asked Questions China EU Authorised Economic Operators Mutual Recognition Decision" at `https://taxation-customs.ec.europa.eu/system/files/2020-04/2015-11_aeo_china_faqs.pdf`.

select a sample period between 2014 and 2016. We capture the use of agents at product level. Mixed use of different types of agents is rare as only 2,571 out of 52,257 firm-product combinations are exported via both types of agents. We further remove the exports that are exported through different types of agents before and after the China MRA. Switching happens in 1,962 out of 52,257 observations, corresponding to 9.84% of our sample value. We replicate our baseline specification as in Equation 3.1.

We assess the impact of the UK-China MRA on entry, exit, and intensive margins. The results are presented in Table 3.11. The results are broadly similar with those found for the UK-US MRA. Coulmn (1) of Table 3.11 shows that the China MRA increased the probability of exporting a new product to China through the use of AEO agents, and the estimated probability increase is around 23.80% which is close to the 22.80% probability shown in Table 3.5. In terms of reducing exit, the China MRA decreases the probability of removing a product line by 9.80% through the use of AEO agents, which is twice the magnitude found in the US MRA. The industry-level results for entry and exit in Columns (4) and (5) are similar in magnitude to those at the product level. In terms of intensive margins, we do not observe any significant changes brought by the China MRA (shown in Columns (3) and (6) in Table 3.11). It appears for the case of China, as a relatively new export market, that the mian impact is on entry and exit rather than intensive margins.

Table 3.11: Entry, exit and intensive margin: UK-China MRA

	Firm-product level			Firm-industry level		
	(1) Entry	(2) Exit	(3) Intensive margin	(4) Entry	(5) Exit	(6) Intensive margin
	D_{ip}^{entry}	D_{ip}^{exit}	Δexp_{ip}	D_{ij}^{entry}	D_{ij}^{exit}	Δexp_{ij}
D_{ip}^{AEO}	0.238***	−0.098***	0.032	0.230***	−0.100***	−0.023
	(0.0189)	(0.0089)	(0.0643)	(0.0115)	(0.0131)	(0.060)
Firm level fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry level fixed effects	No	No	No	Yes	Yes	Yes
Product level fixed effects	Yes	Yes	Yes	No	No	No
Observations	43,286	31,624	9,359	26,811	17,817	6,805
R^2	0.285	0.260	0.309	0.217	0.160	0.110

Notes: For firm-industry and firm-product analysis, standard error are clustered at industry level. Industry is defined as 2-digit SITC. Product is defined as 8-digit HS. ***, **, and * denote 0.1%, 1% and 5% significance level respectively.

3.5 Conclusions

This paper presents the first evidence of the trade facilitation effect of MRAs through the use of certified agents across the entire universe of exporting firms in the UK. We observe a substantial use of agents in the UK exports, comprising 85.75% of the total, indicating a higher prevalence of outsourcing administrative tasks to specialized agents than previously thought.[25] Firms appear to decide on the involvement of an agent at a disaggregated product level, and firms that use different types of agents are broadly similar. As a greater number of firms indirectly access the benefits of MRAs, we extend the heterogeneous firm model à la Melitz (2003) to incorporate administrative costs and highlight the role of specialized agents. Our results support our theoretical conjectures that an MRA increases the probability of exporting a new product and increases the level of exports for firms that use AEO agents compared to those use a non-AEO agents. We also find a positive and significant impact of an MRA on firm-product and firm-industry survival.

This paper complements previous research on intermediaries from the perspective of trade policy. We highlight that an MRA facilitates bilateral trade through specialized agents, and such agents expand an MRA's benefits to more firms. We also contribute to the understanding of the trusted trader programs. Programs like the Authorized Economics Operator (AEO) allow agents to mitigate the rising costs associated with border-related issues. Our results imply that outsourcing administrative tasks to specialized agents is akin to adopting a more efficient exporting technology (Bustos, 2011). When we differentiate firms based on their size, we find evidence that smaller firms seem to benefit the most as they are then able to complete with larger, better resources competitors when it comes to navigating complex customs procedures.

