

**REPUBLIC OF TÜRKİYE
YILDIZ TECHNICAL UNIVERSITY
GRADUATE SCHOOL OF SOCIAL SCIENCES
DEPARTMENT OF ECONOMICS**

DISSERTATION FOR THE DEGREE OF DOCTOR OF PHILOSOPHY

**ICT AND EXPORT PERFORMANCE: FIRM-LEVEL EVIDENCE
FROM TÜRKİYE**

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**ADVISOR
PROF. DR. FERİDE GÖNEL**

2025

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Hikmet KAYA tarafından hazırlanan “ICT and Export Performance: Firm-level Evidence from Türkiye” başlıklı çalışma, **07/03/2025** tarihinde yapılan savunma sınavı sonucunda oybirliği ile başarılı bulunmuş ve jürimiz tarafından İktisat Ana Bilim Dalı İktisat (İngilizce) Programında **DOKTORA** tezi olarak kabul edilmiştir.

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ABSTRACT

ICT AND EXPORT PERFORMANCE: FIRM-LEVEL EVIDENCE FROM TÜRKİYE

This dissertation aims to empirically examine the effects of information and communication technologies (ICT) on the export performance of firms in the Turkish manufacturing sector, considering both the extensive and intensive margins. To achieve this objective, an unbalanced panel dataset covering 2009–2019 was constructed by merging five different datasets compiled by the Turkish Statistical Institute: ICT Usage in Enterprises Survey, Foreign Trade Statistics, Company Accounts Statistics, Annual Industry and Service Statistics, and Annual Business Registers Framework.

The study employs random effects panel probit methodology to estimate the probability of becoming an exporter (extensive margin) and panel random effects methodology to analyze export intensity (intensive margin). Additionally, to address potential endogeneity problems stemming from selection bias, various matching approaches within the propensity score matching framework are implemented.

The findings reveal that Enterprise Resource Planning (ERP) usage increases firms' probability of exporting, with evidence of complementarity between ERP and internet-using employees, though this effect is limited to lower levels of ICT-skilled labor. Firm size analysis shows that ERP usage significantly increases export probability for SMEs, while the effect is absent for large firms. Additionally, complementarity between ERP and ICT labor share is observed only for SMEs, and only up to a 30% threshold. ERP is most strongly associated with medium-high and medium-low technology exports. PSM estimates confirm that ERP usage increases export probability by approximately 5 percentage points, reinforcing the robustness of the results. In contrast, while ERP is positively associated with export intensity in the full sample and for SMEs, PSM estimates suggest no causal relationship, indicating a divergence between export market entry and export intensity.

These findings offer significant implications for policy makers in formulating targeted policies to enhance the export performance of manufacturing firms, particularly SMEs, through strategic ICT investments and digital skill development.

Keywords: Information and communication technologies, export performance, enterprise resource planning, Turkish manufacturing industry

ÖZ

BİT VE İHRACAT PERFORMANSI İLİŞKİSİ: TÜRKİYE İÇİN FİRMA DÜZEYİNDE AMPİRİK BİR ANALİZ

Bu doktora tezi, bilgi ve iletişim teknolojilerinin (BİT) Türk imalat sektöründe faaliyet gösteren firmaların ihracat performansı üzerindeki etkilerini hem yaygın (extensive) hem de yoğun (intensive) marjda ampirik olarak incelemeyi amaçlamaktadır. Bu amaca yönelik olarak, Türkiye İstatistik Kurumu tarafından derlenen beş farklı veri seti (Girişimler Bilişim Teknolojileri Kullanım Araştırması, Dış Ticaret İstatistikleri, Sektör Bilançoları, Yıllık Sanayi ve Hizmet İstatistikleri ve Yıllık İş Kayıtları Çerçevesi) birleştirilerek 2009–2019 dönemini kapsayan dengesiz bir panel veri seti oluşturulmuştur.

Çalışmada, firmaların ihracatçı olma olasılığını (yaygın marj) tahmin etmek için rassal etkiler panel probit yöntemi ve ihracat yoğunluğunu (yoğun marj) analiz etmek için panel rassal etkiler yöntemi kullanılmıştır. Ayrıca, seçim yanlılığından kaynaklanan muhtemel içsellik sorunlarını azaltabilmek için, çeşitli eşleştirme yaklaşımlarını içeren eğilim skoru eşleştirme yöntemi uygulanmıştır.

Bulgular, Kurumsal Kaynak Planlaması (ERP) kullanımının firmaların ihracatçı olma olasılığını artırdığını ve ERP ile internet kullanan çalışanlar arasında tamamlayıcılık ilişkisi bulunduğunu, ancak bu etkinin daha düşük seviyelerdeki BİT yetkinliği ile sınırlı olduğunu göstermektedir. Firma büyüklüğüne göre yapılan analizler, ERP kullanımının KOBİ'lerin ihracat olasılığını artırdığını, ancak büyük firmalar için bu etkinin ortadan kalktığını ortaya koymaktadır. Ayrıca, ERP ile BİT işgücü payı arasındaki tamamlayıcılık yalnızca KOBİ'lerde gözlenmekte ve bu etki sadece %30'luk bir eşiğe kadar görülmektedir. ERP kullanımı daha çok orta-yüksek ve orta-düşük teknoloji ihracatı ile ilişkilendirilmektedir. Eğilim skoru eşleştirme tahminleri, ERP kullanımının ihracatçı olma olasılığını yaklaşık 5 yüzde puan artırdığını doğrulayarak sonuçların sağlamlığını güçlendirmektedir. Buna karşılık, ERP tüm örnekleme ve KOBİ'lerde ihracat yoğunluğu ile pozitif ilişkili olsa da PSM tahminleri nedensel bir ilişki olmadığını göstermekte, bu da ihracat pazarına giriş ile ihracat yoğunluğu arasındaki farklılığı vurgulamaktadır.

Bu bulgular, politika yapıcılarının, özellikle KOBİ'lerin ihracat performansını artırmak için stratejik BİT yatırımlarını ve dijital beceri gelişimini destekleyen hedeflenmiş politikalar geliştirmesine önemli katkı sağlamaktadır.

Anahtar Kelimeler: Bilgi ve iletişim teknolojileri, ihracat performansı, kurumsal kaynak planlaması, Türk imalat sanayisi

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Hikmet KAYA

March 2025; İstanbul

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ABBREVIATIONS

ATC	: Average Treatment Effect on the Control
ATE	: Average Treatment Effect
ATT	: Average Treatment Effect on the Treated
CIA	: Conditional Independence Assumption
CRM	: Customer Relationship Manager
ERP	: Enterprise Resource Planning
ICT	: Information and Communication Technology
ISIC	: International Standard Industrial Classification
MDM	: Multivariate Distance Matching
NACE	: Nomenclature statistique des Activités économiques dans la Communauté Européenne (Statistical Classification of Economic Activities in the European Community)
NN	: Nearest-Neighbor
NUTS	: Nomenclature des Unités Territoriales Statistiques (Nomenclature of Territorial Units for Statistics)
PSM	: Propensity Score Matching
ROA	: Return on Assets
SCM	: Supply Chain Management
SITC	: Standard International Trade Classification
SMEs	: Small and Medium-Sized Enterprises
TurkStat	: Turkish Statistical Institute

1. INTRODUCTION

The revolutionary developments in information and communication technologies (ICT) in the last thirty years have led to radical transformations in global economies, leading to the reshaping of firms' production processes, ways of doing business, and competitive strategies. Moreover, the spread of digital technologies has played an important role in the transformation of commercial dynamics and has provided new opportunities for firms to increase their access to global markets and their export potential. In the highly globalized economic order of our age, the integration of ICT into business operations has become almost a necessity, and the opportunities it provides have gone beyond being a mere facilitator of communication and have become a determinant of enterprise performance. This transformation is evident not only in developed economies but also in developing and underdeveloped economies, where digital technologies are increasingly accepted as critical catalysts for export growth and market expansion.

A critical dimension of ICTs' transformative impact lies in its capacity to reshape the economics of trade itself. ICTs have a significant capacity in terms of their ability to affect trade by reducing trade costs arising from the distance between trade partners. As ICTs have developed rapidly since the 1990s, their implementation has played a significant role in addressing informational asymmetries in trade, eliminating trade barriers and closing geographical distances. As a result, ICT has effectively lowered trading costs, boosted trade efficiency, and expanded trading volumes. According to the World Trade Organization (2018), which classifies trade costs into six categories¹, information and transaction costs constitute the second-largest cost for goods exports (approximately 20%) and the largest for services exports (nearly 30%). It is expected that ICT adoption is likely to decrease these costs and facilitate trade. Given that the World Trade Organization attributes the 15% reduction in

¹ Transport costs, logistics costs, border costs, information and transaction costs, trade policy barriers, and other costs.

international trade costs between 1996 and 2014 to the ICT revolution, this gives sufficient ground to analyze ICTs' impact on firms' trade.

Although Türkiye is classified as a late adopter in the field of ICT compared to developed countries, it has undergone rapid technological adaptation over the past two decades, both at household and enterprise levels. According to World Bank data, internet usage among individuals in Türkiye, an upper middle-income country, expanded from 4% in 2000 to 86% in 2023, surpassing the income group's average of approximately 80%. Mobile cellular penetration shows similar growth, increasing from 25 subscriptions per 100 people in 2000 to 106 in 2022 (World Bank, 2024). At the enterprise level, ICT adoption demonstrates consistent growth across multiple indicators. According to the Turkish Statistical Institute's (TurkStat) (2023) ICT Usage in Enterprises Survey, the percentage of enterprises with internet access has increased from 90% to 96% over the past decade. Similarly, the proportion of enterprises with broadband connections has also reached 96%. The share of enterprises using Enterprise Resource Planning (ERP) systems was approximately 18% in 2012, rising to 30% in 2023. Furthermore, in recent years, companies, particularly in the manufacturing sector, have intensified their investments in artificial intelligence and robotics technologies. This overall trend indicates a significant improvement in the digital infrastructure and management systems adoption among enterprises².

This technological transformation in Turkish enterprises has occurred alongside significant developments in the country's export performance. Looking at the trend of Türkiye's annual total exports during the 2009-2019 period, export volume increased from \$102.1 billion in 2009 to \$171.5 billion in 2019 (TurkStat, 2020), and this growth is reflected in Türkiye's increasing global presence, as United Nations Conference on Trade and Development (UNCTAD) data shows that the country's share in world exports grew from 0.75% to 0.95% during the same period. Notably, throughout this growth trajectory, the share of the manufacturing sector in Türkiye's total exports, which is the focus of our analysis, remained stable at approximately

² For a comparative descriptive analysis of Türkiye's firm-level broadband internet speed, e-commerce activities, and enterprise software systems, including ERP, CRM, and business intelligence, as well as cutting-edge areas such as artificial intelligence, cloud computing, the internet of things, and robotics, in comparison with EU countries, see Taştan (2024).

94% (TurkStat, 2020). While manufacturing's share was around 36% in 1980, it increased rapidly following the adoption of an export-led growth strategy, reaching 76% in 1985 and 90% in 1995, maintaining levels above 90% throughout the 2000s. This study will focus on the manufacturing sector due to both its dominant share in Türkiye's total exports and the fact that our datasets only cover merchandise exports.

While Türkiye's total export volume has increased significantly, another crucial aspect to consider is the distribution of exporting firms. In fact, in the context of this study, even more significant than the trend in total exports is the evolution in the number of exporting firms. The number of exporters in Türkiye has shown remarkable growth, increasing from just over 40,000 in 2005 to approximately 90,000 by 2019 (TİM, 2020). Given that some firms exited the export market over this 15-year period, it is possible to state that the actual increase in the number of exporters has been well above 100%. This rise reflects not only the growing importance of exports in the Turkish economy but also the increasing participation of firms in international trade, further supporting the country's integration into global markets.

Given the simultaneous progress in ICT adoption and export market expansion, as well as ICT's potential to influence trade, it is crucial to empirically investigate the nature of this relationship in the Turkish context. Building upon this premise, the central research question guiding this dissertation is: How does ICT adoption affect the export performance of manufacturing firms in Türkiye? To unpack this question, the analysis adopts a dual methodological approach, distinguishing between the extensive margin (the likelihood of a firm becoming an exporter) and the intensive margin (the share of export value in a firm's total sales). This dual framework acknowledges that ICTs may not only lower entry barriers for firms entering international markets but also enhance the competitiveness of existing exporters. Additionally, this study examines the effect of ICT adoption on firms' export intensity by categorizing exports based on their technological level. By analyzing the impact of ICT usage across different technology groups, this approach provides a more detailed insight into whether ICT adoption has a uniform influence on export performance or if its effects vary depending on the technological sophistication of exported goods.

The empirical analysis in this study is based on an econometric model using a novel panel dataset that, to the best of our knowledge, has not been previously utilized within the context of this research. We constructed an unbalanced panel dataset covering the period 2009-2019 by merging five firm-level micro datasets compiled by TurkStat: ICT Usage in Enterprises Survey, Foreign Trade Statistics, Company Accounts Statistics, Annual Industry and Service Statistics, and Annual Business Registers Framework. The selection of the 2009-2019 period as the analysis timeframe is significant for two reasons: first, it corresponds to the overlapping years available across all five datasets; second, it captures a crucial period between two major shocks affecting the Turkish economy - the 2009 global financial crisis and the 2020 COVID-19 pandemic. Consequently, while the number of firms and observations varies across different model specifications in the econometric analysis, the final dataset comprises 32,767 observations from 14,419 firms operating in the manufacturing industry, including both small and medium-sized enterprises (SMEs) and large firms with more than 250 employees.

Our findings reveal a positive association between ERP and firms' probability of exporting, with complementarity between ERP and internet-using employees at lower levels of ICT-skilled labor. Firm size analysis shows this association exists for SMEs but not for large firms, with complementarity between ERP and ICT labor share existing only for SMEs up to a 30% threshold. ERP has strongest associations with medium-high and medium-low technology exports. Propensity Score Matching confirms that ERP increases export probability by approximately 5 percentage points, addressing endogeneity concerns arising from selection bias. For export intensity, we find positive associations in the full sample and for SMEs, but PSM estimates suggest no causal relationship, contrasting with findings on export market entry.

This study makes several significant contributions to the existing literature. First, it addresses the notable gap in empirical research regarding ICTs' impact on export performance in developing countries by examining the case of Türkiye. Second, while previous studies have largely relied on basic ICT indicators such as computer ownership, internet access, and email usage due to data constraints, this research advances the analytical framework by focusing on more sophisticated indicators of technological advancement. This choice is particularly significant as it better

captures firms' technological sophistication in an era where basic ICT adoption has become nearly universal across firms. Another significant aspect of this study, which can also be considered as a contribution, relates to the dataset used for empirical analysis. The richness of the dataset has enabled analysis across different firm sizes and provided firm-level evidence that can serve as a benchmark not only specific to Türkiye but also for the broader literature examining the ICT-export relationship.

The remainder of this study is structured as follows: Section 2 presents the conceptual framework of the ICT-export relationship, followed by the theoretical model. Section 3 provides a review of the relevant empirical literature. Section 4 introduces the datasets used in the analysis, presents descriptive statistics, and outlines the econometric methodology. Section 5 presents and discusses the empirical results. Finally, Section 6 concludes.

2. CONCEPTUAL AND THEORETICAL FRAMEWORK

This section develops the theoretical framework for analyzing the relationship between information and communication technologies and firms' export performance. Before establishing this framework, we first examine how technology has been integrated into international trade theories throughout history, from classical theories to modern approaches. We then explore the crucial role of firms in international trade, particularly focusing on firm heterogeneity and its implications for trade theory. Finally, we discuss how ICT affects international trade through its impact on distance-related trade barriers.

2.1. Conceptual Framework

The exploration of why countries engage in trade, or the justification for such trade, has been pursued for centuries. The responses have been disproven or enhanced, either by theoretical means or based on empirical evidence. Consequently, numerous trade theories have arisen throughout history. Throughout this theoretical evolution, the understanding of technology's role in trade has also transformed significantly, reflecting the changing nature of international trade and our understanding of its drivers.

Classical theories, such as Smith's absolute advantage and Ricardo's comparative advantage, attributed trade to exogenous technological differences but treated technology as static. Traditional trade theories have played a crucial role in elucidating the basis for and gains from trade, particularly inter-industry trade. Nevertheless, these theories fall short in accounting for intra-industry trade and the observation that a significant portion of global trade occurs between countries with similar technological capabilities or factor endowments. Consequently, economists have sought to refine the Heckscher-Ohlin (H-O) model by relaxing its underlying assumptions and developing complementary or alternative theoretical frameworks.

Subsequent theories, including Krugman's (1979) monopolistic competition and Helpman's (1981) product differentiation models, made significant contributions by explaining how economies of scale and consumer preferences for variety could drive trade between similar countries. Their work showed that even without technological differences or varying factor endowments, countries could benefit from trade through expanded product variety and market competition. These theoretical developments paved the way for neo-technology trade models, which explicitly consider how technological innovation shapes trade patterns over time. Two prominent examples of these models are Posner's (1961) technology gap model and Vernon's (1966) product cycle model. Posner's model emphasizes how technological innovation creates temporary comparative advantages, while Vernon's model explains how production locations shift as products mature and standardize.

These models provide a dynamic perspective on comparative advantage, contrasting with the static approach of traditional trade theories. While these theoretical developments enhanced our understanding of technology's role in trade, a significant transformation in international trade research over the past two decades has shifted focus from industry and country analyses to individual firms and their products. This transformation was catalyzed by the availability of microdata sets that revealed significant heterogeneity in firm performance and characteristics, even within the same industry (Bernard et al., 2007). This empirical reality has necessitated abandoning the simplifying assumption of a representative firm within an industry in favor of models that explicitly account for firm heterogeneity.

Firm-level microdata has revealed several fundamental stylized facts about international trade. One of them is the fact that only a small proportion of firms within a country engage in exporting, with a significant portion of total exports concentrated among an even smaller number of firms³. Notably, both traditional and

³ For instance, in Türkiye, only 2.97% of enterprises engage in exporting activities, with the top 1,000 firms accounting for approximately \$162 billion of the \$254 billion total exports in 2022. This pattern is not unique to Türkiye; Bernard et al. (2018) demonstrate that the top 1% of U.S. exporters control over 80% of total U.S. trade. Similarly, Freund and Pierola (2015) show that in 32 developing countries between 2006 and 2008, the largest firm accounted for an average of 15% of total exports, while the top five firms accounted for 30%.

new trade theories, which presuppose all firms to be similar by assumption, cannot explain this export concentration.

Another stylized fact, particularly emerging from the study by Bernard and Jensen (1995), demonstrates that firms engaged in exporting activities consistently demonstrate superior performance across various metrics compared to non-exporting firms. This phenomenon, often referred to as the 'export premia', suggests that exporting firms tend to be larger in scale, exhibit enhanced productivity, possess greater capital intensity, and rely more heavily on skilled labor, while simultaneously offering higher wage compensation⁴.

The persistent disparity in productivity between exporting and non-exporting firms has ignited a debate regarding the causal direction of the relationship between export participation and productivity. Central to this debate is the question of whether firms inherently more productive before entering export markets, suggesting a selection bias favoring efficient firms (self-selection hypothesis) or whether the act of exporting itself lead to productivity gains through accumulated knowledge and experience (learning-by-exporting hypothesis). While empirical evidence remains inconclusive, there is stronger evidence supporting the validity of the self-selection hypothesis (Bernard et al., 2007; Redding, 2011).

The inability of traditional trade theories to account for these stylized facts has driven the emergence of the so-called "new-new" trade theories. Melitz (2003) emerged as a leading figure in this field by incorporating heterogeneity in firm productivity into the monopolistic competition framework developed by Krugman (1980). By integrating firm-level productivity differentials into the model, Melitz sheds light on the underlying mechanisms that restrict participation in export markets to a select cohort of firms.

Melitz's model posits a single sector producing horizontally differentiated goods with labor as single input. Firms exhibit increasing returns to scale, and each produces a unique good under monopolistic competition. A key contribution of the model is the explicit consideration of firm heterogeneity in productivity. Firms must incur fixed costs to produce their differentiated products, which become sunk costs

⁴ This pattern is supported by numerous studies, including Aw et al. (2000), Bernard and Jensen (1995, 1999), De Loecker (2007), Mayer and Ottaviano (2008).

once incurred. Consequently, only the most productive firms can remain profitable and persist in the market, while the least productive firms exit. Melitz further introduces additional fixed costs to export, such as establishing foreign distribution channels, adapting products to meet legal regulations or consumer preferences, and promotional activities in foreign markets. These costs further explain why only the most productive firms export.

Firms thus decide whether to produce or exit the market based on their level of productivity; if they choose to produce, they may focus solely on the domestic market or expand to export markets. This creates two thresholds, leading to three potential scenarios for a firm depending on its productivity level. If a firm's productivity falls below the zero-profit productivity cutoff (the first threshold), it will incur losses if it continues production, prompting it to exit the sector. If the firm's productivity surpasses the export productivity cutoff (a higher threshold), it will export alongside serving the domestic market, as it can cover both fixed and variable costs while still making a profit. Firms with productivity between these thresholds solely serve the domestic market.

One of the model's key insights is its explanation of how trade affects overall economic productivity. When trade barriers decrease, the least productive firms find it increasingly difficult to compete and are pushed out of the market. Meanwhile, highly productive firms expand their export activities, increasing their market share. This restructuring results in a higher average productivity level within the economy as inefficient firms exit, and productive firms grow. The model also shows how this process affects labor markets. Expanding export firms increase their demand for workers, while firms exiting the market release workers, creating a redistribution of labor towards more productive firms. This process not only improves overall economic efficiency but also typically results in higher average wages, as more workers become employed by high-productivity firms that can afford to pay better wages.

The theoretical evolution of trade analysis, particularly at the firm level through Melitz's contributions, naturally intersects with broader debates about the role of geography and distance in international trade patterns. While the heterogeneous firms framework revolutionized our understanding of which firms engage in trade and why, it also raised important questions about how geographical factors interact with

firm-level characteristics to shape trade outcomes. These questions became particularly prominent in the context of emerging discussions about whether technological progress was fundamentally altering the importance of distance in trade relationships. As theorists were developing more sophisticated models of firm-level trade behavior, a parallel debate emerged in the 1990s about whether technological advancement was making traditional geographic barriers less relevant.

In the 1990s, “the death of distance” (Cairncross, 1997) and “the end of geography” (O’Brien, 1992) have emerged as the two most striking concepts that emphasizes the declining significance of location in terms of foreign trade. Cairncross asserted that some costs pertaining to distance such as transportation and communication would tend to fall in parallel with the advancements in information technologies, which makes the geographical location of trading countries less significant to some extent. Similarly, while focusing on financial integration and innovation, O’Brien argues that the introduction of modern payment systems has facilitated trade with distant parties compared to the past when physical meetings were necessary for exchanging handwritten documents and cash. Later, Friedman (2005) characterized the world as flat to emphasize competition in commerce is a “level playing field” at which competitors have equal opportunities so that competition among countries is unconnected with their location.

However, these views faced significant opposition. Venables (2001) argues that while new technologies may lead to the relocation of some economic activities and contribute more to the economic development of some nations or regions, the notion of the ‘death of distance’ argument would be unrealistic. He argues that this concept implies a convergence that is not supported empirically. Similarly, Agnew (2011) took a historical approach, noting that similar claims about the diminishing role of distance had been made at various points in history such as during the development of railways, roads, and telegraphy, yet distance remained important. Therefore, he argued that ‘distance did not die’ and technological innovations have not rendered the importance of location but rather reformulated it.

While the rise of firm-level trade models has deepened our understanding of why only the most productive firms engage in exporting, these insights naturally intersect with broader debates about the role of geography and trade costs in shaping trade patterns. Although some arguments suggest that technological advancements might

make geographical barriers insignificant, empirical evidence and theoretical models have shown that distance remains a key determinant of trade costs. The persistence of trade costs, as emphasized by Anderson and van Wincoop (2004), not only challenges the idea that globalization has entirely erased spatial constraints but also raises crucial questions about how firms seeking to internationalize can lessen these costs. Given that trade costs encompass more than just tariffs and transport expenses - extending to information asymmetries, contract enforcement, and regulatory compliance - understanding their composition becomes essential for assessing how firms expand into international markets. In this context, the role of ICT in reducing transaction costs emerges as a critical factor in shaping firms' export performance and their ability to engage in global trade.

One of the most important transaction costs is the search cost and it plays an important role in the decision-making processes related to foreign trade activity. A firm seeking to enter foreign markets will primarily aim to find a business partner in the target country. As Besedeš (2008) points out, most foreign trade relationships usually start with small volumes and short terms, and therefore looking for and finding a reliable and suitable foreign trading partner is important for the long-term relationship. However, trade is not solely confined to finding a suitable partner. A firm entering an unfamiliar market must undergo numerous processes such as modifying its products according to the preferences of consumers in that country, complying with the legal regulations and standards of that country, establishing distribution channels, and conducting market research to sell the product at a competitive price. The inability of a firm to possess complete information regarding all these processes will lead to information asymmetry between trading partners, introducing additional costs due to information friction.

Therefore, while high search costs may lead a firm to decide not to enter the foreign trade market, ICT can facilitate trade by reducing costs through its role in significantly reducing the information friction about the market, players, and products, which is the main cause of search costs (Aker, 2010; Allen, 2014; Jensen, 2007).

The other transaction cost where the role of ICT is crucial is the communication cost. The impact of communication on trade has either been ignored in theoretical models or seen as part of transportation costs. Harris (1995), in his pioneering work where he

incorporates communication into the trade model, lists a number of reasons why the communication cost should not be seen as a transportation cost, the most important of which is that the communication cost is actually a fixed cost. Because once the necessary infrastructure is established, the marginal cost of using this network is very low or even zero. However, when we distinguish between supply-side and demand-side approaches, Harris' approach might be correct from a supply-side perspective if communication was only a tool used in the process of searching for a trading partner. However, when we consider the entire trade process from market research and negotiations to the delivery of the product to the buyer and after-sales support, there is constant communication between buyer and seller. This ongoing interaction introduces variable costs, as it requires continuous effort, time, and resources, which can fluctuate depending on the complexity and frequency of the transactions (Mupela & Szirmai, 2012). Therefore, while communication costs may be largely fixed from a supply-side perspective, on the demand side, they exhibit characteristics of variable costs. Fink et al. (2005), who modeled the cost of communication on this distinction and examined its impact on trade, empirically showed that decreases in the cost of communication increase international trade.

The preceding discussion of distance, trade costs, technology, and firm heterogeneity in international trade provides the foundation for developing a theoretical framework that specifically examines how firms' technology choices influence their export market participation. While the debate about the role of distance in trade continues, the following theoretical model focuses on a crucial aspect of modern trade patterns: the relationship between firms' technology decisions and their export behavior.

2.2. Theoretical Model

This subsection presents a simple theoretical model to intuitively support the empirical analysis of the impact of heterogeneous firms' technology upgrading decisions on export market entry. The theoretical framework builds on the work of Caldera (2010), who extends the model of Bustos (2005, 2011). While Caldera's study focuses on the impact of innovation on exports, we make nuanced modifications to her model and employ a similar framework to investigate the effect of a firm's decision to employ high technology or sustain traditional technology on export performance. Using high technology allows firms to reduce their marginal

production costs and upgrade their technological capabilities. Caldera extends the Bustos model to directly compare the exporting decisions of an innovating firm versus a non-innovating firm. In a similar vein, following Caldera, this study directly compares the export decisions of firms employing high versus traditional technology. The core assumption is that firms exhibit heterogeneity in productivity, meaning that more productive firms (e.g., due to superior managerial capabilities) possess an inherent advantage. Within this framework, firms make a strategic decision: they can either continue using traditional/low technology or invest in high technology by incurring a higher fixed cost. This investment, in turn, lowers their marginal production costs and enhances their technological capabilities, thereby influencing their export potential. The model's key prediction is that firms adopting high technology are more likely to engage in exporting activities. This follows from the logic that lower marginal costs improve competitiveness in international markets, making it easier for these firms to absorb fixed export costs and sustain profitability in foreign trade. By explicitly framing technology adoption as a strategic decision within a heterogeneous firm model, this extension enhances the empirical tractability of the framework and better aligns it with the core research question.

2.2.1. Demand Side of the Model

Consumer behavior is characterized by a standard assumption, originally developed by Dixit and Stiglitz (1977). There is a representative consumer with constant elasticity of substitution (CES) preferences over a continuum of horizontally differentiated varieties i of a good q .

$$U = \left[\int_0^N q(i)^\rho di \right]^{1/\rho} \quad (1)$$

where N is the number of existing varieties, $q(i)$ is the consumption of variety i . ρ is the substitution parameter (also called the “love of variety” parameter) with $\rho \in (0,1)$ to ensure the concavity of the utility function. Consumers maximize their utility subject to the budget constraint:

$$\int_0^N p(i)q(i) di = E \quad (2)$$

where $p(i)$ is the price of each variety. Then, consumer's utility maximization leads to demand for a particular variety being:

$$q(i) = \frac{E}{P} \left(\frac{p(i)}{P} \right)^{-\sigma} \quad (3)$$

where $\sigma = 1/(1 - \rho) > 1$ is the constant elasticity of substitution across varieties. σ increases as the desire for variety increases and

$$P = \left[\int_0^N p(i)^{1-\sigma} di \right]^{\frac{1}{1-\sigma}} \quad (4)$$

is the overall level of prices that each firm takes as given.

2.2.2. Supply Side of the Model

On the supply side, the economy is characterized by a monopolistically competitive industry. Each variety i of good q is produced by a single firm and there is free entry into the industry. As in Melitz (2003), firms are heterogeneous in their productivity parameter, denoted by φ_i , such that marginal cost of each firm utilizing the same technology varies depending on the productivity level of the firm. In turn, more productive firms have a lower marginal cost of production. To enter the industry, a firm must make an initial investment, modelled as a fixed cost of entry, which is thereafter sunk. An entrant then draws its productivity from a known and exogenous cumulative distribution function. Upon observing their productivity, firms decide to exit or to produce. Following Yeaple (2005), surviving firms has the option to improve its technology in the following sense: Firms can choose to produce with two different technologies high ($T = H$) and low/traditional ($T = L$) that has a constant marginal cost (c) and a fixed cost (f). Investing and adopting a more productive technology H requires a higher fixed cost ($f_H > f_L$), but it guarantees a lower marginal cost of production ($c_H < c_L$). In short, a firm's productivity is subject to a stochastic factor; however, firms can strategically exploit technological advancements to enhance their productivity.

Under CES preferences, the profit-maximizing price (p^T) of a producer of variety i is the constant markup over marginal cost:

$$p^T(\varphi_i) = \frac{1}{\rho} \frac{c_T}{\varphi_i} \quad (5)$$

The resulting quantity sold (q^T), the revenues (r^T) and the profits (π^T) are defined by the following equations:

$$q^T(\varphi_i) = EP^{\sigma-1} \left[\rho \frac{\varphi_i}{c_T} \right]^\sigma \quad (6)$$

$$r^T(\varphi_i) = p^T(\varphi_i)q^T(\varphi_i) = E \left[P\rho \frac{\varphi_i}{c_T} \right]^{\sigma-1} \quad (7)$$

$$\pi^T(\varphi_i) = \frac{1}{\sigma} r^T(\varphi_i) - f_T \quad (8)$$

Up to this point, the model closely follows Bustos (2005, 2011). However, in alignment with the research question's objective, we will adopt a modification like Caldera's (2010) modification to the Bustos model, comparing firms that enhance their technology utilization levels with those that adhere to traditional technologies.

