Trade Search Frictions: Public Information, Exports, and Concentration

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Abstract

Finding foreign buyers is a major hurdle for exporters, especially small and medium-sized enterprises (SMEs). This paper analyzes Korean data, revealing significant search frictions (the difficulty of identifying potential buyers). Public information on potential buyers, provided by Korea's trade promotion organization, significantly boosted exports, particularly for SMEs, leading to a more diverse export landscape (lower concentration). Our model explains how costly searches limit exports, especially for SMEs. Public information helps overcome this challenge by facilitating more buyer connections. Our quantitative analysis demonstrates that search frictions lead to 40% lower export volumes and 15 percentage points higher export concentration, compared to scenarios with no frictions. These findings suggest that policies easing buyer search, like providing public information, can promote trade and reduce export concentration by empowering SMEs.

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1. Introduction

When deciding what and where to export, firms face a critical challenge: overcoming information frictions, which are the limited knowledge about overseas markets that hinders export activity. Unlike traditional firm-level trade models (e.g., Eaton and Kortum 2002 and Melitz 2003) that assume perfect information, firms in reality struggle to acquire comprehensive information about foreign markets. Understanding market demand, regulations, cultural nuances, and distribution channels requires costly and labor-intensive efforts such as travel, research, and analysis. These expenses act as significant barriers to exporting, contributing to unaccounted-for trade costs (Anderson and Van Wincoop 2004 and Head and Mayer 2013).

This paper focuses on a specific aspect of information frictions: buyer search frictions. These frictions refer to the difficulty firms encounter in identifying and connecting with potential buyers in foreign markets. Overcoming these obstacles demands significant investments in time, resources, and expertise, particularly for small and medium-sized enterprises (SMEs) where securing the first international client is frequently cited as a major hurdle (Leonidou 2004 and Secretariat 2016). Trade Promotion Organizations (TPOs) can play a crucial role in alleviating these barriers by providing public information about potential buyers and market conditions to businesses. In this study, we investigate how search frictions and TPO-provided buyer information impact international trade.

Our work addresses limitations in the existing empirical literature on information and search frictions in trade. Because information is typically unobserved and highly endogenous to trade flows, this literature has relied on proxies of information flows, e.g., the Chinese ethnic network (Rauch and Trindade 2002), mobile phone service (Sreekumar 2011 and Allen 2014) or the Internet (Kneller and Timmis 2016 and Akerman, Leuven and Mogstad 2022).[1] We leverage a more direct measure: a list of international buyer contacts gathered by a Korean TPO (KOTRA). This allows us to uncover more direct evidence of information frictions in international trade and their impact on export activities.

We also develop a theoretical framework to explore how public information from TPOs mitigates these frictions, particularly for SMEs. This framework extends the literature on market penetration and search-ad-matching mechanisms in trade (e.g., Arkolakis 2010, Antràs and Costinot 2011, Allen 2014, Benguria 2021, Eaton, Jinkins, Tybout and Xu 2022 among many others) by explicitly considerting the role of TPO-provided public information. Our quantitative analysis, informed by the framework and regression results, suggests that search frictions can lead to a substantial reduction in exports (around 40 percent) and increased export concentration (around 15 percent points). These findings highlight the importance of publicly available buyer information provided by TPOs in facilitating international trade and promoting a more balanced trade landscape across exporters.

[1]Some recent works attempt to analyze observable information flows (Steinwender 2018 and Juhász and Steinwender 2018). However, these studies focus on a single industry (textiles) in order to establish a plausible exogenous information shock. Our empirical work addresses these limitations by leveraging a more direct measure of information and examining variations across industries and firm sizes.

Our empirical study begins by investigating how KOTRA, Korea's TPO established in 1962, collected and distributed foreign buyer information. KOTRA published potential buyer information in its "Daily KOTRA Overseas Market" magazine from 1962 to 2001. We digitize and analyze sampled data from 1977 to 1990. Our goal is to understand the influence of KOTRA's buyer information on Korean firms' export activities.

One potential challenge in our empirical analysis is addressing reverse causality, as highlighted by Steinwender (2018). Information flows are known to react to the trade environment, potentially leading to a scenario where increased trade activity influences the likelihood of being included in the KOTRA dataset. However, our analysis reveals that KOTRA's information collection demonstrates significant exogenous variation driven by political motivations, such as focusing on specific countries or industries during periods of heightened diplomatic relations. Additionally, idiosyncratic factors, like changes in leadership or internal resource allocation within KOTRA, also contributed to variation in information collection that is not directly related to Korean firms' existing export activities.[2] Unlike export flows, KOTRA's information collection exhibits large variation that cannot be attributed to import potential in destination countries or industries. We leverage this exogenous variation by employing a fixed effects model with controls for import potential, allowing us to identify the causal impact of information on Korean firms' export activities.

We demonstrate the role of search frictions and public information in exports by examining three key relationships between public information on buyers and export behaviors. First, we find a significant positive association between new buyer information from KOTRA and Korean exports at the destination-industry-year level, supporting the notion that search frictions hinder international trade. If firms had perfect information about buyers, the provided information wouldn't boost exports. This result is robust to adding controls and fixed effects that account for spurious links between exports and TPO data, such as sudden increases in demand from new international customers. Additionally, we conduct placebo tests to mitigate concerns of reverse causality. Our findings indicate that KOTRA's information did not lead to increased exports for Taiwan and Japan, despite these countries experiencing similar export shocks due to their economic similarities with Korea. Furthermore, our analysis of dynamic effects and heterogeneity across different contexts reaffirms that the observed impacts are genuinely driven by information effects rather than spurious correlations with trade environments.

Second, we find an interesting difference in how firms benefit from public information. Industries dominated by large firms (higher concentration) show a smaller export boost from buyer information compared to industries with more small firms. This suggests that while search frictions are present for all firms, their severity varies by firm size. Large firms, likely due to their higher productivity, possess greater knowledge of foreign buyers even without TPO's information, making them less responsive to publicly provided information. Consequently, industries where small firms contribute a larger share of exports (lower export concentration) see a larger export increase in

[2]For example, research by Barteska and Lee (2023), using the same magazine data, highlights how the capacity and experience of Korean bureaucrats in KOTRA's overseas offices affect their ability to convey foreign market conditions effectively to Korea.

response to additional buyer information. This aligns with existing literature on firms' endogenous selection of information acquisition levels. Dickstein and Morales (2018) finds a positive correlation between firm size and information investment. Using customs data, Blum, Claro and Horstmann (2010) and Bernard, Moxnes and Ulltveit-Moe (2018a) also support this notion, showing that larger firms sell to a greater number of foreign buyers. This pre-existing knowledge base explains why public information has a smaller impact on their exports compared to smaller firms.

Last but not least, we find evidence that public information lowers the concentration of exporters, implying that smaller firms benefit more from this information. This finding aligns with existing research on high export concentration (e.g., Mayer and Ottaviano 2008, Antràs and Yeaple 2014, Bernard, Jensen, Redding and Schott 2018b, and many others). Our results suggest that a portion of this concentration can be attributed to search frictions.

Motivated by the empirical findings, we develop a theoretical framework—a heterogeneous firm model of overseas buyer search with public information (TPOs). This model helps us understand and quantify the impact of public information on export activities for firms of varying sizes. By applying the model to the context of TPO-provided buyer information, we gain insights into how firms adjust their buyer search and exports in response to such information. Also, the model offers a straightforward framework for quantifying the effects of search frictions on firms' exports and export concentration, facilitating the identification of these frictions from observed data.

In our model, firms search for buyers, and higher levels of search frictions reduce the optimal number of buyers they seek. These frictions result in lower exports compared to a hypothetical scenario where all exporters could sell to all potential foreign buyers. Additionally, more productive (larger) firms engage in more search because they earn larger profits per buyer reached, thus exporting to a larger number of buyers. Consequently, search frictions disproportionately reduce the number of buyers reached by smaller exporters, leading to a more concentrated export market.

The model's implications for public information align with our empirical results. Public information from TPOs assists exporters in reaching buyers, thereby mitigating the negative effects of search frictions. Additionally, this public information benefits smaller exporters more significantly due to diminishing returns in buyer search, leading to a reduction in export concentration.

This model's strength lies in its ability to not only capture the effects of search frictions on individual and aggregate export activities but also to quantify these effects in a clear and measurable way. By employing the semi-elasticity of total exports with respect to the share of buyer information provided, we can compute the overall export reduction due to search frictions. Additionally, combining the observed export concentration level with the semi-elasticity allows us to quantify the increase in concentration caused by search frictions.

Using data from KOTRA and the Korean Mining and Manufacturing Census, we estimate the semi-elasticity to be in the range of 0.5 to 0.6. This estimated value indicates that search frictions significantly distort export activities. Our framework implies that exports are approximately 40 percent lower, and export concentration is roughly 15 percentage points higher under search frictions compared to a frictionless scenario.

Our findings provide strong evidence for the significant role of TPOs in facilitating exports, particularly for SMEs. TPOs can mitigate search frictions through providing public information on potential buyers. This helps level the playing field for smaller firms, fostering a more diversified and inclusive export landscape where SMEs can contribute more meaningfully to international trade. By focusing specifically on the information channel, our work complements previous studies that have documented positive effects of TPO services on exports (e.g., Martincus and Carballo 2008, Van Biesebroeck, Yu and Chen 2015, Munch and Schaur 2018 and Barteska and Lee 2023). This aligns with findings from Carballo, Chatruc, Santa and Martincus (2022) who observed similar benefits from online buyer information platforms. Our research strengthens the case for TPO information provision as a powerful tool for promoting SME exports.

The rest of the paper proceeds as follows: Section 2 describes the historical setting and the data. Section 3 explores the empirical relationships between buyer information and exports. Section 4 develops a theoretical model of buyer search with public information. Section 5 discusses the model mechanisms and predictions. Section 6 presents our quantitative analysis. The last section concludes.

2. Historical Context and Data

2.1. Buyer Information Data

We study buyer information collected by Korea's TPO (KOTRA). The main goal of KOTRA is to promote exports. To achieve this, KOTRA operates a global network of offices and disseminates information between Korean and foreign firms. Between 1962 and 2001, KOTRA gathered information on foreign buyers' contacts and demand, publishing it in its magazine, "Daily KOTRA Overseas Market."[3]

In this paper, we digitize the magazine covering the period from 1977 to 1990. We focus on this timeframe for two key reasons. Firstly, the 1980s were characterized by high costs associated with collecting foreign market information, particularly for SMEs. Before the widespread adoption of the internet in the 1990s, international communication remained expensive (Appendix Figure A.3). This made KOTRA's information on overseas buyers highly valuable. While large corporations also had internal market research capabilities (e.g., Samsung with 36 overseas offices in 1980), KOTRA's network offered wider coverage with 87 offices across 66 countries in 1980, focusing on exploring emerging markets (KOTRA 2012).

Secondly, during this period, Korea transitioned from export-led industrialization under an authoritarian regime to more open trade policies in the democratic era. The government's reduced involvement in industrial policy and focus on a balanced economy diminished the impact of domestic policies on export outcomes (for more context, see Kim 1991 and Lee 2013). Additionally, the 1980s offered a more stable global trading environment compared to the subsequent decade of

[3]The magazine's title evolved over time, transitioning from "Export promotion" (mooyeok-jinheung) to "Daily overseas market information" in 1966 and finally to "Daily KOTRA overseas market" in 1973.

significant trade liberalization (Coelli, Moxnes and Ulltveit-Moe 2022).[4] This stability strengthens our analysis by isolating the effects of public information from potential confounding factors related to domestic and international trade policy changes.

2.2. Measurement of Variables

New Buyer information. Our measure of public information is `NewBuyerInfo`. It is defined as the number of new buyer contacts listed in KOTRA's magazine during the period from 1977 to 1990. This measure is at the level of a triplet consisting of a SITC 4-digit industry k, destination country j, and year t ($\texttt{NewBuyerInfo}^k_{j,t}$). If KOTRA's magazine contains information about a specific buyer interested in products from a particular SITC 4-digit industry in a given year, we count this as one unit of buyer information for that triplet.

KOTRA's magazine dedicated a section to foreign buyer information. We randomly selected one issue per week with such information, resulting in 52 issues per year. The section included inquiries collected by KOTRA from various sources. These inquiries detailed the buyer's country (column 2), contact information (column 3), and a list of desired products (column 4) (see Appendix Figure A.2). For each inquiry, we extracted and matched this information to country codes and SITC 2nd revision codes at the 4-digit level.

Digitizing buyer information presented two main hurdles. Firstly, table structure recognition using computer vision methods proved error-prone for these tables, so we manually labeled table regions in all sampled magazines. Secondly, matching inquired items to SITC codes required text similarity calculations. We employed two steps: [Step 1] Normalizing inquired item text (removing stop words, correcting typos, lemmatization). [Step 2] Calculating text similarity between items and SITC code descriptions using keyword search with TF-IDF weighting and word embedding for tie-breaking. See Appendix A for more details. This process resulted in a dataset containing 12,141 inquiries on 43,239 items from 125 countries between 1977 and 1990.