[25] Data source: authors' calculation from HMRC customs trade statistics excluding EU trade.

Our findings have a number of policy implications. Future policy design should take agents into account and may want to promote the use of the indirect channel. The policymakers may also consider expanding the AEO program so that more firms can benefit from reduced administrative costs directly, the take up of which depends on the costs associated with certification,

We observe a number of interesting patterns for agents, and these open up a number of interesting questions about the mechanisms through which such agents facilitate trade. For instance, understanding the circumstances under which agents are engaged is vital in recognising the trade barriers encountered by exporters. If firms are more inclined to utilise agents for specific products and destinations, further investigation is warranted to pinpoint potential trade barriers. Moreover, such research would provide remedies for trade disruptions during periods of tumultuous trade shocks. It would be important to establish a connection between the trader-agent relationship and trade resilience.

Conclusion

This thesis explores the role of agents in UK trade, examines their market structure, their relationships with traders, and their integral function within trade policy. The findings presented offer key insights into both micro-level firm behaviors and broader market dynamics. Importantly, these findings carry substantial policy implications and highlight key areas for future research.

Chapter 1 analyzes the UK agent market, revealing a dual structure dominated by a small number of powerful agents who control the majority of trade activities. At the same time, a large pool of smaller agents fosters competition and market dynamism. This duality points to the need for targeted policy interventions to support smaller agents, ensuring they remain competitive and capable of counterbalancing the influence of dominant market players. We also find that agents, especially the larger ones, diversify their selection of industries and destinations, while at the same time, new entrants appear to start with a niche market and gradually expand if they manage to survive.

Chapter 2 extends the analysis into the dynamics of trader-agent relationships. The findings further emphasize the importance of big traders and dominant agents: Larger traders are more likely to hire multiple agents and export more intensively through them. Besides, the findings indicate that trader-agent relationships are often short-lived, with only high-value, deeply cooperative relationships enduring over time. The chapter also highlights the impact of Brexit-related trade policy uncertainty, as firms, especially smaller ones, turn to more established agents to navigate new trade barriers. These results suggests that post-Brexit trade policies should prioritize training for smaller agents in regard of potential trade chaos as well as enhancing firms access to suitable agents.

Chapter 3 presents the first evidence of the trade facilitation effect of MRAs through the use of certified agents across the entire universe of exporting firms in the UK. We observe that firms make decisions about engaging agents based on individual product lines, with little variation observed among firms that employ different types of agents. As more firms indirectly benefit from Mutual Recognition Agreements (MRAs) by using AEO-certified agents, we build on the heterogeneous firm model á la Melitz (2003) by factoring in administrative costs and emphasizing the role of specialized agents. Our findings confirm that MRAs increase the likelihood of exporting new products and boost export levels for firms working with AEO agents, compared to those using non-AEO agents. In addition, we observe a positive and significant effect of MRAs on firm-product and firm-industry survival.

The policy implications of these findings are significant. First, the dual structure of the agent market highlights the need for policies that support smaller agents, ensuring they can continue to provide competition and dynamism in the market. Encouraging diversification among agents, especially smaller ones, could make the agent sector more resilient to trade shocks. Second, the long-term and high-value relationships between traders and agents, particularly larger ones, can help firms navigate economic uncertainties and maintain trade performance. Finally, policymakers should consider expanding programs like the AEO and MRA to allow more firms, especially smaller ones, to benefit from reduced trade barriers and more efficient trade operations.

Despite its contributions, several limitations remain. First, the lack of balance sheet data limits the ability to fully capture the agents' performance. Future studies could integrate such data with trade data to gain a broader understanding of the agent market and the trader-agent relationship. In addition, the formal implementation of Brexit and the introduction of the Trade and Cooperation Agreement (TCA) provides an opportunity to further examine whether firms' behaviors have evolved in response to these new trade realities. Post-Brexit compulsory customs reporting on UK-EU trade also opens up new avenues for research. Future studies could leverage UK-EU trade data to precisely assess Brexit's impact on trade dynamics and the evolving role of agents.