2.2.2.1. Technology Upgrade Decision

Firms will prefer to upgrade their technology ($T = H$) as long as the profit from upgrading (π^H) will exceed the profit from sustaining low technology ($T = L$). This can be formally expressed as:

$$\pi^H(\varphi_i) > \pi^L(\varphi_i) \Leftrightarrow \frac{1}{\sigma} E(P\rho\varphi_i)^{\sigma-1} (c_H^{1-\sigma} - c_L^{1-\sigma}) > (f_H - f_L) \quad (9)$$

This expression shows the technology upgrading decision of firms by considering their profit and cost functions. The left-hand side of the equation (9) shows the benefit of upgrading the firm's technology from L to H whereas the right-hand shows the cost difference between the two levels of technology. Therefore, this expression indicates that firms will upgrade their technology when the former (benefit) is higher than the latter (cost). Furthermore, equation (9) implies a self-selection effect, where more productive firms (higher φ_i) are more likely to upgrade their technology. This is because the benefit from upgrading technology, expressed as an increasing function of φ_i , translates to a greater revenue increase from reduced marginal costs for firms with higher initial productivity. In simpler terms, a firm with high initial productivity (low marginal costs) that upgrades its technology can reduce its costs even further. This would lead to a much larger revenue increase compared to a firm with lower initial productivity (already higher marginal costs) that achieves the same cost reduction through technology upgrade. Therefore, technology upgrade is more

attractive for these high-productivity firms because the potential payoff is significantly greater.

2.2.2.2. Export Decision

Following the market entry and technology upgrade decision, firms have the option to engage in international trade alongside domestic market participation. International trade incurs costs, and to export, firms face a dual cost structure associated with exporting as in Melitz (2003): a per-unit iceberg cost, meaning that the firm has to ship $\tau > 1$ unit of a good for one unit to arrive at a destination and has to incur an initial fixed cost of f_x to start exporting. In this setting, exporting profits are:

$$\pi_x^T(\varphi_i) = \tau^{1-\sigma^*} E^* (P^* \rho^*)^{\sigma^*-1} \frac{1}{\sigma^*} c_T^{1-\sigma^*} \varphi_i^{\sigma^*-1} - f_x \quad (10)$$

where E^* is the foreign spending in good q , P^* is the price index in the foreign country, and σ^* is the constant elasticity of substitution across varieties in foreign country where $\rho^* = \frac{\sigma^*-1}{\sigma^*}$.

The model posits that firms upgrading their technology are more likely to become exporters compared to those that do not upgrade. This conclusion is derived from comparing the profit increases of firms using technology H versus technology L upon entering the export market. A firm will opt to export if its total profits from both domestic and export markets exceed the profits it would earn solely from the domestic market. This can be formally expressed as:

$$\pi^T(\varphi_i) + \pi_x^T(\varphi_i) > \pi^T(\varphi_i) \quad (11)$$

A firm using technology H chooses to export under the following condition:

$$\left[\tau^{1-\sigma^*} E^* (P^* \rho^*)^{\sigma^*-1} \frac{1}{\sigma^*} \varphi_H^{\sigma^*-1} \right] c_H^{1-\sigma^*} > f_x \quad (12)$$

whereas a firm using technology L chooses to export if:

$$\left[\tau^{1-\sigma^*} E^* (P^* \rho^*)^{\sigma^*-1} \frac{1}{\sigma^*} \varphi_L^{\sigma^*-1} \right] c_L^{1-\sigma^*} > f_x \quad (13)$$

The left-hand of both equation (12) and (13) shows the profits from exporting for firms using technology H and technology L , respectively. The right-hand side of both equations shows the fixed cost of exporting (f_x), which is the same for firms using

both types of technologies. However, the left-hand side of equation (12) exceeds that of equation (13), because, by assumption, the productivity of firm using technology H is greater than that of firms using technology L ($\varphi_H > \varphi_L$), while their marginal cost of production is lower ($c_H < c_L$).

In this model, the direction of causal inference is initially from productivity to the firm's technology upgrade decision and subsequently from the technology upgrade decision to the export decision. The intuitive reasoning behind this causal relationship can be explained as follows: initially, after entering the market and observing their own productivity, firms with higher productivity levels select the more advanced of the two technologies. Although choosing high technology involves higher fixed costs, it enables production at lower marginal costs. Consequently, firms that choose high technology set lower prices compared to other firms, thereby increasing their sales more than proportionally due to the assumption of elastic demand. This outcome persists due to the inherent productivity advantage of firms using high technology over those using low technology. Because, as evident from equation (9), the expected gains from employing advanced technology outweigh the associated fixed costs.

Completing the model requires characterizing the productivity cutoff points that determine firms' decisions regarding high technology adoption and export market participation. Bustos (2005, 2011) shows that there are two possible productivity configurations:

1) $\varphi_x < \varphi_H$

In the first case, when the fixed cost of upgrading technology is significantly higher than the fixed cost of exporting, ($f_H - f_L > f_x$), the minimum productivity level needed to use high technology is sufficiently higher than the minimum productivity level needed to export profitably. This means that firms need to be much more productive to afford high technology than is required to export, implying that some firms will be able to export even if they do not adopt high technology. In this scenario, firms fall into three categories:

- a) $\varphi_L < \varphi_i < \varphi_x$: Firms only serve the domestic market and use low technology.
- b) $\varphi_x < \varphi_i < \varphi_H$: Firms export and use low technology.
- c) $\varphi_H < \varphi_i$: Firms export and use high technology.

2) $\varphi_x > \varphi_H$

In the second case, if the fixed cost of exporting is higher than the fixed cost of upgrading technology, ($f_H - f_L < f_x$), the productivity threshold required for exporting (φ_x) is higher than the threshold needed for adopting high technology (φ_H). In this case, only firms that upgrade their technology will be able to afford exporting, meaning that all exporters use high technology. We will not focus on this case as there are exporters that use low technology in the dataset.

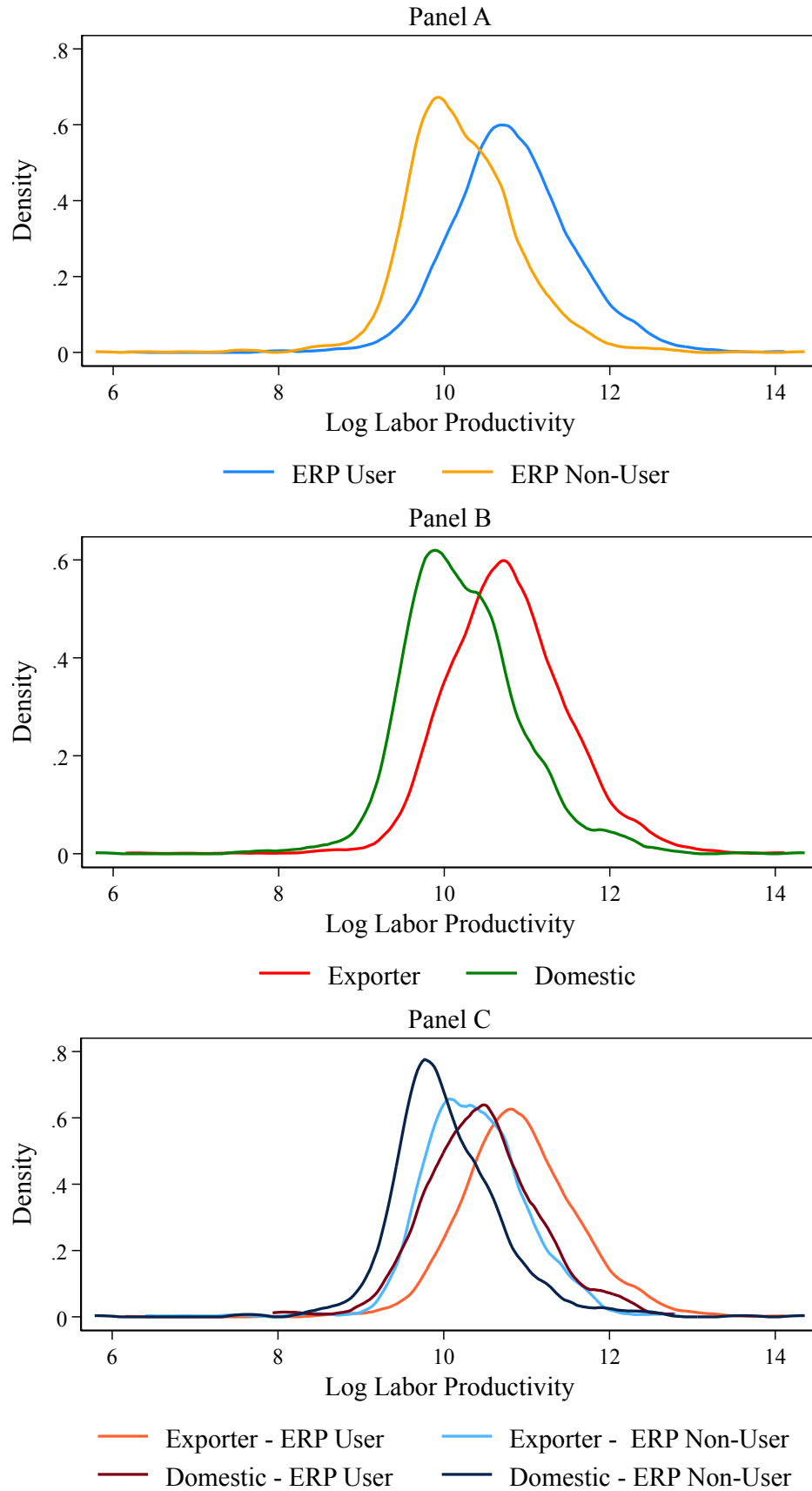
The theoretical model provides insights into the productivity ordering we can expect from the data according to firms' export market participation and technology status. In this study, we proxy firms' technology level (high vs. low technology) through their ERP usage status, where ERP users represent firms employing high technology and non-users represent firms using low technology. To investigate whether the predicted productivity orderings are supported by the data, we examine labor productivity patterns across different groups of firms classified according to their ERP usage and export status as shown in Figure 1.

Panel A plots the distribution of labor productivity comparing firms using high technology (proxied by ERP users) with those using traditional technology (ERP non-users). The figure shows that the productivity distribution of ERP users lies to the right of non-users, supporting the theoretical model's assumption that firms employing high technology are more productive than those using traditional technology since there are fixed to adopt high technology.

Panel B compares the distribution of labor productivity between exporters and non-exporters. As predicted by the theoretical model, the productivity distribution of exporters is situated to the right of domestic firms, suggesting that more productive firms are more likely to engage in export markets.

Panel C presents a more detailed productivity ordering by combining both technology level and export status. It reveals four distinct groups of firms: exporter-ERP users display the highest productivity levels, followed by domestic-ERP users and exporter-ERP non-users with intermediate productivity levels, while domestic-ERP non-users show the lowest productivity. Based on our theoretical model, if the fixed costs of technology upgrade are higher than the costs of exporting, we would expect domestic firms using high technology to be more productive than exporters using low technology. The figure shows that the productivity distribution of domestic-ERP users lies to the right of the distribution of exporter-ERP non-users.

Figure 1. Productivity Distributions for Different Groups of Firms



Source: Author's own calculations.

Note: All graphs are kernel distributions of the log labor productivity (value-added per worker) in the last year of the sample, 2019.

3. A REVIEW OF EMPIRICAL LITERATURE

There exists a vast amount of empirical literature related to the effect of ICT on a broad range of economic activities such as determinants of ICT adoption, ICT-productivity relationship or ICT usage, and its effect on various fields such as education, agriculture, energy, etc. In terms of empirical studies, there has been a significant increase in studies based on observational data with the recent proliferation of panel data in this field (albeit mostly for developed countries). However, a complete review of ICT literature is beyond the scope of this study and therefore, we only review and present a subset of the literature focusing on studies that are investigating the relationship between ICT and export performance of firms.

In the empirical literature, studies have mostly focused on the impact of ICT use on bilateral trade within the framework of gravity models (Bojnec & Fertő, 2009; Martínez-Zarzoso & Márquez-Ramos, 2005; Ozcan, 2018; Xing, 2018; Yushkova, 2014). In the absence of firm-level data, the gravity model approach can be useful in understanding the impact of a specific policy on trade between two countries or, more broadly, between groups of countries, as in the case of ICT. As an example of such studies, Rodriguez-Crespo et al. (2021), using panel data covering the period 1996-2014 for 121 countries, find a positive relationship between internet use and exports, and show that this effect is higher in developed countries than in developing countries. With a similar approach, Vemuri and Siddiqi (2009) analyzed the bilateral trade of 64 countries at different levels of development for the period 1985-2005 and found that telephone lines, internet users, and computers positively affect the volume of trade. Freund and Weinhold (2004) examined the impact of the internet on bilateral trade through web host ownership of 56 countries for the period 1997-1999 and found that a 10% increase in a country's web host ownership increases exports by 0.2%. Lin (2015), in critiquing the methodological limitations of Freund and Weinhold's study, conducted a comprehensive analysis of around 200 countries from 1990 to 2006, revealing that a 10% increase in internet users is associated with a 0.2% to 0.4% increase in international trade.

Although cross-country studies show the average effect of ICT on export performance, when we take into account the fact that the share of exporting firms among all firms operating in the country is very small and even within exporting firms, a large share of total exports are made by a limited number of very large firms, studies of the above-mentioned type are insufficient to reflect the average firm performance of that country. In order to overcome the shortcomings of these studies with aggregated data in reflecting firm performance, microdata at the firm level are needed, and with the proliferation of such data in recent years, there has been an increase in firm-level studies. For instance, Clarke (2008) examines the effect of the internet on exports at the firm level in low and middle-income countries from Eastern Europe and Central Asia and finds that firms with internet access are more likely to export than those without. Clarke also shows that firms that are already exporting do not export more when they have internet access, suggesting that the impact of the internet is related to the decision to export rather than the amount the firm exports. Yadav (2014) argues that e-mail usage and website ownership have a similar effect on firms' export and import behavior for 52 developing countries from Asia and Sub-Saharan Africa using World Bank Enterprise Surveys data for the period 2006-2010.

As can be seen in the studies mentioned so far, indicators of ICT usage consist of very basic tools such as the internet, website, and e-mail. In recent years, more comprehensive ICT indicators have been collected from firms through surveys. As an example of studies using these data, Hagsten and Kotnik (2017) examined SMEs operating in 12 European countries. In addition to basic indicators such as website ownership, they also examined the impact of relatively more advanced indicators such as e-sales, number of employees using the internet, number of employees with ICT training on exports, which they call ICT capacity, and found that ICT capacity positively affects the export performance of SMEs. Moreover, they find that advanced ICT indicators affect export intensity, which is the share of exports in total output, more than firms' decisions on whether to become exporters or not.

As another firm-level example, Goldar (2023) investigated the impact of ICT intensity on export performance using data from approximately 150,000 manufacturing firms in India covering the period 2008-2018. In the study, ICT intensity was defined as the share of computer and software assets in total fixed capital stock, while export intensity was measured as the ratio of exports to total

production value. Empirical findings revealed that increases in ICT intensity positively affected export intensity.

Compared to earlier studies in the literature, there are also more recent studies that measure ICT adoption using advanced technologies. For instance, Cao et al. (2025) analyze the impact of robot adoption on firms' export performance in China for the period 2011–2013. Their findings suggest that the use of robots enhances firms' export value and export intensity (exports' share in total sales) through productivity gains. Specifically, the researchers find that a 1% increase in the stock of robots (total number of robots in an industry per year) raises export value by 0.18%, while a 1% increase in robot density (number of robots per million working hours) increases export value by 0.15%. Similarly, robot stock increases export intensity by 0.03%, while robot density leads to a 0.026% increase in export intensity. Examining the impact of robot usage in Spain for 1990-2016, Shahin et al. (2024) found that firms using robots had an average of 5.14 percentage points higher export-to-sales ratio compared to non-users. Using the same dataset but focusing on the manufacturing sector between 1990 and 2014, Alguacil et al. (2022) investigated the effect of robot usage on extensive (probability of being an exporter) and intensive (export value and export-to-sales ratio) margin export performance using propensity score matching and difference-in-differences methods. They estimated that robot usage increased firms' probability of being an exporter by 9.4% and increased the export-to-sales ratio by 2.4%.

Cloud computing technologies represent a recent shift in ICT investment strategies, providing firms with operational flexibility by eliminating the high fixed costs associated with traditional infrastructure investments. Within the framework of "scale-without-mass", this technological development, which offers growth potential without additional investments in physical assets and human resources, is particularly crucial for businesses in developing economies. Boccia et al. (2022) focus on manufacturing firms in Italy during the 2014–2017 period and conduct a regional analysis showing that an increase in the share of firms using cloud computing in a region positively affects the region's total export value.

Acknowledging the complexity of ICT adoption, which cannot be reduced to a single indicator, Añón Higón and Bonvin (2024) develop a digitalization index to analyze how digital transformation influences the international trade behavior of SMEs in

Spain's manufacturing sector between 2001 and 2014. The index consists of 13 indicators across four dimensions, capturing various aspects of ICT investment, such as capital investments in ICT, computer programming services, software implementation, employee training in software and IT, robot usage, LAN networks, computer-aided design systems, domain name ownership, website ownership, and e-commerce applications. Their findings indicate that digitalization positively affects SMEs' probability of engaging in export and import activities, but the impact of productivity improvements on trade behavior is stronger than the direct effect of digitalization itself.

Another study measuring ICT usage with an index focused on SMEs in Colombia's manufacturing industry (Gomez-Sanchez et al., 2023). Covering the period 2013-2018, researchers define ICT adoption using an index based on the use of electronic devices (such as desktop computers, laptops, tablets, mobile phones, and mobile data collection devices), fiber optic usage, intranet/extranet systems, internet access, and website ownership. Their analysis reveals that an increase in the ICT index positively influences export intensity. In their previous study, the same researchers found that increases in the ICT index with the same components increased firms' probability of being exporters in Colombia during 2013-2016 (Gomez-Sanchez et al., 2022).

Several studies investigating the ICT-export relationship at the firm level can also be found in the business and marketing literature (Bianchi & Mathews, 2016; Racela & Thoumrungroje, 2020; Trainor et al., 2011). Nevertheless, these studies face significant methodological constraints that affect the robustness of their findings. First, their reliance on Likert scales in questionnaires introduces potential subjective measurement bias, as respondents' self-reported assessments may not accurately reflect actual ICT usage levels. Second, they tend to oversimplify ICT adoption by focusing primarily on internet usage, failing to capture the complexity of modern ICT systems that can include various technologies such as enterprise resource planning systems, cloud computing, automation technologies, and other advanced digital tools. Therefore, while these studies suggest a positive relationship between ICT and export performance, their methodological constraints affect the reliability of their findings. This underscores the need for more comprehensive and objective measurement approaches to establish the precise magnitude of this relationship with statistical confidence.

There are a limited number of studies focusing on Türkiye in the literature. Studies analyzing the role of the internet on Türkiye's bilateral trade use the gravity model framework and find a positive relationship between them (Aykulteli & Töngür, 2020; Şeker, 2017). On the other hand, studies (Basılğan, 2020; Melemen, 2006) using firm-level data based on questionnaires either concentrate on a specific industry or are very descriptive and far from understanding the extent of the relationship.

In early studies, firms' ICT adoption and utilization were measured through indicators such as computer ownership, e-mail usage, internet access, and website ownership. However, when we consider the present level of technology, we see that almost all firms in an upper-middle income country like Türkiye have such tools. Therefore, empirical studies focusing on firms' ICT use need more complex indicators than these basic tools to adequately reflect the firm heterogeneity. At this point, data availability is still a serious concern for developing countries, in particular. In this study, we argue that whether a firm uses ERP or not is an important tool to understand the level of ICT utilization of that firm.

Briefly describing what kind of a system ERP is will also reveal why we use ERP as a proxy for ICT. ERP is characterized as a comprehensive and multidimensional system that encompasses the planning, control, and optimization of production processes. It plays a crucial role in facilitating the flow of information among all functions within a firm. Kurbel (2013) states that the most important factor in the emergence of ERP is the need for integration. The main feature of similar software before ERP was that they were stand-alone systems. Such systems caused problems such as storing the same data by different departments within the organization or storing the same data in different ways. This could cause extra workload for the organization and even lead to making wrong decisions. On the contrary, ERP enables a firm to control all processes such as sales, distribution, quality management, human resources, finance, accounting, and inventory through a single database. In the absence of ERP, the lack of integration between departments will increase transaction costs within the organization. Therefore, ERP has a productivity-enhancing and cost-reducing role for the company. When we consider the hardware, software and human capital requirements that ERP needs while performing this role for the firm, it is clear why ERP is superior to the basic tools mentioned above in terms of reflecting the level of ICT usage of the firm.

To the best of our knowledge, there is no study in the literature that examines the impact of ERP on the export performance of firms. Besides, a complete review of the ERP implementation literature is beyond the scope of this study, as we use ERP only as a proxy for ICT. Nevertheless, we can say that numerous studies have examined the impact of ERP on various measures of firm performance from both financial and non-financial perspectives (Aburub, 2015; Hunton et al., 2003; Poston & Grabski, 2001). In the financial dimension, especially the effect of ERP on firm profitability has been the subject of examination, while in the non-financial dimension, the effect of ERP on operational, managerial, and organizational decisions of the firm has been examined. Overall, studies conducted since the early 2000s have consistently revealed a significant difference between companies that adopt ERP and those that do not.

4. EMPIRICAL ANALYSIS OF ICT-EXPORT RELATIONSHIP

4.1. Data and Summary Statistics

To analyze the ICT-export relationship empirically, we combine five micro data sets compiled by the TurkStat to reach a firm-level panel data set for the period 2009-2019. The panel data set is constructed by matching firms in the ICT Usage in Enterprises survey, Foreign Trade Statistics, Company Accounts Statistics, Annual Industry and Service Statistics, and Annual Business Registers Framework.

The ICT usage survey has been conducted to determine the extent to which firms adopt and use information technologies, to determine what possible factors may hinder this, and to reveal whether they engage in e-commerce activities. The surveys collect data from firms with 10 or more employees. TurkStat employs a sampling procedure for firms with fewer than 250 employees while including all firms with 250 or more employees. The survey includes questions about ICT usage, such as the number of employees using computers and/or the internet, whether the firm has a website (and if so, for what purposes), the type of internet connection, and whether they employ ICT specialists, as well as questions regarding e-commerce activities and the use of enterprise systems like Enterprise Resource Planning (ERP), Customer Relationship Management (CRM), and Supply Chain Management (SCM). Despite the dataset's apparently comprehensive scope, it has a major drawback as the same variables are not consistently collected each year, creating many gaps in the data, preventing the construction of a comprehensive ICT usage index and limiting the use of some panel data methods. For this reason, the econometric analysis utilizes only two variables from this dataset: whether firms use ERP systems and the number of internet users within the firm, which serves as a proxy for the ICT labor.

Foreign trade statistics encompass the cross-border trade of goods between Türkiye and other countries. These statistics are compiled based on both the general trade system and the special trade system. The key distinction between these two systems lies in their treatment of trade from free zones and customs warehouses - while the

general trade system includes transactions from these areas, the special trade system excludes them as it is based on the country's customs border. In this study, the special trade system statistics will be utilized since TurkStat provides data based on the general trade system only for the period after 2013. The dataset includes normal exports and imports, inward and outward processing regimes, financial leasing, non-monetary gold, and border trade. Transactions below \$100 are excluded from the statistics, and the micro dataset does not cover service exports and imports, focusing solely on the trade of goods. All transactions are recorded at the NUTS3 (province) level and classified under multiple product categorization systems, including NACE, SITC, and ISIC. Since this dataset is at the transaction level, all transactions were first aggregated at the firm level to calculate each firm's total exports for each specific year. The export unit value index was then used to deflate the values for all years to 2009 constant prices. Firms with an export value greater than zero were classified as exporters.

Company Accounts Statistics were compiled by the Central Bank of the Republic of Türkiye (CBRT) through surveys conducted with real sector firms between 1990 and 2016. Since 2020, in collaboration with TurkStat, a new micro dataset has been developed, relying entirely on administrative records from the Revenue Administration and the Social Security Institution at the firm level. The primary aim of these statistics is to track the financial performance of real sector firms using balance sheets and income statements. The data set includes financial statements of 860,382 firms and when compared to the turnover size reported in TurkStat's Annual Industry and Service Statistics, it achieves an approximate representation rate of 88%. From this dataset, tangible fixed assets were used to represent firm capital, and net profit/loss items were utilized to calculate the profitability of the firm.

The Annual Industry and Service Statistics provide data on various firm characteristics, including the number of employees, turnover, value added at factors costs, changes in stocks of goods and services, personnel costs, total purchase of goods and services, and production value. The statistics are compiled from administrative records and cover more than 3,2 million enterprises. In this dataset, value added at factor cost and employment data were used to calculate firms' labor productivity. The employment data was also used to classify firms in the dataset as SMEs (those with fewer than 250 employees) and large firms (those with 250 or

more employees). The dataset was also used to obtain firms' turnover data, and all nominal values were deflated to 2009 using the producer price index at the two-digit manufacturing industry subsector level.

Lastly, the Annual Business Registers Framework is a system that maintains records of all legally registered entities contributing to Gross Domestic Product, including their addresses, identification details, stratification variables, and demographic information. From this dataset, two key variables were utilized: The firm's commencement year to calculate enterprise age, and the province-level information to control for provincial fixed effects in the econometric analysis⁵.

All data sets are matched using a unique firm identifier provided by TurkStat. The merged data set is an unbalanced panel because TurkStat uses a sampling procedure for firms with less than 250 employees in the ICT usage survey. Consequently, some firms were surveyed in all years, while others were only surveyed in certain years of the analysis period. The merged dataset contains approximately 100,000 observations for around 49,000 firms across all sectors. As our analysis focuses solely on the manufacturing industry, after removing observations from other sectors (construction, wholesale and retail trade, services, and others), we obtain 32,767 observations for 14,419 firms. The number of firms per year varies from its lowest level of 1,678 firms in 2009 to its highest level of 3,742 firms in 2019. A similar trend is observed for exporting firms, increasing from 1,110 firms in 2009 to 2,525 firms in 2019.

The theoretical model demonstrated that firms, after entering the market and observing their productivity, would choose between high and low technology types. In this study, low or traditional technology adoption is associated with basic ICT tools such as computer ownership, internet access, and website ownership. Within the dataset, computer ownership and internet access rates are approximately 98%, while website ownership is around 80%. In testing the theoretical model, ERP system usage represents the high technology choice in firms' technology upgrade decisions. The rationale for characterizing ERP as high technology compared to other ICT tools is explained when introducing the variables in the econometric model. In other words, firms using only basic tools (computers, internet, and

⁵ Table A1 in the appendix provides the descriptions and sources of the variables used in the analysis.

websites) are considered to have made a low technology choice, while those implementing ERP systems are viewed as choosing high technology, despite higher fixed costs, because the expected productivity gains from ERP usage outweigh the investment costs.

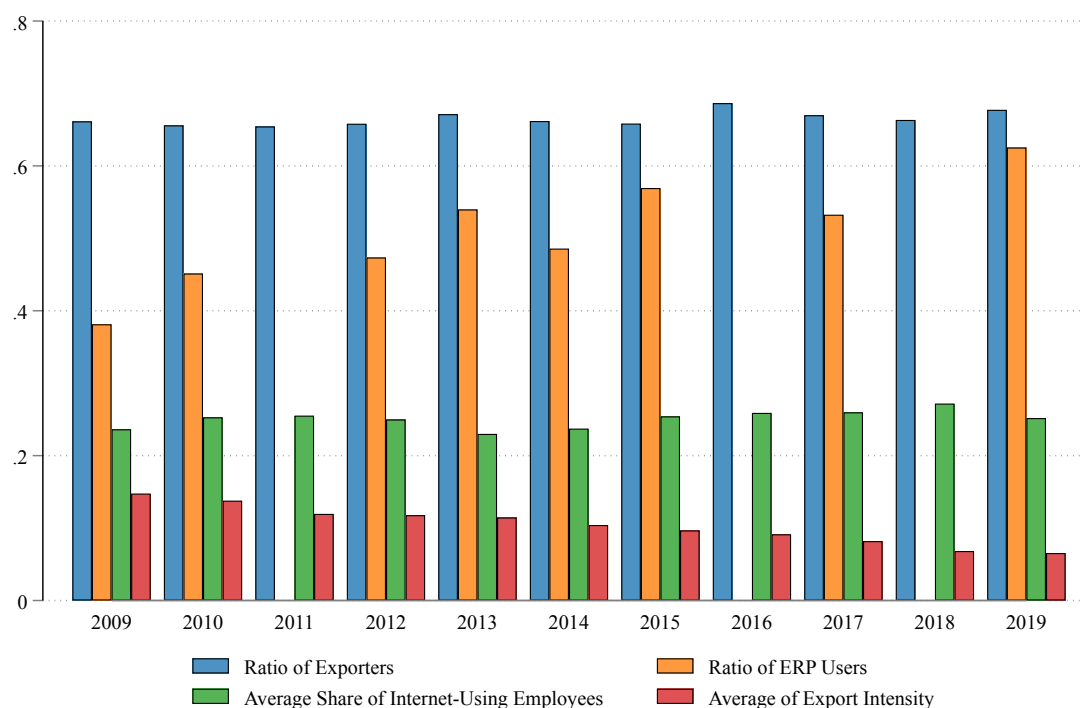
Since ERP system usage represents the high technology choice in firms' technology upgrade decisions and serves as a proxy for advanced technology adoption, it is a key variable in assessing the relationship between technology and export performance. Additionally, due to the lack of specific indicators linking ICT usage to human capital in our dataset, the number and proportion of internet-using employees are used as proxy variables to measure firms' ICT labor. While we do not have detailed data on the specific purposes or qualitative aspects of internet usage, this metric provides insights into the extent of technology penetration within firms and their level of digital transformation integration. Given these considerations, we will examine their patterns alongside firms' export status and export intensity to better understand their potential role in shaping export performance.

Figure 2 provides an overview of the evolution of ERP users, the share of exporting firms, the ratio of internet-using employees to the total number of employees, and average export intensity across all firms between 2009 and 2019. The data reveal that the share of exporting firms has remained relatively stable over the years, consistently exceeding 65%. While there are minor fluctuations, this suggests that the proportion of firms engaged in export activities has not undergone dramatic changes. Notably, despite the high percentage of exporting firms, average of export intensity has remained relatively low and stable throughout the period, fluctuating around 10% and showing a slight downward trend towards 2019. This indicates that while many firms are engaged in export activities, exports constitute only a relatively small portion of their total business volume, suggesting potential limitations in scaling up their international trade operations.

ERP usage has shown a significant upward trend, increasing from approximately 40% in 2009 to nearly 60% in 2019. Looking at all observations in the dataset, approximately 52% of firm-year observations have used ERP systems. This trend indicates that firms are increasingly investing in enterprise-wide digitalization strategies, recognizing the potential efficiency and productivity gains offered by ERP systems. While ERP usage showed significant growth, the share of internet-using

employees increased only modestly, rising from 23 percent to 27 percent between 2009 and 2019. The average number of internet-using employees, however, showed a more substantial increase, rising from around 18 in 2009 to over 24 in 2019.

Figure 2. Evolution of Exporters, ERP Users, Internet-Using Employees, and Export Intensity



Source: Author's own calculations.

Note: The absence of ERP usage data for the years 2011, 2016, and 2018 results from TurkStat's decision to exclude the relevant question from its survey during these periods. Export intensity refers to the ratio of exports to total sales.

Table 1 provides transition rates into and out of exporting. Columns 1 and 2 indicate the initial and following year export status, respectively. The table shows the percentage distribution of how firms' exporter or non-exporter status in a given year evolves in the following year. For instance, 81.08% of firms that were non-exporters in 2009 remained non-exporters in 2010, while 96.01% of exporters continued exporting. One of the most striking findings from the transition matrix is that export activities exhibit strong path dependence. In particular, the fact that approximately 95% of exporters maintain their status suggests the influence of sunk costs and established network relationships. This persistence underscores the significant role of past export experience in shaping firms' continued participation in international trade.

From another perspective, the likelihood of exporters losing their export status in the following year is relatively low. This rate ranges between 3.98% and 6.17%,

indicating that the majority of exporting firms remain active in international markets over time. Similarly, a comparable degree of status persistence is observed among non-exporting firms. Each year, a substantial proportion of non-exporters (between 77% and 82%) continue to remain outside export markets, reinforcing the idea that non-exporters face significant barriers to entering global trade.