Market sizes and Korea's exports. Our SITC 4-digit bilateral trade data come from NBER-United Nations Trade Data (Feenstra, Lipsey, Deng, Ma and Mo, 2005), with a minimum value of $100,000. We calculate a market size variable for each industry-destination pair as the sum of log imports from the rest of the world, excluding Korea.

$$\texttt{ImportSize}^k_{j,t} = 0.01 \times \sum_{i \neq \text{Korea}} \ln \texttt{EX}^k_{j,t}(i), \tag{1}$$

where $\texttt{EX}^k_{j,t}(i)$ represents exports from origin country i to destination country j in industry k for year t. Multiplying the sum by 0.01 ensures the estimated coefficients have values with up to three decimal places. Our primary dependent variable, destination-industry level exports from Korea, is

[4] The 1990s, often referred to as the "Great Liberalization," saw significant reductions in policy barriers, particularly tariffs, across both developed and developing countries. Researchers frequently study this era to understand the impact of trade liberalization on economic outcomes (e.g., Coelli et al. 2022).

denoted as $\texttt{EX}^k_{j,t} = \texttt{EX}^k_{j,t}(\text{Korea})$.

The number and fraction of exporters. We utilize establishment-level exports and domestic sales data from the Korean Mining and Manufacturing Census, which covers all Korean manufacturers and mining establishments. We collect the number of firms and exporters in each 3-digit Korean Standard Industry Classification (KSIC, indexed by $\tilde{k}$) industry, denoted as $\texttt{NofFirms}^{\tilde{k}}_t$ and $\texttt{NofExporters}^{\tilde{k}}_t$, respectively. We also compute the fraction of exporters within each industry: $\texttt{ExporterFraction}^{\tilde{k}}_t$. These values are then assigned to 4-digit SITC industries (k) using the concordance by Muendler (2009).

Concentration. We measure industry-level concentration using establishment-level sales and export data from the Korean Mining and Manufacturing Census. Our concentration measures are the sales shares of the top N Korean firms (by sales) in each 3-digit KSIC manufacturing industry ($\texttt{Top}N\texttt{SalesShare}^{\tilde{k}}_t$, $\texttt{Top}N\texttt{DomesticShare}^{\tilde{k}}_t$, and $\texttt{Top}N\texttt{ExportShare}^{\tilde{k}}_t$, for total sales, domestic sales, and exports, respectively). We also utilize the Herfindahl-Hirschman Index for sales ($\texttt{HHI}^{\tilde{k}}_t$).

Recognizing that the total number of firms can influence these concentration measures, we introduce the following measure of top firm dominance, which aims to be relatively independent of this extensive margin factor:

$$\texttt{Top}N_1/\texttt{Top}N_2\texttt{Sales}^{\tilde{k}}_t \equiv \frac{\ln(\texttt{Top}N_1\texttt{SalesShare}^{\tilde{k}}_t/N_1) - \ln\left(\texttt{Top}N_2\texttt{SalesShare}^{\tilde{k}}_t/N_2\right)}{\ln N_2 - \ln N_1}, \tag{2}$$

where N_1 and N_2 are integers with $N_1 < N_2$. This measure normalizes sales concentration between the top N_1 and the top N_2 firms relative to the difference between N_1 and N_2. For a given N_1 and N_2, a higher value indicates greater sales concentration towards the top N_1 firms compared to the top N_2 firms. We set $N_1 = 8$ and $N_2 = 20$ for empirical analysis.[5] Results are robust unless N_1 is smaller than 4. Similar measures are constructed for export and domestic sales concentration ($\texttt{Top}N_1/\texttt{Top}N_2\texttt{Export}$ and $\texttt{Top}N_1/\texttt{Top}N_2\texttt{Domestic}$). We assign these concentration measures to each 4-digit SITC industry using the concordance table from Muendler (2009).

Other variables. For gravity variables, we utilize nominal GDP and GDP deflator data from the World Bank. Distance from Korea is calculated using a weighted distance measure that considers within-country spatial distribution of activity, provided by CEPII (Mayer and Zignago 2011). The official language of each country is also obtained from the same dataset. Furthermore, we classify each 4-digit industry into homogeneous goods, reference-priced goods, and differentiated goods based on the SITC 4-digit classification system from Rauch (1999). Details on the data merge process can be found in Appendix A.

[5] Choosing relatively higher numbers helps to minimize the effects of idiosyncratic shocks on the larger firms or errors arising from connecting the standard model, which considers firms as mass-zero agents in a continuum, to the real world where firms are discrete positive mass agents.

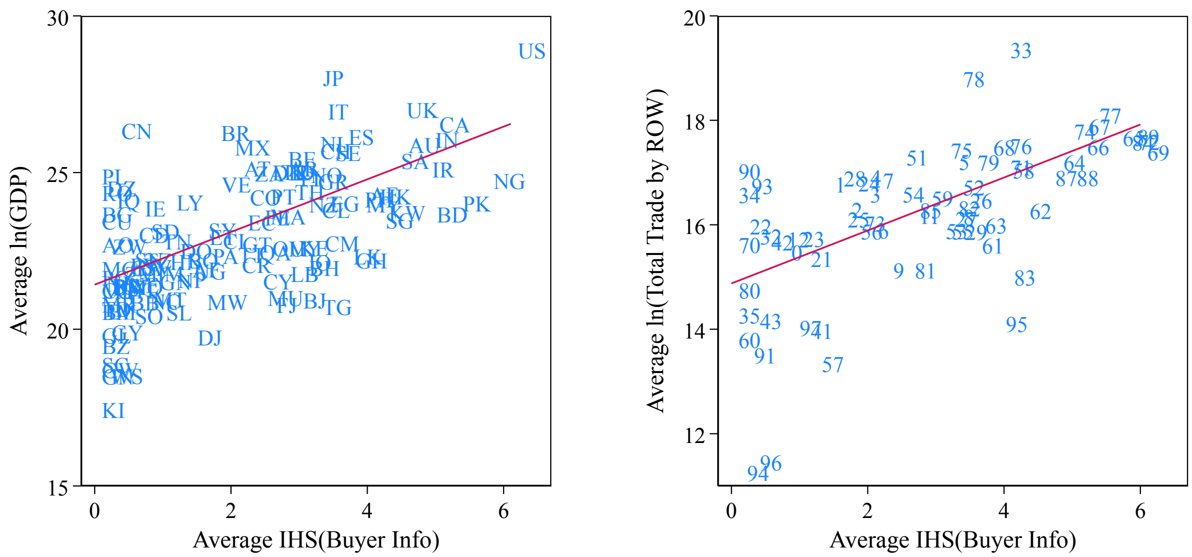

Figure 1: Average New Buyer Information

Notes: The left panel is a scatter plot between the average log(GDP) and the average IHS transformed new buyer information for each destination country. The right panel is a scatter plot between the average logarithmic total trade flow among the rest of the world (excluding Korea) and the average IHS transformed new buyer information for each SITC 2-digit industry. Averages are over the sample years.

2.3. Descriptive Analysis of Buyer Information Data

To understand KOTRA's data collection process, we examine the determinants of its information gathering. Economic factors played an important role. For instance, Figure 1 shows that more information is collected for larger markets, both in terms of countries and product categories. KOTRA's overseas network likely influenced this; for example, in 1980, the US had 12 KOTRA offices, while Mexico and Canada had only 1 and 3 offices, respectively.

However, KOTRA's search efforts were not solely driven by economic factors. For example, Figure 2 illustrates that in 1981, smaller economies like Ghana and Nigeria had more buyer contacts than the larger US market. Following the 1970s oil shocks, Korea sought stronger ties with oil-producing West African nations, competing with North Korea. These political efforts led to the establishment of embassies and increased information collection from these regions post-1980.

Additionally, KOTRA's unorganized search process introduced significant variation in the collected buyer information. Ideally, targeted searches would yield large or consistent information flows for specific product-destination pairs over the years. However, around 76% of positive buyer information flows at the destination-year-SITC 4-digit level involve only one buyer (Appendix Figure A.4a), and 75.6% of these positive counts disappear the following year. Even at the SITC 2-digit level, these percentages remain high at 56% and 57%, respectively. A KOTRA document confirms that local employees, rather than market research specialists, conducted these searches as routine work (KOTRA 2012), making individual-level idiosyncratic shocks more prominent in the

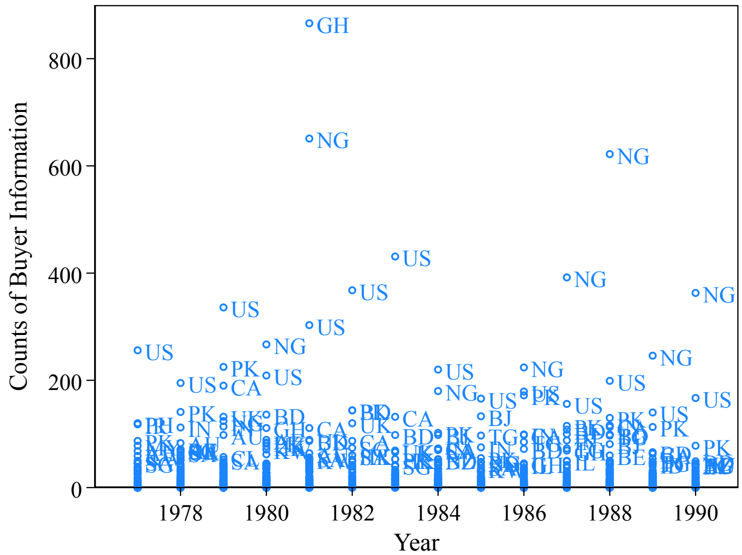

Figure 2: The Number of New Buyer Information from Each Destination Country

search process.

This variation, unrelated to the economic factors affecting Korea's exports, provides exogenous variation in information flows that helps identify the informational effects. To assess this, we compare how well economic factors explain buyer information and exports using a gravity equation-type regression analysis (details in Appendix B). Appendix Table A.1 highlights two key points: Firstly, economic factors like market size explain much less variation in buyer information compared to exports, as indicated by the R-squared values. Secondly, the correlation between market size (`ImportSize`) and buyer information disappears once detailed fixed effects are added, while the correlation between market size and Korea's exports remains strong. These findings support the notion that KOTRA's search was not well-organized to promptly reflect current market conditions, showing sizable variation that economic factors cannot explain.

Finally, the data indicates that most of the collected information pertains to distinct buyers, supported by the low number of repeat inquiries from the same firm across years. For example, in the US (with the most collected buyer contacts), only six out of 98 firms inquired twice in 1981, with the remaining firms making only one inquiry. Moreover, only nine firms out of 255 had information collected in both 1981 and 1982. Hence, we interpret the collected buyer contacts as new buyer information.

3. Reduced Form Regression Analysis

This section examines the effects of KOTRA's buyer information on Korean firms' exports and their distribution. Subsection 2.3 showed that our buyer information data has ample variation that is unrelated to economic fundamentals. Our empirical strategy leverages this variation while controlling for systematic factors like market size that influence KOTRA's search. Additionally, we conduct several robustness tests to ensure that the observed effects arise from the information channels rather than confounding factors.

3.1. Public Information on Buyers Promotes Exports

Baseline specification. Identifying the effect of public information relies on exploiting exogenous changes in collected information that are not correlated with trade environments. Subsection 2.3 shows that ample variation in information originates from political motives or KOTRA's unorganized search, which are not related to economic factors. Our baseline specification aims to exploit this variation by controlling for economic factors using detailed fixed effects and market demand controls:

$$\mathtt{EX}^k_{j,t} = \exp\left[\alpha \times \mathtt{NewBuyerInfo}^k_{j,t} + \gamma \times \mathtt{ImportSize}^k_{j,t} + \delta^k_j + \delta_{j,t} + \delta^k_t + \epsilon^k_{j,t}\right], \tag{3}$$

where $\mathtt{EX}^k_{j,t}$ is the export value of SITC 4-digit industry k from Korea to country j in year t, and $\mathtt{NewBuyerInfo}^k_{j,t}$ is the number of new buyer contacts collected by the TPO. The sum of log imports from the rest of the world, $\mathtt{ImportSize}^k_{j,t}$, controls for market size. Each δ represents fixed effects at its respective level.

The coefficient on $\mathtt{NewBuyerInfo}^k_{j,t}$, denoted by α, is our main focus. If the variation in $\mathtt{NewBuyerInfo}^k_{j,t}$ after controlling for $\mathtt{ImportSize}^k_{j,t}$ and the fixed effects is exogenous to the error term $\epsilon^k_{j,t}$, the estimated α can be interpreted as the effect of buyer information on exports. A positive α indicates that an increase in new buyer contacts positively affects exports, suggesting the existence of search frictions.[6]

Specification issues. Identification of the main coefficient α relies on whether the baseline specification can address confounding factors that affect both information flows and Korea's exports. The fixed effects in equation (3) aim to control for these factors: δ^k_j for time-invariant destination-industry determinants (e.g., overall market size, which showed clear correlation to collected buyer information in Figure 1), $\delta_{j,t}$ for time-varying destination factors (e.g., changes in income), δ^k_t for time-varying industry factors (e.g., Korea's domestic policy). [7]

[6] Due to the large ratio of zero trade flows in the dataset, we primarily use PPML estimators for the estimations (Silva and Tenreyro 2006). In the appendix, for intensive margin estimation that restricts the samples to positive trade flows, we also present estimates from the OLS estimator.