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Appendix A

Appendix to Chapter 2

A.1 Tables

Table A.1: Dropping agents: over 1, 3, and 5 years

	(1)	(2)	(3)
$Drop_{ia}$	*Over 1 year*	*Over 3 years*	*Over 5 years*
$RValue_{ia}$	-0.072^{***}	-0.056^{***}	-0.043^{***}
	(0.0006)	(0.0006)	(0.0005)
$RLength_{ia}$	-0.194^{***}	-0.168^{***}	-0.134^{***}
	(0.0017)	(0.0017)	(0.0016)
Agent-level fixed effects	Yes	Yes	Yes
Firm-level fixed effects	Yes	Yes	Yes
Observations	232,983	232,983	232,983
R^2	0.276	0.313	0.316

Note: We include all the active relationships between 2009 and 2019. Data of other years yield very similar results. ***, **, and * denote 0.1%, 1% and 5% significance level respectively.

Table A.2: Brexit and agents: 2014-2019

	(1) $AgentSize_{it}$	(2) $RValue_{it}$	(3) $NumAgent_{it}$
$Referendum_t$	0.087^{***}	-0.027^{**}	0.027^{**}
	(0.0233)	(0.0087)	(0.0087)
$FirmSize_{it}$	0.056^{***}	0.778^{***}	0.222
	(0.0027)	(0.0010)	(0.0010)
$Referendum_t \times FirmSize_{it}$	-0.004	-0.003^{***}	-0.003^{***}
	(0.0019)	(0.0007)	(0.0007)
Firm-level fixed effects	Yes	Yes	Yes
Time trends	Yes	No	No
Observations	217,514	217,514	217,514
R^2	0.592	0.958	0.870

Note: We include incumbent exporters. The estimated coefficient for time trend X_t is not reported. ***, **, and * denote 0.1%, 1% and 5% significance level respectively.

Appendix B

Appendix to Chapter 3

B.1 Theoretical Framework

B.1.1 Demand and production

Consider a world consisting of two symmetric economies that we denote as Home (i) and Foreign (j). In each of them a continuum of individuals with measure L have preferences over a continuum of varieties described by a standard C.E.S utility function.[1] The demand for each variety produced at Home and sold at Foreign j is given by:

$$x_{kij}(\omega) = \frac{R_j}{P_j} \left(\frac{p_{ij}(\omega)}{P_j} \right)^{-\sigma}$$

where $x_{kij}(\omega)$ is the quantity consumed of variety ω of good k produced at Home i and sold at Foreign j, R_j denotes the total expenditure at Foreign j, $p_{ij}(\omega)$ is the price of the variety ω produced at Home i and sold at Foreign j, and $P_j^{1-\sigma} = \int (p_{ij}(\omega)^{1-\sigma} d\omega$

[1]In particular the utility function is given by the following functional form $U = \left[\int_{\omega \in \Omega} c_{ij}(\omega)^{\frac{\sigma-1}{\sigma}} d\omega \right]^{\frac{\sigma}{\sigma-1}}$.

is the Foreign aggregate price index. As in Melitz (2003) there is a continuum of prospect entrants. To enter in the industry, firms need to bear a fixed cost of entry, f_e, in terms of labour, the unique factor of production, to create a new variety to enter in the market. Once the firm has created this variety it has the monopoly rights to produce it. Associated with this variety there is a technology that is described by its unit labour requirements z, which are unknown to the firm at the moment of entry. In particular, the production costs associated with a firm with labour unit requirements, z, are given by:

$$c(z) = w\left(zq(z) + f\right)$$

where w, is the wage, $q\left(z\right)$ is the quantity produced, and f is a fixed cost of production that the firm incurs in every period. For simplicity, we assume that each firm produces a single variety and we abstract from multi-product firms.