When examining the entry dynamics of non-exporting firms into export markets, we observe fluctuations ranging between 17% and 24%. While this variability reflects the impact of changes in macroeconomic conditions and foreign trade policies, it may also indicate that the decision to begin exporting is closely related to the firm characteristics.

Table 1. Transitions in Export Behavior of Firms (in percentage)

Year t	Year t+1	2009-2010	2010-2011	2011-2012	2012-2013	2013-2014
Non-exporter	Non-exporter	81,08	78,47	77,94	80,67	75,48
	Exporter	18,92	21,53	22,06	19,33	24,52
Exporter	Non-exporter	3,99	3,98	4,36	5,53	5,08
	Exporter	96,01	96,02	95,64	94,47	94,92
Year t	Year t+1	2014-2015	2015-2016	2016-2017	2017-2018	2018-2019
Non-exporter	Non-exporter	78,70	77,22	80,94	82,15	79,70
	Exporter	21,30	22,78	19,06	17,85	20,30
Exporter	Non-exporter	4,72	4,39	6,17	4,71	4,59
	Exporter	95,28	95,61	93,83	95,29	95,41

Source: Author's own calculations.

Table 2 provides a comparative analysis of the subsectoral distribution of firms in the Turkish manufacturing industry based on firm size and export behavior. Firms are categorized as SMEs (fewer than 250 employees) and large firms (250 or more employees), and the table presents the share of firms in each subsector along with their respective export participation rates. Columns (1), (3), and (5) display the distribution of observations across different subsectors in the dataset, while columns (2), (4), and (6) provide the percentage of firms that are exporters within each subsector. An examination of the distribution of observations across manufacturing sub-sectors reveals that the textile (11.55%), food (10.79%), and apparel (10.60%) industries have the highest representation.

Table 2. Export Behavior of Subsectors by Firm Size

Subsectors	All firms		SMEs		Large firms	
	% of obs.	% of exporters	% of obs.	% of exporters	% of obs.	% of exporters
	(1)	(2)	(3)	(4)	(5)	(6)
10 Food	10.79	58.07	9.56	33.47	12.19	79.93
11 Beverages	0.53	71.43	0.51	50.00	0.57	93.10
12 Tobacco	0.14	100.00	0.02	100.00	0.28	100.00
13 Textiles	11.55	71.18	6.94	49.92	16.78	81.14
14 Wearing apparel	10.60	60.70	8.12	46.43	13.41	70.49
15 Leather	1.28	61.28	1.74	49.34	0.77	91.60
16 Wood	1.86	56.46	2.61	42.86	1.02	96.15
17 Paper	2.85	80.86	3.22	70.41	2.43	96.52
18 Printing	1.97	36.02	3.13	30.51	0.65	66.00
19 Coke and refined petroleum	0.10	61.76	0.11	52.63	0.10	73.33
20 Chemicals	2.36	81.99	2.13	68.92	2.62	94.03
21 Pharmaceutical	1.01	87.61	0.30	59.62	1.82	92.83
22 Rubber and plastic	5.37	73.38	5.50	59.08	5.21	90.50
23 Other non-metallic minerals	6.68	56.62	5.62	33.81	7.88	75.06
24 Basic metals	4.11	78.75	2.52	59.00	5.90	88.31
25 Fabricated metals	7.33	65.74	8.44	51.94	6.07	87.46
26 Computer, electronic and optic	6.14	65.84	10.59	63.81	1.09	88.10
27 Electrical equipment	3.82	80.29	3.10	63.82	4.65	92.72
28 Machinery and equipment n.e.c.	6.19	75.43	7.76	68.15	4.41	89.96
29 Motor vehicles and trailers	6.78	75.97	6.85	62.03	6.70	92.13
30 Other transport equip.	1.29	60.66	1.41	46.53	1.15	80.23
31 Furniture	3.89	59.07	4.94	52.27	2.70	73.19
32 Other manufacturing	1.78	65.69	2.53	63.41	0.93	72.73
33 Repair and install. of machi. and equip.	1.57	32.56	2.37	26.88	0.67	55.34
Total	100	66.64	100	52.37	100	82.81

Source: Author's own calculations.

Beyond the sectoral composition, there are striking differences in export participation across firm size categories. Export participation rates are substantially higher among

large firms relative to SMEs. While 52.37% of SMEs across the manufacturing industry have exporter status, this rate rises to 82.81% for large firms. A sectoral breakdown further confirms that SMEs consistently have lower export participation rates across all subsectors. These findings indicate that large firms are more actively engaged in export activities, while SMEs face greater challenges in accessing international markets. In other words, this pattern suggests a strong relationship between firm size and export performance, implying that larger firms may benefit from greater resources, economies of scale, and established networks, which facilitate their success in global trade.

Another noteworthy observation is that export participation rates vary significantly across sectors. While some industries exhibit high levels of export engagement (e.g., pharmaceuticals, chemicals, and basic metals), others have relatively lower export participation rates (e.g., food, wood, and printing). These findings emphasize the importance of sectoral differences as a key determinant of export performance, suggesting that industry-specific factors play a crucial role in shaping firms' ability to compete in international markets.

Table 2 provides a foundation for examining the impact of ICT adoption on export performance. It can be expected that sectors with higher export participation rates also tend to have higher levels of digitalization. In particular, the high rate of large firms in export activities may be linked to the effective use of tools such as ERP, which play a crucial role in enhancing operational efficiency and international competitiveness. For instance, the high export participation rates observed in sectors such as chemicals, motor vehicles, electrical equipment, and pharmaceuticals-classified as high or medium-high technology industries- underscore the importance of digitalization and technological infrastructure in facilitating firms' engagement in global markets.

Table 3 shows the distribution of all firms in the dataset according to their export status. Firms are categorized into three groups: those that are exporters in all years (continuous exporters), those that have never exported (continuous non-exporters), and those whose export status has changed over time (switchers). A significant portion of the 14,419 firms in the dataset (43.7%) have never engaged in exporting, indicating that a large share of firms remain domestically focused throughout the observation period. Each row in the "continuous exporters" category represents the

number of years a firm has been observed in the dataset and confirms that it was an exporter for the entire duration of its presence. The unbalanced structure of the panel dataset is clearly visible in this distribution. Among continuous exporters, firms that exported for one year constitute the largest group (26.8%). In contrast, the share of firms that remained exporters continuously for 11 years is only 2%, indicating that long-term sustained export activity is relatively rare. The high proportion of firms observed for only one year particularly leads to a reduction in the number of firms and observations available for panel data methods (such as fixed effects) in econometric analysis. This becomes even more pronounced when using dynamic panel data models, as these models require the use of lagged variables and thus necessitate including only firms with at least two consecutive years of observations.

Table 3. Distribution of Firms by Export Status

Export status	Number of firms	Share (%)
Continuous exporters		
1 year	3868	26.8
2 years	1256	8.7
3 years	399	2.8
4 years	256	1.8
5 years	141	1.0
6 years	142	1.0
7 years	111	0.8
8 years	139	1.0
9 years	109	0.8
10 years	267	1.9
11 years	287	2.0
Continuous non-exporters	6295	43.7
Switchers	1149	8.0
Total	14419	100

Source: Author's own calculations.

Table 4 presents summary statistics for the variables used in the econometric models, comparing exporters and non-exporters. Notably, variables representing ICT adoption and usage depth, such as ERP usage, the proportion of internet-using

employees, and the number of internet-using employees, exhibit significant differences between exporters and non-exporters. Specifically, ERP usage is substantially higher among exporting firms, with 62.4% of exporters using ERP systems, compared to only 30.7% of non-exporters. Similarly, while the proportion of internet-using employees is relatively close between the two groups (25.6% for exporters and 24.4% for non-exporters), the absolute number of internet-using employees is significantly higher in exporting firms. These findings indicate that exporting firms tend to have a higher intensity of ICT usage, suggesting that digitalization and advanced technology adoption may play a crucial role in firms' ability to compete in international markets.

Table 4. Summary Statistics

Variables	All firms			Exporters			Non-exporters		
	N	Mean	SD	N	Mean	SD	N	Mean	SD
ERP	22820	0.520	0.500	15306	0.624	0.484	7514	0.307	0.461
Share of Internet-Using Employees	32767	25.210	23.101	21837	25.610	21.812	10930	24.413	25.464
Log Internet-Using Employees	32308	3.159	1.611	21782	3.636	1.483	10526	2.172	1.405
Log Value Added per Worker	32127	10.435	0.867	21517	10.635	0.818	10610	10.028	0.822
Log Capital per Worker	32457	10.594	1.511	21792	10.858	1.304	10665	10.054	1.744
Age	32732	17.185	9.685	21826	18.765	9.932	10906	14.024	8.316
Profitability (ROA)	32767	-696	3.49×10^5	21837	985	3.09×10^5	10930	-4056	4.17×10^5
Log Employment	32767	4.925	1.484	21837	5.339	1.383	10930	4.097	1.326

Source: Author's own calculations.

Moreover, variables representing labor productivity (value added per worker) and capital intensity (capital per worker) indicate that exporting firms are more productive and more capital intensive. In terms of firm age, exporting firms appear to be older on average, suggesting that more established firms are more likely to engage in export activities. A notable difference is also observed in profitability (measured as return on assets), where exporting firms exhibit positive average profitability,

whereas non-exporting firms, on average, have negative profitability. Furthermore, exporting firms, on average, have a higher number of employees than non-exporting firms, indicating that they are larger in scale.

4.2. Econometric Approach

This section outlines the empirical methodology to test the primary prediction of the theoretical model, which posits that firms adopting high technology are more likely to export. To empirically validate this theoretical implication, a reduced linear version of the export decision outlined in equation (11) is estimated. In other words, a firm will choose to export ($XD_{it} = 1$) if the profits from exporting exceed the profits it would obtain by solely serving the domestic market. This decision can be formally expressed by the following binary outcome model, where the profits from export market of firm i at time t (π_{it}^*) is a reduced function of the firm characteristics:

$$XD_{it} = \begin{cases} 1 & \text{if } \pi_{it}^* = \beta ICT_{it} + \gamma \mathbf{Z}_{it} + \eta_t + \delta_s + \theta_p + \varepsilon_{it} > 0 \\ 0 & \text{otherwise} \end{cases} \quad (14)$$

The baseline econometric model based on equation (14) is defined as a random effects probit model as:

$$P(XD_{it} = 1) = \Phi(\beta ICT_{it} + \gamma \mathbf{Z}_{it} + \eta_t + \delta_s + \theta_p + \varepsilon_{it}) \quad (15)$$

where $\Phi(\cdot)$ is the standard normal cumulative distribution function. XD_{it} denotes the export status of firm i at time t , taking the value of 1 if the firm is an exporter and 0 otherwise. $\mathbf{Z}$ is a vector of explanatory variables representing firm characteristics, including labor productivity, capital intensity, age, age squared, profitability, and employment. The variable δ_s is the 2-digit sector fixed-effects and it is included to consider the differences across sectors. η_t is the year fixed effects to control for the business cycles, exchange rate movements and other macroeconomic effects. Province fixed-effects (θ_p) are also included to control for time-invariant cross-city differences. Lastly, ε_{it} is assumed to be independent and identically distributed.

We are mainly interested in the parameter estimate on ICT usage. β measures the effect of ICT usage on the probability of being an exporter. To test the predictions of the theoretical model, ICT usage is primarily proxied by whether a firm uses ERP. The ERP variable takes the value of 1 if the firm uses ERP and 0 otherwise. In

accordance with the predictions outlined in equations (12) and (13) of the theoretical model, firms using ERP are expected to achieve lower marginal costs, leading to higher profits. This would be reflected in a positive and statistically significant β coefficient, indicating that ERP users are more likely to export.

Briefly discussing what an ERP system is and its impact on firm performance is important for justifying its use as an ICT indicator. Additionally, it would be beneficial to position ERP within the broader set of technologies that a manufacturing firm can utilize. ERP is a highly integrated digital system that facilitates the coordination of various business processes, including production, planning, supply chain management, customer management, asset management, finance, quality control, and human resources. In the technology classification framework outlined by Jung and Gómez-Bengoechea (2025), ERP falls within the category of advanced technologies, positioned above essential/basic ICT tools (such as internet access, email usage, web sites, social media, e-commerce) but below cutting-edge technologies like artificial intelligence, big data analytics, internet of things, 3D printing, robotics, and blockchain⁶. From the perspective of a manufacturing firm, ERP represents a crucial step in digital transformation, enabling firms to enhance efficiency, reduce costs, and improve decision-making by centralizing data and automating workflows. Firms can activate all functions of internal and external management processes within the scope of ERP (Hitt et al., 2002).

The impact of ERP on firm performance has been widely studied, with research showing that ERP implementation leads to improved productivity, cost efficiency, and better coordination across business functions (Beheshti & Beheshti, 2010). ERP systems allow firms to reduce transaction costs, enhance customer satisfaction, and increase profitability by streamlining operational processes and integrating information across different departments. A well-executed ERP system not only improves internal coordination but also strengthens a firm's ability to engage in global trade and export activities. By integrating supply chain processes and financial

⁶ Since 2020, TurkStat has started collecting data on artificial intelligence, cloud computing, robotics, and 3D printing in the ICT Usage Survey. However, as our analysis period covers 2009-2019, there is no available data on these technologies for that period.

management, ERP usage helps exporting firms handle international logistics, regulatory compliance, and customer management more effectively.

Given these advantages, ERP is a reliable proxy for ICT adoption and depth, as it reflects not only a firm's investment in digital transformation but also the extent of its technological integration and sophistication. However, to ensure that the results are not solely driven by ERP usage, this study also incorporates two complementary ICT indicators: the number of employees using the internet and the proportion of employees using the internet (ICT labor share). While ERP usage signifies a firm's commitment to advanced digital infrastructure, employee-level internet usage reflects the extent of digital engagement across different operational levels. By incorporating both measures, this study provides a more comprehensive perspective on ICT adoption, distinguishing itself from prior research that primarily relies on basic ICT indicators.

Labor productivity is calculated as the ratio of a firm's value added to the number of employees. The theoretical model posits that firms with higher productivity self-select into exporting, reflected in a positive and significant coefficient for productivity's impact on export participation. The theories of heterogeneous firms, particularly the approach pioneered by Melitz (2003), suggest that the most productive firms enter export markets by self-selection, meaning that firms that are already more productive before engaging in export activities are the ones that become exporters. In this context, the labor productivity variable allows us to test the self-selection hypothesis. The relationship between labor productivity and export participation has been empirically examined in numerous studies. For instance, Ottaviano and Martincus (2011) provide evidence for Argentina that labor productivity, measured as the ratio of total sales to employment, is positively and statistically significantly associated with the probability of exporting. Similarly, Yi and Wang (2012) find that productivity, defined as the ratio of value added to employment, positively influences the likelihood of firms in China becoming exporters.

Capital intensity refers to the ratio of a firm's physical capital to the number of employees. In this study, a firm's capital is measured using the fixed tangible assets item reported in its balance sheet. Fixed tangible assets typically include machinery, equipment, buildings, and other physical infrastructure used in production processes,

serving as a key indicator of the firm's production capacity. The impact of capital intensity on export decisions has been studied both theoretically and empirically. For instance, Rho and Rodrigue (2016) construct a structural model for Indonesian manufacturing firms, examining the relationship between firm-level capital accumulation and export dynamics. Their findings suggest that firms, once they achieve sufficient capital accumulation, develop capacities that enhance productivity over time and increase their chances of surviving longer in export markets. Empirical studies also support this relationship. De Matteis et al. (2019) demonstrate that capital intensity, measured as the ratio of fixed tangible asset investments to employment, positively influenced the probability of exporting in the Italian manufacturing sector during the 2000-2013 period. Similarly, Eliasson et al. (2012) find that firms with higher capital intensity in the Swedish manufacturing sector are more likely to become exporters.

The age variable is the firm age in years. In some research, such as the works of Majocchi et al. (2005) and D'Angelo et al. (2013), age is acknowledged as a proxy for a firm's internationalization experience, showing a positive correlation with the scope of the firm's trade connections. Since it will take time for companies to recognize and learn the foreign market culture, languages and distribution system, older and experienced companies will be more likely to export. On the other hand, the age of a firm also mirrors its conservative identity, suggesting a potential association with the firm's resistance to behavioral changes. Consequently, the likelihood of a firm becoming an exporter may be adversely influenced (Love et al., 2016; Williams, 2011). The model also includes the squared value of the age to test whether age is curvilinearly related to export decision (Kapri, 2019).

Firm profitability is represented by the Return on Assets (ROA). ROA is the ratio of a firm's net profit in a given period to its total assets. This can also be considered as an indicator of the firm's financial health. In the literature, the relationship between a firm's financial health and export behavior has been addressed from two perspectives: First, as an element of firm characteristics that constitute the determinants of firms' entry into the export market, and second, as an element of changes in firms' financial health after they enter the export market. The latter approach is beyond the scope of this study and there are numerous studies on the former approach in the literature. These studies emphasize that the sunk costs that

firms must incur when entering the export market can only be borne by financially sound firms, suggesting that firms with high profitability are more likely to become exporters (Bellone et al., 2010; Srinivasan & Archana, 2011).

The employment variable is the log of total employment of the firm. As Wagner (2001) pointed out, larger firms can effectively capitalize on the potential of foreign markets by achieving economies of scale in production. Additionally, larger firms benefit from lower financing costs and a higher risk tolerance when entering foreign markets, potentially due to internal diversification. Moreover, some costs related to international business activities, such as conducting market research or locating a foreign distributor or agent, are fixed costs. As firm size increases, the unit costs of these activities decrease. For these reasons, it is expected that the probability of being an exporter increases as firm size increases.

Following these specifications, we further investigate the impact of ICT on export probability by estimating separate models based on the technological classification of exported products, as defined by Eurostat. Specifically, we construct a dummy variable for each technology category, where the variable takes a value of 1 if the firm exports within a given technology level and 0 otherwise. Exports are categorized into high-technology, medium-high-technology, medium-low-technology, and low-technology groups to examine how the effect of ICT varies across different technological levels of exported goods. This approach allows us to assess whether the role of ICT in facilitating export participation differs depending on the technological sophistication of the products firms sell in international markets.

Complementarity Between ERP and ICT Labor

Following Taştan and Gönel (2020), we also augment the baseline model to test the complementarity between ICT labor and ERP usage by including an interaction term:

$$P(XD_{it} = 1) = \Phi(\beta_1 ERP_{it} + \beta_2 L_{it}^{ICT} + \theta ERP_{it} \times L_{it}^{ICT} + \gamma \mathbf{Z}_{it} + \eta_t + \delta_s + \theta_p + \varepsilon_{it}) \quad (16)$$

The interaction term $(ERP_{it} \times L_{it}^{ICT})$ tests the complementarity between ICT labor and ERP usage. Specifically, it allows us to examine whether the effectiveness of ERP implementation is enhanced when combined with a digitally skilled workforce, reflecting the importance of the human factor in successfully adopting complex

information systems (Mthupha & Bruhns, 2022; Stoean, 2015). However, as noted by Ai and Norton (2003), in nonlinear models such as probit, the magnitude of an interaction effect does not correspond directly to the marginal effect of the interaction term and may even have the opposite sign. Therefore, in models incorporating the interaction between ERP and ICT labor variables, interpreting the interaction terms directly may lead to misleading conclusions. Following the approach recommended by Long and Mustillo (2021), rather than focusing on the coefficients of the interaction terms, the interpretation should rely on visualizing the marginal effects – specifically, how the probability of export changes for ERP users and non-users as ICT labor changes.

Intensive Margin

Thus far, the analysis has focused on the determinants of firms' export participation (extensive margin) and assessed the impact of ICT adoption on the probability of exporting. However, to gain a more comprehensive understanding of the relationship between ICT and export performance, it is also crucial to analyze the intensive margin, referring to the extent to which firms engage in export activities. To this end, we estimate the following model to examine the impact of ICT adoption on export intensity:

$$XI_{it} = \alpha_0 + \beta ICT_{it} + \gamma Z_{it} + \eta_t + \delta_s + \theta_p + \varepsilon_{it} \quad (17)$$

where XI_{it} represents the ratio of total exports to total sales for firm i at time t . All other variables and fixed effects maintain their definitions from the export participation model presented in equation (15). Since export intensity is a continuous outcome variable, we estimate equation (17) using random effects model. We employ the random effects approach instead of fixed effects because fixed effects estimators rely on within-firm variation, requiring multiple observations per firm. However, in our dataset, more than half of the firms are observed for only one year, making fixed effects estimation unsuitable. Additionally, fixed effects estimation would not allow us to control for time-invariant explanatory variables, such as sector and province fixed effects, which are key controls in our analysis. Given these limitations, the random effects model is the more appropriate choice as it allows us to account for both firm-level and time-invariant heterogeneity.

To further investigate the potential complementarity between ERP usage and ICT-skilled labor, we extend the baseline model in a manner similar to equation (16) by incorporating an interaction term:

$$\begin{aligned}
XI_{it} = & \alpha_0 + \beta_1 ERP_{it} + \beta_2 L_{it}^{ICT} + \theta ERP_{it} \times L_{it}^{ICT} \\
& + \gamma Z_{it} + \eta_t + \delta_s + \theta_p + \varepsilon_{it}
\end{aligned} \tag{18}$$

The estimation procedure follows a stepwise approach, applied consistently to all models examining both the extensive and intensive margins. In the first specification, we analyze the effect of the main explanatory variable, ERP usage, on export participation and export intensity while controlling only for year fixed effects. In the second specification, province and sector fixed effects are introduced alongside year fixed effects to account for provincial and industry-level heterogeneity. In the third specification, variables controlling for firm characteristics are included in the model. The fourth specification replaces ERP with the ICT labor share variable as the main technology indicator, while keeping all firm-level controls and fixed effects. The fifth specification introduces an alternative measure of ICT labor (the logarithm of the number of internet-using employees) while maintaining the same control variables and fixed effects structure. The sixth specification includes both ERP and ICT labor share in the same model, allowing us to examine their simultaneous effects. The seventh specification includes an interaction term between ERP usage and ICT labor share to examine the complementarity between them. The eighth specification follows a similar approach to the sixth but replaces ICT labor share with the logarithm of internet-using employees as an alternative measure of ICT-skilled labor, allowing for a robustness check on the impact of ICT labor on export participation. Finally, the ninth specification mirrors the seventh in incorporating an interaction term to examine the complementarity between ERP usage and ICT-skilled labor, but instead of ICT labor share, it uses the logarithm of internet-using employees as the ICT labor measure.

All estimations have also been conducted separately for SMEs and large firms to account for potential differences in how ICT adoption influences export performance. Firms with fewer than 250 employees are classified as SMEs, while those with 250 or more employees are categorized as large firms. This distinction is important because SMEs and large firms differ in several key aspects, such as access

to financial resources, economies of scale, organizational complexity, and export market entry barriers. Larger firms typically have greater financial capacity, allowing them to absorb the costs of ICT investments more easily, while SMEs may rely on ICT to overcome informational and logistical challenges when entering foreign markets. Additionally, differences in human capital and digital skills across firm sizes may influence the effectiveness of ICT adoption. By estimating the models separately, we can capture these heterogeneous effects and provide a more precise understanding of how ICT impacts export performance in firms of different sizes.

Endogeneity Concerns: Propensity Score Matching

While the panel probit and linear models provide insights into the relationship between ICT adoption and export performance, there are potential endogeneity concerns that need to be addressed. The decision to adopt ICT technologies, particularly ERP systems, may not be random and could be correlated with unobserved firm characteristics that also affect export performance. For instance, firms with better management practices might be more likely to both implement ERP systems and engage in exporting. This self-selection into ICT adoption could lead to biased estimates of the true causal effect of ICT on export performance. To address these concerns and provide a more robust causal interpretation of the results, we complement the baseline random effects probit model with a Propensity Score Matching (PSM) approach (Rosenbaum & Rubin, 1983).

PSM is a quasi-experimental method that aims to estimate average treatment effects by constructing a counterfactual group of untreated units that are similar to treated units in observable characteristics. Let T_i be an indicator variable denoting whether firm i uses ERP, where $T_i = 1$ if firm i uses ERP and $T_i = 0$ otherwise. Accordingly, the group of firms with $T_i = 1$, representing ERP users, constitutes the treatment group, while firms with $T_i = 0$, representing non-users, form the control group. For each firm, we also observe a vector of covariates, $\mathbf{Z}$, as previously defined. A common formulation of the problem is:

$$Y_i = \alpha \mathbf{Z}_i + \beta T_i + \varepsilon_i \quad (19)$$

where Y_i represents either export participation or export intensity. The coefficient of interest, β , captures the causal effect of ERP usage on export performance.

Because the main independent variable of interest, T_i , indicates whether a firm uses ERP, it is a binary variable that can take only two values: 0 or 1. If firm i uses ERP, the observed outcome of interest is $Y_i(1)$, while the counterfactual outcome $Y_i(0)$ remains unobserved. Conversely, if firm i does not use ERP, the observed outcome is $Y_i(0)$ and $Y_i(1)$ becomes the unobserved counterfactual. Thus, the observed outcome variable Y_i can be expressed as:

$$Y_i = \begin{cases} Y_i(0) & \text{if } T_i = 0 \\ Y_i(1) & \text{if } T_i = 1 \end{cases} = Y_i(0) + T_i[Y_i(1) - Y_i(0)] \quad (20)$$

The difference $Y_i(1) - Y_i(0)$ is the firm-level treatment effect of ERP usage on firm i 's outcome of interest. This formulation demonstrates the fundamental problem of causal inference: We can never observe both $Y_i(1)$ and $Y_i(0)$ for the same firm simultaneously, making direct estimation of the treatment effect impossible (Holland, 1986). In other words, we lack data on what the outcome would have been for ERP users had they not used ERP or for non-users had they used ERP, necessitating an appropriate counterfactual estimation strategy.

To address this challenge and mitigate the endogeneity concerns arising from self-selection into ERP usage, we employ PSM as a robust quasi-experimental approach. By matching ERP users (treatment group) with non-users (control group) based on observable characteristics, PSM constructs a counterfactual that approximates the missing potential outcomes. This approach reduces selection bias and enhances the credibility of causal inference, allowing for a more reliable estimation of the impact of ERP usage on export performance.

The matching methods rely on the conditional independence assumption (CIA), which posits that, conditional on a set of observable covariates, the potential outcomes are independent of the treatment assignment (Angrist & Pischke, 2009). In the specific context of ERP and export performance, CIA implies that, after controlling for relevant firm characteristics, the decision to use ERP is as good as random (Cunningham, 2021). In other words, any differences in export participation or export intensity between ERP users and non-users are assumed to be attributable to ERP usage rather than to unobserved confounding factors that simultaneously affect both ERP usage and export performance.

The second key identifying assumption for matching methods, the common support assumption, ensures that there is sufficient overlap in the characteristics of treated and untreated units to make meaningful comparisons. It can be formally expressed as: $0 < Pr(T_i = 1|Z) < 1$, meaning that for any probability, there exists comparable units in the control group for each treated unit. In our context, this assumption implies that for each ERP user, there exists a comparable non-user firm with similar observable characteristics. If this assumption does not hold, constructing a credible counterfactual becomes impossible, as there would be no suitable matches to estimate what the export performance of an ERP user might have been had it not used ERP.

Matching methods consist of four essential steps, where the first three steps are part of the design phase, while the fourth step focuses on the analysis (Stuart, 2010). The first step in matching methods is defining closeness, which refers to the distance measure used to determine whether one unit is a suitable match for another. Once this measure is established, the next step involves implementing a matching method based on the chosen closeness criterion. A critical step that follows is diagnosing the quality of the matched sample, ensuring that the treatment and control groups are well balanced in terms of observable characteristics. Finally, the last step involves analyzing the outcome and estimating the treatment effect.

While the most widely used distance measure is propensity scores, which summarize multiple covariates into a single scalar representing the probability of treatment assignment, multivariate distance matching (MDM) methods, such as Mahalanobis or Euclidean distance, are also viable alternatives. The key difference lies in their approach: Propensity scores reduce dimensionality by collapsing covariates into one score, facilitating easier matching, whereas multivariate distance matching directly calculates the distance between firms based on multiple covariates rather than reducing them to a single score.

Regarding the matching methods, several approaches exist, each with different advantages. Some studies show that the use of propensity scores turns out to be inefficient when making a match (King & Nielsen, 2019). However, in most cases, these problems can be avoided by incorporating models with Mahalanobis or Euclidean distance matching, as is the case with the kernel model, which can better account for covariate distributions (Jann, 2017a, 2017b).

To ensure robustness in our analysis, we employ both PSM and MDM. Specifically, for PSM, we use the nearest neighbor and kernel matching methods to estimate the treatment effect of ERP usage on export performance. To test the robustness of our results, we also apply nearest neighbor and kernel matching within the MDM framework. This allows us to assess whether our findings remain consistent across different matching approaches, strengthening the validity of our causal estimates. Across all methods, exact matching was performed using the 2-digit subsector and year variables, ensuring that firms are only matched if they operate in the same subsector and are observed in the same year.

In the third step of the matching process, we assess the quality of the matched sample to ensure that the treatment and control groups are well balanced in terms of observable characteristics. This evaluation is crucial for verifying that any observed differences in export performance between ERP users and non-users are attributable to ERP usage rather than pre-existing firm characteristics. To diagnose balance, we compare the distribution of covariates before and after matching. This involves examining whether firm characteristics are more closely aligned between the treated and control groups after the matching procedure. Successful matching should result in a reduction of initial disparities, ensuring that firms being compared are more similar in their observable traits and minimizing bias in the treatment effect estimation.

Furthermore, we conduct visual inspections of the propensity score distributions for both ERP users and non-users. By plotting the density of propensity scores before and after matching, we verify whether there is sufficient overlap in their distributions. This examination confirms that the common support assumption holds, ensuring that treatment effects are estimated within a comparable range of firm characteristics rather than relying on unmatched observations.

Finally, the treatment effect can be quantified using three distinct parameters: the average treatment effect (ATE), the average treatment effect on the treated (ATT), and the average treatment effect on the control (or untreated) group (ATC, also referred to as ATU). These measures provide different perspectives on the causal impact of a treatment. The ATE represents the average effect of ERP usage on export performance across all firms, irrespective of whether they used ERP. It is defined as the expected difference in potential outcomes under treatment and control conditions

for the entire population: $ATE = E[Y_i(1) - Y_i(0)]$. The ATT focuses solely on firms that used ERP, measuring the average effect of usage for this treated group: $ATT = E[(Y_i(1) - Y_i(0)|T_i = 1)]$. Lastly, the ATC captures the hypothetical impact of ERP usage on firms that did not use it: $ATC = E[(Y_i(1) - Y_i(0)|T_i = 0)]$. It answers the counterfactual question: What would have been the effect of ERP usage for firms that chose not to use it? The primary difference lies in their scope: ATE considers the full population, ATT targets the treated subgroup, and ATC focuses on the untreated subgroup, each addressing distinct counterfactual questions.

In the context of our study examining the impact of ERP usage on export performance, ATT is the most appropriate parameter. Since our interest lies in understanding the causal effect of ERP usage for firms that chose to implement it, ATT directly captures the benefit experienced by these users. Specifically, ATT answers the question: What is the effect of ERP usage on export performance for firms that actually used ERP, compared to what their performance would have been had they not used it?

In summary, this study employs a comprehensive empirical strategy combining panel probit models for export participation, random effects estimation for export intensity, and propensity score matching techniques to address potential endogeneity concerns. This multifaceted approach, supplemented by various robustness checks and subsample analyses across firm sizes and technological categories, enables us to thoroughly examine the relationship between ICT adoption and export performance while accounting for potential selection bias and heterogeneous effects.

5. RESULTS AND DISCUSSION

5.1. Results of the Export at the Extensive Margin

Table 5 reports the marginal effects derived from estimating the econometric models presented in equations (15) and (16) using the random effects panel probit method for all firms⁷. The marginal effects are calculated at the mean values of the control variables. According to the results of the first model (column 1), a positive and statistically significant relationship is observed between ERP usage and the export decision. Although the magnitude of this relationship decreases after including province and sector fixed effects (column 2), it remains positive and statistically significant. With the inclusion of firm characteristics (column 3), the magnitude of the relationship between ERP and export decision decreases further, but it continues to be positive and statistically significant. In this model, examining the firm characteristics, the first notable finding is that the value added per worker, representing labor productivity, is positive and statistically significant. This supports the self-selection hypothesis, consistent with the theories of heterogeneous firms (Melitz, 2003).