[7] However, the severity of the omitted variable bias might be limited here. Firstly, after controlling for fixed effects, omitted variables may not significantly impact Korea's export flow. Regarding trade costs, the main tariff changes during the sample period were related to the Tokyo Round and changes in Korea's GSP (Generalized System of Preference) status. Suppose these resulting tariff changes can be approximated as uniform increases or decreases in tariff rates. In that case, the combination of country-industry fixed effects and country-year fixed effects could effectively control for them. Additionally, if transport costs are a product of country-industry-specific factors and time-varying components like oil prices, the fixed effects would partially control for them. Secondly, systematic correlation between omitted variables and collected buyer information counts may be limited if the variation remaining after adding controls stems from the untargeted search process.

However, these fixed effects do not capture changes in demand or trade frictions specific to a country, industry, and year (e.g., a surge in US shoe demand). While Subsection 2.3 shows that KOTRA's search did not promptly reflect market conditions, these factors could still bias our results if correlated with collected information. The direction of this bias depends on how KOTRA prioritizes information gathering during favorable or unfavorable trade conditions. Ideally, we would directly control for these factors, but the lack of bilateral country-industry specific tariffs, transportation costs, or demand data in the 1980s prevents this.

To address this, our baseline specification includes a proxy for a country's import demand: imports from the rest of the world for a specific country-industry in a given year (excluding Korea), defined as $\texttt{ImportSize}^k_{j,t}$ in equation (1). This captures common demand and trade cost changes across exporters to the same destination. For instance, if overall TV demand increases in the US, it would be reflected in increased imports from all countries, not just Korea. Including this variable helps control for such common factors.

However, this approach does not capture changes specific to Korean exports compared to others. For instance, certain tariff rules for Korea might have changed differently from those for other countries. If KOTRA's search efforts were influenced by such Korea-specific changes, it could bias our estimates. First, we include an inverse hyperbolic sine (IHS) transformed value of Korea's previous export level for the same industry-destination, denoted as $\text{IHS}(\texttt{EX}^k_{j,t-1})$. This helps control for Korea-specific effects that persist over time. Second, we introduce more detailed fixed effects (at the country-SITC 2- or 3-digit-year level) to account for Korea-specific effects correlated at slightly more aggregated industry groups.

Lastly, we conduct a placebo test using exports from Japan and Taiwan, which have similar export profiles to Korea. If the positive effect of buyer information on Korean exports is due to a spurious correlation with uncontrolled market conditions, we would expect similar effects for these countries. However, if we don't observe positive effects for Japan and Taiwan, it is likely that the effects on Korea's exports can be attributed to the information channel rather than to market conditions.

Timing of effects. The baseline approach assumes that new buyer information immediately impacts exports. However, it might take time for new buyer information to translate into increased exports due to delays in firms acquiring the information or establishing contact with potential buyers. To explore this possibility, we investigate two specifications. First, we replace the current term for new buyer information in equation (3) with its value from the previous year ($\texttt{NewBuyerInfo}^k_{j,t-1}$) to assess if past information has a continuing effect on exports in the current period. Secondly, we split the new buyer information into two variables: $\texttt{NewBuyerInfoQ1-Q3}^k_{j,t}$ and $\texttt{NewBuyerInfoQ4}^k_{j,t}$, capturing the number of new buyer contacts during the first three quarters and the last quarter of the year, respectively. We replace $\texttt{NewBuyerInfo}^k_{j,t}$ with these variables in equation (3). If the estimated coefficient for the first three quarters is positive and significantly larger than that for the last quarter, it suggests that information takes time to be utilized and to affect trade flows.

Table 1: Impacts of New Buyer Information on Exports

Dep. Variable	(1) Export	(2) Export	(3) Export	(4) Export	(5) Export
$\texttt{NewBuyerInfo}^k_{j,t}$	0.008	0.027***			
	(0.015)	(0.009)			
$\texttt{NewBuyerInfo}^k_{j,t-1}$			0.028***	0.047***	
			(0.005)	(0.007)	
$\texttt{NewBuyerInfoQ1-Q3}^k_{j,t}$					0.032***
					(0.008)
$\texttt{NewBuyerInfoQ4}^k_{j,t}$					0.012
					(0.018)
$\texttt{ImportSize}^k_{j,t}$		0.614***		0.637***	0.613***
		(0.099)		(0.100)	(0.100)
Observations	241,565	241,565	236,570	236,570	241,565
Country-Industry FE	✓	✓	✓	✓	✓
Year-Country FE	✓	✓	✓	✓	✓
Year-Industry FE	✓	✓	✓	✓	✓

Notes: The table reports estimates of PPML regression equation (3). The dependent variable is export at the Country-Industry(4-digit SITC)-Year level. Explanatory variables include the counts of collected new buyer information ($\texttt{NewBuyerInfo}^k_j$) and their lagged value ($\texttt{NewBuyerInfo}^k_{j,t-1}$), new buyer information counts from the first three quarters ($\texttt{NewBuyerInfoQ1-Q3}^k_{j,t}$) and the last quarter ($\texttt{NewBuyerInfoQ4}^k_{j,t}$), and the sum of log imports from the rest of the world ($\texttt{ImportSize}^k_{j,t}$). *p<0.1, **p<0.05, ***p<0.01. Standard errors in parenthesis are corrected for arbitrary correlation within country and industry.

Regression results. Table 1 summarizes the estimated impacts of buyer information on exports. The coefficient (α) from the baseline model (Column 2) is positive and statistically significant, indicating that new buyer information boosts exports. Notably, comparing the first two columns, adding the control variable $\texttt{ImportSize}^k_{j,t}$ inflates the coefficient and improves its precision. This suggests that KOTRA may have collected more information when a market faced negative shocks (decreased demand or increased trade costs). Failing to control for this correlation can underestimate the true effect of buyer information on exports.

The lagged information coefficients (Columns 3 and 4) are substantially larger than those for contemporaneous information. Similarly, Column (5) a stronger and more precise effect for information collected earlier in the year. These findings suggest that information takes time to influence export outcomes, supporting the idea that the coefficients reflect genuine information effects rather than spurious correlations.

Given the compelling evidence for lagged effects, we focus on the previous period's new buyer information for the rest of our analysis. The coefficient in Column (4) implies that, on average, each additional public buyer contact during the sample period increases exports in the following year by 4.7%. A one standard deviation increase in new buyer information leads to a 2.06% increase in exports.

Table 2: Impacts of Lagged New Buyer Information on Exports

Dep. Variable	(1) Export	(2) Export	(3) Export	(4) Export
$\texttt{NewBuyerInfo}^k_{j,t}$	0.018**	0.020***	0.014	0.016**
	(0.008)	(0.007)	(0.010)	(0.008)
$\texttt{NewBuyerInfo}^k_{j,t-1}$	0.042***	0.050***	0.046***	0.047***
	(0.010)	(0.012)	(0.010)	(0.013)
$\texttt{NewBuyerInfo}^k_{j,t-2}$	0.031***	0.038***	0.035***	0.040***
	(0.008)	(0.011)	(0.011)	(0.014)
$\texttt{NewBuyerInfo}^k_{j,t-3}$	0.029***	0.031***	0.024***	0.032***
	(0.007)	(0.009)	(0.008)	(0.010)
$\texttt{NewBuyerInfo}^k_{j,t-4}$			0.024***	0.027***
			(0.005)	(0.005)
$\texttt{NewBuyerInfo}^k_{j,t-5}$			0.026***	0.028***
			(0.007)	(0.009)
$\texttt{ImportSize}^k_{j,t}$	0.591***	0.593***	0.574***	0.481***
	(0.093)	(0.084)	(0.096)	(0.118)
$\texttt{ImportSize}^k_{j,t-1}$		0.032		0.033
		(0.042)		(0.046)
$\texttt{ImportSize}^k_{j,t-2}$		–0.011		–0.025
		(0.046)		(0.045)
$\texttt{ImportSize}^k_{j,t-3}$		–0.062		–0.007
		(0.052)		(0.055)
$\texttt{ImportSize}^k_{j,t-4}$				–0.027
				(0.068)
$\texttt{ImportSize}^k_{j,t-5}$				–0.149
				(0.118)
Observations	146,855	126,799	90,041	67,544
Country-Industry FE	✓	✓	✓	✓
Year-Country FE	✓	✓	✓	✓
Year-Industry FE	✓	✓	✓	✓

Notes: The table reports estimates of PPML equation (3) including lagged values. The dependent variable is the log export value at the Country-Industry(4-digit SITC)-Year level. The explanatory variables are the counts of collected buyer information ($\texttt{NewBuyerInfo}^k_{j,t}$) and their lagged values up to the previous five years, sums of log imports from the rest of the world for each Destination Country-Industry(4-digit SITC)-Year ($\texttt{ImportSize}^k_{j,t}$), their lagged variables up to previous five years. *p<0.1, **p<0.05, ***p<0.01. Standard errors in parenthesis are corrected for arbitrary correlation within country and industry.

Our baseline model assumes that fixed effects and market size effectively address destination-industry-year specific confounding factors. Appendix Table A.6 tests this assumption. To control for Korean exporter-specific potential confounders, Column (1) includes the previous period's export value as an additional control, and Columns (2) and (3) introduce more detailed fixed effects. The results remain similar to the baseline and statistically significant, suggesting the model controls for confounding factors effectively.

Additionally, Columns (4) and (5) of Appendix Table A.6 show that our buyer information measure does not positively correlate with Japanese or Taiwanese exports. Since these countries are likely exposed to similar destination-industry-year changes as Korea, this further supports that our findings are not driven by confounding factors. These robustness checks and placebo tests provide strong evidence for the validity of our results.

Long-term effects of buyer information. Public information might have long-term effects due to learning and dynamic mechanisms (Atkin, Khandelwal and Osman 2017, Eaton, Eslava, Jinkins, Krizan and Tybout 2021, and Eaton et al. 2022). While initial buyer matches might not always lead to successful trade, those that do persist can have a growing impact on trade flows over time. The magnitude of these initial and long-term effects will ultimately determine the overall dynamic impact of buyer information. To investigate this empirically, we extend our main specification (equation 3) by including lagged values of both new buyer information and control variables up to five periods.

Table 2 presents the estimated coefficients. The results reveal that the effects are strongest one year after receiving buyer information. They then gradually decrease over time but remain positive and statistically significant. This confirms that information takes time to be utilized and suggests it has persistent positive effects beyond the initial impact. Interestingly, these dynamics resemble the exporter-importer pair dynamics observed in Eaton et al. (2021). Furthermore, the coefficients for new buyer information display a distinct pattern compared to the market size variable and its lags, which quickly diminish over time. This contrast adds further weight to the interpretation that our coefficients capture genuine information effects rather than spurious correlations with market conditions.

Concentration and heterogeneous effects across size. We expect the benefits of public information to be greater for smaller exporters. Larger, more productive firms likely already possess a wider network of potential buyers (higher information capacity). For them, publicly provided information may be less novel due to their existing extensive information on customers. Therefore, we hypothesize that the impact of public information on export growth will be stronger for smaller exporters with a limited initial information.

Lacking detailed firm-level export data, we test this by examining whether public information has smaller effects in industries dominated by large firms. We use industry sales concentration in 1980 (the first year of our census data) as a proxy for large firm dominance. This avoids potential endogeneity concerns that might arise if we used current concentration data. The regression equation is:

$$\begin{aligned}\mathtt{EX}_{j,t}^{k} = \exp\big[(\alpha_0 + \alpha_1 \times \mathtt{Concentration}_{1980}^{\tilde{k}(k)} + \alpha_2 \times \mathtt{ExporterFraction}_{1980}^{\tilde{k}(k)}) \times \mathtt{NewBuyerInfo}_{j,t-1}^{k} \\ + \gamma \times \mathtt{ImportSize}_{j,t}^{k} + \delta_j^k + \delta_{j,t} + \delta_t^k + \epsilon_{j,t}^k\big],\end{aligned} \tag{4}$$

where $\mathtt{Concentration}_{1980}^{\tilde{k}(k)}$ and $\mathtt{ExporterFraction}_{1980}^{\tilde{k}(k)}$ represent (export or domestic or total) sales concentration and the fraction of exporters in each industry (both from 1980).

The coefficient of interest α_1 indicates how large firms' dominance affects the buyer information effect. While concentration is informative, it might not fully capture the information capacity of leading firms in different industries. For example, export concentration will be high in less productive industries with few exporters, but those top firms may still have smaller buyer networks compared to firms in more productive industries. To account for these differences, we introduce an interaction term between buyer information and the exporter share (number of exporters divided by firms with positive shipments). This controls for differences in information capacity across industries with similar sales concentration.