B.1.2 Trade and administrative costs of exporting

One of the novelties of our framework consists on establishing a trade-cost function that embeds custom procedures and the possibility that these are sped up by means of the trade facilitation program described above. In particular, exporting involves a per destination fixed cost of exporting f_x in terms of labour and a variable iceberg trade cost which takes the following functional form:

$$T_{ij} = \left(e^{\tau_{ii}}\right)^{\alpha}\left(e^{\tau_{ij}}\right)^{\beta}\left(e^{\tau_{jj}}\right)^{\psi}$$

where τ_{ij} is the standard transportation costs found in most existing trade models which includes all related costs in transit from Home to Foreign or vice versa in a symmetric set-up.[2] We extend this structure by introducing two extra costs: τ_{ii} rep-

[2]The fixed cost captures the cost of creating a distribution network (such as retailers search costs) and advertising in the foreign market (marketing costs).

resents the cost that the firm bears from the administrative procedures incurred in the domestic border, whereas τ_{jj} consists of the administrative costs born by the firm in the foreign border. The parameters α, β and ψ control for the trade elasticities associated with internal administrative trade barriers at home and abroad, α and ψ, and the ones related to the transit of goods across borders, β (those ones associated with transportation and trade policy).[3]

Our other main novelty is the inclusion of the firm's option to deal with the administrative requirements associated with exporting, either by themselves or through agents. If the firm decides to process its own export operations, they will require a specialized team within the firm that could be independent of their trade volume. We model this with an extra fixed cost of f_d in terms of labour. Alternatively, the firm can hire a specialist agent that deals with all the customs procedures. In this case the firm does not incur in any fixed cost of operation but the firm will need to compensate the agent for their services. We model this as considering that the firm will need to ship $\lambda \geqslant 1$ units of output per unit sold in the foreign market when the shipment is dealt with an agent.[4]

B.1.3 Trade facilitating policy

Finally, we now introduce a trusted trader scheme (as a trade facilitating policy with the feature of mutual recognition across countries) into the model. In particular, firms

[3]More precisely $\frac{\partial T_{ij}}{\partial \tau_{ii}} \frac{\tau_{ii}}{T_{ij}} = \alpha \tau_{ii}$.

[4]In another words, we are assuming that each agent charge a fee per unit shipped of $(\lambda - 1)$ units of the firm's product.

can apply to become an AEO trusted trader.[5] We assume that participating in such scheme implies to incur in a fixed investment of f_a units of labour. This reflects the bureaucratic procedures that firms need to follow in order to belong to the scheme and the adoption of safer regulations that are mandatory for AEO holders.[6] The main benefit of becoming an AEO licence holder is simplified customs declaration procedure with faster and less frequent checks. We model this cost reduction by assuming that AEO holders incur an internal trade cost of $e^{\gamma\tau_{ii}}$ rather than $e^{\tau_{ii}}$ with $0 \leq \gamma < 1$.

Let us also assume that the two countries can sign a Mutual Recognition Agreements (MRA) by means of which both countries mutually recognize each other's AEO holders. In our symmetric set-up with identical cost reduction γ for AEO holders, this implies that an AEO holder faces the following trade costs when exporting:

$$T_{ij} = e^{\alpha\gamma\tau} e^{\beta\tau_{ij}} e^{\nu\psi\gamma\tau}$$

where $\tau_{ii} = \tau_{jj} = \tau$, ν is an indicator which takes the value of one if a MRA exists between countries, and zero otherwise.[7].

[5]As we are going to explain further below, in this version of the model we abstract from the agent's decision to become AEO trusted traders to simplify the analysis. Although we do recognize that an important margin of adjustment would come from agents becoming AEO holders as a consequence of the policy, in our empirical evidence for the UK we have found that firms do not switch often between different types of agents (not even around the same time as the signing of an MRA). We therefore exclude the cases where firms switch to AEO agents and agents self-select into the program following an MRA. In our empirical exercise, we restrict our sample to non-switchers (which covers the majority of firms) to be consistent with this theoretical assumption.

[6]As described in the AEO compendium from the WCO, in order to become part of the AEO program the enterprise needs to enter in numerous bureaucratic procedures to verify that the transportation of the product has been done in a safe environment. This does not only refer to physical conditions of transport itself, (i.e. whether the correct packaging has been used), but also it aims to prevent illegal behaviour regarding the payment of customs or whether the shipping report accurately details the characteristics of the merchandise that it is transported.