Additionally, firm age exhibits a positive association with export participation, but this effect diminishes at higher levels, as indicated by the negative coefficient on the squared term. This suggests a nonlinear relationship where firms initially benefit from accumulated knowledge and internationalization experience, but beyond a certain point, factors such as structural rigidities or reduced adaptability may limit further export expansion. Furthermore, as expected, a positive and statistically significant relationship is observed between capital intensity and the probability of exporting, suggesting that firms with greater capital investment are more likely to engage in international markets. Profitability, however, is not statistically significant,

⁷ Pooled probit results are presented in the Appendix: Table A1 for all firms, Table A2 for SMEs, and Table A3 for large firms. The pooled probit estimates serves as a benchmark to compare with the panel models, allowing for an assessment of how unobserved firm heterogeneity influences the estimated effects.

contrary to expectations. One possible explanation for this finding is methodological: since marginal effects are calculated at the mean values of explanatory variables, the effect of profitability might be statistically significant at different points in the distribution. Finally, the positive and statistically significant association between employment size and the likelihood of exporting indicates that larger firms, as proxied by employment, benefit from economies of scale, reducing unit costs and gaining a competitive advantage in international markets.

When ICT labor variables are introduced as alternative technology indicators in models (4) and (5), additional insights emerge. Model (4) replaces ERP usage with ICT Labor Share, which is found to be positive and highly significant, suggesting that firms with a greater proportion of employees using the internet are more likely to engage in export activities. Similarly, model (5) substitutes ICT labor share with Log internet-using Employees, and this variable also exhibits a positive and statistically significant effect, further reinforcing the notion that digital skills and technological adoption at the workforce level play an important role in export participation.

The significance of these ICT labor variables suggests that beyond the sole reliance on the usage of ERP systems, the broader utilization of digital technologies by employees enhances firms' ability to integrate into international markets. The introduction of these variables does not substantially alter the significance of other explanatory variables, with firm age, capital intensity, labor productivity, and employment continuing to exhibit similar relationships with export participation. The main difference arises in the profitability variable (ROA). While it is statistically insignificant in models (3) and (4), it becomes significant at the 1% level in model (5), with a negative coefficient. This suggests that more profitable firms are less likely to enter export markets.

Moving to models (6) and (8), we examine how the estimation results change when controlling for ICT labor variables alongside ERP, capturing the firm's broader technological engagement through its workforce. Given that ERP is our primary variable of interest, we observe that ERP retains positive and statistically significant associations in these specifications, even after controlling for ICT labor. Moreover, the variables representing ICT labor maintain their statistical significance when compared to models (4) and (5). This may suggest a potential complementarity between ERP and ICT labor.

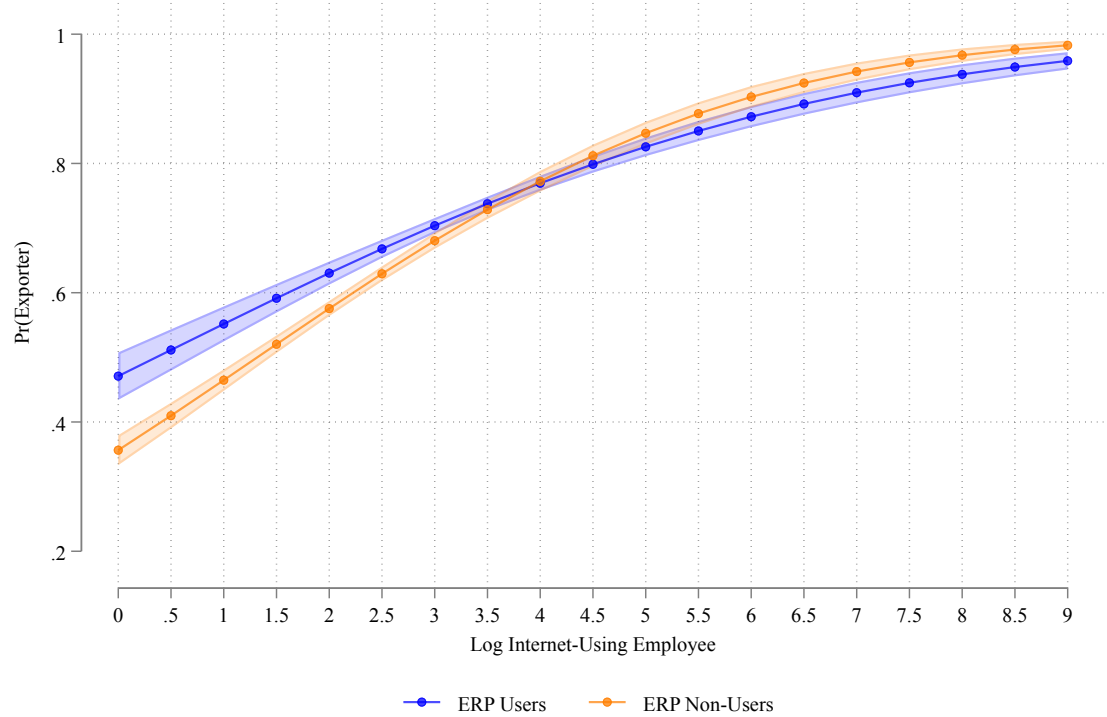
Table 5. ICT and Export Market Participation: Random Effects Panel Probit Results (Marginal Effects) for All Firms

Dependent variable: Export decision	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ERP	0.150*** (0.008)	0.130*** (0.008)	0.022*** (0.007)			0.017** (0.007)	0.023*** (0.009)	0.025*** (0.007)	0.103*** (0.018)
ICT Labor Share				0.001*** (0.000)		0.001*** (0.000)	0.001*** (0.000)		
Log Internet-Using Employee					0.089*** (0.003)			0.085*** (0.003)	0.098*** (0.004)
ERP x ICT Labor Share							-0.041 (0.028)		
ERP x Log Internet-Using Employee									-0.027*** (0.006)
Age/10			0.040*** (0.006)	0.041*** (0.006)	0.057*** (0.006)	0.039*** (0.006)	0.039*** (0.006)	0.052*** (0.007)	0.053*** (0.007)
Age-Squared/100			-0.001* (0.001)	-0.001* (0.001)	-0.002** (0.001)	-0.001* (0.001)	-0.001* (0.001)	-0.002** (0.001)	-0.002** (0.001)
Log Capital per Worker			0.032*** (0.003)	0.034*** (0.003)	0.025*** (0.003)	0.031*** (0.003)	0.030*** (0.003)	0.024*** (0.003)	0.024*** (0.003)
Log Value Added per Worker			0.074*** (0.007)	0.063*** (0.005)	0.062*** (0.005)	0.070*** (0.007)	0.068*** (0.007)	0.068*** (0.007)	0.068*** (0.007)
Return on Assets (ROA)			-0.000 (0.000)	-0.000 (0.000)	-0.000*** (0.000)	-0.000 (0.000)	-0.000* (0.000)	-0.000** (0.000)	-0.000** (0.000)
Log Employment			0.100*** (0.003)	0.111*** (0.003)		0.105*** (0.003)	0.106*** (0.003)		
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector Dummies	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province Dummies	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Firms	12036	11987	11670	13867	13605	11670	11576	11574	11574
Observations	22820	22742	22237	31710	31352	22237	22125	22121	22121
Log Likelihood	-11038.593	-10511.565	-9212.650	-12393.037	-12374.080	-9198.232	-9143.268	-9236.761	-9224.242

Robust standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions include a constant.

To further explore this potential complementarity, model (7) introduces an interaction term between ERP usage and ICT Labor Share, yet the interaction effect is found to be statistically insignificant (Figure A1). In contrast, model (9), which includes the interaction between ERP and Log internet-using employees, shows a statistically significant interaction effect. The marginal effects associated with this interaction are visualized in Figure 3, illustrating how the probability of exporting differs between ERP users and non-users depending on the level of ICT-skilled labor.

Figure 3. All Firms' Probability of Exporting for ERP Users and Non-Users by Internet-Using Employees



Note: The confidence intervals are at the 95% level.

The results reveal that while an increase in internet-using employees enhances the likelihood of exporting for all firms, the marginal effect is significantly larger for ERP users. This suggests a complementarity between ERP usage and ICT-skilled labor within the workforce. This difference is particularly pronounced at lower levels of ICT labor, suggesting that ERP provides a substantial advantage for firms with fewer ICT-skilled labor. This trend is particularly evident up to approximately 20 (e^3) internet-using employees, after which the marginal gains appear to diminish. This suggests that the integration of advanced ICT systems like ERP with a digitally engaged workforce amplifies firms' export capabilities, especially when ICT labor is relatively limited. Beyond this point (approximately 20 internet-using employees) the

difference in export probability between ERP users and non-users narrows, and the lines converge. This convergence indicates that the additional benefits of ERP usage diminish as ICT labor becomes more abundant, potentially reflecting a pattern of decreasing marginal returns. In other words, while ERP provides a substantial boost to export likelihood in the early stages of building ICT capacity, its incremental advantage over non-ERP firms lessens as the workforce's digital engagement reaches higher levels.

The statistically significant interaction between the number of internet-using employees and ERP but not between ICT labor share and ERP might suggest that the way digital capabilities are measured plays a crucial role in understanding their impact on export probability. The ICT labor share is a relative measure (i.e., the proportion of ICT-skilled employees to total employees), whereas the number of internet-using employees is an absolute measure. While having a high percentage of ICT-skilled employees may indicate a firm's digital prioritization, it is the actual size of the digitally skilled workforce that creates complementarities with enterprise systems like ERP. In other words, a high ICT labor share might suggest digital engagement, but it does not necessarily translate into a firm's overall capacity to leverage digital tools effectively, especially in smaller firms where a high proportion of ICT-skilled employees could still correspond to a relatively small workforce.

Tables 6 and 7 present the estimation results of the random effects panel probit models, respectively for SMEs and large firms. A comparative analysis of these tables reveals notable differences in how ICT adoption is associated with export market participation between SMEs and large firms. The most striking difference emerges in the relationship between ERP usage and export decisions. For SMEs, ERP usage demonstrates a consistently positive and statistically significant association across all model specifications. In contrast, for large firms, ERP's significance is limited to models (1) and (2), and this association becomes statistically insignificant once firm characteristics are included. This finding might suggest that SMEs benefit more from ERP usage in overcoming export barriers, possibly because they initially face greater constraints in managing complex business operations and supply chain logistics. In contrast, large firms likely already have well-established organizational structures and international networks, making the marginal impact of ERP less pronounced.

Table 6. ICT and Export Market Participation: Random Effects Panel Probit Results (Marginal Effects) for SMEs

Dependent variable: Export decision	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ERP	0.172*** (0.011)	0.144*** (0.010)	0.042*** (0.011)			0.033*** (0.011)	0.060*** (0.014)	0.026** (0.011)	0.065** (0.028)
ICT Labor Share				0.001*** (0.000)		0.001*** (0.000)	0.002*** (0.000)		
Log Internet-Using Employee					0.121*** (0.005)			0.119*** (0.006)	0.123*** (0.007)
ERP x ICT Labor Share							-0.125*** (0.039)		
ERP x Log Internet-Using Employee									-0.017 (0.011)
Age/10			0.058*** (0.018)	0.070*** (0.016)	0.091*** (0.017)	0.060*** (0.018)	0.062*** (0.019)	0.080*** (0.019)	0.079*** (0.019)
Age-Squared/100			-0.010* (0.005)	-0.013*** (0.005)	-0.016*** (0.005)	-0.011* (0.005)	-0.011** (0.005)	-0.014*** (0.005)	-0.014** (0.005)
Log Capital per Worker			0.034*** (0.004)	0.036*** (0.003)	0.026*** (0.004)	0.033*** (0.004)	0.032*** (0.004)	0.026*** (0.004)	0.026*** (0.004)
Log Value Added per Worker			0.096*** (0.011)	0.092*** (0.008)	0.080*** (0.008)	0.090*** (0.011)	0.088*** (0.011)	0.079*** (0.011)	0.079*** (0.011)
Log Return on Assets (ROA)			-0.000 (0.000)	-0.000 (0.000)	-0.000** (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000** (0.000)	-0.000** (0.000)
Log Employment			0.131*** (0.006)	0.145*** (0.005)		0.141*** (0.006)	0.144*** (0.006)		
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector Dummies	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province Dummies	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Firms	9967	9928	9621	11846	11582	9621	9527	9525	9525
Observations	12155	12115	11742	16619	16275	11742	11635	11632	11632
Log Likelihood	-7622.923	-7163.490	-6354.804	-8632.848	-8500.281	-6340.076	-6280.480	-6300.585	-6299.395

Robust standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions include a constant.

Table 7. ICT and Export Market Participation: Random Effects Panel Probit Results (Marginal Effects) for Large Firms

Dependent variable: Export decision	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ERP	0.031*** (0.007)	0.032*** (0.009)	0.009 (0.008)			0.008 (0.008)	0.001 (0.009)	0.011 (0.008)	-0.017 (0.027)
ICT Labor Share				0.000* (0.000)		0.000 (0.000)	-0.000 (0.000)		
Log Internet-Using Employee					0.023*** (0.003)			0.024*** (0.004)	0.019*** (0.006)
ERP x ICT Labor Share							0.064 (0.043)		
ERP x Log Internet-Using Employee									0.008 (0.007)
Age/10			0.055*** (0.008)	0.054*** (0.007)	0.062*** (0.007)	0.055*** (0.008)	0.055*** (0.008)	0.061*** (0.008)	0.061*** (0.008)
Age-Squared/100			-0.002*** (0.001)	-0.002*** (0.000)	-0.002*** (0.000)	-0.002*** (0.001)	-0.002*** (0.001)	-0.002*** (0.001)	-0.002*** (0.001)
Log Capital per Worker			0.027*** (0.004)	0.025*** (0.004)	0.019*** (0.004)	0.026*** (0.004)	0.027*** (0.004)	0.020*** (0.004)	0.020*** (0.004)
Log Value Added per Worker			0.035*** (0.007)	0.022*** (0.005)	0.020*** (0.006)	0.034*** (0.007)	0.034*** (0.007)	0.031*** (0.007)	0.031*** (0.007)
Log Return on Assets (ROA)			0.023 (0.023)	0.017 (0.018)	0.037* (0.020)	0.026 (0.024)	0.025 (0.024)	0.046* (0.028)	0.046* (0.028)
Log Employment			0.055*** (0.006)	0.059*** (0.006)		0.058*** (0.006)	0.054*** (0.007)		
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector Dummies	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province Dummies	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Firms	2666	2635	2601	2748	2747	2601	2601	2601	2601
Observations	10665	10563	10431	15034	15020	10431	10426	10425	10425
Log Likelihood	-3198.311	-3035.784	-2825.796	-3737.278	-3765.284	-2824.725	-2822.644	-2842.882	-2842.198

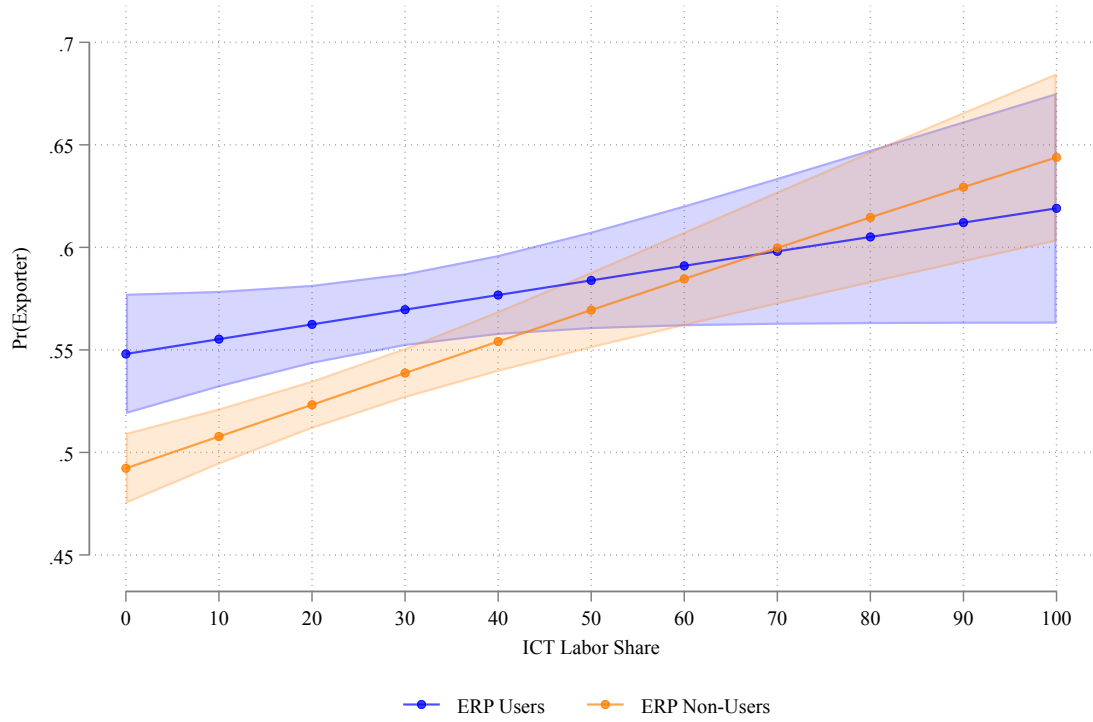
Robust standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions include a constant.

Second, the association between ICT labor share and export participation also differs significantly between SMEs and large firms. For SMEs, the association between ICT labor share and export participation is positive and statistically significant across all relevant specifications. Conversely, for large firms, ICT labor share shows only marginal significance in model (4) and becomes insignificant in other specifications, suggesting that ICT-skilled labor plays a less pivotal role in their export decisions, likely due to their existing resource advantages and established market presence. On the other hand, while the number of internet-using employees remains significant for large firms, the magnitude of this association is substantially higher for SMEs. This pattern suggests that developing digital workforce capacity provides a greater comparative advantage for smaller enterprises seeking to access international markets.

When examining the associations of firm characteristics, the most striking difference is that the association between value added per worker and export participation is significantly stronger for SMEs compared to large firms. This finding suggests that productivity gains play a more critical role in the export decisions of SMEs, as higher efficiency may help them overcome barriers to entering international markets. Similarly, the association between firm size (measured by employment) and export participation is also more pronounced for SMEs. This could be linked to the fact that achieving economies of scale and reducing unit costs provides a greater advantage for SMEs, making expansion into export markets more viable.

When examining the complementarity between ICT labor and ERP usage (models (7) and (9)), we observe distinct patterns across SMEs and large firms. For SMEs, the interaction between ERP usage and the number of internet-using employees is not statistically significant (Figure A2), whereas the interaction between ERP usage and ICT labor share appears negative and statistically significant. This finding aligns with the caution raised by Ai and Norton (2003) regarding the interpretation of interaction terms in nonlinear models. Although the coefficient is negative, Figure 4 indicates that firms using ERP have a higher probability of exporting than non-users up until the ICT labor share reaches 30%. Beyond this threshold, the difference between ERP users and non-users becomes statistically insignificant.

Figure 4. SMEs' Probability of Exporting for ERP Users and Non-Users by ICT Labor Share



Note: The confidence intervals are at the 95% level.

For large firms, however, neither of the ICT labor variables exhibits a statistically significant interaction with ERP (Figure A3 & Figure A4). This suggests that there is no strong evidence of complementarity between ERP and ICT-skilled labor in large firms. One possible explanation is that large firms may already have well-integrated ICT and ERP systems, meaning that additional ICT labor does not significantly alter their export participation. In contrast, for SMEs, the relationship between ERP and ICT labor appears more nuanced, with potential complementarity existing at lower levels of ICT penetration but diminishing at higher levels.

Table 8 presents the random effects panel probit results examining how ICT adoption is associated with firms' export market participation across different technological categories of exported products. The table organizes the findings into four technology levels (high, medium-high, medium-low, and low) as classified by Eurostat, with each category featuring three model specifications examining different ICT indicators. A comparative analysis across these technological categories reveals that the relationship between ICT adoption and export participation varies significantly depending on the technological sophistication of exported products. For ERP usage (models 1, 4, 7, and 10), the strongest association is observed for medium-high technology exports, followed by medium-low technology exports. This

pattern suggests that ERP systems provide the greatest advantage for firms exporting products of intermediate technological complexity, where production and supply chain management may be particularly challenging but manageable with appropriate enterprise systems.

The relationship between ICT labor share and export probability (models 2, 5, 8, and 11) shows a consistent pattern across most technology categories, with identical coefficients for high, medium-high, and medium-low technology exports, and a slightly lower coefficient for low technology exports. All associations are statistically significant. This suggests that while a digitally skilled workforce is important across all technological categories, its contribution may be marginally lower for exporting low-technology products.

For internet-using employees (models 3, 6, 9, and 12), a pattern similar to ERP usage emerges, with the strongest association observed for medium-high technology exports, followed by medium-low, low, and high technology exports. Both ERP and internet-using employees show the greatest association with export probability for products of intermediate technological complexity. However, while ERP's association drops sharply for both high and low technology categories, the association between internet-using employees and export probability declines more gradually toward low-technology exports, with high-technology exports showing the lowest association. This suggests that while both digital infrastructure components are most strongly associated with intermediate technology products, a digitally connected workforce has a relatively stronger association with low-technology exports compared to ERP systems.

Tables A4 and A5, presented in the appendix, extend the analysis of ICT and export market participation based on technological classification by examining the relationships separately for SMEs and large firms. These tables provide more detailed insights into how the associations between ICT adoption and export participation across different product technology levels vary by firm size.

For SMEs (Table A4), several notable patterns emerge. ERP usage shows no significant association with high-technology exports for smaller firms, while maintaining significant positive associations with medium-high, medium-low, and low technology exports. This suggests that SMEs may face barriers to utilizing ERP

systems for high-technology exports, possibly due to the specialized knowledge requirements that go beyond standard enterprise systems.

In contrast, for large firms (Table A5), ERP usage shows significant positive associations across all technology categories, with the strongest associations observed for medium-low and medium-high technology exports. This indicates that large firms are better positioned to use enterprise systems for exporting across the entire technological spectrum, including high-technology products.

Another interesting observation is the pattern of ICT labor share coefficients across firm sizes. For SMEs, the coefficients are consistent across all technology categories, while for large firms, there is a clear decreasing pattern from high technology to low technology. This suggests that the relative proportion of digitally skilled workforce is particularly important for large firms exporting high-technology products.

**Table 8. ICT and Export Market Participation Based on Technological Classification:
Random Effects Panel Probit Results (Marginal Effects) for All Firms**

Dependent variable: Export Status Based on Technology	High			Medium-High			Medium-Low			Low		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
ERP	0.010* (0.006)			0.045*** (0.007)			0.036*** (0.007)			0.013* (0.008)		
ICT Labor Share		0.001*** (0.000)			0.001*** (0.000)			0.001*** (0.000)			0.000*** (0.000)	
Log Internet-Using Employee			0.056*** (0.002)			0.093*** (0.003)			0.088*** (0.003)			0.080*** (0.003)
Age/10	0.029*** (0.007)	0.031*** (0.007)	0.037*** (0.007)	0.023*** (0.007)	0.026*** (0.006)	0.043*** (0.006)	0.022*** (0.007)	0.026*** (0.007)	0.042*** (0.007)	0.019** (0.007)	0.020*** (0.007)	0.036*** (0.007)
Age-Squared/100	-0.004*** (0.001)	-0.005*** (0.001)	-0.005*** (0.001)	-0.001** (0.001)	-0.001* (0.001)	-0.002** (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.002 (0.001)	0.000 (0.001)	0.000 (0.001)	-0.001 (0.001)
Log Capital per Worker	0.012*** (0.002)	0.011*** (0.002)	0.007*** (0.002)	0.029*** (0.003)	0.031*** (0.003)	0.023*** (0.003)	0.023*** (0.003)	0.026*** (0.003)	0.018*** (0.003)	0.026*** (0.003)	0.025*** (0.003)	0.016*** (0.003)
Log Value Added per Worker	0.042*** (0.004)	0.035*** (0.004)	0.033*** (0.003)	0.072*** (0.008)	0.064*** (0.006)	0.065*** (0.006)	0.055*** (0.007)	0.048*** (0.005)	0.047*** (0.005)	0.048*** (0.007)	0.042*** (0.005)	0.038*** (0.005)
Return on Assets (ROA)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001** (0.000)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.000** (0.000)	-0.000** (0.000)	-0.000*** (0.000)	0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)
Log Employment	0.061*** (0.003)	0.067*** (0.002)		0.102*** (0.004)	0.116*** (0.003)		0.104*** (0.004)	0.113*** (0.003)		0.105*** (0.004)	0.113*** (0.003)	
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Firms	11359	13457	13213	11671	13858	13596	11653	13835	13574	11662	13855	13593
Observations	21807	31078	30742	22262	31732	31374	22238	31697	31341	22222	31688	31330
Log Likelihood	-6082.672	-8321.067	-8324.068	-9493.688	-12980.236	-13039.437	-9619.526	-13066.305	-13133.098	-9898.370	-13286.161	-13360.536

Robust standard errors are in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01. All regressions include a constant.

PSM Results of the Extensive Margin

The results presented so far might be biased due to possible endogeneity concerns arising from self-selection bias. Firms that use ERP systems may systematically differ from non-users in ways that also influence their export decisions. Since ERP usage is not randomly assigned but rather a strategic decision made by firms, comparing ERP users to non-users without adequately accounting for this self-selection may lead to biased estimates of ERP's actual impact on exporting. To mitigate these concerns, we employ PSM, which improves comparability between ERP users and non-users by balancing observed firm characteristics. By matching firms with similar probabilities of ERP usage, PSM reduces selection bias due to observable factors. However, it is important to note that PSM does not address endogeneity arising from unobserved confounders or simultaneity, as it only controls for observed characteristics. Therefore, while PSM strengthens the reliability of the results, the findings should be interpreted with caution, recognizing that some degree of endogeneity may persist.

Before proceeding to the PSM results, we assess the quality of the matching process by conducting balance tests and verifying the common support condition. Balance tests compare the distribution of covariates between ERP users and non-users before and after matching to ensure that differences in observed firm characteristics are minimized. Additionally, we check the common support condition, which ensures sufficient overlap in propensity scores between treated and control firms. Observations without comparable matches are excluded to improve the validity of the matching process. These checks confirm that PSM has effectively improved comparability between ERP users and non-users, allowing for a more reliable estimation of the treatment effect.

Table 9 presents a comparison of covariates before and after matching (PSM using kernel matching) for all firms, assessing the balance between treated (firms using ERP) and untreated (firms not using ERP) groups. The table reports means and standard differences (StdDif) for key covariates, along with variances and their ratios before (Raw) and after matching (Matched), to evaluate the effectiveness of matching in reducing selection bias. Before matching, significant imbalances are observed between treated and untreated groups, as indicated by high standardized differences for several covariates. After matching, the results show a substantial

improvement in covariate balance, with standardized differences reduced to negligible levels across all variables.

Table 9. Comparison of Covariates Before and After Matching (PSM, Kernel Matching, All Firms)

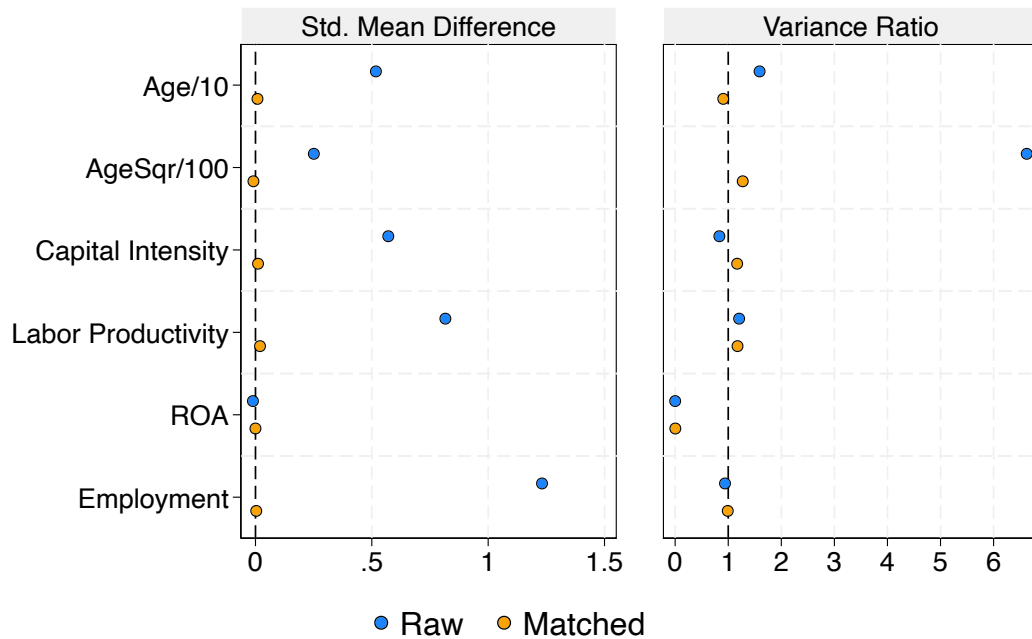
	Raw			Matched		
	Treated	Untreated	StdDif	Treated	Untreated	StdDif
Means						
Age/10	1.941	1.459	0.518	1.704	1.696	0.009
Log Capital per Worker	10.961	10.145	0.571	10.575	10.559	0.011
Log Value Added per Worker	10.734	10.113	0.816	10.410	10.395	0.020
Return on Assets (ROA)	0.049	0.227	-0.011	0.034	0.034	-0.000
Log Employment	5.694	4.142	1.232	4.917	4.912	0.003
Variances						
	Treated	Untreated	Ratio	Treated	Untreated	Ratio
Age/10	1.062	0.667	1.591	0.954	1.052	0.907
Log Capital per Worker	1.854	2.225	0.833	2.352	2.013	1.168
Log Value Added per Worker	0.633	0.526	1.206	0.662	0.564	1.175
Return on Assets (ROA)	0.022	525.927	0.000	0.031	8.248	0.004
Log Employment	1.540	1.639	0.940	2.036	2.054	0.991

Source: Author's own calculations.

Figure 5 offers a visual representation of the reduction in imbalances reported in Table 9. It displays standardized mean differences and variance ratios for each matching variable in both the unmatched and matched samples. As seen in the figure, the standardized mean differences for all matching variables in the matched sample are centered around zero, suggesting that kernel matching has successfully produced a balanced sample where the mean values of covariates are nearly equivalent between treated and control groups. Additionally, the variance ratios indicate that, apart from ROA, all other matching variables move closer to unity after matching.