Table 3 shows that the estimated coefficients for α_1 are all negative across different measures of concentration, indicating that the dominance of large firms reduces the impact of public information.[8]

One concern is that factors beyond sales concentration might influence this relationship. For instance, Korean industries dominated by large firms often had lower sales and produced more homogeneous products. To address this, we included additional industry-level controls in the regression (Appendix Table A.7), such as capital intensity, total domestic sales, number of firms and exporters, and product differentiation. The estimated coefficient on sales concentration remains stable with these additional controls.

These findings show that industries dominated by large firms experience smaller growth in exports from public information, aligning with the idea of heterogeneous information capacity across firms. Subsection 3.2 further confirms this by showing that industries receiving more public information saw a reduction in export concentration. Together, these results highlight the importance of information capacity heterogeneity in understanding the effects of public information.

Mechanisms of the effects. In Appendix C, we provide additional evidence on the mechanisms of the observed effects. Appendix Tables A.2 and A.3 show that buyer information effects are mainly driven by the intensive margin, with limited effects on the extensive margin (whether Korea

[8]While the estimated effects can be negative for industries with very high sales concentration or very low exporter share (implying negative export increases for some industries), roughly half of all 3-digit KSIC industries exhibit this based on the estimated coefficients. This suggests potential missing mechanisms in the model, such as competition among firms, that could be influencing the results.

Table 3: Impacts of Concentration on the New Buyer Information's Effects

Dep. Variable	(1) Export	(2) Export	(3) Export	(4) Export	(5) Export	(6) Export	(7) Export
$\texttt{NewBuyerInfo}^{k}_{j,t-1}$	0.081***	0.126***	0.072***	0.009	0.084***	0.136***	0.094***
	(0.025)	(0.029)	(0.026)	(0.025)	(0.025)	(0.025)	(0.030)
$\texttt{NewBuyerInfo}^{k}_{j,t-1}$							
$\times\texttt{Top20SalesShare}^{\tilde{k}(k)}_{1980}$	–0.255***						
	(0.031)						
$\times\texttt{Top20ExportShare}^{\tilde{k}(k)}_{1980}$		–0.248***					
		(0.035)					
$\times\texttt{Top20DomesticShare}^{\tilde{k}(k)}_{1980}$			–0.255***				
			(0.045)				
$\times\texttt{HHI}^{k}_{1980}$				–0.422***			
				(0.045)			
$\times\texttt{Top8/Top20Sales}^{\tilde{k}(k)}_{1980}$					–0.186***		
					(0.014)		
$\times\texttt{Top8/Top20Exports}^{\tilde{k}(k)}_{1980}$						–0.224***	
						(0.008)	
$\times\texttt{Top8/Top20Domestic}^{\tilde{k}(k)}_{1980}$							–0.207***
							(0.068)
$\times\texttt{ExporterFraction}^{\tilde{k}(k)}_{1980}$	0.426***	0.343***	0.497***	0.254***	0.298***	0.200***	0.345***
	(0.054)	(0.058)	(0.091)	(0.050)	(0.066)	(0.070)	(0.103)
$\texttt{ImportSize}^{k}_{j,t}$	0.667***	0.670***	0.665***	0.661***	0.661***	0.662***	0.661***
	(0.101)	(0.101)	(0.101)	(0.103)	(0.103)	(0.103)	(0.103)
Observations	207,804	207,804	207,804	207,804	207,804	207,804	207,804
Country-Industry FE	✓	✓	✓	✓	✓	✓	✓
Year-Country FE	✓	✓	✓	✓	✓	✓	✓
Year-Industry FE	✓	✓	✓	✓	✓	✓	✓

Notes: The table reports estimates of the PPML regression equation (4). The dependent variable is the export value at the Year-Country-Industry (4-digit SITC) level. The explanatory variables are the one-period lagged new buyer contacts ($\texttt{NewBuyerInfo}^{k}_{j,t-1}$), including interactions with concentration measures and exporter share. See Section 2.2 for the definition of each concentration measure. The control variable includes the sum of log imports from countries other than Korea ($\texttt{ImportSize}^{k}_{j,t}$). *p<0.1, **p<0.05, ***p<0.01. Standard errors in parenthesis are corrected for arbitrary correlation within country and industry.

started to export at the country-industry level from public information).[9] Additionally, Appendix Table A.4 shows that products described with units and numbers in text experienced quicker and larger export increases from the provided information. This aligns with the idea that improvements in information-communication technology benefit products that are easier to codify using that technology (Juhász and Steinwender 2018). We believe these additional empirical findings support our interpretation of the baseline effects, suggesting that the observed buyer information effects influence exports through information channels rather than other spurious correlations.

3.2. Public Information on Buyers Lowers Export Concentration

Building on the empirical results in Table 3, which showed that higher industry sales concentration (indicating large firm dominance) reduced the effect of buyer information on exports, we further explore the concept of heterogeneous information capacity. Here, we examine the effects of public information on exporters' concentration. If smaller exporters, with their lower information capacity, respond more elastically to public information, the supplied information could decrease exporters' concentration, other things being equal.

Regression specification. We examine the impact of provided information on export concentration in Korean 3-digit KSIC manufacturing industries ($\tilde{k}$) using the following regression model:

$$\begin{aligned}&\Delta \ln \texttt{Top4ExportShare}_t^{\tilde{k}} \quad \text{or} \quad \Delta \ln \texttt{Top4/Top20Exports}_t^{\tilde{k}} \\ &\qquad = \alpha \times \Delta\texttt{NewBuyerInfo}_t^{\text{resid},\tilde{k}} + \gamma \times \Delta \ln \texttt{Top20DomesticShare}_t^{\tilde{k}} + \delta^{\tilde{k}} + \delta_t + \varepsilon_t^{\tilde{k}},\end{aligned} \tag{5}$$

where Δ is the time-difference operator ($\Delta x_t = x_t - x_{t-1}$). The dependent variable is measured by the share of exports by top 4 firms in industry $\tilde{k}$ at time t ($\texttt{Top4ExportShare}_t^{\tilde{k}}$).[10] Additionally, we consider an alternative measure, the export share of the top 4 firms among the top 20 firms in industry $\tilde{k}$ at time t ($\texttt{Top4/Top20Exports}_t^{\tilde{k}}$), corresponding to $N_1 = 4$ and $N_2 = 20$ in equation (2). This alternative measure is relatively independent of the effects of the extensive margin (total number of exporters) on the concentration measure.

The main independent variable, $\Delta\texttt{NewBuyerInfo}_t^{\text{resid},\tilde{k}}$, is the residual new buyer information for industry $\tilde{k}$ at time t, controlling for industry and year effects to isolate the information effect. The coefficient of interest is α, representing the impact of providing public information on changes in export concentration.

In addition to the main regressor ($\Delta\texttt{NewBuyerInfo}_t^{\text{resid},\tilde{k}}$), we include three sets of control vari-

[9] This contrasts with Carballo et al. (2022), who found that information from internet platforms helped Peruvian firms export to more destinations and products. We discuss potential explanations in Appendix C, including differences in data aggregation and the functions of information-communication technologies.

[10] We focus on the top 4 exporters to ensure sufficient variation in exporter concentration over time. In 1980, the median and average number of exporters across KSIC 3-digit industries were 171 and 195, respectively, but the 10th percentile had only 12 exporters. Using a higher number, like the top 8 exporters, would result in some industries having a concentration measure close to 1, with minimal variation over time. However, the qualitative results are similar even when using the top 8 exporters.

ables to account for systematic determinants of exporter concentration unrelated to the information channel: (i) We control for industry-level shocks (e.g., domestic policies, production technology changes) that could affect both domestic and export sales concentration. This is achieved by including the difference of domestic sales concentration measure in log for each KSIC 3-digit industry ($\Delta \ln \texttt{Top20DomesticShare}_t^{\tilde{k}}$).[11] (ii) We include fixed effects for the industry and year. These control for unobserved industry-specific and time-specific factors that might influence export concentration.

Residualized buyer information. In regression equation (5), we employ residuals of buyer information ($\texttt{NewBuyerInfo}^{\text{resid}}$) instead of the raw variable ($\texttt{NewBuyerInfo}$). This helps minimize the effect of spurious relationships between collected information and exporter concentration. For example, an increase in foreign import demand might simultaneously boost information collection (more data) and reduce concentration by enabling more firms to enter the export market. However, this wouldn't reflect the direct impact of information on export behavior.

Precisely, $\texttt{NewBuyerInfo}_t^{\text{resid},\tilde{k}}$ is an export-weighted sum of the residual buyer information. This sum includes all SITC 4-digit industries matched to the KSIC 3-digit industry:

$$\texttt{NewBuyerInfo}_t^{\text{resid},\tilde{k}} \equiv \sum_{j \in D} \sum_{k \in K(\tilde{k})} \left[\left(\frac{\texttt{EX}_{j,t}^k}{\sum_{j \in D} \sum_{k \in K(\tilde{k})} \texttt{EX}_{j,t}^k} \right) \hat{\epsilon}_{j,t}^k \right], \tag{6}$$

where D and $K(\tilde{k})$ represent the set of all destination countries and the set of SITC 4-digit industry k matched to KSIC 3-digit industry $\tilde{k}$, respectively. The residual of buyer information, $\hat{\epsilon}_{j,t}^k$, is what remains of $\texttt{NewBuyerInfo}_{j,t}^k$ after removing the systemic part that can be accounted for by $\texttt{ImportSize}_{j,t}^k$ and fixed effects used in the main regression.

To ensure the residuals effectively capture information not explained by these factors, we regressed them on industry and year fixed effects. None of the resulting coefficients were significant at the 50% level besides one industry (p-value = 0.237), and the overall R-squared was only 0.06. These results suggest minimal influence from industry-specific or time-varying factors on the residuals.

Export participation margin. We also examine whether public information encourages more (non-exporting) firms to start exporting, using similar specifications. Specifically, we use the change of the number of exporters for each KSIC 3-digit manufacturing industry each year as the dependent variable in regression (5).

$$\Delta \ln \texttt{NofExporters}_t^{\tilde{k}} = \alpha \times \Delta \texttt{NewBuyerInfo}_t^{\text{resid},\tilde{k}} + \gamma \times \Delta \ln \texttt{NofFirms}_t^{\tilde{k}} + \delta^{\tilde{k}} + \delta_t + \varepsilon_t^{\tilde{k}}, \tag{7}$$

[11] Firm-level domestic sales are defined by subtracting export shipments from total shipments. Hence, domestic sales and export sales have a spurious correlation, especially when there are measurement errors in export shipments (see Almunia, Antràs, Lopez-Rodriguez and Morales 2021 for a detailed discussion on this issue). Therefore, we use a larger number of firms (20) to minimize the effects of such correlation when calculating domestic concentration.

Table 4: Impacts of Buyer Information on Export Concentration vs Participation

Dep. Variable	(1) $\Delta \ln$ `Top4ExportShare`	(2)	(3) $\Delta \ln$ `Top4/Top20Exports`	(4)	(5) $\Delta \ln$ `NofExporters`	(6)
$\Delta\texttt{NewBuyerInfo}_t^{\text{resid},\tilde{k}}$	-0.037**	-0.042**	-0.044**	-0.047**	-0.009	-0.002
	(0.016)	(0.016)	(0.019)	(0.019)	(0.009)	(0.011)
R-squared	0.019	0.186	0.035	0.142	0.077	0.377
Observations	284	284	284	284	284	284
Controls	✓	✓	✓	✓	✓	✓
Industry FE		✓		✓		✓
Year FE		✓		✓		✓

Notes: Columns (1)–(4) and (5)–(6) report estimates of equations (5) and (7), respectively. The independent variable is the first-difference of residual of buyer information defined as equation (6) ($\Delta\texttt{NewBuyerInfo}^{\text{resid},\tilde{k}}$). The dependent variable in Columns (1) and (2) is the log-difference of the top 4 exporters' share ($\Delta \ln$ `Top4ExportShare`) for each KSIC 3-digit industry. The dependent variable in Columns (3) and (4) is the log-difference of the top 4 exporters' share among top 20 firms ($\Delta \ln$ `Top4/Top20Exports`). The dependent variable in Columns (5) and (6) is the log-difference of the number of exporters ($\Delta \ln$ `NofExporters`) . Columns (1)–(4) control for the log-difference of the domestic sales share of the top 20 firms. Columns (5) and (6) control for the first difference of the logged number of firms and its one-year lagged value. *p<0.1, **p<0.05, ***p<0.01. Standard errors in parenthesis are corrected for arbitrary correlation within KSIC 3-digit industry.

In this regression, we control for the number of firms, instead of domestic concentration, as in the previous regression from a similar motivation. Similarly, the effect of providing public information on the number of exporters can be inferred from the estimated coefficients for α_l.