[7]Note that the functional form for T_{ij} has been chosen in such a way that a full reduction of the costs associated with customs (i.e. $\gamma = 0$) would imply that the firm will just need to bear the cost of transportation and the costs of customs abroad. In the limit if $\gamma = 0$ and $\tau_{ij} = \tau_{jj} = 0$, $T_{ij} = 1$, the firm's cost of serving the foreign and the domestic market will be identical

We make a further assumption regarding the AEO status of the specialists agents. In particular, we assume that there is an exogenous proportion χ of specialist agents who already get accredited in the AEO program, and firms are matched randomly with agents, implying that all firms have the same probability of getting matched with an AEO agent. Intuitively, trader-agent relationship is typically established due to many considerations of the firm, such as storage location, network coverage, industry clustering, etc., not necessarily related to the AEO status of the agent or internal specific characteristics of the firm. Given that the main focus of the paper is the impact of the bilateral MRA, we assume random matching for the sake of simplicity. The type of AEO assigned to each firm is unknown for the firm before the firm pays the fixed cost of exporting $f_{x.}$

B.2 Model Solution

The timing of the events for the firm is as follows. First, the firm decides whether to enter in the industry. At the moment of entry, the unit input requirement, z, is unknown to the firm, but the firm knows that z is the result of a random draw from a continuous distribution $G(z)$ with support $[0, \infty)$. The firm also knows that their unit input requirement is static and that each period the firm faces the possibility of a bad shock with positive probability δ that will expel the firm out of the market. Next, the firm decides whether to stay and produce, which markets to serve and in the case in which the firm decides to serve the foreign market, through which mode (either as a direct or indirect exporter). The firm also considers whether to join the AEO program. Finally, pricing and production decisions are taken. The model is solved by backward induction, and we consider labour to be the numeraire. In this section of the model, we omit the subscripts i, j for simplicity.

B.2.1 Operating profits

We first obtain the firm's operating profits in the domestic market as:

$$\pi(z) = \frac{Bz^{1-\sigma}}{\sigma} - f$$

where $B = \frac{R}{(\rho P)^{1-\sigma}}$, and $\rho = \frac{\sigma-1}{\sigma}$. If the firm decides to become a direct exporter, the firm's operating profits in the foreign market are given by:

$$\pi_d(z) = \frac{T^{1-\sigma}Bz^{1-\sigma}}{\sigma} - f_x - f_d \tag{B.1}$$

where we denote the variables associated with these firms with a subscript d.

If the firm joins the AEO program, the firm will enjoy lower trade costs at the border. In particular the firm will charge $p_a(z) = T'p(z)$, where $p(z)$ is the price charged by the firm in the domestic market. The firm's operating profits will be given by:

$$\pi_a(z) = \frac{T'^{1-\sigma}Bz^{1-\sigma}}{\sigma} - f_a - f_x - f_d \tag{B.2}$$

If, instead, the firm decides to use an agent, its operating profits will depend, however, on the AEO status of the agent. This is the case as the AEO agent enjoys lower costs of processing the firm's exports at the border and will pass through part of the saving costs into its customers. The operating profits of an indirect exporter using AEO and non-AEO agent are given respectively by:

$$\begin{aligned}\pi_x^a(z) &= \frac{(\lambda T')^{1-\sigma} Bz^{1-\sigma}}{\sigma} - f_x \\ \pi_x^x(z) &= \frac{(\lambda T)^{1-\sigma} Bz^{1-\sigma}}{\sigma} - f_x\end{aligned}$$

and the corresponding prices are $p_x^a(z) = \lambda T' p(z)$, and $p_x^x(z) = \lambda p(z)$, respectively.

B.2.2 Distribution of firms

Different equilibria can be described in our model, depending on the parameter configuration. We focus on an equilibrium in which firms are sorted into the following categories depending on their unit input requirement z : as follows: the most productive firms (i.e., lowest unit input requirements) will become AEO direct exporters, the middle ones will be non-AEO direct exporters while the least productive exporters will rely on agents. Finally there will be a group of firms with the lowest productivities which will just serve the home market.