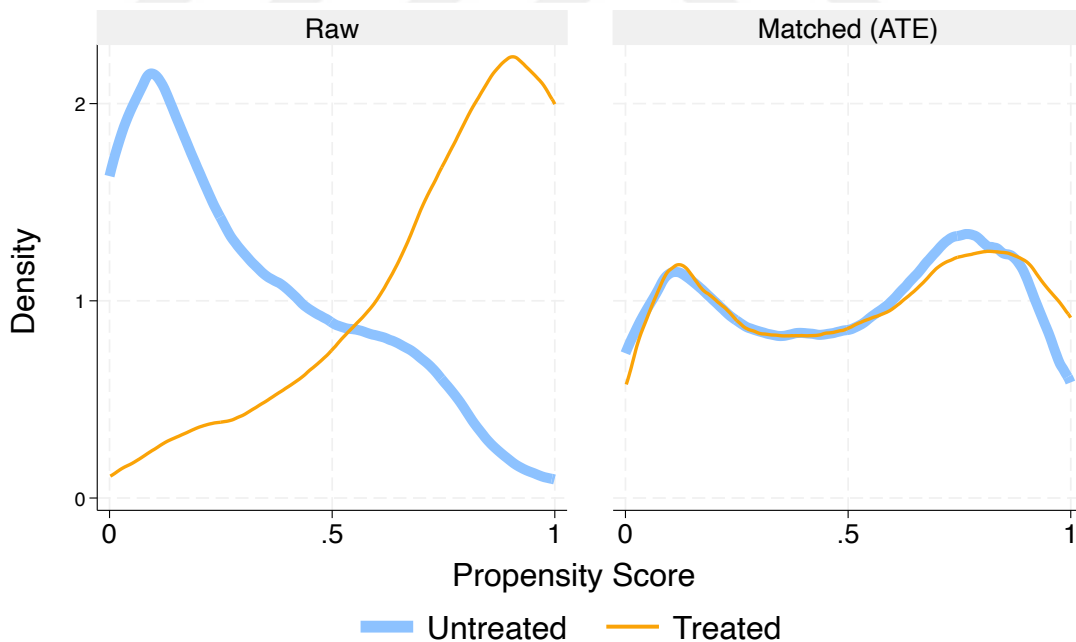
To assess whether a common support region exists, the density distribution of propensity scores across the entire sample can be visually examined. The left panel of Figure 6 presents the propensity score distribution in the unmatched sample, while the right panel demonstrates that kernel matching results in nearly identical propensity score distributions for treated and control groups. The presence of common support ensures that firms with similar covariates have a positive probability of being assigned to both the treatment and control groups, thereby improving the comparability of the matched sample.

Figure 5. Covariate Balancing Before and After Matching (PSM, Kernel Matching, All Firms)



Source: Author's own calculations.

Figure 6. Density Plot of Propensity Score Before and After Matching (PSM, Kernel Matching, All Firms)

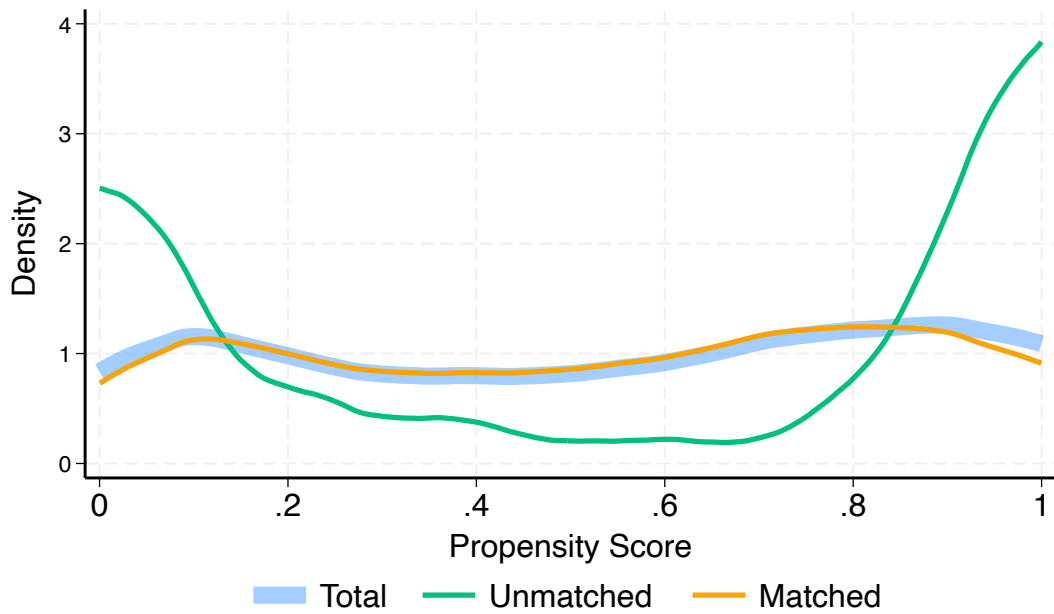


Source: Author's own calculations.

Lastly, to assess whether excluding unmatched firms significantly alters the composition of the sample, we analyze the density distribution of propensity scores before and after matching. Figure 7 presents the density distributions for the total, unmatched, and matched samples. The total distribution represents the full sample

before matching, while the unmatched distribution includes firms that could not be successfully matched due to a lack of similar counterparts. The matched distribution shows the propensity scores of firms that remained in the sample after matching. The figure indicates that the matched and total distributions closely align, suggesting that the exclusion of unmatched observations has not substantially altered the overall sample composition. This confirms that the estimated ATE is unlikely to be severely biased due to sample reduction.

Figure 7. Kernel Density Plot of Propensity Score for the Total, Unmatched and Matched Samples (PSM, Kernel Matching, All Firms)



Source: Author's own calculations.

After completing the matching process and confirming that covariate imbalances have been effectively minimized, we proceed with estimating the treatment effects. Table 10 presents the estimated treatment effects of ERP usage on export participation using different matching approaches. The table compares results obtained from PSM and MDM, employing both kernel matching and nearest neighbor (NN) matching methods⁸.

⁸ Balancing properties and common support diagnostics are reported only for PSM kernel matching in the main text (Figures 5, 6, and 7), while corresponding diagnostics for other matching methods are provided in the appendix. Unlike PSM, where common support is assessed based on the distribution of propensity scores, MDM does not rely on propensity scores. Instead, common support in MDM was evaluated by comparing means and variances between matched and unmatched samples, as presented in the appendix tables.

NN (1) matching method refers to a one-to-one matching approach, where each treated firm is paired with the single most similar untreated firm based on propensity scores or Mahalanobis distances. Unlike kernel matching, which assigns weighted averages of multiple control observations, NN (1) provides an exact match for each treated unit. While our primary focus is on ATT, we also report ATE results for comparison. Additionally, Table 10 includes details on the number of matched and unmatched observations, the number of control units used and unused in the estimation, and the automatic bandwidth parameter applied in kernel matching.

Table 10. Treatment Effects of ERP Usage on the Probability of Exporting (All Firms)

	PSM		MDM	
	Kernel Matching	NN (1)	Kernel Matching	NN (1)
ATE	0.047*** (0.011)	0.060*** (0.012)	0.236*** (0.008)	0.154*** (0.010)
ATT	0.048*** (0.013)	0.055*** (0.015)	0.222*** (0.009)	0.099*** (0.012)
N	22309			
Matched				
Yes	10936	11626	10980	11626
No	722	32	678	32
Total	11658	11658	11658	11658
Controls				
Used	10292	3826	9416	4492
Unused	359	6825	1235	6159
Total	10651	10651	10651	10651
Bandwidth	0.106		10.126	

Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

ERP usage raises the probability of exporting by 4.8 percentage points under PSM with kernel matching for firms that use ERP compared to similar non-users. In this matching approach, out of 11,658 treated observations, 10,936 were matched, while in the control group, 10,292 out of 10,651 observations were used in the estimation. The results from PSM with NN (1) matching are consistent with those from kernel matching, with ERP usage increasing the probability of exporting by 5.5 percentage points. However, due to the one-to-one matching approach in NN (1), only 3,826 control observations could be utilized, compared to the larger number of control

observations used in kernel matching. The similarity in estimates between the two methods suggests that the estimated effect of ERP usage is not sensitive to the choice of matching method within PSM, reinforcing the robustness of the findings.

The estimates obtained from MDM are generally higher than those from PSM, suggesting a stronger impact of ERP usage on export probability under this matching approach. However, an examination of the MDM diagnostics reveals that its balancing properties are weaker compared to PSM, indicating that the matched samples may be less comparable in terms of observed characteristics. This imbalance could potentially influence the estimated treatment effects, leading to larger differences between treated and control observations that are not solely attributable to ERP usage. Therefore, the higher estimates observed under MDM should be interpreted with caution, as they may be partially driven by imbalances in covariates rather than the true effect of ERP usage.

The differences in treatment effect estimates between MDM and PSM can be partially attributed to the higher bandwidth automatically determined in MDM. In kernel matching, bandwidth controls the range of control observations included in the estimation, with a higher bandwidth allowing more distant matches to contribute to the weighted average. While this approach reduces variance by increasing the number of control observations, it also weakens the precision of the matches, potentially introducing bias if less comparable firms are included. Since MDM does not rely on propensity scores and instead matches firms based on Mahalanobis distances, the data-driven selection of a higher bandwidth in MDM leads to less restrictive matching criteria, which may explain why MDM estimates are consistently higher than those obtained from PSM. In contrast, PSM with kernel matching applies a more restrictive bandwidth choice based on propensity scores, leading to better balancing properties and more comparable treatment and control groups. This suggests that the observed differences in estimated effects may not solely reflect the true impact of ERP usage but could also be influenced by the broader bandwidth used in MDM, which results in a less precise matching process.

Tables 11 and 12 present the treatment effects of ERP usage on the probability of exporting, separately for SMEs and large firms⁹. Under PSM with kernel matching, ERP usage increases the probability of exporting by 4.1 percentage points for SMEs and 5.9 percentage points for large firms, suggesting a stronger effect for larger firms. A similar trend is observed under PSM with NN (1) matching, where export probability rises by 3.8 percentage points for SMEs and 8.7 percentage points for large firms. The larger difference in NN (1) estimates may be due to the smaller number of control observations in one-to-one matching, which increases variability. Despite these differences, the consistency between kernel and NN (1) matching results confirms the robustness of the PSM estimates across firm sizes. As in the full sample, MDM produces higher treatment effect estimates than PSM for both SMEs and large firms. The differences in estimates between the two methods follow the same pattern observed in the full sample, and their explanation remains consistent with the discussion provided for all firms.

Table 11. Treatment Effects of ERP Usage on the Probability of Exporting (SMEs)

	PSM		MDM	
	Kernel Matching	NN (1)	Kernel Matching	NN (1)
ATE	0.055*** (0.013)	0.063*** (0.015)	0.186*** (0.011)	0.162*** (0.014)
ATT	0.041*** (0.013)	0.038** (0.016)	0.153*** (0.012)	0.063*** (0.016)
N	11779			
Matched				
Yes	3275	3532	3334	3532
No	263	6	204	6
Total	3538	3538	3538	3538
Controls				
Used	7603	2169	7128	2232
Unused	638	6072	1113	6009
Total	8241	8241	8241	8241
Bandwidth	0.067		13.506	

Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

⁹ Balancing properties and common support diagnostics for SMEs and large firms are provided in the Appendix under the sections “Diagnostics for PSM and MDM (SMEs)” and “Diagnostics for PSM and MDM (Large Firms)”, respectively.

Table 12. Treatment Effects of ERP Usage on the Probability of Exporting (Large Firms)

	PSM		MDM	
	Kernel Matching	NN (1)	Kernel Matching	NN (1)
ATE	0.050*** (0.016)	0.073*** (0.020)	0.110*** (0.017)	0.064*** (0.018)
ATT	0.059*** (0.017)	0.087*** (0.023)	0.113*** (0.019)	0.053** (0.021)
N	10530			
Matched				
Yes	7421	7904	7536	7904
No	699	216	584	216
Total	8120	8120	8120	8120
Controls				
Used	2350	1672	2237	1597
Unused	60	738	173	813
Total	2410	2410	2410	2410
Bandwidth	0.145		15.830	

Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5.2. Results of the Export at the Intensive Margin

Table 13 presents the random effects estimation results examining the relationship between ICT usage and export intensity for all firms in the sample. The dependent variable, export intensity, in these models reflects the extent of firms' engagement in international markets. The results provide insights into how digital capabilities influence not just the likelihood of exporting but also the degree to which firms participate in export markets.

The results indicate that ERP adoption is positively associated with export intensity across all model specifications. In the first specification with only year dummies, the ERP coefficient is at its highest among the models without interaction terms. This coefficient gradually decreases as we add sector and province fixed effects in the second specification, and further controls for firm characteristics in the third specification.

When examining ICT labor indicators separately in models (4) and (5), both ICT labor share and the number of internet-using employees show statistically significant associations with export intensity. However, although ICT labor share is statistically significant, its coefficient is effectively zero in models (4) and (6), indicating a negligible economic impact. When controlling for both ERP usage and ICT labor indicators simultaneously in models (6) and (8), the coefficients of ERP and the number of internet-using employees remain positive and statistically significant.

In model (7), the interaction between ICT labor share and ERP usage is statistically significant, suggesting a potential significant relationship. However, when examining the marginal effects visualization in Figure 8, there is no statistically significant difference in export intensity between ERP users and non-users across different levels of ICT labor share.

By contrast, in model (9), the interaction between ERP adoption and the number of internet-using employees presents a different pattern. As shown in Figure 9, a complementarity effect is observed up to approximately 20 (e^3) internet-using employees. Up to this threshold, firms with ERP systems see a stronger increase in export intensity compared to non-user firms as the number of internet-using employees grows. Beyond this point, however, the difference between ERP users and non-users becomes statistically insignificant. This suggests that ERP and workforce digitalization initially reinforce each other in enhancing export intensity, but this effect does not persist indefinitely, indicating potential diminishing returns to ERP's incremental benefits in firms that already have a high number of internet-using employees.

Table 13 also provides insights into the relationship between firm characteristics and export intensity. Firm age exhibits a positive association with export intensity, but this relationship diminishes at higher ages, as indicated by the negative coefficient on the squared term. This suggests that while older firms may benefit from accumulated market experience and established networks, at a certain point, their export engagement plateaus or even declines, possibly due to organizational inertia or limited adaptability to changing global market conditions.

Capital intensity is positively associated with export intensity, reflecting that firms with higher capital investment are more engaged in international trade. This aligns

with the idea that capital accumulation facilitates export activities by improving production capacity and efficiency. Similarly, employment size is positively related to export intensity, suggesting that larger firms are more likely to be active in export markets, potentially due to economies of scale, stronger supply chain networks, and greater financial and human resources to handle international operations.

One notable finding is that labor productivity is statistically insignificant in all models, which contrasts with its significance in the export probability model. This suggests that while higher productivity increases the likelihood of a firm becoming an exporter, it does not necessarily determine the extent of export engagement once a firm enters international markets. This distinction may imply that different firm characteristics influence export market entry and export intensity, with productivity being more relevant for the initial decision to export rather than for deepening export participation.

Finally, profitability (ROA) remains statistically insignificant across all specifications, indicating that financial performance does not play a direct role in shaping firms' export intensity. This finding suggests that export intensity is driven more by structural factors, such as firm size, capital intensity, and digital adoption, rather than by immediate financial conditions.

Tables 14 and 15 present the random effects estimation results examining the relationship between ICT usage and export intensity separately for SMEs and large firms. A comparative analysis of these tables reveals important differences in how ICT factors relate to export performance across firm size categories.

For SMEs, ERP usage shows a consistently positive and statistically significant association with export intensity across most specifications. In the baseline specification with firm controls (column 3), SMEs using ERP have approximately 1.1 percentage points higher export intensity compared to non-users. This association remains robust even when controlling for ICT labor indicators in models (6) and (8), though with slight reductions in magnitude.

In contrast, for large firms, the association between ERP usage and export intensity is weaker and mostly insignificant, which aligns with our earlier findings from the probability models where ERP lost significance for large firms once firm characteristics were controlled for. The ERP coefficient is marginally significant in

the first specification and becomes statistically insignificant once additional controls are introduced. This suggests that ERP systems may play a more critical role in enhancing the export intensity of SMEs compared to large firms. This consistent pattern across both extensive and intensive margins reinforces the conclusion that ERP systems may play a more critical role in the export performance of SMEs compared to large firms.

When considering ICT labor indicators, both ICT labor share and the number of internet-using employees exhibit positive and statistically significant associations with export intensity in both SMEs and large firms. However, the economic significance of ICT labor share is minimal, as its coefficient is effectively zero in Models (4) and (6) for SMEs and Model (4) for large firms, despite being statistically significant. For SMEs, the number of internet-using employees demonstrates a stronger association with export intensity compared to large firms. This mirrors our findings from the probability models.

For both SMEs and large firms, there is no evidence of a complementarity effect between ERP adoption and the number of internet-using employees, as the interaction term between Log Internet-Using Employee and ERP is statistically insignificant in both cases. Similarly, while the interaction between ICT Labor Share and ERP appears negative and statistically significant in both SMEs and large firms, a closer examination of the marginal effects graphs—evaluated at the mean values of other control variables—reveals no statistically significant difference in export intensity between ERP users and non-users at varying levels of ICT labor share. This contrasts with our findings for export probability, where we observed clearer complementarity patterns, especially for SMEs at lower levels of ICT labor share.

When comparing firm characteristics across SMEs and large firms, notable differences emerge in their relationship with export intensity. Firm age is positively associated with export intensity in large firms but is not statistically significant in SMEs, suggesting that accumulated experience plays a more crucial role in sustaining export activities for larger firms.

Capital intensity is positively associated with export intensity in both SMEs and large firms, though the effect is stronger for larger firms. Labor productivity is statistically significant in both groups but exhibits opposite signs: it is positively

associated with export intensity in SMEs, whereas in large firms, the relationship is negative. This suggests that while higher productivity supports export expansion for smaller firms, larger firms with high productivity may prioritize efficiency improvements or domestic market advantages over further export growth.

Profitability (ROA) is negative and statistically significant in SMEs, but the coefficient is close to zero, implying a negligible economic impact. In contrast, ROA is positively associated with export intensity in large firms, indicating that financial strength plays a more substantial role in sustaining export activities for larger enterprises.

Finally, employment size shows a positive association with export intensity in SMEs, reinforcing the idea that expanding workforce capacity supports smaller firms' internationalization efforts. However, in large firms, employment size is negatively associated with export intensity, suggesting that beyond a certain scale, labor expansion may not necessarily translate into higher export engagement, possibly due to increasing administrative complexity or a focus on domestic market operations.

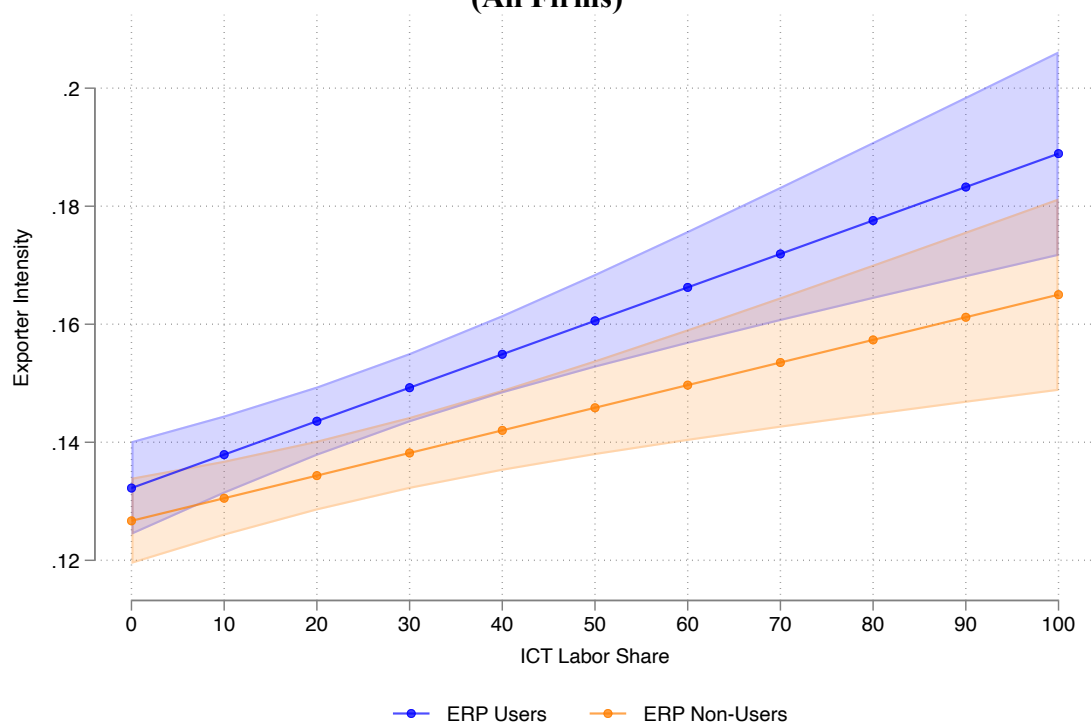
The findings reveal that ERP adoption significantly enhances export intensity for SMEs, while its effect for large firms is weaker and mostly insignificant. ICT labor indicators show positive associations with export intensity in both groups, but ICT labor share has minimal economic significance. No strong complementarity effects between ERP and ICT labor are observed for export intensity, contrasting with the export probability results. Firm characteristics differ across firm sizes—capital intensity positively correlates with export intensity for both, while labor productivity is positive for SMEs but negative for large firms. Profitability (ROA) is negligible for SMEs but positive for large firms, and employment size supports SME exports but hinders large firms' export engagement. These results suggest that ERP and ICT integration play a larger role in SMEs' export growth, whereas large firms' export intensity depends more on firm-specific structural factors such as financial strength and capital investment. Overall, the impact of digitalization on export intensity varies significantly by firm size. The contrast between SMEs and large firms emphasizes the need for differentiated strategies when promoting digital transformation to enhance export performance.

Table 13. ICT and Export Intensity: Random Effects Results for All Firms

Dependent variable: Export intensity	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ERP	0.025*** (0.003)	0.023*** (0.003)	0.011*** (0.003)			0.009*** (0.003)	0.018*** (0.004)	0.008*** (0.003)	0.035*** (0.007)
ICT Labor Share				0.000*** (0.000)		0.000*** (0.000)	0.001*** (0.000)		
Log Internet-Using Employee					0.016*** (0.001)			0.016*** (0.001)	0.021*** (0.002)
ERP x ICT Labor Share							-0.051*** (0.014)		
ERP x Log Internet-Using Employee									-0.008*** (0.002)
Age/10			0.014*** (0.003)	0.014*** (0.003)	0.014*** (0.003)	0.014*** (0.003)	0.013*** (0.003)	0.013*** (0.003)	0.013*** (0.003)
Age-Squared/100			-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)
Log Capital per Worker			0.009*** (0.002)	0.009*** (0.002)	0.007*** (0.002)	0.009*** (0.002)	0.008*** (0.002)	0.008*** (0.002)	0.007*** (0.002)
Log Value Added per Worker			0.003 (0.003)	0.003 (0.003)	0.002 (0.003)	0.001 (0.003)	-0.000 (0.003)	-0.000 (0.003)	-0.001 (0.003)
Log Return on Assets (ROA)			-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
Log Employment			0.013*** (0.002)	0.016*** (0.002)		0.016*** (0.002)	0.017*** (0.002)		
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector Dummies	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province Dummies	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Firms	12036	12036	11715	13919	13652	11715	11618	11616	11616
Observations	22820	22820	22309	31804	31440	22309	22194	22190	22190

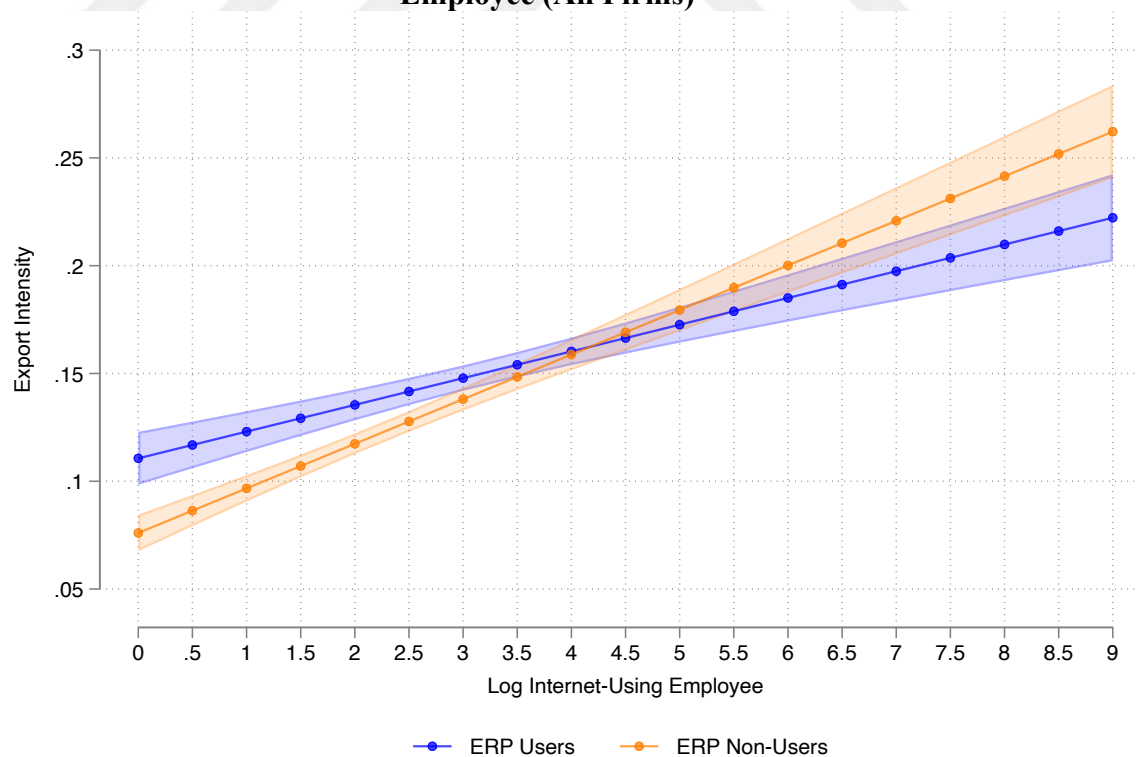
Robust standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions include a constant.

Figure 8. Export Intensity for ERP Users and Non-Users by ICT Labor Share (All Firms)



Note: The confidence intervals are at the 95% level.

Figure 9. Export Intensity for ERP Users and Non-Users by Internet-Using Employee (All Firms)



Note: The confidence intervals are at the 95% level.

Table 14. ICT and Export Intensity: Random Effects Results for SMEs

Dependent variable: Export intensity	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ERP	0.031*** (0.004)	0.028*** (0.004)	0.011*** (0.004)			0.010** (0.004)	0.016*** (0.006)	0.009** (0.004)	0.013 (0.009)
ICT Labor Share				0.000*** (0.000)		0.000*** (0.000)	0.000*** (0.000)		
Log Internet-Using Employee					0.024*** (0.002)			0.024*** (0.002)	0.025*** (0.002)
ERP x ICT Labor Share							-0.027* (0.016)		
ERP x Log Internet-Using Employee									-0.002 (0.004)
Age/10			0.003 (0.007)	0.007 (0.006)	0.011* (0.006)	0.004 (0.007)	0.004 (0.007)	0.008 (0.007)	0.008 (0.007)
Age-Squared/100			-0.000 (0.002)	-0.001 (0.002)	-0.002 (0.002)	-0.000 (0.002)	-0.000 (0.002)	-0.001 (0.002)	-0.001 (0.002)
Log Capital per Worker			0.003** (0.002)	0.004*** (0.001)	0.002 (0.001)	0.003* (0.002)	0.003* (0.002)	0.002 (0.002)	0.002 (0.002)
Log Value Added per Worker			0.019*** (0.005)	0.019*** (0.003)	0.016*** (0.003)	0.018*** (0.005)	0.017*** (0.005)	0.015*** (0.005)	0.015*** (0.005)
Log Return on Assets (ROA)			-0.000** (0.000)	-0.000* (0.000)	-0.000*** (0.000)	-0.000* (0.000)	-0.000** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)
Log Employment			0.028*** (0.003)	0.029*** (0.002)		0.030*** (0.003)	0.030*** (0.003)		
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector Dummies	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province Dummies	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Firms	9967	9967	9657	11892	11623	9657	9560	9558	9558
Observations	12155	12155	11779	16667	16317	11779	11669	11666	11666

Robust standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions include a constant.

Table 15. ICT and Export Intensity: Random Effects Results for Large Firms

Dependent variable: Export intensity	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ERP	0.008* (0.004)	0.006 (0.004)	0.006 (0.004)			0.005 (0.004)	0.019*** (0.006)	0.002 (0.004)	0.016 (0.013)
ICT Labor Share				0.000*** (0.000)		0.001*** (0.000)	0.001*** (0.000)		
Log Internet-Using Employee					0.005*** (0.002)			0.006*** (0.002)	0.009*** (0.003)
ERP x ICT Labor Share							-0.116*** (0.028)		
ERP x Log Internet-Using Employee									-0.004 (0.003)
Age/10			0.037*** (0.007)	0.036*** (0.007)	0.026*** (0.007)	0.035*** (0.007)	0.034*** (0.007)	0.026*** (0.007)	0.026*** (0.007)
Age-Squared/100			-0.002*** (0.000)	-0.002*** (0.001)	-0.002*** (0.001)	-0.002*** (0.000)	-0.002*** (0.000)	-0.002*** (0.000)	-0.002*** (0.000)
Log Capital per Worker			0.012*** (0.004)	0.010*** (0.003)	0.016*** (0.004)	0.011*** (0.003)	0.010*** (0.003)	0.017*** (0.004)	0.017*** (0.004)
Log Value Added per Worker			-0.022*** (0.005)	-0.019*** (0.005)	-0.019*** (0.005)	-0.024*** (0.005)	-0.023*** (0.005)	-0.023*** (0.006)	-0.023*** (0.006)
Log Return on Assets (ROA)			0.059*** (0.011)	0.037*** (0.012)	0.030** (0.012)	0.060*** (0.011)	0.061*** (0.011)	0.052*** (0.011)	0.052*** (0.011)
Log Employment			-0.039*** (0.009)	-0.030*** (0.009)		-0.033*** (0.008)	-0.026*** (0.008)		
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector Dummies	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province Dummies	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Firms	2666	2666	2631	2769	2768	2631	2631	2631	2631
Observations	10665	10665	10530	15137	15123	10530	10525	10524	10524

Robust standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions include a constant.

PSM Results of the Intensive Margin

Table 16 presents the estimated treatment effects of ERP usage on export intensity for all firms, comparing results across PSM and MDM approaches. Under PSM with kernel matching, the estimated ATT suggests that ERP usage leads to 1.1 percentage point increase in export intensity, but the result is statistically insignificant. Similarly, under PSM with NN (1) matching, ERP usage leads to a 1.0 percentage point increase, which also lacks statistical significance. These findings suggest that PSM-based approaches do not provide strong evidence that ERP usage raises export intensity.

In contrast, MDM-based estimates suggest a stronger impact of ERP usage. Under MDM with kernel matching, ERP usage raises export intensity by 5.3 percentage points, with statistical significance at the 1% level. A similar but smaller effect is observed under MDM with NN (1) matching, where ERP usage increases export intensity by 2.8 percentage points. The ATE estimates follow the same trend, confirming that MDM yields larger and statistically significant treatment effects compared to PSM.

A key factor behind the higher estimates in MDM is the broader bandwidth selection (10.126 in MDM vs. 0.106 in PSM). A larger bandwidth increases the number of control firms included in the matching process, potentially leading to less precise matches. While this may enhance statistical power, it also increases the risk of introducing bias by matching firms that are not truly comparable (see Figures A8 & A9 in the appendix). Additionally, the number of matched treated firms is very similar across methods (10,936 in PSM with kernel matching vs. 10,980 in MDM with kernel Matching), suggesting that differences in estimated effects stem from methodological variations rather than sample composition.

Overall, while PSM does not provide strong evidence that ERP usage increases export intensity, MDM estimates suggest a statistically significant positive effect. However, the stronger effects in MDM should be interpreted with caution, as they may be driven by weaker balancing properties and broader bandwidth selection, rather than solely reflecting the true impact of ERP usage.

Table 16. Treatment Effects of ERP Usage on the Export Intensity (All Firms)

	PSM		MDM	
	Kernel Matching	NN (1)	Kernel Matching	NN (1)
ATE	0.011* (0.007)	0.011 (0.007)	0.055*** (0.005)	0.039*** (0.006)
ATT	0.011 (0.103)	0.010 (0.011)	0.053*** (0.006)	0.028*** (0.016)
N	22309			
Matched				
Yes	10936	11626	10980	11626
No	722	32	678	32
Total	11658	11658	11658	11658
Controls				
Used	10292	3826	9416	4492
Unused	359	6825	1235	6159
Total	10651	10651	10651	10651
Bandwidth	0.106		10.126	

Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 17 and Table 18 present the estimated treatment effects of ERP usage on export intensity separately for SMEs and large firms, comparing results across PSM and MDM approaches. For SMEs, PSM-based estimates do not provide strong evidence that ERP usage increases export intensity. Under PSM with kernel matching, the estimated ATT suggests only a 0.5 percentage point increase, which is statistically insignificant. Similarly, under PSM with NN (1) matching, the effect is close to zero, further indicating that PSM does not detect a meaningful impact of ERP usage on export intensity for SMEs. In contrast, MDM-based estimates yield notably larger and statistically significant effects. Under MDM with kernel matching, ERP usage raises export intensity by 3.4 percentage points, with significance at the 1% level, while under MDM with NN (1) matching, the increase is 1.1 percentage points, though it is not statistically significant.