Regression results. Table 4 summarizes the findings on how public information affected export sales concentration (intensive margin) and firm entry into exporting (extensive margin). The first four columns show the results for export concentration. The estimated coefficients on the current period $\Delta\texttt{NewBuyerInfo}_t^{\text{resid},\tilde{k}}$ are statistically significant and negative, indicating that increases in the provided information are associated with larger decreases in exporters' concentration compared to the previous year. These coefficients become more stable and precisely estimated after adding fixed effects, further validating the use of residuals to mitigate spurious correlations. These findings, along with the earlier results showing a link between lower information capacity (higher sales concentration) and weaker buyer information effects, provide strong support for the heterogeneity in information capacity across firms.

The last two columns investigate whether public information induces more (non-exporting) firms to start exporting. While the estimated coefficients for $\Delta\texttt{NewBuyerInfo}_t^{\text{resid},\tilde{k}}$ are generally positive, they are not statistically significant. Therefore, the focus of the following discussion and model will be on the intensive margin of incumbent exporters, examining how information provision affects their export performance.

4. A Trade Model with Buyer Search and Public Information

To understand the underlying mechanisms of Section 3's findings, we build a buyer search trade model with public information.[12] The model focuses on the intensive margin of export decisions, where high-productivity firms can choose to gather more information and export to a larger pool of buyers. The model highlights how search frictions hinder exports, contribute to export concentration, and how TPOs' information provision mitigate these frictions, reducing concentration. In Section 6, we will utilize the model to quantify these effects.

4.1. Search and Matching

Firms seek buyers to sell their single product in a foreign market. The market has a fixed number (mass) of potential buyers, denoted by M. Each period, each buyer participates in the market a certain number of times, denoted by $1 + \zeta \geq 1$. The firm allocates search effort (S) to increase the chances of buyers finding their product. This effort has a constant marginal cost, where one unit of effort requires $1/\psi$ units of labor. Firms cannot buy or sell information about buyers to each other.

During each participation, buyers are randomly exposed to the firm's product. The visibility of the product is determined by the ratio of the firm's search effort to the total number of buyer participations, i.e., $S/[(1 + \zeta)M]$. If a buyer encounters the product at least once during their searches, the firm can sell to them. Then, this matching process follows a binomial distribution with the number of trial $1 + \zeta$ and a success probability per trial of $S/[(1 + \zeta)M]$. Additionally, we assume that additional matches beyond the first do not increase the buyer's demand for the product.

This model captures the key aspects of uncertainty and information frictions in the search process. The parameter ζ serves as a key indicator of search frictions. The expected number of matches a buyer has with the product depends on the firm's search effort relative to the total number of buyers (S/M), regardless of ζ. However, higher ζ values mean that buyers need to participate more frequently due to a lower chance of encountering a specific product. As a result, the uncertainty in the search process increases with ζ, as reflected by the growing variance of the binomial distribution. This greater uncertainty intensifies search frictions, requiring buyers to participate more often (higher ζ) to achieve the same level of exposure. Additionally, the matching probability $S/[(1 + \zeta)M]$ provides another perspective. Higher values of ζ decrease the matching probability, indicating more severe search frictions and greater challenges for firms in efficiently connecting with potential buyers.

The probability that a buyer does not get any successful matches to a given seller at all is $[1 - s/(1 + \zeta)]^{1+\zeta}$. Thus, the number of buyers matched to a firm, given that the firm chooses

[12] Additionally, we introduce endogenous information provision of TPOs into the model in Appendix D.

$s = S/M$ as its search efforts, is $B = b(s)M$, where $b(s)$ is the fraction of matched buyers:

$$b(s) = 1 - \left(1 - \frac{s}{1+\zeta}\right)^{1+\zeta} \times \mathbb{1}_{\{s \le 1+\zeta\}}, \tag{8}$$

where $\mathbb{1}_{\{\cdot\}}$ is an indicator function. If $s \le 1+\zeta$, $\mathbb{1}_{\{s\le 1+\zeta\}} = 1$. Otherwise ($s > 1+\zeta$), $\mathbb{1}_{\{s\le 1+\zeta\}} = 0$. The fraction of matched buyers is an increasing and concave function of search efforts for $0 \le s \le 1+\zeta$. Rearranging the equation, we get the labor needed to reach a fraction b of potential M buyers:

$$c(b, M) = \frac{1+\zeta}{\psi}\left[1 - (1-b)^{\frac{1}{1+\zeta}}\right] M. \tag{9}$$

Interestingly, $b(s)$ shares the formula with the generalized Pareto distribution with a negative shape parameter, $-(1+\zeta)^{-1}$, a zero location parameter, and a unit scale parameters.[13] Entropy, a measure of the average level of information/uncertainty inherent to the possible outcomes, relates to buyer search frictions in our model. The entropy of this generalized Pareto distribution is $\mathrm{H} = \zeta/(1+\zeta)$, increasing with ζ. When $\zeta = 0$ and $\zeta \to \infty$, the entropy is $\mathrm{H} = 0$ and $\mathrm{H} \to 1$, respectively. Hence, the larger frictions in our search process can also be interpreted as higher entropy in the resulting outcomes.

4.2. Information Intermediary and Public Information

Now consider a case where a TPO collects and publicly provides contacts of a fraction ι of foreign buyers (in the following discussion, called *informed buyers*). In the previous empirical setup, (potential) exporters could identify buyers' contacts who are interested in importing their products from the provided public information. To incorporate it into our search process, we set ζ as zero for these *informed buyers* since a firm already knows about these buyers' contacts and their interests in its product. Setting $\zeta = 0$ in equation (9), the marginal labor required to approach an additional informed buyer is $1/\psi$. Note that for any given b, the requirement of labor $c(b, M)$ in search always increases with ζ, and thereby $c(b, M) > bM/\psi$ when $\zeta > 0$. Hence, a firm first reaches out to the informed buyers, ιM, with a low marginal cost and then expands its search to the buyers without public information, $(1-\iota)M$.

Given M and ι, a firm needs to employ the following amount of labor to get matched to a b fraction of buyers.

$$c(b, M|\iota;\zeta) = \frac{1+\zeta}{\psi}\left\{(1-\iota)\left[1 - \left(\frac{1-b}{1-\iota}\right)^{\frac{1}{1+\zeta}}\right] + \iota\right\} M \times \mathbb{1}_{\{b>\iota\}} + \frac{1}{\psi} bM \times \mathbb{1}_{\{b\le\iota\}} \tag{10}$$

The search cost is an increasing and convex function in the fraction of matched buyers, b; $f_b(b, M|\iota) > 0$ and $f_{bb}(b, M|\iota) \ge 0$ for $b \in [0, 1]$. In other words, the marginal buyer search efficiency/productivity

[13] The generalized Pareto distribution with zero location parameter, unit scale parameter, and $-(1+\zeta)^{-1}$ shape parameter has a support $[0, (1+\zeta)^{-1}]$. The generalized Pareto random variable z with shape parameter $-(1+\zeta)^{-1}$ can be generated by $z \sim (1+\zeta)v$ or $z \sim \zeta(1-u^{1/(1+\zeta)})$, where $v \sim \mathrm{beta}(1, (1+\zeta)^{-1})$ and $u \sim \mathrm{uniform}(0, 1)$.

decreases with a firm's fraction of buyer matches. Also, note that public information decreases a firm's cost of searching a given fraction of buyers ($c(b, M|\iota) \geq c(b, M|\iota'), \forall b, M$ when $\iota < \iota'$).

4.3. Other Environments

In the following discussion, we explore the effects of the information provided by KOTRA to Korean firms. Since the source country is always Korea, we omit the subscript for the sourcing country for notational simplicity. Also, we assume that Korea is a small open economy, so that the public information provided by the TPO does not affect the foreign countries' aggregate variables. Since each firm operates within a single industry, and the firm's export decisions are independent across different destinations, we omit the industry (k), destination (j), and origin (i) indices when their omission does not lead to confusion.

Production technology. Production is identical to the standard trade model with constant marginal costs. Each firm ϕ in source country produces a variety within an industry, using a constant return to scale production. Labor (l) is the only production factor, and its price is w. Firm ϕ requires $1/\phi$ units of labor to produce one unit of its variety. There are the standard iceberg costs that delivering one unit of a product from source country to destination country requires τ units of the goods to be produced and shipped. Also, the firm productivity distribution follows the Pareto distribution with a cumulative distribution and probability density functions $F(\phi) = 1 - (\underline{\phi}/\phi)^{\theta}$ and $f(\phi) = \theta(\underline{\phi}/\phi)^{\theta}/\phi$, respectively, where $\underline{\phi}$ is the minimum of the support.

Preference and Demand. Each industry in each destination country has a continuum of buyers dealing with varieties within the industry, and their mass is denoted by M. We assume that they are homogeneous, and they equally divide the market. Also, each buyer that sells the final good in the perfectly competitive market, aggregates intermediate goods (varieties of product) produced with the constant ($\sigma > 1$) elasticity of substitution across varieties. If exporter ϕ is successfully matched with $b(\phi)M$ buyers, the total effective demand at the destination equals the sum of the demand from the fraction of buyers reached.

4.4. Firm's Problem and Decision

Given public information on a fraction ι of buyers provided by the TPO, a Korean firm with productivity ϕ maximizes its profit by choosing the optimal price (p), quantity (q), and fraction (b) of buyers to reach:

$$\pi(p, q, b; \phi|\iota) = \max_{p,q,b} \; pq - w\tau\left(\frac{q}{\phi}\right) - wc(b, M|\iota), \quad \text{subject to } pq = b\left(\frac{p}{P}\right)^{1-\sigma} Q,$$

where Q and P are the destination's aggregate market demand and price index.

The first-order condition with respect to price gives us the standard markup rule: $\mu = \sigma/(\sigma - 1)$. To the reached buyers, the firm charges the same price: $p(\phi) = \mu\tau w/\phi$. The optimal buyer fraction,

b, reached by firm ϕ can be characterized by the following first-order condition:

$$\pi^{\text{operation}}(\phi) = w\frac{\partial c(b, M|\iota)}{\partial b} = \frac{w}{\psi}M\left\{\left(\frac{1-b}{1-\iota}\right)^{-(1+1/\zeta)^{-1}} \times \mathbb{1}_{\{b>\iota\}} + \mathbb{1}_{\{b\leq\iota\}}\right\}, \tag{11}$$

where $\pi^{\text{operation}}(\phi)$ represents the operating profit per reached consumer (the profit net of the production labor cost, excluding search costs $w \times c(b, M|\iota)$). The first-order condition requires a firm to choose b such that the increase in operating profit from securing an additional buyer (left-hand side of the equation) is equivalent to the marginal cost of reaching her (right-hand side of the equation). Note that the marginal cost stays constant until the buyer fraction reaches ι. However, the left-hand side strictly increases with productivity but does not depend on the level of b, as the operating profit increases linearly with the fraction of reached buyers. Consequently, there is a productivity cutoff ensuring that the operating profit matches the constant marginal cost of wM/ψ when $b \leq \iota$. The cutoff can be calculated by setting the operating profit equal to the constant marginal cost of wM/ψ:

$$\pi^{\text{operation}}(\phi^*) = \frac{1}{\sigma}\left(\mu\frac{\tau w}{\phi^*}\right)^{1-\sigma} QP^{1-\sigma} = \frac{w}{\psi}M \quad \Leftrightarrow \quad \phi^* = \left(\frac{\sigma}{\psi}\frac{wM}{Q}\right)^{\frac{1}{\sigma-1}}\left(\frac{\mu\tau w}{P}\right) \tag{12}$$

Firms with productivity above the cutoff will make additional search efforts to reach buyers beyond those informed by the TPO. In other words, they will target a fraction of buyers greater than ι. In contrast, firms with lower productivity will opt not to search or export. For this reason, the cutoff serves as the entry cutoff. Note that the entry cutoff does not depend on the provided information, ι. Thus, in a partial equilibrium setup, the provided buyer information only affects the incumbent exporters but does not induce new entry.

5. The Model Mechanisms and Predictions

This section studies our theoretical model's predictions and mechanisms. We focus on how information provision by TPOs influences firm decisions and market outcomes: (i) How do search frictions and access to public information affect a firm's search intensity, export decisions, and ultimately, its export performance? (ii) How do these firm-level decisions translate into aggregate exports and export concentration (the distribution of exports across firms)? By answering these questions, we aim to explain how the model's predictions align with the observed effects of information provision on exports and concentration (Section 3). It's important to note that our analysis relies on the assumption that Korea is a small open economy, implying the TPO's information has a negligible impact on the destination country's market.

5.1. Firm-Level Behavior: Buyer Search and Export Performance

Firm's search under frictions. With public information on a fraction ι of foreign buyers provided by the TPO, a firm chooses the optimal level of search efforts by solving a maximization problem (details in equation 11). This optimization determines the optimal fraction of buyers the firm reaches (matched buyers) as follows:

$$b(\phi|\iota;\zeta) = \max\left\{1-(1-\iota)\times \mathrm{g}(\phi;\zeta), 0\right\}, \quad \text{where} \quad \mathrm{g}(\phi;\zeta) = (\phi/\phi^*)^{-(\sigma-1)(1+1/\zeta)}. \tag{13}$$

The proportion of unmatched buyers, $\mathrm{g}(\phi;\zeta)$, is less than one and decreases with productivity ϕ when $\phi > \phi^*$ and $\zeta > 0$.