A direct exporter will join the AEO program when the following condition holds: $\pi_a(z) \geqslant \pi_d(z)$. As $\pi(z)$ is a monotonically decreasing function of z that there exists z_a such that if $z \leqslant z_a$ the firm will become an AEO holder direct exporter. Substituting into (B.1) and (B.2) yields the following condition for the cut-off level z_a for self-selecting into the AEO program as direct exporter:

$$\frac{(\theta^{1-\sigma} - 1)\, T^{1-\sigma} B\, (z_a)^{1-\sigma}}{\sigma} = f_a \tag{B.3}$$

where we denote with $\theta^{1-\sigma} = e^{(1-\gamma)(\sigma-1)(\alpha+\nu\psi)} > 1$, the advantage in terms of trade costs provided by the AEO status.[8] Note that participating in the AEO program reduces the internal trade costs proportionally (i.e., $T' = \theta T$, $\theta < 1$). The latter allows the firm to charge lower prices in the foreign market, increasing the potential sales, ceteris paribus (i.e., $\theta^{1-\sigma} > 1$).

A firm instead will export directly (without participating in the AEO program) when the benefits from arranging its external operations internally are larger than outsourcing them to an agent: $\pi_d(z) \geqslant \pi_x(z)$. Since a firm must decide to become an indirect exporter before knowing the agent's AEO status, the firm's ex-ante operating profit of using an agent is given by

$$\pi_x(z) = \lambda'^{1-\sigma} T^{1-\sigma} B z^{1-\sigma} - f_x - f_d$$

with $\lambda'^{1-\sigma} = \left(\chi(\theta^{1-\sigma} - 1) + 1\right) \lambda^{1-\sigma}$. The monotonic properties of the profit function allow us to conclude that there exists a unit input labour requirement z_d, $z_a < z \leqslant z_d$ such that

$$\frac{T^{1-\sigma}(1 - \lambda'^{1-\sigma}) B \left(z_d\right)^{1-\sigma}}{\sigma} = f_d \tag{B.4}$$

As described above, we have focused on an equilibrium in which the least productive exporters use agents to process their exports. A firm will end up indirect exporting if the following condition holds: $\pi_x(z) > 0$, and therefore there exists $z_x, z_d < z \leqslant z_x$ such that

[8]Without MRA, $\nu = 0$ and the expression reduces to $\theta'^{1-\sigma} = e^{(1-\gamma)(\sigma-1)\alpha}$; with MRA, $\nu = 1$ and the expression becomes $\tilde{\theta}^{1-\sigma} = e^{(1-\gamma)(\sigma-1)(\alpha+\psi)}$.

$$\frac{(T\lambda')^{1-\sigma} B (z_x)^{1-\sigma}}{\sigma} = f_x \tag{B.5}$$

Finally, we can also define a unit input requirement threshold z^* such that if $z_x < z \leqslant z^*$, the firm just serves the domestic market and if $z > z^*$, the firm leaves the market. This is given by:

$$\frac{Bz^{*1-\sigma}}{\sigma} = f \tag{B.6}$$

B.2.3 Industry exporting structure

The trade facilitating policy alters the industry's exporting behavior in the following manner. First, we note that the program increases the proportion of incumbent firms that export. This can be seen by dividing (B.5) by (B.6) and we have that

$$\frac{z_x}{z^*} = (T\lambda')^{-1} \left(\frac{f_x}{f}\right)^{\frac{1}{1-\sigma}} \tag{B.7}$$

where the proportion of incumbent firms that export depends positively on $\frac{z_x}{z^*}$. This ratio increases as the AEO program reduces λ' (through the trade cost benefit term $\theta^{1-\sigma}$). The improvement in efficiency in exporting enjoyed by agents, as a consequence of participating in the AEO program, reduces the variable costs of exporting. Consequently the proportion of incumbent firms that export increases.

Through a similar mechanism, we can conclude that the signing of an MRA between countries will further increase the proportion of firms that export. Note that the signing of an MRA further increases $\theta^{1-\sigma}$ as the reduction in costs enjoyed at the border are now applied to the foreign border. This leads to a further increase in $\frac{z_x}{z^*}$.