For large firms, PSM results do not provide evidence that ERP usage increases export intensity, mirroring the findings for SMEs. Under PSM with kernel matching, the ATT estimate indicates a 0.8 percentage point increase, but this effect is statistically insignificant. Similarly, PSM with NN (1) matching yields an ATT of 1.6 percentage points, which also lacks statistical significance, suggesting that ERP

adoption does not have a meaningful impact on export intensity for large firms under this method. MDM estimates produce relatively larger effects, but their significance remains limited despite the broader bandwidth selection. Under MDM with kernel matching, ERP usage increases export intensity by 2.1 percentage points, but this effect is not statistically significant, despite the method's inclusion of a wider range of control observations. Under MDM with NN (1) matching, ERP usage is estimated to increase export intensity by 2.5 percentage points, but this effect is only statistically significant at the 10% level, indicating weak evidence of a positive relationship. These findings suggest that, even under MDM, the estimated effects for large firms are less pronounced compared to SMEs.

Overall, the findings suggest that ERP usage does not have a robust impact on export intensity under PSM, with statistically insignificant effects across all firm sizes. In contrast, MDM-based estimates consistently yield higher and statistically significant effects, particularly for SMEs, where ERP usage appears to play a more substantial role in increasing export intensity. However, the larger effects observed under MDM should be interpreted with caution, as they may be influenced by weaker balancing properties and broader bandwidth selection.

Table 17. Treatment Effects of ERP Usage on the Export Intensity (SMEs)

	PSM		MDM	
	Kernel Matching	NN (1)	Kernel Matching	NN (1)
ATE	0.009 (0.006)	0.008 (0.006)	0.042*** (0.006)	0.039*** (0.007)
ATT	0.005 (0.007)	0.000 (0.008)	0.034*** (0.005)	0.011 (0.007)
N	11779			
Matched				
Yes	3275	3532	3334	3532
No	263	6	204	6
Total	3538	3538	3538	3538
Controls				
Used	7603	2169	7128	2232
Unused	638	6072	1113	6009
Total	8241	8241	8241	8241
Bandwidth	0.067		13.506	

Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 18. Treatment Effects of ERP Usage on the Export Intensity (Large Firms)

	PSM		MDM	
	Kernel Matching	NN (1)	Kernel Matching	NN (1)
ATE	0.006 (0.013)	0.013 (0.013)	0.018 (0.012)	0.024* (0.013)
ATT	0.008 (0.015)	0.016 (0.015)	0.021 (0.013)	0.025* (0.015)
N	10530			
Matched				
Yes	7421	7904	7536	7904
No	699	216	584	216
Total	8120	8120	8120	8120
Controls				
Used	2350	1672	2237	1597
Unused	60	738	173	813
Total	2410	2410	2410	2410
Bandwidth	0.145		15.830	

Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

6. CONCLUSION

This study aims to empirically examine the effects of information and communication technologies (ICT) on the export performance of firms in the Turkish manufacturing sector. To achieve this objective, a panel dataset covering the period 2009–2019 was constructed by merging five different datasets: the Turkish Statistical Institute’s ICT Usage in Enterprises Survey, Foreign Trade Statistics, Company Accounts Statistics, Annual Industry and Service Statistics, and Annual Business Registers Framework.

This study makes several significant contributions to the literature. First, it is among the few studies that analyze the ICT-export relationship at the firm level in the context of a developing country using a comprehensive dataset. Second, unlike previous studies that measure ICT usage through more basic tools, this study investigates the impact of an advanced enterprise software such as ERP. Lastly, it offers a novel perspective to the literature by testing the complementarity between ICT usage and ICT-skilled labor in shaping firms’ export performance.

The random effects panel probit results demonstrate a positive and statistically significant relationship between ERP system usage and the probability of exporting in the full sample. This positive association persists when ICT adoption is measured using ICT-skilled labor instead of ERP usage. When examining complementarity effects, we find evidence of complementarity between ERP and internet-using employees, though this effect is only present at lower levels of digitalization, specifically up to approximately 20 internet-using employees.

Disaggregating the analysis by firm size reveals important heterogeneity in the relationship between ICT adoption and export propensity. The ERP usage is found to have a positive and significant association with the probability of exporting for SMEs, whereas the association disappears for large firms. Additionally, when examining the complementarity between ERP and ICT-skilled labor in these sub-samples, the only significant interaction effect is observed for SMEs when ICT-

skilled labor is measured by ICT labor share, but this effect is limited to cases where ICT labor share does not exceed 30%.

Further differentiation by technological intensity of exports shows that the strongest association between ERP usage and export probability is observed for medium-high technology exports, followed by medium-low technology exports in the full sample. In the SME subsample, the relationship between ERP and high-technology exports is the only one that remains statistically insignificant, while large firms demonstrate significant associations across all technology levels, with the strongest associations observed for medium-low and medium-high technology exports.

To address potential endogeneity concerns arising from selection bias, PSM estimates confirm that ERP usage raises the probability of exporting by 4.8 percentage points under kernel matching, while the effect remains consistent at 5.5 percentage points under NN matching. The similarity in estimates across matching approaches suggests that the results are robust. When PSM is applied separately for SMEs and large firms, ERP usage is again found to increase the probability of exporting in both groups.

Regarding the intensive margin, random effects panel estimations reveal a positive and statistically significant relationship between ERP usage and export intensity in the full sample. Complementarity analysis shows that ERP and internet-using employees exhibit complementarity, but only up to approximately 20 internet-using employees. Size-disaggregated analyses indicate that while ERP maintains a positive and significant association with export intensity for SMEs, this relationship becomes insignificant for large firms. Moreover, no complementarity effects are detected in either size group when analyzed separately. Finally, PSM estimates suggest that there is no causal relationship between ERP and export intensity in either the full sample or the size-disaggregated subsamples, contrasting with our findings on the extensive margin.

This study has several limitations. First, the presence of gaps in the dataset for ERP usage, which is the primary variable of interest, restricts the application of certain econometric methods. Additionally, these data limitations prevent the estimation of a dynamic model, which would have been particularly relevant given the importance of sunk costs in export decisions. Furthermore, although this study proxies ICT

adoption using ERP as an advanced enterprise software, a more comprehensive measurement, such as an index incorporating multiple ICT indicators, could provide a more robust assessment of firms' digital adoption and its impact on export performance.

Policy Implications

The findings of this study emphasize the important role of ERP adoption and digital workforce integration in facilitating firms' export participation, particularly for SMEs. However, the lack of a robust impact on export intensity and the heterogeneous effects across firm sizes suggest that targeted policies are needed to maximize the benefits of digital adoption for firms' internationalization strategies. First, given that ERP usage significantly increases the probability of exporting, especially for SMEs, policymakers should promote the adoption of enterprise systems such as ERP through financial incentives, tax credits, or subsidies, particularly for smaller firms that face resource constraints in implementing such advanced digital tools. Additionally, awareness campaigns and training programs tailored for SMEs could help firms better understand the potential benefits of ERP systems in managing international operations and supply chains.

Second, the complementarity between ERP and internet-using employees suggests that the effectiveness of digital transformation is enhanced when firms invest in both technological infrastructure and human capital. Therefore, policies should not only focus on promoting ICT adoption but also on developing digital competencies among employees. Public-private partnerships to provide ICT training programs, digital upskilling initiatives, and vocational education could strengthen firms' ability to leverage enterprise systems effectively.

Third, firm-size heterogeneity in the impact of ICT adoption suggests that a one-size-fits-all digitalization policy may not be effective. While SMEs benefit more from ERP adoption in terms of export participation, large firms already engaged in international trade may require more specialized digital solutions beyond ERP, such as artificial intelligence, cloud computing, and robotics. Policymakers should therefore consider sector-specific and firm-size-specific digitalization strategies, ensuring that digital policies align with firms' technological needs and market conditions.

Finally, given the absence of a causal relationship between ERP usage and export intensity, policymakers should be cautious in assuming that ICT adoption alone is sufficient to sustain export growth. Instead, complementary policies increasing access to financing for export-oriented firms and facilitating integration into global value chains should be implemented alongside digital adoption initiatives.

Future research could enhance the causal identification of ERP usage on export performance by applying staggered adoption difference-in-differences approaches, which account for firms adopting ERP at different points in time and provide a more robust estimation. Additionally, incorporating a broader set of digitalization indicators beyond ERP would allow for a more comprehensive analysis of how different forms of technological adoption influence export performance.

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APPENDIX

Table A1. The Descriptions and Sources of the Variables

	Variable	Description	Source
<i>XD</i>	Export decision	Exporter = 1, otherwise = 0	FTS
<i>XI</i>	Export intensity	Ratio of total export to total sales	FTS & AISS
<i>ERP</i>	Enterprise resource planning	Users = 1, non-users = 0	ICTS
	ICT labor share	Ratio of total internet-using employee to total employment	ICTS & AISS
	Internet-using employee	Total number of internet-using employee	ICTS
<i>Y/L</i>	Labor productivity	Value-added (at factor costs) per worker	AISS
<i>K/L</i>	Capital intensity	Capital stock (tangible fixed assets) per worker	CAS & AISS
	Age	Firm age in years	BR
<i>ROA</i>	Return on Assets	Ratio of net profit/loss to total assets	CAS
	Employment	Total employment of a firm	AISS
	Province dummy	The location of a firm at NUTS-3 level	BR
	Sector dummy	2-digit NACE rev. 2 industry code	AISS

ICTS: ICT Usage in Enterprises Survey, **FTS:** Foreign Trade Statistics, **AISS:** Annual Industry and Service Statistics, **CAS:** Company Accounts Statistics, **BR:** Annual Business Registers Framework

Table A2. ICT and Export Market Participation: Pooled Probit Results (Marginal Effects) for All Firms

Dependent variable: Export decision	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ERP	0.285*** (0.008)	0.245*** (0.008)	0.040*** (0.009)			0.033*** (0.009)	0.044*** (0.011)	0.032*** (0.009)	0.101*** (0.020)
ICT Labor Share				0.001*** (0.000)		0.001*** (0.000)	0.001*** (0.000)		
Log Internet-Using Employee					0.098*** (0.003)			0.091*** (0.004)	0.103*** (0.005)
ERP x ICT Labor Share							-0.067** (0.033)		
ERP x Log Internet-Using Employee									-0.024*** (0.007)
Age/10			0.048*** (0.008)	0.049*** (0.007)	0.059*** (0.007)	0.048*** (0.008)	0.048*** (0.008)	0.058*** (0.008)	0.058*** (0.008)
Age-Squared/100			-0.002** (0.001)	-0.001** (0.001)	-0.002*** (0.001)	-0.002** (0.001)	-0.002** (0.001)	-0.002** (0.001)	-0.002** (0.001)
Log Capital per Worker			0.030*** (0.004)	0.031*** (0.003)	0.021*** (0.003)	0.029*** (0.004)	0.028*** (0.004)	0.023*** (0.004)	0.022*** (0.004)
Log Value Added per Worker			0.088*** (0.008)	0.086*** (0.007)	0.071*** (0.006)	0.083*** (0.008)	0.081*** (0.008)	0.070*** (0.008)	0.071*** (0.008)
Return on Assets (ROA)			-0.000* (0.000)	-0.000* (0.000)	-0.000** (0.000)	-0.000* (0.000)	-0.000* (0.000)	-0.000** (0.000)	-0.000** (0.000)
Log Employment			0.095*** (0.004)	0.106*** (0.004)		0.100*** (0.004)	0.101*** (0.004)		
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector Dummies	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province Dummies	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Firms	12036	11987	11670	13867	13605	11670	11576	11574	11574
Observations	22820	22742	22237	31710	31352	22237	22125	22121	22121
Log Likelihood	-13413.354	-12683.575	-10821.364	-15413.860	-15294.622	-10808.969	-10746.446	-10808.194	-10797.594

Robust standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions include a constant.

Table A3. ICT and Export Market Participation: Pooled Probit Results (Marginal Effects) for SMEs

Dependent variable: Export decision	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ERP	0.216*** (0.010)	0.174*** (0.010)	0.047*** (0.012)			0.037*** (0.012)	0.066*** (0.016)	0.025** (0.012)	0.059* (0.030)
ICT Labor Share				0.001*** (0.000)		0.001*** (0.000)	0.002*** (0.000)		
Log Internet-Using Employee					0.131*** (0.005)			0.123*** (0.006)	0.127*** (0.007)
ERP x ICT Labor Share							-0.135*** (0.043)		
ERP x Log Internet-Using Employee									-0.014 (0.012)
Age/10			0.064*** (0.019)	0.069*** (0.018)	0.085*** (0.018)	0.066*** (0.019)	0.067*** (0.019)	0.083*** (0.020)	0.083*** (0.020)
Age-Squared/100			-0.011** (0.006)	-0.012** (0.005)	-0.015*** (0.005)	-0.012** (0.006)	-0.012** (0.006)	-0.015*** (0.006)	-0.015** (0.006)
Log Capital per Worker			0.032*** (0.004)	0.035*** (0.004)	0.024*** (0.004)	0.032*** (0.004)	0.030*** (0.004)	0.025*** (0.004)	0.025*** (0.004)
Log Value Added per Worker			0.109*** (0.012)	0.107*** (0.009)	0.089*** (0.009)	0.102*** (0.012)	0.099*** (0.012)	0.087*** (0.011)	0.088*** (0.011)
Return on Assets (ROA)			-0.000* (0.000)	-0.000 (0.000)	-0.000** (0.000)	-0.000* (0.000)	-0.000* (0.000)	-0.000** (0.000)	-0.000** (0.000)
Log Employment			0.129*** (0.007)	0.145*** (0.006)		0.139*** (0.007)	0.143*** (0.007)		
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector Dummies	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province Dummies	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Firms	9967	9928	9621	11846	11582	9621	9527	9525	9525
Observations	12155	12115	11742	16619	16275	11742	11635	11632	11632
Log Likelihood	-8161.360	-7623.586	-6712.699	-9462.065	-9274.275	-6698.286	-6632.200	-6641.858	-6641.009

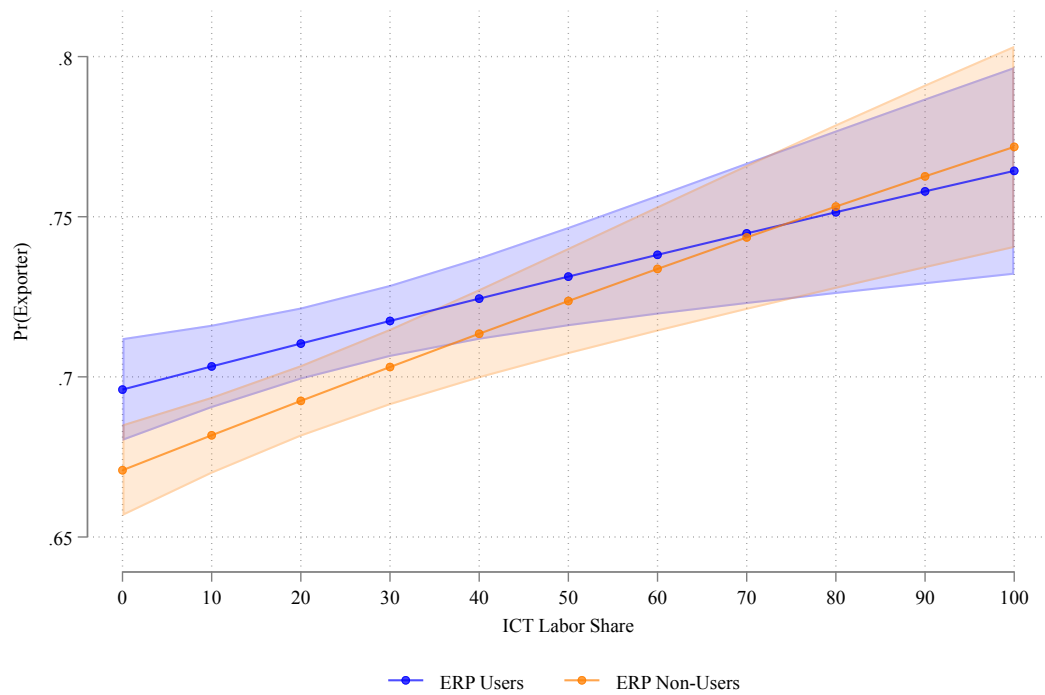
Robust standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions include a constant.

Table A4. ICT and Export Market Participation: Pooled Probit Results (Marginal Effects) for Large Firms

Dependent variable: Export decision	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ERP	0.142*** (0.014)	0.097*** (0.013)	0.032*** (0.011)			0.030*** (0.011)	0.019 (0.013)	0.027** (0.011)	0.009 (0.035)
ICT Labor Share				0.000 (0.000)		0.000 (0.000)	-0.000 (0.000)		
Log Internet-Using Employee					0.039*** (0.005)			0.034*** (0.005)	0.030*** (0.008)
ERP x ICT Labor Share							0.097* (0.050)		
ERP x Log Internet-Using Employee									0.005 (0.009)
Age/10			0.051*** (0.010)	0.051*** (0.009)	0.054*** (0.009)	0.051*** (0.010)	0.051*** (0.010)	0.054*** (0.010)	0.054*** (0.010)
Age-Squared/100			-0.002*** (0.001)	-0.002*** (0.001)	-0.002*** (0.001)	-0.002*** (0.001)	-0.002*** (0.001)	-0.002*** (0.001)	-0.002*** (0.001)
Log Capital per Worker			0.024*** (0.005)	0.024*** (0.005)	0.018*** (0.005)	0.024*** (0.005)	0.025*** (0.005)	0.019*** (0.005)	0.019*** (0.005)
Log Value Added per Worker			0.051*** (0.009)	0.049*** (0.008)	0.039*** (0.009)	0.049*** (0.009)	0.049*** (0.009)	0.040*** (0.010)	0.040*** (0.010)
Return on Assets (ROA)			-0.019 (0.036)	-0.014 (0.024)	0.014 (0.027)	-0.016 (0.035)	-0.018 (0.035)	0.012 (0.033)	0.012 (0.033)
Log Employment			0.060*** (0.008)	0.067*** (0.008)		0.061*** (0.008)	0.058*** (0.009)		
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector Dummies	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province Dummies	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Firms	2666	2635	2601	2748	2747	2601	2601	2601	2601
Observations	10665	10563	10431	15034	15020	10431	10426	10425	10425
Log Likelihood	-4714.816	-4299.378	-3900.381	-5671.256	-5690.534	-3899.858	-3896.499	-3919.355	-3919.139

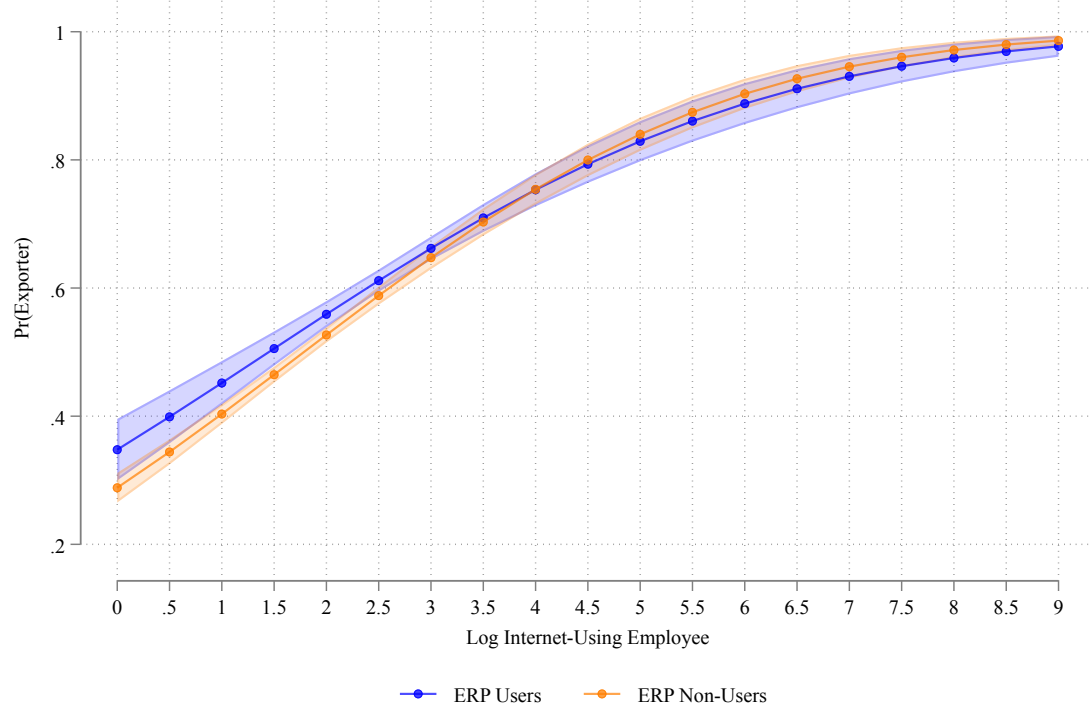
Robust standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions include a constant.

Figure A1. All Firms' Probability of Exporting for ERP Users and Non-Users by ICT Labor Share



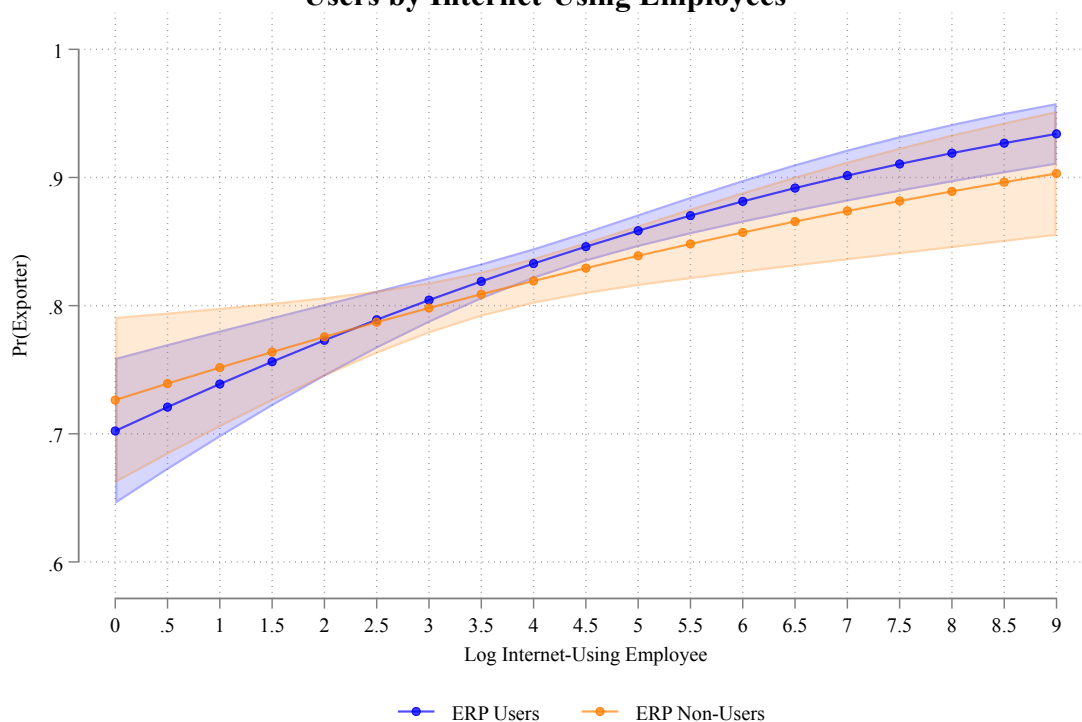
Note: The confidence intervals are at the 95% level.

Figure A2. SMEs' Probability of Exporting for ERP Users and Non-Users by Internet-Using Employees



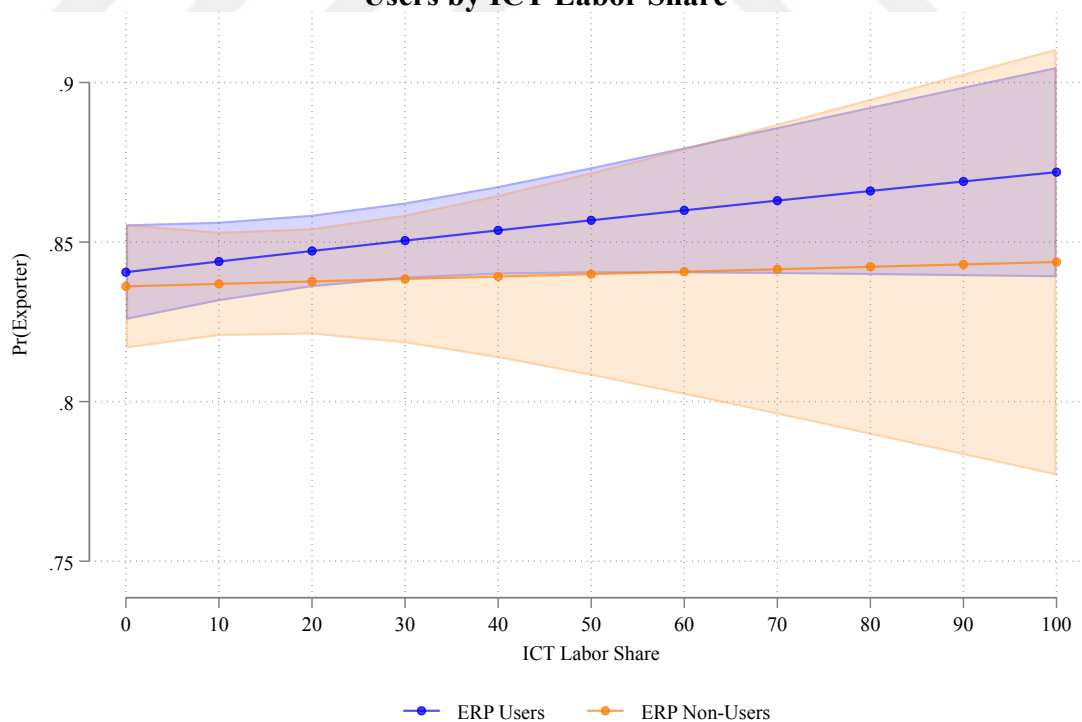
Note: The confidence intervals are at the 95% level.

Figure A3. Large Firms' Probability of Exporting for ERP Users and Non-Users by Internet-Using Employees



Note: The confidence intervals are at the 95% level.

Figure A4. Large Firms' Probability of Exporting for ERP Users and Non-Users by ICT Labor Share



Note: The confidence intervals are at the 95% level.

**Table A5. ICT and Export Market Participation Based on Technological Classification:
Random Effects Panel Probit Results (Marginal Effects) for SMEs**

Dependent variable: Export Status Based on Technology	High			Medium High			Medium Low			Low		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
ERP	0.005 (0.006)			0.044*** (0.010)			0.039*** (0.010)			0.022** (0.010)		
ICT Labor Share		0.001*** (0.000)			0.001*** (0.000)			0.001*** (0.000)			0.001*** (0.000)	
Log Internet-Using Employee			0.041*** (0.003)			0.087*** (0.004)			0.096*** (0.004)			0.088*** (0.004)
Age/10	0.013 (0.011)	0.019* (0.010)	0.018* (0.010)	0.042** (0.017)	0.052*** (0.016)	0.059*** (0.016)	0.044*** (0.017)	0.048*** (0.016)	0.059*** (0.016)	0.028* (0.016)	0.033** (0.013)	0.045*** (0.014)
Age-Squared/100	0.000 (0.003)	-0.002 (0.003)	-0.001 (0.003)	-0.010** (0.005)	-0.012*** (0.005)	-0.013*** (0.005)	-0.011** (0.005)	-0.011** (0.004)	-0.012*** (0.005)	-0.005 (0.004)	-0.007* (0.004)	-0.009** (0.004)
Log Capital per Worker	0.005** (0.002)	0.005*** (0.002)	0.003 (0.002)	0.022*** (0.004)	0.022*** (0.003)	0.017*** (0.003)	0.020*** (0.004)	0.022*** (0.003)	0.015*** (0.003)	0.020*** (0.004)	0.020*** (0.003)	0.014*** (0.003)
Log Value Added per Worker	0.034*** (0.005)	0.028*** (0.004)	0.023*** (0.004)	0.072*** (0.010)	0.070*** (0.008)	0.059*** (0.007)	0.059*** (0.009)	0.057*** (0.007)	0.043*** (0.007)	0.051*** (0.009)	0.048*** (0.007)	0.033*** (0.006)
Return on Assets (ROA)	-0.001** (0.000)	-0.001 (0.000)	-0.000 (0.000)	-0.000 (0.001)	-0.000* (0.000)	-0.000*** (0.000)	-0.000** (0.000)	-0.000** (0.000)	-0.000*** (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Log Employment	0.036*** (0.004)	0.042*** (0.003)		0.076*** (0.005)	0.093*** (0.005)		0.100*** (0.006)	0.110*** (0.005)		0.096*** (0.005)	0.104*** (0.005)	
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Firms	8834	10962	10737	9556	11753	11495	9550	11748	11491	9573	11837	11573
Observations	10862	15535	15237	11675	16508	16170	11664	16495	16159	11693	16610	16266
Log Likelihood	-2551.043	-3651.875	-3591.987	-5337.176	-7508.766	-7403.544	-5753.900	-8118.472	-8040.934	-5687.014	-7951.908	-7845.143

Robust standard errors are in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01. All regressions include a constant.