Firms with productivity below a cutoff (ϕ^*) choose not to search at all, resulting in zero matched buyers. For firms with productivity above the cutoff, higher productivity incentivizes them to search more intensively and secure matches with a larger fraction of buyers because they can generate more profits from each buyer they reach. This is formalized in the following equation:

$$\frac{\partial b(\phi|\iota;\zeta)}{\partial \phi} = -(1-\iota)\mathrm{g}_\phi(\phi;\zeta) > 0 \quad \text{if} \quad \phi > \phi^*, \quad \zeta > 0, \quad \text{and} \quad \iota < 1, \tag{14}$$

where $\mathrm{g}_\phi(\phi;\zeta) = \partial \mathrm{g}(\phi;\zeta)/\partial\phi < 0$ is the partial derivative of the proportion of unmatched buyers with respect to productivity.

Note that equation (13) can be written as $b(\phi|\iota;\zeta) = \iota + [1-\mathrm{g}(\phi;\zeta)] \times (1-\iota)$. It allows an intuitive interpretation in the sense that a firm reaches ι fraction of buyers for certain, and it search buyers among $1-\iota$ fraction of uninformed buyers with matching probability $1-\mathrm{g}(\phi;\zeta)$.[14] Without the known buyers from public information ($\iota = 0$), the expression boils down to $b(\phi|0;\zeta) = \max\{1-\mathrm{g}(\phi;\zeta), 0\}$.

The term $\mathrm{g}(\phi;\zeta)$ represents the relative reduction in the fraction of buyers a firm can reach compared to a scenario without search frictions. Its value reflects the trade-off between marginal changes in profits and search costs. When a firm's productivity increases, the potential profit also rises due to the CES demand assumption (represented by $\sigma - 1$). Higher profit incentivizes reaching more buyers. However, the marginal search cost also increases (at a rate of $(1+1/\zeta)^{-1}$). Firms with different productivity levels decide on the optimal fraction of matched buyers (or equivalently, the fraction of unreached buyers) by comparing these two rates, resulting in the power term of $\mathrm{g}(\phi;\zeta)$, $(\sigma-1)(1+1/\zeta)$. For example, lower search frictions (lower ζ) lead to slower increases in marginal search costs. As a result, a given profit increase from higher productivity translates into a larger increase in the share of matched buyers. This implies that the fraction of unreached buyers decreases faster with lower search frictions.

When the TPO provides overseas buyer contacts ($\iota > 0$), the optimal fraction of reached buyers increases for each firm by the term $[\mathrm{g}(\phi;\zeta)] \times \iota$. However, the magnitude of this increase diminishes

[14] This formulation will cause the buyers informed from the provided information to have a bigger number of contacted sellers than other buyers. Hence, the assumption that Korea is a small open economy is necessary.

with the firm's productivity:

$$\frac{\partial b(\phi|\iota;\zeta)}{\partial \iota} = \mathrm{g}(\phi;\zeta) > 0 \quad \text{and} \quad \frac{\partial}{\partial \phi}\left[\frac{\partial b(\phi|\iota;\zeta)}{\partial \iota}\right] = \mathrm{g}_\phi(\phi;\zeta) < 0 \quad \text{if} \quad \phi > \phi^* \quad \text{and} \quad \zeta > 0, \tag{15}$$

where the entry cutoff (ϕ^*) is independent of both the matching inefficiency (ζ) and the public information (ι).

The intuition behind these results is straightforward. Even without public information, more productive firms would have been more likely to find buyers due to their higher search intensity. However, public information eliminates search friction for informed buyers, guaranteeing a match. Consequently, the impact of public information is less pronounced for highly productive firms since they would have likely reached these buyers anyway.

Firm's exports under search frictions. We now explore how search frictions and public information provision from TPOs influence a firm's export sales. A firm's exports with information provided by a TPO (fraction ι) are $\mathrm{ex}(\phi|\iota;\zeta) = b(\phi|\iota;\zeta)[p(\phi)/P]^{1-\sigma}\lambda Y$. This expression incorporates the optimal fraction of reached buyers ($b(\phi|\iota;\zeta)$) from equation (13):

$$\mathrm{ex}(\phi|\iota;\zeta) = \big[1 - (1-\iota)\mathrm{g}(\phi;\zeta)\big] \times \overline{\mathrm{ex}}(\phi) \times \mathbb{1}_{\{\phi \geq \phi^*\}}, \tag{16}$$

where $\overline{\mathrm{ex}}(\phi) = \sigma(w/\psi)(\phi/\phi^*)^{\sigma-1}M$ is equal to $\mathrm{ex}(\phi|\iota;0)$, which represents firm ϕ's export value in a scenario without search frictions $\zeta = 0$. This frictionless scenario aligns with the conventional model described in Melitz (2003).

Equation (16) highlights how search frictions (ζ) deter exports, while public information (ι) promotes them. Compared to the frictionless case, search frictions reduce exports by a factor of $(1-\iota)\mathrm{g}(\phi;\zeta)$. Firms connect with an ι fraction of buyers known through public information but fail to connect with a $\mathrm{g}(\phi;\zeta)$ fraction of unidentified buyers due to search difficulties. When there's no public information ($\iota = 0$), the expression reflects the total export reduction caused by search frictions. Conversely, with full information provision ($\iota = 1$), firm exports reach their frictionless level $\mathrm{ex}(\phi|1;\zeta) = \overline{\mathrm{ex}}(\phi)$.

Importantly, the export increases from information provision come from selling to more buyers, not selling more to each buyer. The percentage increase in exports due to information matches the percentage increase in matched buyers:

$$\frac{\partial \ln \mathrm{ex}(\phi|\iota;\zeta)}{\partial \iota} = \frac{\partial \ln b(\phi|\iota;\zeta)}{\partial \iota} = \frac{\mathrm{g}(\phi;\zeta)}{1-(1-\iota)\mathrm{g}(\phi;\zeta)} > 0 \quad \text{if} \quad \phi > \phi^* \quad \text{and} \quad \zeta > 0. \tag{17}$$

However, larger firms experience a smaller percentage increase in exports due to diminishing returns from improved search efficiency. While the absolute increase in exports might still be larger for high-productivity firms due to their higher baseline exports, the relative benefit (percentage increase) diminishes with firm size.

$$\frac{\partial^2 \ln \text{ex}(\phi|\iota;\zeta)}{\partial\phi\partial\iota} = \frac{\text{g}_\phi(\phi;\zeta)}{[1-(1-\iota)\text{g}(\phi;\zeta)]^2} < 0 \quad \text{if} \quad \phi > \phi^* \quad \text{and} \quad \zeta > 0. \tag{18}$$

Additionally, it can be shown that bigger firms experience smaller increases in exports in absolute terms compared to smaller firms.[15] This is because the fraction of unmatched buyers from a firm's search, $\text{g}(\phi;\zeta)$, decreases with productivity at a higher rate ($(\sigma-1)(1+1/\zeta)$) than the rate of increase in per-buyer exports ($\sigma - 1$). Therefore, the increases in firm-level exports in the absolute term, which is a product of the fraction of unmatched buyers and per-buyer exports, are smaller for larger firms than smaller firms.

Higher search inefficiency (ζ) leads to lower exports compared to the frictionless scenario (equation 19). The higher the cost of finding buyers, the fewer buyers a firm can reach. This directly results in a proportional decrease in export value.

$$\frac{\partial \ln \text{ex}(\phi|\iota;\zeta)}{\partial\zeta} = \frac{\partial \ln b(\phi|\iota;\zeta)}{\partial\zeta} = -\frac{(1-\iota)\text{g}_\zeta(\phi;\zeta)}{1-(1-\iota)\text{g}(\phi;\zeta)} < 0 \quad \text{if} \quad \phi > \phi^* \quad \text{and} \quad \zeta > 0, \tag{19}$$

where $\text{g}_\zeta(\phi;\zeta) = \partial\text{g}(\phi;\zeta)/\partial\zeta > 0$ is the partial derivative of $\text{g}_\zeta(\phi;\zeta)$ with search friction parameter.

Lastly, we have assumed that the TPO provides buyer information free of charge to encourage exports. Now, suppose firms must pay a price to acquire this information (ι). In this scenario, highly productive firms might opt not to purchase the provided information. This can be shown by noting that the value of this information to firm ϕ is the increased profits from additional exports:

$$\text{ex}(\phi|\iota;\zeta) - \text{ex}(\phi|0;\zeta) = \text{g}(\phi;\zeta) \times \overline{\text{ex}}(\phi) \times \iota \quad \text{if} \quad \phi > \phi^*, \tag{20}$$

which decreases with a firm's productivity. Therefore, if there is a cost associated with using this information, firms with productivity above a certain level will not choose not to use it. This prediction aligns with empirical findings in trade literature that suggest smaller firms are more likely to export through trading intermediaries when fixed costs of intermediary services exist (e.g., Ahn, Khandelwal and Wei 2011).

5.2. Market-Level Outcomes: Export and Concentration

Aggregate exports. In equilibrium, the total industry exports to a market are the sum of sales from all exporters:

$$\text{EX}(\iota;\zeta) = J \times \int_{\phi^*}^{\infty} \text{ex}(\phi|\iota;\zeta)\text{d}F(\phi) = [1-(1-\iota)\mathsf{G}(\zeta)]\,\overline{\text{EX}}, \tag{21}$$

[15] In absolute terms, $\partial\text{ex}(\phi|\iota;\zeta)/\partial\iota = \text{g}(\phi;\zeta)\overline{\text{ex}}(\phi) > 0$ and $\partial^2\text{ex}(\phi|\iota;\zeta)/(\partial\phi\partial\iota) = \overline{\text{ex}}(\phi) \times \text{g}_\phi(\phi;\zeta)/(1+\zeta) < 0$ if $\phi > \phi^*$ and $\zeta > 0$.

where J is the measure of potential entrants, and $\overline{\mathrm{EX}}$ is the total exports of the standard model without search frictions ($\overline{\mathrm{EX}} = \mathrm{EX}(\iota; \zeta = 0)$; Melitz 2003) in which the fixed cost of exporting is given as (w/ψ) and so that the same set of exporters export, but to all buyers in destination.[16] In the above equation, $\mathsf{G}(\zeta)$ captures how search frictions reduce aggregate exports:

$$\mathsf{G}(\zeta) = \frac{\overline{\mathrm{EX}} - \mathrm{EX}(0;\zeta)}{\overline{\mathrm{EX}}} = \frac{\theta - (\sigma - 1)}{\theta + (\sigma - 1)/\zeta} \geq 0. \tag{22}$$

This ratio reflects the total percentage decrease in exports due to search frictions when no public information is available ($\iota = 0$), compared to the frictionless case. As expected, this decrease ($\mathsf{G}(\zeta)$) increases with search frictions (ζ) because higher search costs lead firms to reach fewer buyers. Consequently, total exports decrease as search frictions increase (ζ and $\iota < 1$):

$$\frac{\partial \ln \mathrm{EX}(\iota;\zeta)}{\partial \zeta} = -\frac{(1-\iota)[\partial \mathsf{G}(\zeta)/\partial \zeta]}{1 - (1-\iota)\mathsf{G}(\zeta)} < 0, \tag{23}$$

where $\partial \mathsf{G}(\zeta)/\partial \zeta > 0$ is the partial derivative of the percentage export reduction with respect to search frictions.[17]

Public Information provided by TPOs (ι) can mitigate the export losses caused by search frictions. In the best-case scenario, when TPOs connect exporters with all buyers ($\iota = 1$), they can achieve the frictionless export level ($\mathrm{EX}(1;\zeta) = \overline{\mathrm{EX}}$) as described in Melitz (2003). For $\zeta > 0$, provided information promotes aggregate exports as follows.[18]

$$\frac{\partial \ln \mathrm{EX}(\iota;\zeta)}{\partial \iota} = \frac{\mathsf{G}(\zeta)}{1 - (1-\iota)\mathsf{G}(\zeta)} > 0. \tag{24}$$

The positive effect of information provision on aggregate exports is amplified with a higher shape parameter (θ) of the Pareto distribution of firm productivity (indicating a thinner right tail). However, it weakens with a higher elasticity of substitution (σ) across varieties (implying less differentiated products or equivalently high price elasticity).

$$\frac{\partial^2 \ln \mathrm{EX}(\iota;\zeta)}{\partial \theta \partial \iota} = \frac{[\partial \mathsf{G}(\zeta)/\partial \theta]}{[1 - (1-\iota)\mathsf{G}(\zeta)]^2} > 0 \quad \text{and} \quad \frac{\partial^2 \ln \mathrm{EX}(\iota;\zeta)}{\partial (\sigma - 1) \partial \iota} = \frac{[\partial \mathsf{G}(\zeta)/\partial \sigma]}{[1 - (1-\iota)\mathsf{G}(\zeta)]^2} < 0, \tag{25}$$

where $\partial \mathsf{G}(\zeta)/\partial \theta > 0$ and $\partial \mathsf{G}(\zeta)/\partial \sigma < 0$. Because the smaller shape parameter and the higher elasticity of substitution imply more concentrated sales distribution (fewer firms with a larger share of the market), the above model prediction in equation (25) indicates that high concentration of firms dampens export promotion from provided public information by the TPO. This aligns with the findings from the reduced-form regression presented in Table 3 of Section 3.