Note that the trade facilitation policy can also alter the export structure favouring indirect rather than direct exporters. Formally, this can be seen by dividing (B.4) by (B.5) which gives the following expression:

$$\frac{z_d}{z_x} = \lambda'(1-\lambda'^{1-\sigma})^{\frac{1}{\sigma-1}} \left(\frac{f_d}{f_x}\right)^{\frac{1}{1-\sigma}} \tag{B.8}$$

which captures the proportion of exporting firms engaged in direct exporting. When the AEO program is present (with lower λ'), the ratio decreases. This result is quite intuitive: since the least productive direct exporters cannot afford to become AEO licence holders, the benefits of using an agent increase with the AEO program. These firms can therefore take advantage of the program indirectly through an agent.

In a similar way, an MRA will further contribute to skew the proportion of exporting firms towards indirect exports by further reducing λ'. The reduction in administrative costs at the foreign border will further reduce the costs of using agents to export, and therefore the least productive direct exporters will switch their export mode towards the use of an agent.

Conditions B.7, B.8 describe a relationship between z_x, z_d and z^*. To obtain the value for z^* we use B.6 and the free entry condition,

$$E(V_i) = f_e \tag{B.9}$$

where

$$E(V_i) = \frac{[G(z^*)]}{\delta} \left[\begin{array}{c} \int\limits_0^{z^*} \pi(z)\mu(z)dz + \frac{G(z_x)}{G(z^*)} \int\limits_0^{z_x} \pi_x(z)\mu_x(z)dz \\ + \frac{G(z_d)}{G(z^*)} \int\limits_0^{z_d} \left(\pi_d(z) - \pi_x(z)\right) \mu_d(z)dz + \frac{G(z_d)}{G(z^*)} \int\limits_0^{z_a} \left(\pi_a(z) - \pi_d(z)\right) \mu_d(z)dz \end{array} \right]$$

$\mu(z) = \left\{ \begin{array}{cc} \frac{g(z)}{G(z^*)} & \text{if } z \leq z^* \\ 0 & \text{otherwise} \end{array} \right\}$ and $\mu_l(z) = \left\{ \begin{array}{cc} \frac{g(z)}{G(z_l)} & \text{if } z \leq z^*, z_i \\ 0 & \text{otherwise} \end{array} \right\}$ $l = x, d$ represents the conditional unit input requirement distribution. The subscript l indicates the state in which the distribution is conditional.

Finally, the equilibrium number of firms is obtained by combining the previous conditions with the stability condition. We denote with M_e the number of entrants, the stability condition implies that in steady state

$$\delta M = G(z^*)M_e \tag{B.10}$$

In order to obtain closed form solutions for the model, which facilitates comparative statics, let us study the case of the Pareto distribution. In particular the variable z follows a probability distribution with cumulative density function given by $G(z) = \left(\frac{z}{z_M}\right)^k$, $k > \sigma - 1$, $k > 2$. Assuming this we obtain that the expressions for the unit input requirements cutoffs of the model are given by the following expressions:

$$z^* = \left(\frac{\sigma - 1}{k - (\sigma - 1)} \frac{f}{\delta f_e} \left[\begin{array}{c} 1 + (T\lambda')^{-k} \left(\frac{f_x}{f}\right)^{\frac{\sigma-1-k}{\sigma-1}} \\ +T^{-k} \left(1 - \lambda'^{1-\sigma}\right)^{\frac{k}{\sigma-1}} \left(\frac{f_d}{f}\right)^{\frac{\sigma-1-k}{\sigma-1}} \\ + \frac{T^{-k}}{\left((\theta)^{1-\sigma} - 1\right)^{\frac{k}{1-\sigma}}} \left(\frac{f_a}{f}\right)^{\frac{\sigma-1-k}{\sigma-1}} \end{array} \right] \right)^{\frac{-1}{k}} z_M$$