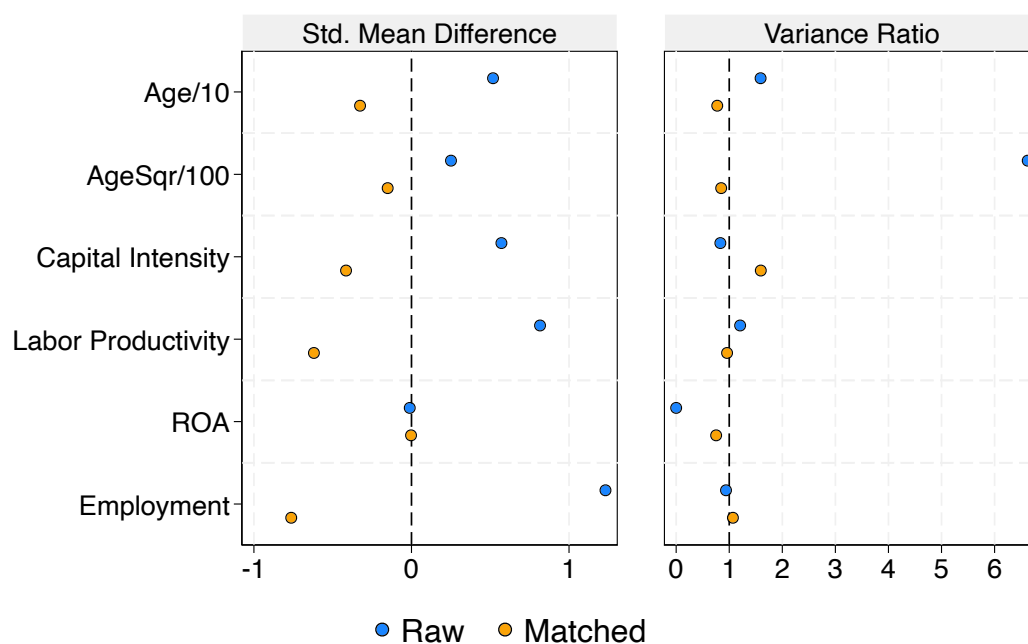
**Table A6. ICT and Export Market Participation Based on Technological Classification:
Random Effects Panel Probit Results (Marginal Effects) for Large Firms**

Dependent variable: Export Status Based on Technology	High			Medium High			Medium Low			Low		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
ERP	0.056*** (0.013)			0.085*** (0.015)			0.097*** (0.016)			0.026* (0.015)		
ICT Labor Share		0.003*** (0.000)			0.002*** (0.000)			0.002*** (0.000)			0.001*** (0.000)	
Log Internet-Using Employee			0.107*** (0.006)			0.104*** (0.007)			0.095*** (0.007)			0.067*** (0.007)
Age/10	0.039** (0.017)	0.043** (0.018)	0.048*** (0.018)	0.038*** (0.013)	0.035*** (0.012)	0.046*** (0.012)	0.031** (0.013)	0.026** (0.012)	0.032*** (0.012)	0.022* (0.013)	0.023* (0.012)	0.029** (0.012)
Age-Squared/100	-0.007** (0.003)	-0.009** (0.004)	-0.009** (0.004)	-0.002 (0.002)	-0.002 (0.001)	-0.002** (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.000 (0.001)	-0.000 (0.001)	-0.000 (0.001)
Log Capital per Worker	0.003 (0.006)	0.003 (0.006)	-0.005 (0.005)	0.023*** (0.007)	0.021*** (0.007)	0.009 (0.006)	0.003 (0.007)	0.004 (0.007)	-0.005 (0.007)	0.019*** (0.007)	0.017*** (0.006)	0.010 (0.006)
Log Value Added per Worker	0.112*** (0.011)	0.090*** (0.010)	0.076*** (0.009)	0.113*** (0.012)	0.105*** (0.011)	0.089*** (0.011)	0.099*** (0.012)	0.078*** (0.011)	0.065*** (0.011)	0.050*** (0.012)	0.037*** (0.011)	0.024** (0.011)
Return on Assets (ROA)	-0.111** (0.044)	-0.071*** (0.027)	-0.033 (0.032)	-0.056 (0.047)	-0.062* (0.034)	-0.010 (0.037)	-0.047 (0.054)	-0.002 (0.036)	0.040 (0.040)	-0.042 (0.056)	-0.016 (0.039)	0.023 (0.041)
Log Employment	0.126*** (0.009)	0.144*** (0.009)		0.149*** (0.010)	0.172*** (0.011)		0.096*** (0.011)	0.123*** (0.011)		0.099*** (0.011)	0.110*** (0.011)	
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Firms	2554	2692	2691	2608	2743	2742	2612	2748	2747	2600	2744	2743
Observations	10296	14836	14822	10494	15083	15069	10492	15098	15084	10430	15031	15017
Log Likelihood	-4139.668	-5866.815	-5900.963	-5185.375	-7480.611	-7575.410	-5359.717	-7755.272	-7721.594	-5923.287	-8521.894	-8559.574

Robust standard errors are in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01. All regressions include a constant.

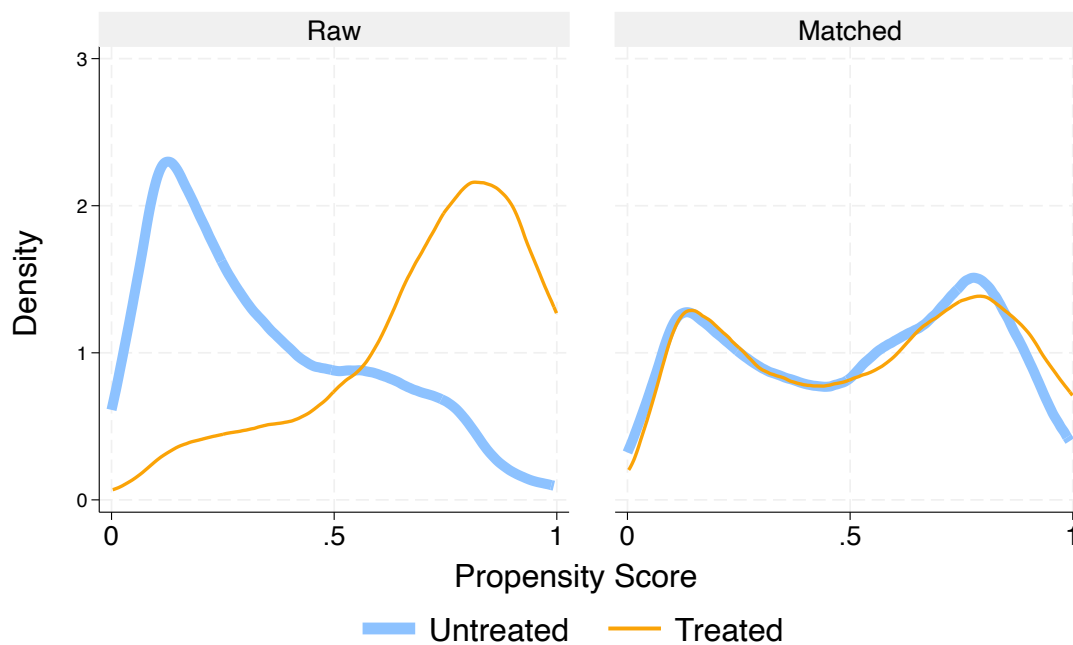
DIAGNOSTICS FOR PSM AND MDM (ALL FIRMS)

Figure A5. Covariate Balancing Before and After Matching (PSM, NN (1) Matching, All Firms)



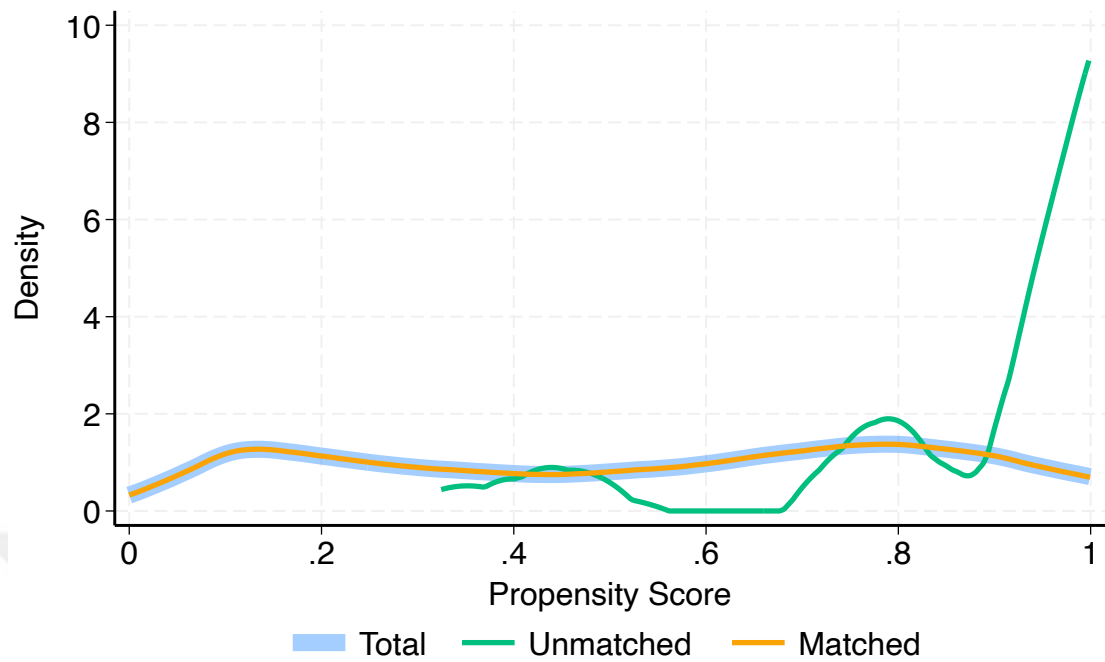
Source: Author's own calculations.

Figure A6. Density Plot of Propensity Score Before and After Matching (PSM, NN (1) Matching, All Firms)



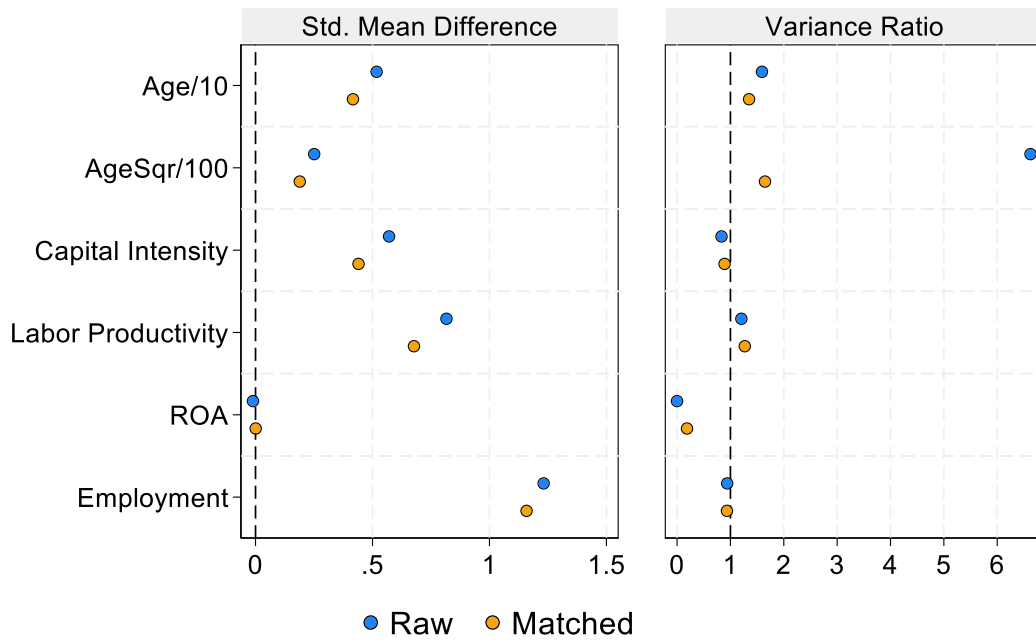
Source: Author's own calculations.

Figure A7. Kernel Density Plot of Propensity Score for the Total, Unmatched and Matched Samples (PSM, NN (1) Matching, All Firms)



Source: Author's own calculations.

Figure A8. Covariate Balancing Before and After Matching (MDM, Kernel Matching, All Firms)



Source: Author's own calculations.

Table A7. Common Support Diagnostics (MDM, Kernel Matching, All firms)

Means	Common Support			Standardized Difference		
	Matched	Unmatched	Total	(1)-(3)	(2)-(3)	(1)-(2)
Age/10	1.707	1.781	1.711	-0.004	0.072	-0.076
AgeSqr/100	3.750	5.740	3.859	-0.013	0.227	-0.240
Log K/L	10.564	10.689	10.571	-0.005	0.079	-0.084
Log Y/L	10.450	10.224	10.438	0.015	-0.259	0.274
ROA	0.029	1.950	0.134	-0.007	0.115	-0.121
Log Employment	4.960	4.827	4.953	0.005	-0.086	0.090

Variances	Common Support			Variance Ratio		
	Matched	Unmatched	Total	(1)/(3)	(2)/(3)	(1)/(2)
Age/10	0.836	2.572	0.931	0.898	2.761	0.325
AgeSqr/100	22.117	873.237	68.791	0.322	12.694	0.025
Log K/L	2.161	2.808	2.197	0.984	1.278	0.770
Log Y/L	0.652	1.093	0.678	0.961	1.612	0.596
ROA	2.982	4543.856	251.101	0.012	18.096	0.001
Log Employment	2.179	2.353	2.189	0.995	1.075	0.926

(1) Matched, (2) Unmatched, (3) Total.

K/L: Capital Intensity, Y/L: Value Added per Worker, ROA: Return on Assets

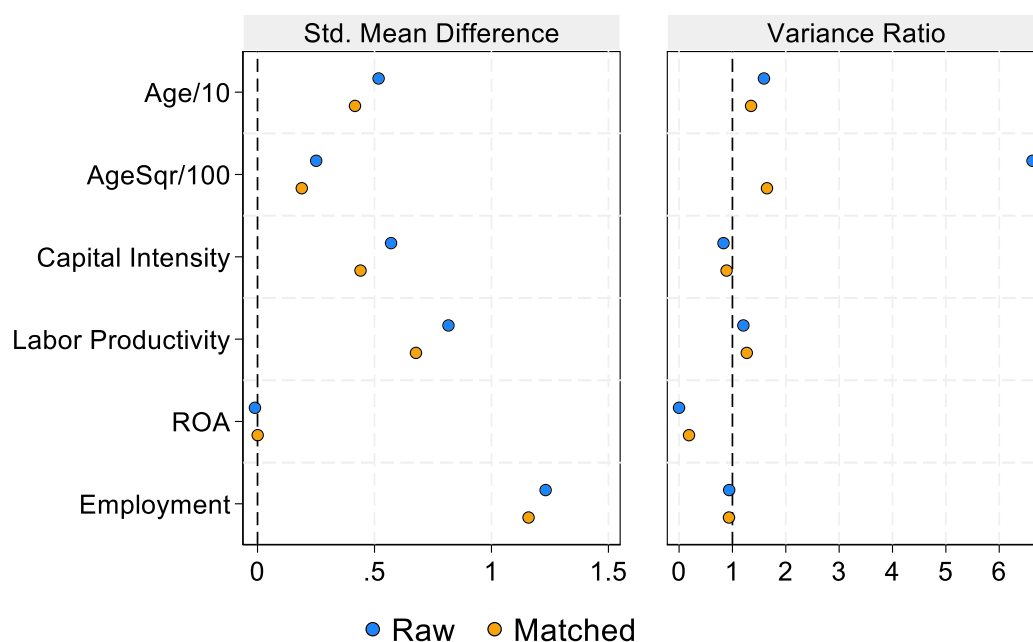
Figure A9. Covariate Balancing Before and After Matching (MDM, NN (1) Matching, All Firms)*Source: Author's own calculations.*

Table A8. Common Support Diagnostics (MDM, NN (1) Matching, All firms)

Means	Common Support			Standardized Difference		
	Matched	Unmatched	Total	(1)-(3)	(2)-(3)	(1)-(2)
Age/10	1.711	1.703	1.711	0.000	-0.008	0.008
AgeSqr/100	3.858	4.222	3.859	0.000	0.044	-0.044
Log K/L	10.568	12.857	10.571	-0.002	1.542	-1.544
Log Y/L	10.435	12.015	10.438	-0.003	1.915	-1.918
ROA	0.134	0.065	0.134	0.000	-0.004	0.004
Log Employment	4.952	6.039	4.953	-0.001	0.734	-0.735

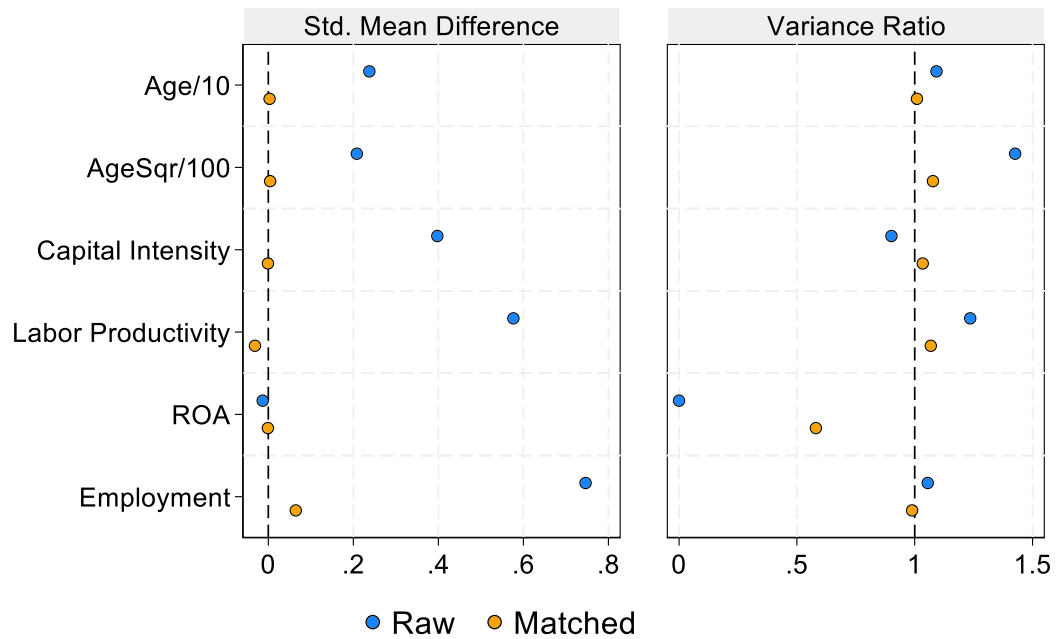
Variances	Common Support			Variance Ratio		
	Matched	Unmatched	Total	(1)/(3)	(2)/(3)	(1)/(2)
Age/10	0.931	1.363	0.931	0.999	1.463	0.683
AgeSqr/100	68.824	48.281	68.791	1.000	0.702	1.425
Log K/L	2.190	1.618	2.197	0.997	0.737	1.353
Log Y/L	0.674	1.324	0.678	0.993	1.952	0.509
ROA	251.473	0.010	251.101	1.001	0.000	25678.990
Log Employment	2.188	1.629	2.189	1.000	0.744	1.343

(2) Matched, (2) Unmatched, (3) Total.

K/L: Capital Intensity, Y/L: Value Added per Worker, ROA: Return on Assets

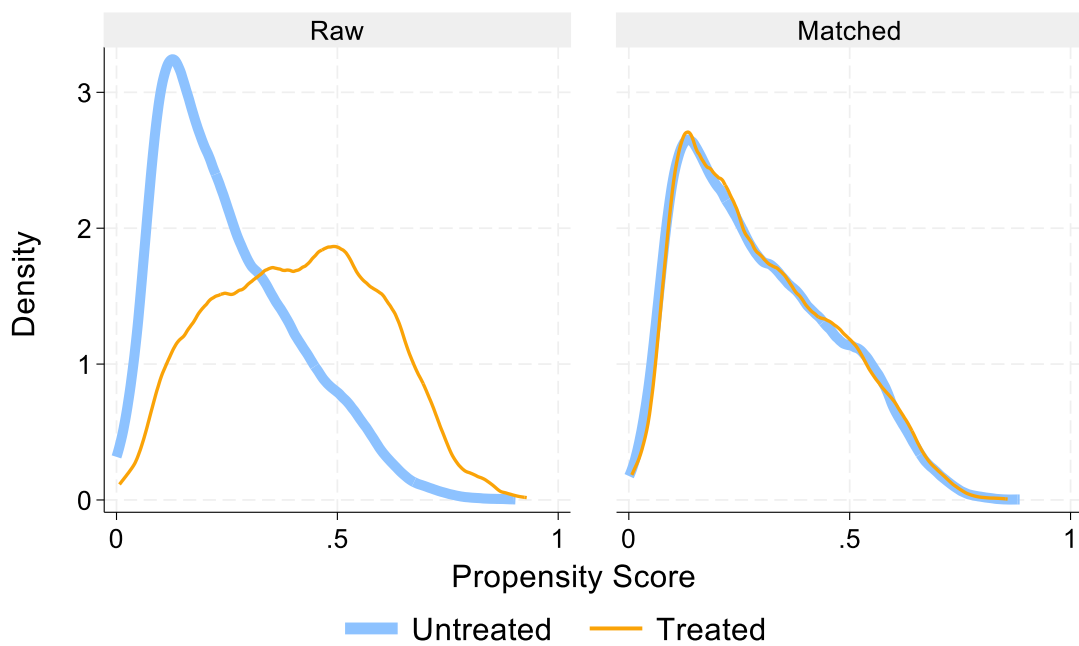
DIAGNOSTICS FOR PSM AND MDM (SMES)

Figure A10. Covariate Balancing Before and After Matching (PSM, Kernel Matching, SMEs)



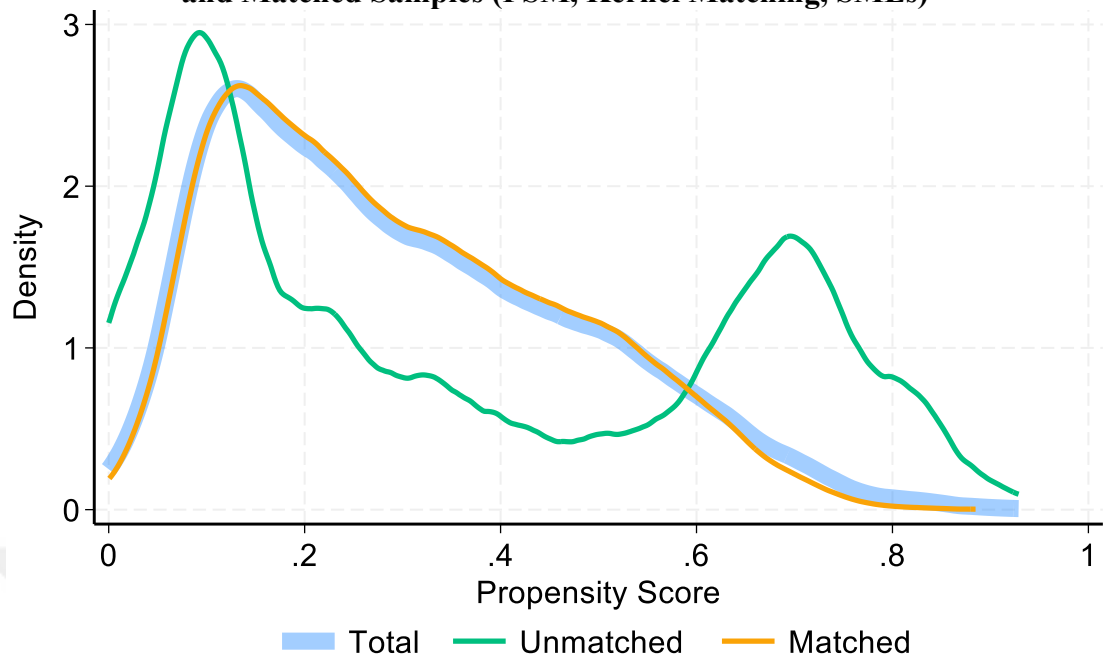
Source: Author's own calculations.

Figure A11. Density Plot of Propensity Score Before and After Matching (PSM, Kernel Matching, SMEs)



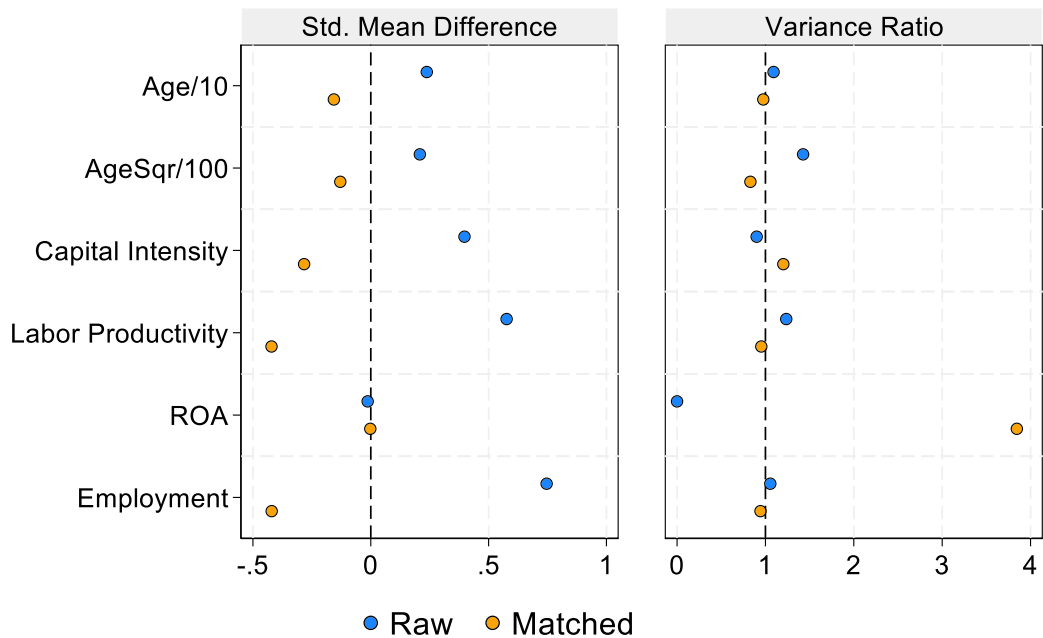
Source: Author's own calculations.

Figure A12. Kernel Density Plot of Propensity Score for the Total, Unmatched and Matched Samples (PSM, Kernel Matching, SMEs)



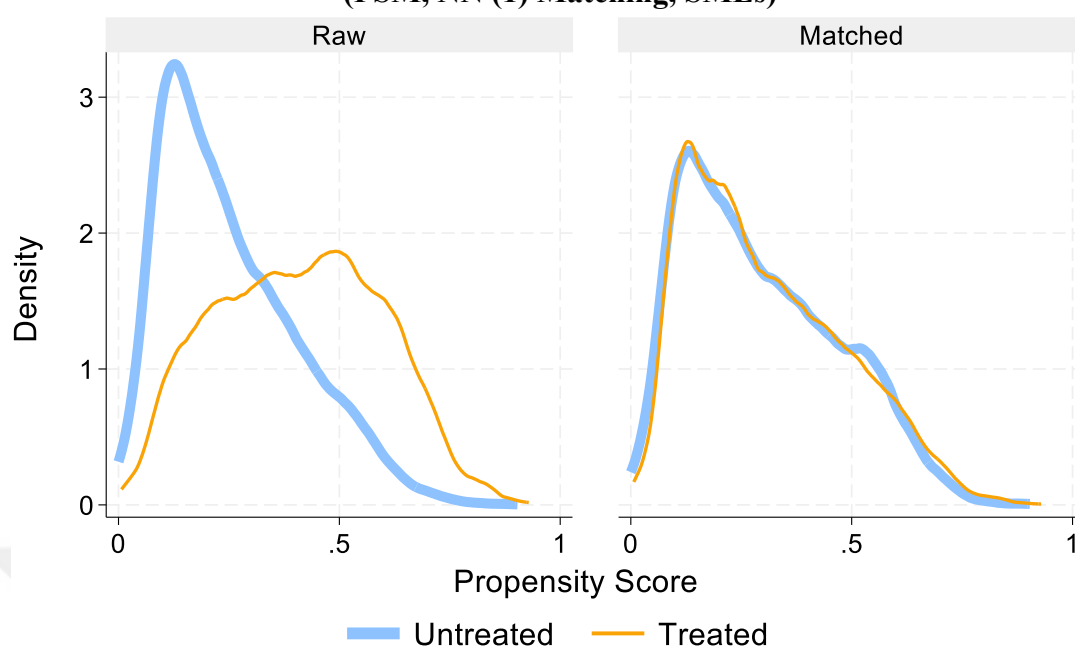
Source: Author's own calculations.

Figure A13. Covariate Balancing Before and After Matching (PSM, NN (1) Matching, SMEs)



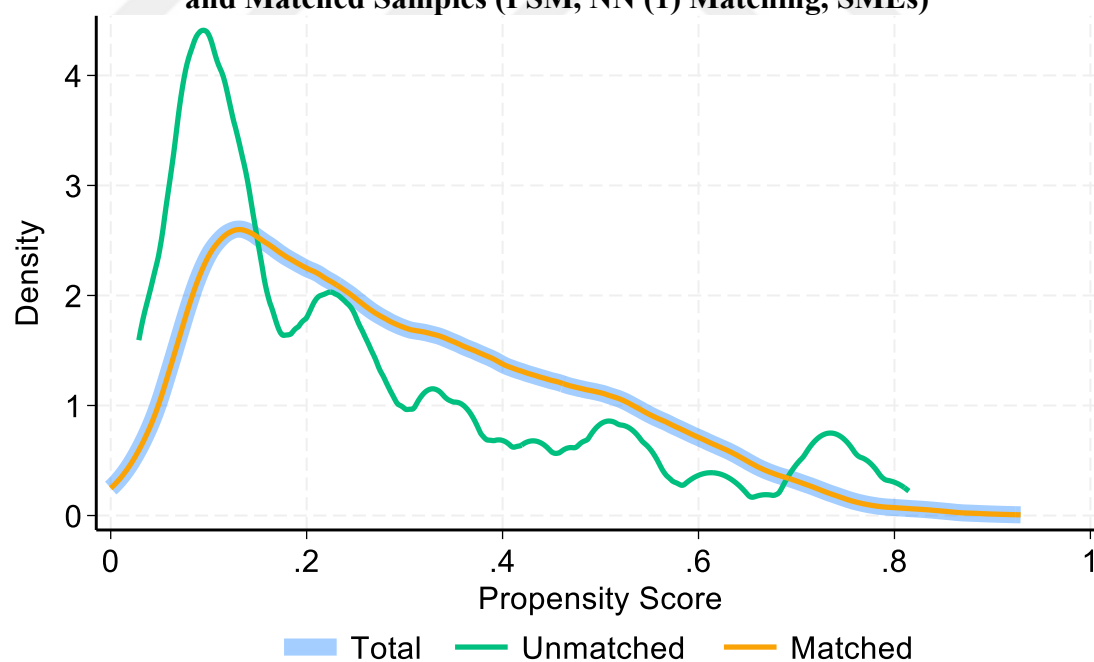
Source: Author's own calculations.

Figure A14. Density Plot of Propensity Score Before and After Matching (PSM, NN (1) Matching, SMEs)



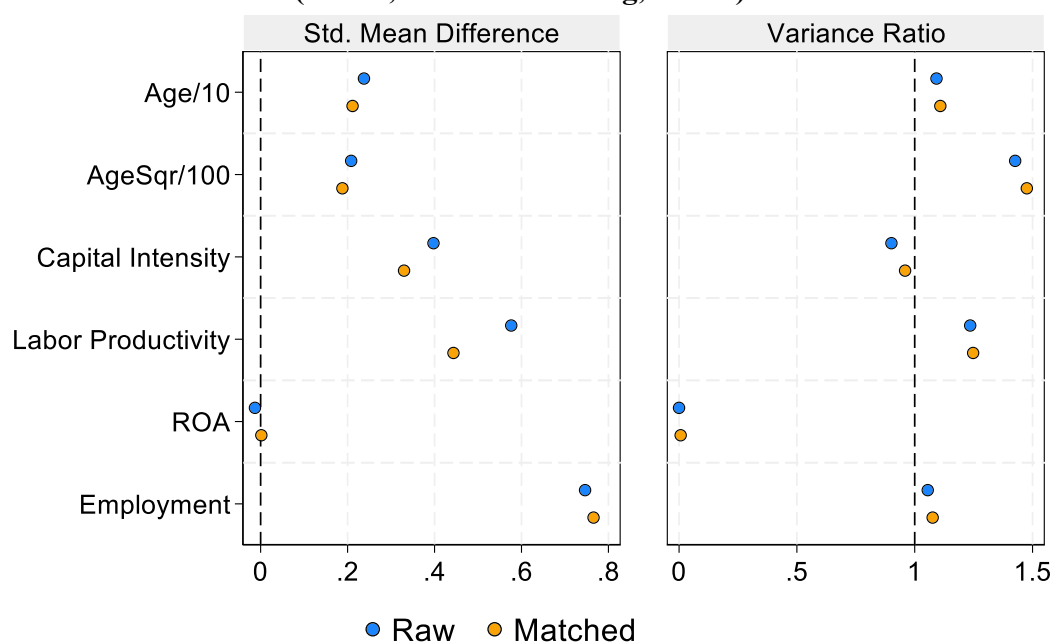
Source: Author's own calculations.

Figure A15. Kernel Density Plot of Propensity Score for the Total, Unmatched and Matched Samples (PSM, NN (1) Matching, SMEs)



Source: Author's own calculations.

Figure A16. Covariate Balancing Before and After Matching (MDM, Kernel Matching, SMEs)



Source: Author's own calculations.