[16] The total exports without search frictions is $\overline{\mathrm{EX}} = J \times \int_{\phi^*}^{\infty} \overline{\mathrm{ex}}(\phi) \mathrm{d}F(\phi) = J \times [1 - F(\phi^*)](\sigma w/\psi)M/[1 - (\sigma - 1)/\theta]$.

[17] This also holds in the level of aggregate exports: $\partial \mathrm{EX}(\iota;\zeta)/\partial \zeta = -(1-\iota)\overline{\mathrm{EX}} \times \mathsf{G}'(\zeta) < 0$.

[18] This also holds in the level of aggregate exports: $\partial \mathrm{EX}(\iota;\zeta)/\partial \iota = \overline{\mathrm{EX}} \times \mathsf{G}(\zeta) > 0$.

Export concentration. Our model shows that under search frictions, more productive firms connect with more buyers (equation 14). Therefore, combined with their higher per-buyer exports, this leads to increased export concentration compared to a frictionless scenario. Search frictions disproportionately reduce the matched buyer fraction for smaller firms, leading to increased concentration. In contrast, information provision proportionally boosts exports more for smaller firms (equation 18), reducing concentration, as shown in our data analysis (Table 4 in Section 3).

We introduce expressions for exporters' concentration and illustrate how search frictions and public information influence concentration as expected. Here, we use the export sales share of the top N firms (e.g., Autor, Dorn, Katz, Patterson and Van Reenen 2020) as a measure of concentration. In our model where firms export under search frictions, potentially facilitated by public information from TPOes, the share of the top N exporters' sales to a particular country within a specific industry can be defined as:

$$\mathrm{C}(N|\iota;\zeta) \equiv \frac{\int_{\phi^N}^{\infty} \mathrm{ex}(\phi|\iota;\zeta)\mathrm{d}F(\phi)}{\int_{\phi^*}^{\infty} \mathrm{ex}(\phi|\iota;\zeta)\mathrm{d}F(\phi)} = \left\{ \frac{1-(1-\iota)\mathsf{G}(\zeta)[\overline{\mathrm{C}}(N)]^{\frac{1}{\mathsf{G}(\zeta)}-1}}{1-(1-\iota)\mathsf{G}(\zeta)} \right\} \overline{\mathrm{C}}(N) \geq \overline{\mathrm{C}}(N), \tag{26}$$

where $\phi^N = \underline{\phi}(J/N)^{1/\theta}$ is the productivity cut-off for the top N (mass) firms, which ensures that $J \times [1-F(\phi^N)] = N$.[19] Here, $\underline{\phi}$ is the minimum productivity level for exporting and J is the total number of potential entrants. Furthermore, $\overline{\mathrm{C}}(N) = (\phi^N/\phi^*)^{-[\theta-(\sigma-1)]}$ is the concentration level corresponding to the standard model without search frictions (Melitz 2003). Similar to the discussion on aggregate exports, when there are no search frictions or all buyers' information is provided ($\mathrm{C}(N|\iota;0)$ or $\mathrm{C}(N|1;\zeta)$, respectively), every exporter reaches all buyers, so the concentration equals the standard model.

As shown in equation (18), the positive impact of public information provision on an individual firm's exports decreases with its size (productivity). Therefore, the share of smaller exporters expands, but the share of larger exporters shrinks, implying a less concentrated export market share.

$$\frac{\partial \mathrm{C}(N|\iota;\zeta)}{\partial \iota} = -\left\{ \frac{1-[\overline{\mathrm{C}}(N)]^{\frac{1}{\mathsf{G}(\zeta)}}}{[1-(1-\iota)\mathsf{G}(\zeta)]^2} \right\} \mathsf{G}(\zeta)\overline{\mathrm{C}}(N) < 0 \tag{27}$$

This prediction is consistent with our empirical findings reported in Appendix C.3.2. Industries with increased public information on buyers experienced reduced export concentration.

To measure the role of search frictions in export concentration, we introduce the percentage point (pp) decrease in export concentration due to search frictions without any public information, compared to exports without search frictions as in equation (22):

$$\mathrm{C}(N|0;\zeta) - \overline{\mathrm{C}}(N) = \left\{ \frac{1-[\overline{\mathrm{C}}(N)]^{\frac{1}{\mathsf{G}(\zeta)}-1}}{\frac{1}{\mathsf{G}(\zeta)}-1} \right\} \overline{\mathrm{C}}(N), \tag{28}$$

[19] In the following discussion, we focus on the case where N is chosen small enough so that these top N firms all export to the given destination (i.e., $\phi^N > \phi^*$).

which is increasing in ζ because $\mathsf{G}'(\zeta) > 0$ and $\overline{\mathrm{C}}(N) < 1$. This increase in export concentration grows with the increase in search frictions, ζ, as higher search frictions affect small firms' exports more intensively. The large value of the measure implies that search frictions can account for the observed severe export concentration in previous literature for the U.S. and European economies as well as in Korean data.

6. Quantification of Search Frictions

Building upon the theoretical framework, we demonstrate how to leverage the expressions for export flows and concentration to estimate hypothetical levels of exports and export concentration under different information scenarios, including a frictionless case. This method requires only data on information collected by TPOs and aggregate export data. By eliminating the need for separate estimates of the various model parameters, particularly the often-challenging search friction parameter, our approach offers a straightforward way to quantify the impact of search frictions and information provision on exports and concentration.

6.1. Sufficient Statistics Approach

The aggregate export equation (21) illustrates the impact of provided information on exports. It can be used to determine the reduction in exports resulting from search frictions ($\mathsf{G}(\zeta)$). However, as shown in equation (22), $\mathsf{G}(\zeta)$ is a nonlinear function of the productivity Pareto shape parameter (θ), the demand substitution parameter (σ), and the degree of search frictions (ζ). Estimating these parameters directly is challenging.

To overcome this challenge, we utilize the semi-elasticity (β) of total exports relative to the share of the provided buyer information, where $\beta = \mathsf{G}/[1-(1-\iota)\mathsf{G}]$ in equation (24). The semi-elasticity can be estimated from data on information collected by KOTRA and Korea's exports. The estimated value of β can then be used to calculate the total export reduction from search frictions as follows:

$$\mathsf{G} = \frac{\beta}{(1-\iota)\beta+1} \in \left[\frac{\beta}{\beta+1}, \beta\right], \quad \text{where} \quad \beta \equiv \frac{\partial \ln \mathrm{EX}(\iota;\zeta)}{\partial \iota}. \tag{29}$$

In equation (29), a high semi-elasticity value indicates a significant reduction in exports, which in turn represents high search frictions in international trade.

Furthermore, the elasticity can also be used to compute the counterfactual level of export concentration under different information scenarios. Specifically, by using the observed level of exporter concentration from our data ($\mathrm{C}(N|\iota;\zeta)$) and the estimated value of β from the previous steps, we can compute the concentration level without search frictions ($\overline{\mathrm{C}}(N)$) from its non-linear equation derived from equations (26) and (29): $\mathrm{C}(N|\iota;\zeta) = \langle 1+(1-\iota)\beta\{1-[\overline{\mathrm{C}}(N)]^{\frac{1}{\beta}-\iota}\}\rangle\overline{\mathrm{C}}(N)$. Then, we can calculate the excess export concentration due to search frictions using the equation (28):

$$\mathrm{C}(N|0;\zeta) - \overline{\mathrm{C}}(N) = \beta\left\{1-[\overline{\mathrm{C}}(N)]^{\frac{1}{\beta}}\right\}\overline{\mathrm{C}}(N). \tag{30}$$

6.2. Estimation of Semi-Elasticity

We estimate the semi-elasticity (β). Unlike the previous regression (equation 3), the main regressor is the fraction of foreign buyers with known information from KOTRA ($\texttt{BuyerInfoFraction}^k_{j,t}$, equivalently, ι in the model) instead of the absolute number of newly informed buyers ($\texttt{NewBuyerInfo}^k_{j,t}$). The regression equation is:

$$\mathrm{EX}^k_{j,t} = \exp\left[\beta \times \texttt{BuyerInfoFraction}^k_{j,t-1} + \gamma \times \texttt{ImportSize}^k_{j,t} + \delta^k_j + \delta_{j,t} + \delta^k_t + \epsilon^k_{j,t}\right], \tag{31}$$

where β captures the proportional change in exports due to a change in the share of informed buyers.

The fraction of informed buyers is defined as $\texttt{BuyerInfoFraction}^k_{j,t} = \iota^k_{j,t} = I^k_{j,t}/M^k_{j,t}$, which requires information on both the numbers of active buyers known by KOTRA's information up to year t ($I^k_{j,t}$) and the total number of buyers ($M^k_{j,t}$) for each destination-industry-year triplets. Since such detailed data is unavailable, we construct proxies for each variable.

Since detailed data on total buyers is unavailable, we estimate it using import data. We assume the number of buyers increases with the size of imports from other countries (excluding Korea) for each country-industry-year as follows:

$$M^k_{j,t} = \left[\sum_{i \neq \text{Korea}} \mathrm{EX}^k_{j,t}(i)\right]^\eta, \tag{32}$$

where $\sum_{i\neq\text{Korea}} \mathrm{EX}^k_{j,t}(i)$ is the import of country j for industry k in year t from all sourcing countries other than Korea.[20] We estimate the elasticity η from the exporters' side using Exporter Dynamics Database (EDD) from the World Bank, which covers exporters from up to 70 countries obtained from customs agencies. Since most of the exporters are importers at the same time and vice versa (Bernard, Jensen and Schott 2009 and Amiti, Itskhoki and Konings 2014), looking at the exporters in EDD can help estimate the elasticity. Specifically, we regress the log number of exporters on the log total exports (in thousands of U.S. dollars) at the country-HS4d-year level. The estimated coefficient is highly precise, and it alone can explain a large portion (54.6%) of the variation in the log number of exporters within and across countries.[21] The estimated coefficient from EDD is

[20] The exclusion of Korean exports is justifiable under the small country assumption, which is empirically validated for Korea during the late 1970s and 1980s. This approach helps minimize the endogeneity issue that arises because our outcome variable is Korea's exports. Including imports from Korea could introduce a bias into our results, as these exports directly influence the size of the buyer base.

[21] However, since total imports are computed from the data by a multiplication of the number of firms and the mean exports of firms, the explained variation of exporter numbers by the total exports could be overstated. Alternatively, indicators for each country and each industry (or indicators for each pair of country and industry) can explain 71% (96%) of the variation.

0.2166 (the standard error clustered at country and industry is 0.0005).[22] With this estimate of η, we use equation (32) to compute the buyer mass at each country-industry-year triple.[23]

Our data includes information on newly collected buyer information, but not updates on buyer activity. Some of the buyers previously informed through public information may no longer be active. To address this issue, we construct the stock of informed active buyers ($I_{j,t}^k \in (0, M_{j,t}^k]$) by applying an exogenous buyer exit rate $\varphi \in [0, 1]$ to the information collected over time.

$$I_{j,t}^k = \sum_{l=0}^{t-1977} (1-\varphi)^l \times \texttt{NewBuyerInfo}_{j,t-l}^k, \tag{33}$$

where $(1-\varphi)^l$ represents the survival rates of buyers after l years. The higher the exit rate, the faster the depreciation of the informed buyer information stock. Since our historical public information only extends back to 1977, we lack data prior to this year. Hence, we drop the samples from the first five years starting in 1977 to minimize bias in the construction of $\texttt{BuyerInfoFraction}_{j,t-1}^k$ for the earlier years of the sample.

Lastly, we compute the fraction of informed buyer contacts by dividing the number of active buyer contacts by the estimated total mass of importers (equation. 33).[24]

6.3. Estimation Results and Quantification

This subsection leverages the estimated semi-elasticity parameter to quantify the impact of search frictions on both total export reductions and exporter concentration. This parameter captures the percentage change in exports due to a one-unit change in the share of buyer information provided by the TPO (KOTRA), holding all other factors constant. We begin by estimating the semi-elasticity (β) in equation (31). The fraction of informed buyers from public information (ι), constructed in Section 6.2, serves as the key explanatory variable.