$$z_x = \left(\frac{\sigma-1}{k-(\sigma-1)} \frac{f_x}{\delta f_e} \left[\begin{array}{c} 1 + (T\lambda')^k \left(\frac{f}{f_x}\right)^{\frac{\sigma-1-k}{\sigma-1}} \\ +\lambda'^k \left(1-\lambda'^{1-\sigma}\right)^{\frac{k}{\sigma-1}} \left(\frac{f_d}{f_x}\right)^{\frac{\sigma-1-k}{\sigma-1}} \\ +\frac{\lambda'^k}{\left((\theta)^{1-\sigma}-1\right)^{\frac{k}{1-\sigma}}} \left(\frac{f_a}{f_x}\right)^{\frac{\sigma-1-k}{\sigma-1}} \end{array} \right] \right)^{\frac{-1}{k}} z_M$$

$$z_d = \left(\frac{\sigma-1}{k-(\sigma-1)} \frac{f_d}{\delta f_e} \left[\begin{array}{c} 1 + T^k \left(1-\lambda'^{1-\sigma}\right)^{\frac{k}{1-\sigma}} \left(\frac{f}{f_d}\right)^{\frac{\sigma-1-k}{\sigma-1}} \\ +\lambda'^{-k} \left(1-\lambda'^{1-\sigma}\right)^{\frac{k}{1-\sigma}} \left(\frac{f_x}{f_d}\right)^{\frac{\sigma-1-k}{\sigma-1}} \\ + \left(\frac{\left(\theta^{1-\sigma}-1\right)^{\frac{k}{\sigma-1}}}{\left(1-\lambda'^{1-\sigma}\right)^{\frac{k}{\sigma-1}}}\right) \left(\frac{f_a}{f_d}\right)^{\frac{\sigma-1-k}{\sigma-1}} \end{array} \right] \right)^{\frac{-1}{k}} z_M$$

$$z_a = \left(\frac{\sigma-1}{k-(\sigma-1)} \frac{f_a}{\delta f_e} \left[\begin{array}{c} 1 + \frac{T^k}{\left(\theta^{1-\sigma}-1\right)^{\frac{k}{\sigma-1}}} \left(\frac{f}{f_a}\right)^{\frac{\sigma-1-k}{\sigma-1}} + \\ \frac{(\lambda')^{-k}}{\left(\theta^{1-\sigma}-1\right)^{\frac{k}{\sigma-1}}} \left(\frac{f_x}{f_a}\right)^{\frac{\sigma-1-k}{\sigma-1}} \\ + \left(\frac{n\left(\theta^{1-\sigma}-1\right)^{\frac{k}{1-\sigma}}}{\left(1-\lambda'^{1-\sigma}\right)^{\frac{k}{1-\sigma}}}\right) \left(\frac{f_d}{f_a}\right)^{\frac{\sigma-k-1}{\sigma-1}} \end{array} \right] \right)^{\frac{-1}{k}} z_M$$

Based on the cut-off levels, we summarize the following implications of an MRA for the aggregate economy.

Proposition 4. *A mutual recognition agreement (MRA):*

a) Reduces the survival unit input cutoff

b) Increases the proportion of incumbents that export

c) Reduces the proportion of firms engaged into direct exporting

d) Increases the proportion of firms that become AEO holders

Proof. Note that $\frac{\partial \ln z_l}{\partial \theta^{1-\sigma}} = \frac{\partial z_l}{\partial \theta^{1-\sigma}}$ since $\frac{\partial \ln z_l}{\partial \theta^{1-\sigma}} = \frac{1}{z_i}\frac{\partial z_i}{\partial \theta^{1-\sigma}}$ and $z_l > 0 \; \forall z_i, l = \varnothing, x, d$. Taking logs of the solutions presented in the previous sections and differentiating with respect to λ, effect a) comes from checking that $\frac{\partial z^*}{\partial \theta^{1-\sigma}} < 0$; effect b) comes from $\frac{\partial z_x^*}{\partial \theta^{1-\sigma}} > 0$; effect c) comes from $\frac{\partial z_d^*}{\partial \theta^{1-\sigma}} < 0$ and effect d) comes from $\frac{\partial z_a^*}{\partial \theta^{1-\sigma}} > 0$.

$\square$