Table A9. Common Support Diagnostics (MDM, Kernel Matching, SMEs)

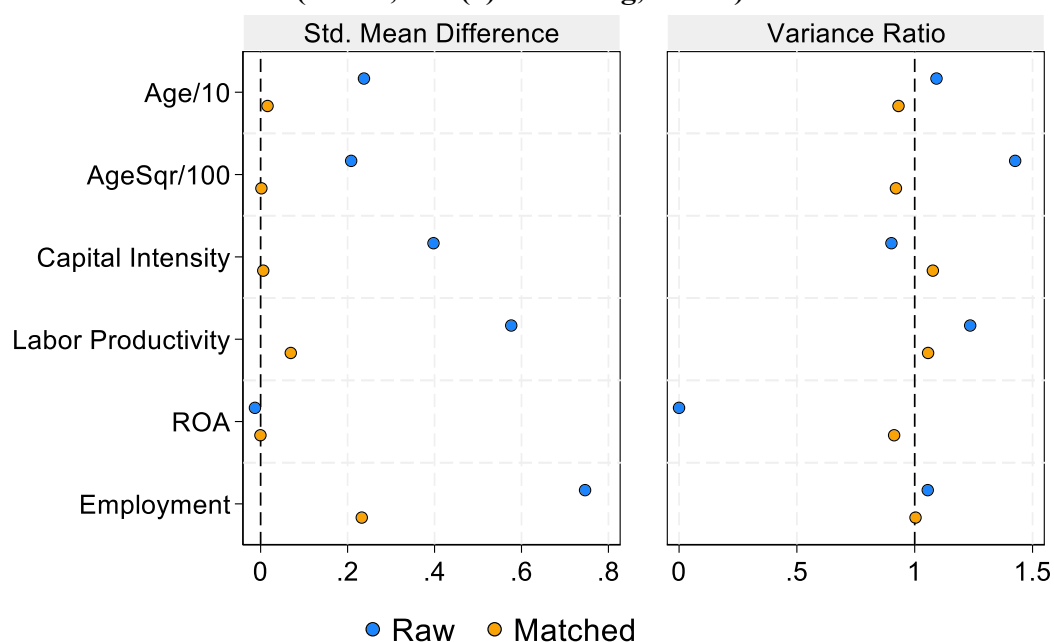
Means	Common Support			Standardized Difference		
	Matched	Unmatched	Total	(1)-(3)	(2)-(3)	(1)-(2)
Age/10	1.391	1.451	1.394	-0.003	0.076	-0.079
AgeSqr/100	2.483	3.024	2.505	-0.008	0.199	-0.207
Log K/L	10.201	10.466	10.211	-0.007	0.171	-0.178
Log Y/L	10.204	10.032	10.197	0.009	-0.213	0.222
ROA	0.011	5.082	0.211	-0.009	0.223	-0.233
Log Employment	3.786	3.816	3.787	-0.001	0.032	-0.034

Variances	Common Support			Variance Ratio		
	Matched	Unmatched	Total	(1)/(3)	(2)/(3)	(1)/(2)
Age/10	0.547	0.920	0.562	0.974	1.638	0.594
AgeSqr/100	6.184	21.691	6.807	0.909	3.187	0.285
Log K/L	2.203	2.933	2.234	0.986	1.313	0.751
Log Y/L	0.594	0.686	0.599	0.992	1.146	0.866
ROA	5.547	11885.710	475.557	0.012	24.993	0.000
Log Employment	0.788	0.813	0.789	0.999	1.031	0.968

(3) Matched, (2) Unmatched, (3) Total.

K/L: Capital Intensity, Y/L: Value Added per Worker, ROA: Return on Assets

Figure A17. Covariate Balancing Before and After Matching (MDM, NN (1) Matching, SMEs)



Source: Author's own calculations.

Table A10. Common Support Diagnostics (MDM, NN (1) Matching, SMEs)

Means	Common Support			Standardized Difference		
	Matched	Unmatched	Total	(1)-(3)	(2)-(3)	(1)-(2)
Age/10	1.395	1.258	1.394	0.001	-0.181	0.182
AgeSqr/100	2.506	2.300	2.505	0.000	-0.078	0.079
Log K/L	10.215	9.442	10.211	0.003	-0.514	0.517
Log Y/L	10.198	10.041	10.197	0.001	-0.201	0.202
ROA	0.212	0.080	0.211	0.000	-0.006	0.006
Log Employment	3.788	3.637	3.787	0.001	-0.169	0.170

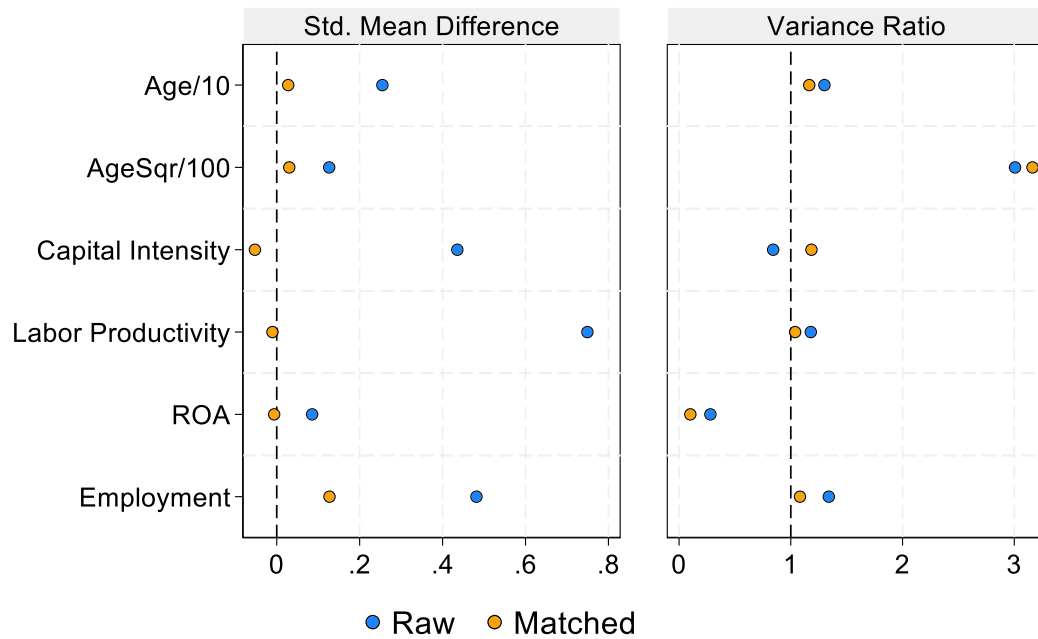
Variances	Common Support			Variance Ratio		
	Matched	Unmatched	Total	(1)/(3)	(2)/(3)	(1)/(2)
Age/10	0.561	0.727	0.562	0.998	1.295	0.771
AgeSqr/100	6.762	15.096	6.807	0.993	2.218	0.448
Log K/L	2.224	3.636	2.234	0.995	1.627	0.612
Log Y/L	0.597	0.949	0.599	0.997	1.585	0.629
ROA	478	0.025	475	1.006	0.000	18891
Log Employment	0.789	0.705	0.789	1.001	0.894	1.119

(4) Matched, (2) Unmatched, (3) Total.

K/L: Capital Intensity, Y/L: Value Added per Worker, ROA: Return on Assets

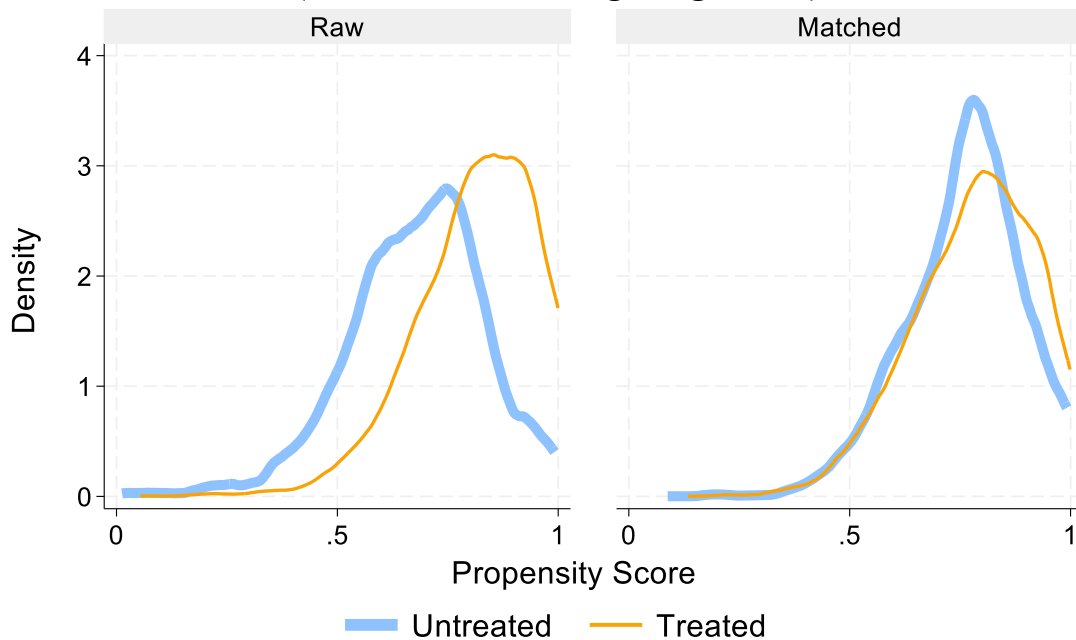
DIAGNOSTICS FOR PSM AND MDM (LARGE FIRMS)

Figure A18. Covariate Balancing Before and After Matching (PSM, Kernel Matching, Large Firms)



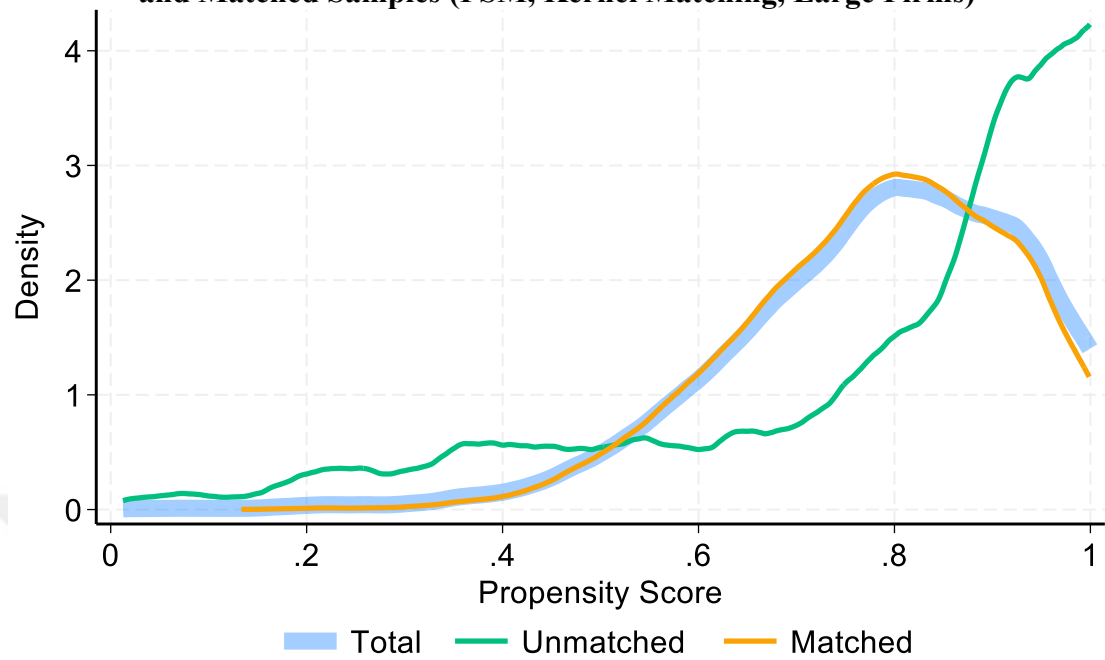
Source: Author's own calculations.

Figure A19. Density Plot of Propensity Score Before and After Matching (PSM, Kernel Matching, Large Firms)



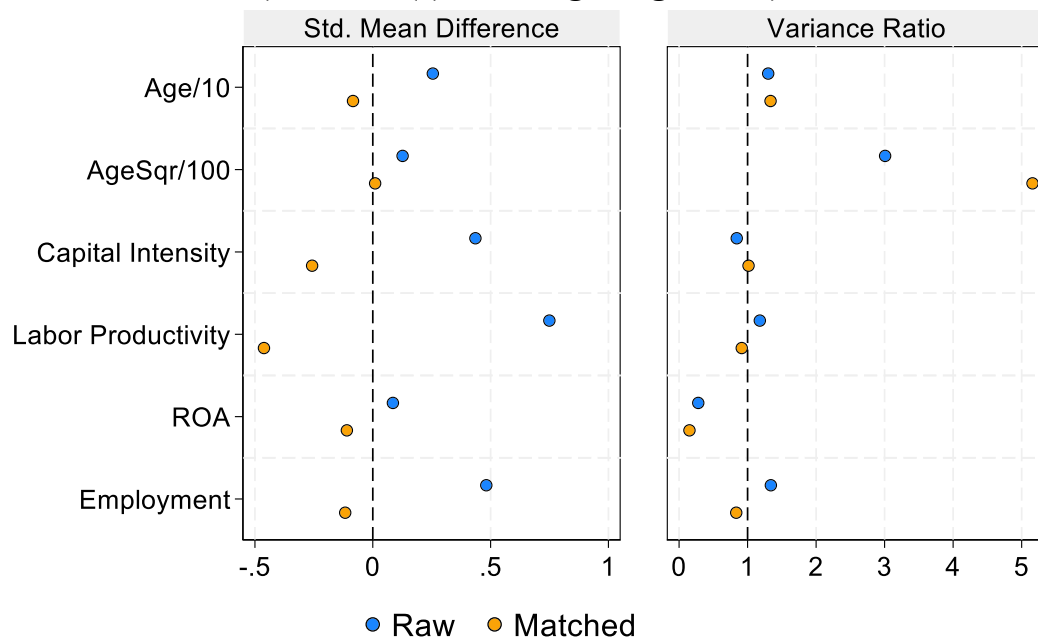
Source: Author's own calculations.

Figure A20. Kernel Density Plot of Propensity Score for the Total, Unmatched and Matched Samples (PSM, Kernel Matching, Large Firms)



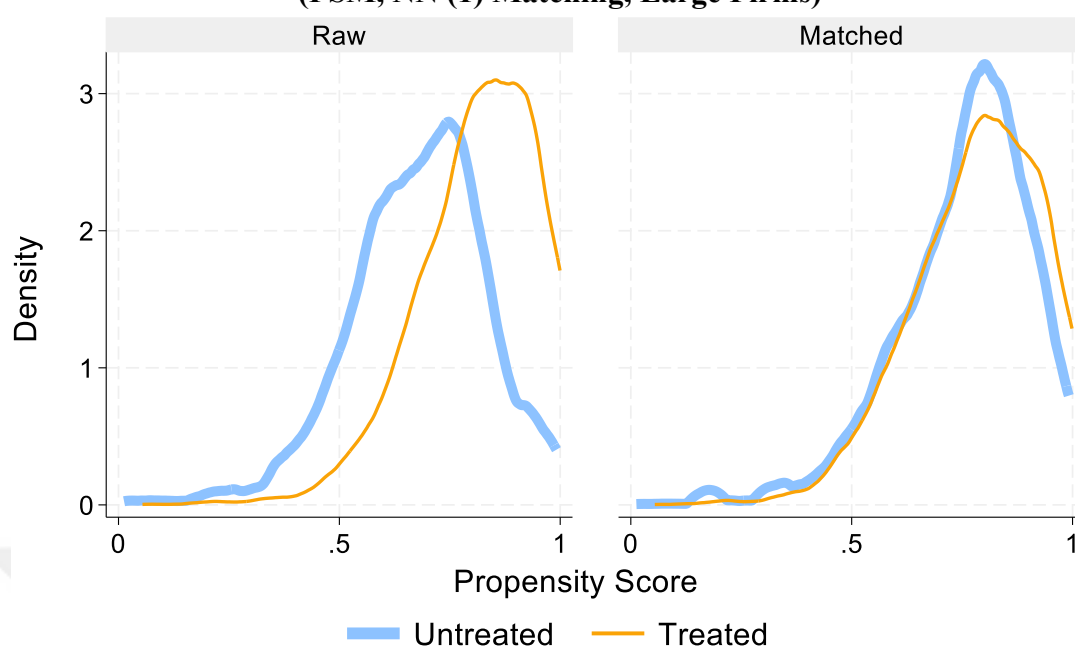
Source: Author's own calculations.

Figure A21. Covariate Balancing Before and After Matching (PSM, NN (1) Matching, Large Firms)



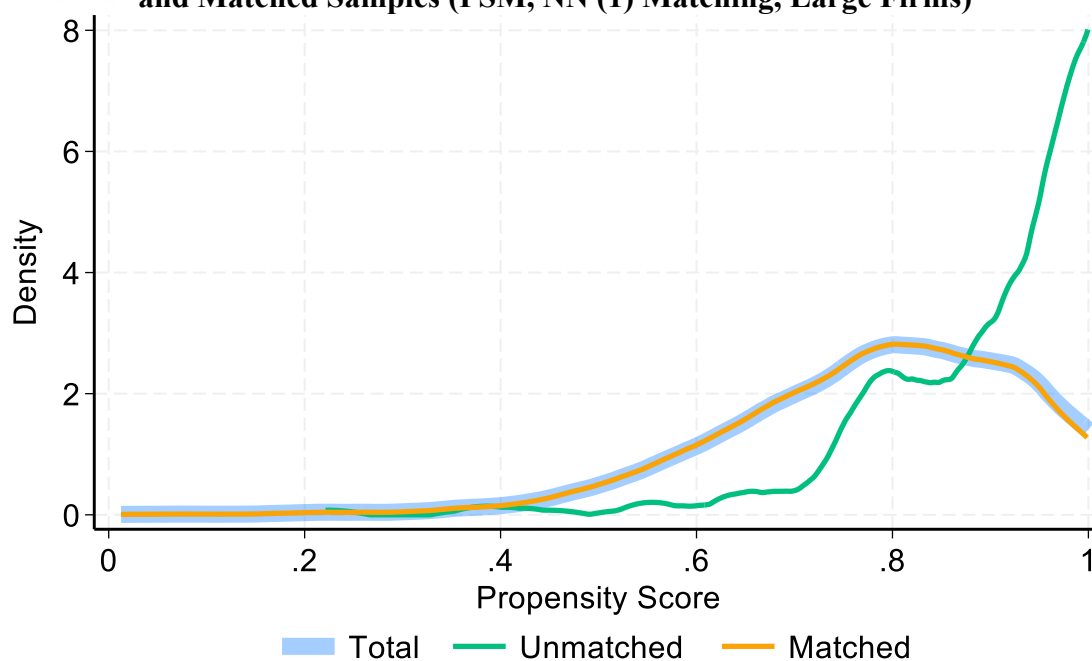
Source: Author's own calculations.

Figure A22. Density Plot of Propensity Score Before and After Matching (PSM, NN (1) Matching, Large Firms)



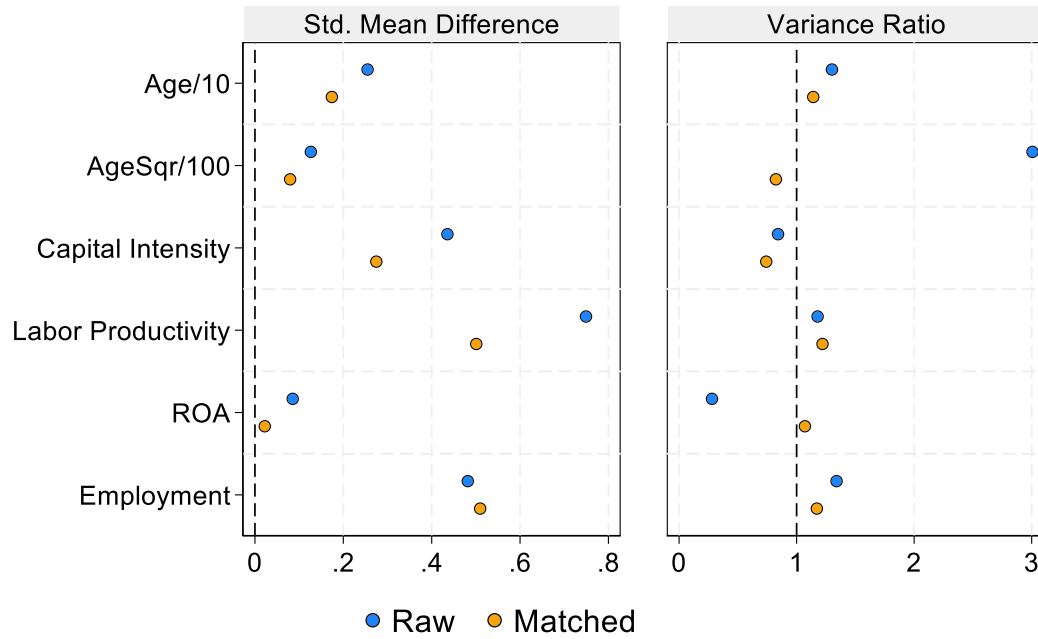
Source: Author's own calculations.

Figure A23. Kernel Density Plot of Propensity Score for the Total, Unmatched and Matched Samples (PSM, NN (1) Matching, Large Firms)



Source: Author's own calculations.

Figure A24. Covariate Balancing Before and After Matching (MDM, Kernel Matching, Large Firms)



Source: Author's own calculations.

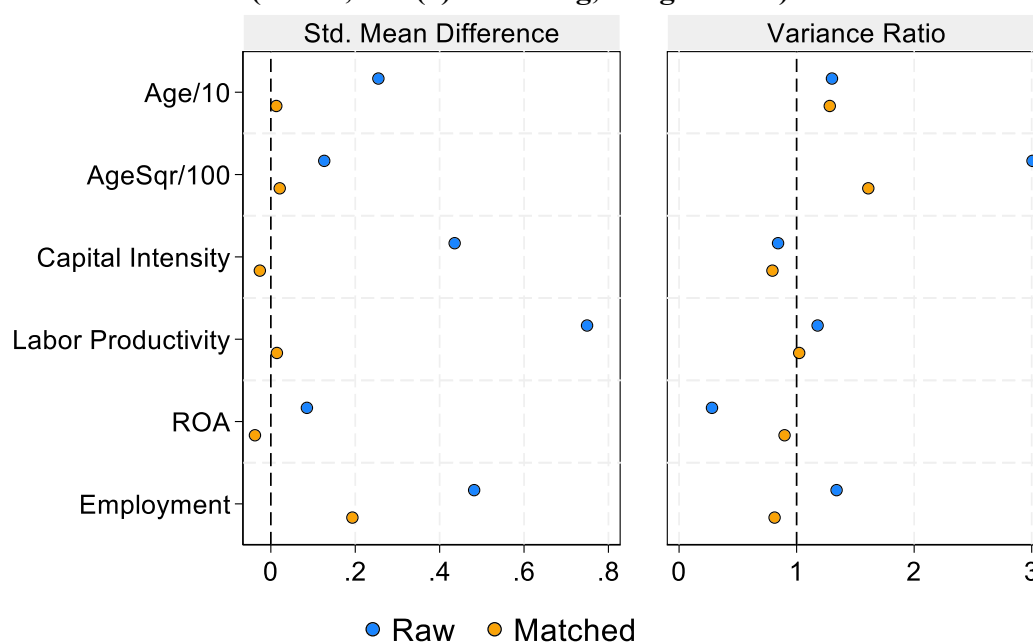
Table A11. Common Support Diagnostics (MDM, Kernel Matching, Large Firms)

	Common Support			Standardized Difference		
	Matched	Unmatched	Total	(1)-(3)	(2)-(3)	(1)-(2)
Means						
Age/10	2.053	2.237	2.066	-0.011	0.163	-0.174
AgeSqr/100	5.134	8.762	5.373	-0.021	0.293	-0.314
Log K/L	10.965	11.099	10.974	-0.006	0.092	-0.098
Log Y/L	10.698	10.843	10.707	-0.012	0.171	-0.183
ROA	0.050	0.010	0.047	0.015	-0.216	0.231
Log Employment	6.254	6.296	6.257	-0.004	0.053	-0.057
	Common Support			Variance Ratio		
	Matched	Unmatched	Total	(1)/(3)	(2)/(3)	(1)/(2)
Variances						
Age/10	0.917	3.765	1.107	0.829	3.402	0.244
AgeSqr/100	35.079	1520.413	133.790	0.262	11.364	0.023
Log K/L	1.757	3.115	1.848	0.951	1.686	0.564
Log Y/L	0.593	1.133	0.630	0.942	1.799	0.523
ROA	0.011	0.279	0.029	0.384	9.675	0.040
Log Employment	0.527	0.660	0.535	0.983	1.233	0.798

(5) Matched, (2) Unmatched, (3) Total.

K/L: Capital Intensity, Y/L: Value Added per Worker, ROA: Return on Assets

**Figure A25. Covariate Balancing Before and After Matching
(MDM, NN (1) Matching, Large Firms)**



Source: Author's own calculations.

Table A12. Common Support Diagnostics (MDM, NN (1) Matching, Large Firms)

Means	Common Support			Standardized Difference		
	Matched	Unmatched	Total	(1)-(3)	(2)-(3)	(1)-(2)
Age/10	2.066	2.027	2.066	0.001	-0.036	0.037
AgeSqr/100	5.376	5.240	5.373	0.000	-0.011	0.012
Log K/L	10.960	11.659	10.974	-0.011	0.504	-0.515
Log Y/L	10.689	11.578	10.707	-0.023	1.097	-1.120
ROA	0.047	0.046	0.047	0.000	-0.008	0.008
Log Employment	6.254	6.425	6.257	-0.005	0.229	-0.234

Variances	Common Support			Variance Ratio		
	Matched	Unmatched	Total	(1)/(3)	(2)/(3)	(1)/(2)
Age/10	1.106	1.135	1.107	1.000	1.026	0.974
AgeSqr/100	135.816	37.216	133.790	1.015	0.278	3.649
Log K/L	1.831	2.155	1.848	0.991	1.166	0.850
Log Y/L	0.610	0.825	0.630	0.968	1.310	0.739
ROA	0.029	0.013	0.029	1.012	0.449	2.253
Log Employment	0.533	0.610	0.535	0.996	1.140	0.874

(6) Matched, (2) Unmatched, (3) Total.

K/L: Capital Intensity, Y/L: Value Added per Worker, ROA: Return on Assets

Table A13. ICT and Export Intensity: OLS Results for All Firms

Dependent variable: Export intensity	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ERP	0.065*** (0.005)	0.054*** (0.005)	0.010* (0.005)			0.008 (0.005)	0.020*** (0.007)	0.005 (0.005)	0.046*** (0.011)
ICT Labor Share				0.000* (0.000)		0.000** (0.000)	0.001*** (0.000)		
Log Internet-Using Employee					0.022*** (0.002)			0.022*** (0.002)	0.029*** (0.003)
ERP x ICT Labor Share							-0.062*** (0.018)		
ERP x Log Internet-Using Employee									-0.014*** (0.004)
Age/10			0.017*** (0.004)	0.016*** (0.004)	0.017*** (0.004)	0.017*** (0.004)	0.017*** (0.004)	0.017*** (0.005)	0.018*** (0.005)
Age-Squared/100			-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)
Log Capital per Worker			0.005** (0.002)	0.006*** (0.002)	0.003* (0.002)	0.005** (0.002)	0.004** (0.002)	0.003 (0.002)	0.003 (0.002)
Log Value Added per Worker			0.012*** (0.004)	0.014*** (0.004)	0.009*** (0.004)	0.010** (0.004)	0.010** (0.004)	0.006 (0.004)	0.006 (0.004)
Log Return on Assets (ROA)			-0.000*** (0.000)	-0.000** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)
Log Employment			0.020*** (0.002)	0.022*** (0.002)		0.021*** (0.003)	0.022*** (0.003)		
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector Dummies	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province Dummies	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Firms	12036	12036	11715	13919	13652	11715	11618	11616	11616
Observations	22820	22820	22309	31804	31440	22309	22194	22190	22190

Robust standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions include a constant.

Table A14. ICT and Export Intensity: OLS Results for SMEs

Dependent variable: Export intensity	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ERP	0.040*** (0.005)	0.037*** (0.005)	0.010** (0.005)			0.008 (0.005)	0.014* (0.007)	0.003 (0.005)	0.006 (0.011)
ICT Labor Share				0.000*** (0.000)		0.000*** (0.000)	0.001*** (0.000)		
Log Internet-Using Employee					0.028*** (0.002)			0.028*** (0.002)	0.028*** (0.003)
ERP x ICT Labor Share							-0.028 (0.020)		
ERP x Log Internet-Using Employee									-0.001 (0.004)
Age/10			0.008 (0.007)	0.009 (0.006)	0.011* (0.006)	0.009 (0.007)	0.009 (0.007)	0.011 (0.007)	0.011 (0.007)
Age-Squared/100			-0.002 (0.002)	-0.002 (0.002)	-0.003 (0.002)	-0.002 (0.002)	-0.002 (0.002)	-0.003 (0.002)	-0.003 (0.002)
Log Capital per Worker			0.003* (0.002)	0.004*** (0.001)	0.002 (0.002)	0.003* (0.002)	0.003* (0.002)	0.002 (0.002)	0.002 (0.002)
Log Value Added per Worker			0.024*** (0.005)	0.024*** (0.004)	0.019*** (0.004)	0.022*** (0.005)	0.021*** (0.005)	0.017*** (0.005)	0.017*** (0.005)
Log Return on Assets (ROA)			-0.000* (0.000)	-0.000 (0.000)	-0.000*** (0.000)	-0.000* (0.000)	-0.000* (0.000)	-0.000*** (0.000)	-0.000*** (0.000)
Log Employment			0.027*** (0.003)	0.029*** (0.002)		0.029*** (0.003)	0.030*** (0.003)		
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector Dummies	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province Dummies	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Firms	9967	9967	9657	11892	11623	9657	9560	9558	9558
Observations	12155	12155	11779	16667	16317	11779	11669	11666	11666

Robust standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions include a constant.

Table A15. ICT and Export Intensity: OLS Results for Large Firms

Dependent variable: Export intensity	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ERP	0.023** (0.010)	0.009 (0.010)	0.006 (0.010)			0.004 (0.010)	0.021* (0.011)	-0.001 (0.010)	0.047 (0.034)
ICT Labor Share				0.000 (0.000)		0.000 (0.000)	0.001*** (0.000)		
Log Internet-Using Employee					0.008* (0.004)			0.010** (0.005)	0.020** (0.008)
ERP x ICT Labor Share							-0.143*** (0.042)		
ERP x Log Internet-Using Employee									-0.013 (0.009)
Age/10			0.028*** (0.008)	0.027*** (0.008)	0.025*** (0.008)	0.027*** (0.008)	0.027*** (0.008)	0.025*** (0.008)	0.025*** (0.008)
Age-Squared/100			-0.002*** (0.000)	-0.002*** (0.000)	-0.002*** (0.000)	-0.002*** (0.001)	-0.002*** (0.001)	-0.002*** (0.001)	-0.002*** (0.001)
Log Capital per Worker			0.009* (0.005)	0.009* (0.004)	0.008* (0.005)	0.008* (0.005)	0.007 (0.005)	0.008* (0.005)	0.008* (0.005)
Log Value Added per Worker			-0.009 (0.008)	-0.004 (0.007)	-0.008 (0.007)	-0.011 (0.008)	-0.011 (0.008)	-0.014* (0.008)	-0.014* (0.008)
Log Return on Assets (ROA)			0.063** (0.025)	0.050** (0.021)	0.053** (0.022)	0.069*** (0.026)	0.072*** (0.026)	0.070*** (0.026)	0.070*** (0.025)
Log Employment			-0.003 (0.007)	-0.002 (0.007)		-0.002 (0.008)	0.002 (0.008)		
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector Dummies	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province Dummies	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Firms	2666	2666	2631	2769	2768	2631	2631	2631	2631
Observations	10665	10665	10530	15137	15123	10530	10525	10524	10524

Robust standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions include a constant.