Estimated semi-elasticity. Table 5 shows the estimated semi-elasticity parameter (β) for various buyer exit rate ($\varphi = 0.2$). The estimates are ranging from 0.56 to 0.69 across different specifications. For example, even after introducing additional control variables, incorporating more detailed fixed effects, or selecting a different initial year (to account for missing public information before 1977), the estimates remain stable. Figure 3 (blue circles) depicts these estimates visually across different $\varphi \in \{0.1, 0.2, \cdots, 1\}$, robustness is further confirmed by Figure A.5, which shows the estimates

[22] Appendix D explores an alternative method to estimate η using import data and buyer information. This method involves solving an optimization problem for an export promotion agency aiming to maximize export growth with a budget constraint. The solution determines the optimal information collection level for each country-industry pair, considering factors like the number of buyers. We then compute η by comparing the predicted information collection from this model with the actual data. The resulting estimate (0.1932) is smaller but aligns with the estimates from the main analysis.

[23] The mean and median of the computed buyer mass are 6.44 and 5.42, respectively. Also, the maximum value is 56.33.

[24] We assign one to ι for destination-industry-year triples where the count of buyer information is larger than the computed mass of buyers.

Table 5: Estimated Semi-elasticity Parameters

Dep. Variable	(1) Export	(2) Export	(3) Export	(4) Export	(5) Export
$\texttt{BuyerInfoFraction}^k_{j,t-1}$(i.e., $\iota^k_{j,t-1}$)	0.685***	0.672***	0.705***	0.560***	0.657***
	(0.159)	(0.140)	(0.173)	(0.171)	(0.196)
$\texttt{ImportSize}^k_{j,t}$	0.610***	0.531***	0.712***	0.903***	0.652***
	(0.094)	(0.077)	(0.087)	(0.126)	(0.085)
IHS($\texttt{EX}^k_{j,t-1}$)		0.157***			
		(0.021)			
Observations	119,101	119,101	100,502	70,269	85,400
Initial Sample Year	1983	1983	1983	1983	1986
Country-Industry FE	✓	✓	✓	✓	✓
Year-Country FE	✓	✓			✓
Year-Industry FE	✓	✓	✓	✓	✓
Year-Country-SITC2d FE			✓		
Year-Country-SITC3d FE				✓	

Notes: The table reports estimates from the PPML regression equation (31). The dependent variable is the export value at the Country-Industry(4-digit SITC)-Year level. The explanatory variables are the lagged value of the fraction of informed buyers from public information ($\iota^k_{j,t-1}$). For constructing the buyer information fraction, we follow the approach detailed in Section 6.2, specifically setting $\delta = 0.2$. Control variables include the sum of log imports from the rest of the world for each Destination Country-Industry (4-digit SITC) Year ($\texttt{ImportSize}^k_{j,t}$) in all columns. Columns (2) to (4) additionally include the IHS transformed Korea's lagged export value (IHS($\texttt{EX}^k_{j,t-1}$)), Year-Country-SITC2d fixed effects, and Year-Country-SITC3d fixed effects, respectively. Column (5) repeats the baseline specification in Column (1), but restricts the samples to those from 1986. *p<0.1, **p<0.05, ***p<0.01. Standard errors in parenthesis are corrected for arbitrary correlation within country and industry.

remain relatively consistent across different specifications. The estimates are around 0.7, ranging between 0.55 and 0.79 across different φ values.

Therefore, we use 0.7 as the baseline value of the semi-elasticity parameter and additionally consider two other values, 0.5 and 0.9, representing low and high search friction scenarios, respectively. A high semi-elasticity (β) value indicates a significant reduction (G) in exports, which in turn represents high search frictions in international trade.

Quantitative result I: Export reductions. The fraction of informed buyers from a TPO (ι) is crucial in connecting the estimated semi-elasticity parameter to the reduction in trade due to search frictions (G). When public information covers all foreign buyers, the estimated semi-elasticity directly translates to the upper bound of trade reduction caused by search frictions, i.e., $\lim_{\iota \to 1} \mathsf{G} = \beta$. However, as the coverage of public information decreases, the reduction in trade from search frictions also decreases for a given semi-elasticity parameter. This is because with less publicly available buyer information, firms lose access to a larger share of potential buyers, leading to a smaller reduction in trade compared to a scenario with complete information. In the extreme case without any public information, trade reduction is $\lim_{\iota \to 0} \mathsf{G} = \beta/(1+\beta)$. Red squares in Figure 3 represent these lower bounds of G which are estimated to be around 0.4, consistently

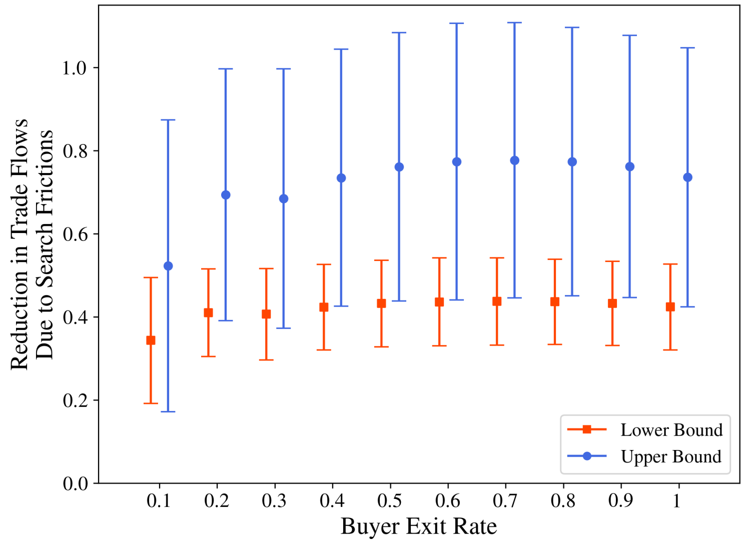

Figure 3: Impact of Search Frictions on Trade Flow Reductions

Notes: The figure reports estimates of the lower bound ($\beta/(1+\beta)$) and upper bound (β) of the reduction in trade from search frictions relative to the frictionless case (G) along with their 95% confidence intervals. These are derived from PPML regression estimates of β from PPML regression based on equation (31). Standard errors in parenthesis are corrected for arbitrary correlation within country and industry. The dependent variable in this analysis is the export value at the Country-Industry (4-digit SITC)-Year level. The explanatory variable is the lagged fraction of informed buyers from public information ($\iota^k_{j,t-1}$), constructed with various values of buyer exit rates (φ).

rejecting the null hypothesis that search frictions have no negative effects on trade flows.

The buyer information fractions in our data are generally small. For instance, when the buyer exit rate is 20%, the median and average ι used in the regression are 0% and 3.8%, respectively. Because these buyer information fractions are close to zero, the estimated lower bound of 0.4 is close to the actual value of G.[25] This finding suggests that without public information, exports under search frictions are approximately 40% lower compared to a frictionless scenario, where all current exporters have access to all buyers as in standard trade models. Additionally, equation (24) indicates that a one percentage point increase in ι at the median and average ι in the data can boost exports by about 0.67% and 0.65%, respectively.

Quantitative result II: Export concentration. Next, we quantify the impact of search frictions on exporters' concentration using the export share of the top 4 exporters as a measure. Equation (28) is used to calculate the increases in the top 4 exporters' share due to search frictions for each 3-digit KSIC manufacturing industry. For each industry, we leverage the observed level of concentration and the fraction of informed buyers from public information, averaged over the sample period (1983–1990). Figure 4 summarizes the percentage point (pp) increases in exporters' concentration across different industries. The left panel plots these increases in concentration against the observed

[25]There is variation across KSIC 3-digit manufacturing industries; the 10th and 90th percentiles of the average ι across these industries are 0.6% and 7.3%. However, using these values in equation (29) with the baseline estimate of $\beta = 0.7$ yields very similar values of G, 0.412 and 0.425.

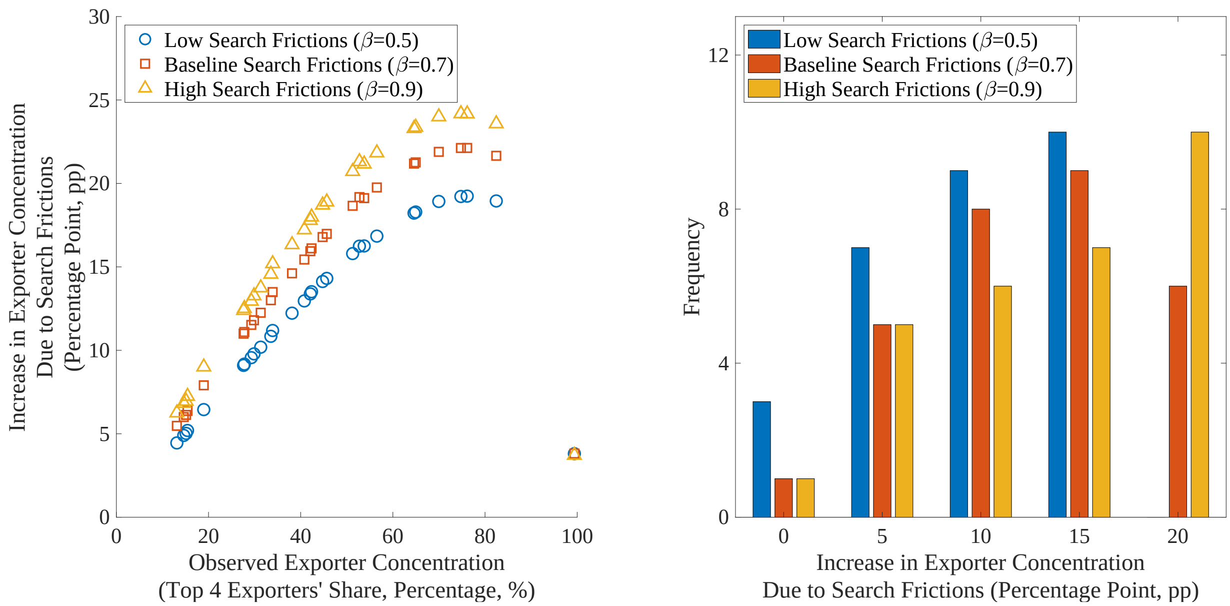

Figure 4: Impact of Search Frictions on Exporters' Concentration

Note: The figure illustrates the effects of search frictions on the export share of the top-4 exporters. The increase in exporters' concentration is calculated using equation (28) for each KSIC 3-digit industry. For each industry, the observed top-4 exporters' export share and the fraction of informed buyers, averaged over the sample period (1983–1990), are used for the calculation. The left panel shows a histogram of this increase in exporters' concentration, measured in percentage points, across 29 manufacturing KSIC 3-digit industries. The right panel presents a scatter plot of the increase in exporter concentration against the observed level of concentration. Each point represents a KSIC 3-digit manufacturing industry. Blue, red, and yellow indicate calculations assuming low, baseline, and high search frictions, respectively, with semi-elasticity parameter β values of 0.5, 0.7, and 0.9.

level of concentration for each industry. At the baseline search friction (red dots), the median and average increases in the top 4 exporters' export share due to search frictions are 16.5pp and 14.6pp, respectively. This translates to a roughly 40% increase compared to the median observed top 4 share of 42.1%. Furthermore, this increase in export concentration rises with the level of search frictions: at a higher level of search frictions, the median and average increases in concentration are 18.4pp and 16.2pp, while at a lower level, they are 13.9pp and 12.4pp. (Appendix Figure A.6 shows the results as a percentage (%) increase, i.e., $100 \times [\mathrm{C}(4|0;\zeta)/\bar{\mathrm{C}}(4) - 1]$.)

For example, consider an industry with the median top 4 exporters' share ($\mathrm{C}(4|\iota;\zeta)$=42.1%) and median average fraction (ι=3.1%). Without search frictions, the hypothetical concentration would be 26.8%. However, with search frictions but no public information (i.e., $\iota = 0$), the concentration jumps to 42.7%. This implies that search frictions contribute to a 15.9pp increase in concentration, while public information can mitigate this effect by a small but positive 0.6pp increase. These findings are further illustrated in Appendix Figure A.7 for each industry.

These results suggest that search frictions significantly contribute to the observed concentration of exporters. Previous empirical literature, such as Mayer and Ottaviano (2008), Antràs and Yeaple (2014), and Bernard et al. (2018b), documents that exports are highly concentrated among superstar and global firms in the U.S. and European countries. Our findings align with this literature, indicating that search frictions are one of the mechanisms driving high export concentration.

7. Conclusion

Information is typically unobserved and difficult to separate from overall market fluctuations. To overcome this challenge, we leverage a unique data advantage: information on foreign buyers gathered by a Korean TPO (KOTRA). This allows us to isolate the impact of information provision from general market fluctuations. Leveraging this unique data advantage, this paper investigated how difficulty finding foreign buyers (search frictions) hinders exports and how public information from a TPO. Our regression analysis shows that search frictions were a major barrier for Korean firms. Public information on foreign buyers, provided by KOTRA, significantly boosted Korean exports. This effect was especially strong for smaller exporters, who benefited more from the information.

To rationalize these observations, we extend the conventional search model by incorporating publicly provided information. In this model, firms adjust their search efforts based on the information. Public information helps firms find more buyers, especially smaller firms who face greater search frictions. This leads to a less concentrated export market overall. Our model also provide a straightforward sufficient statistics approach to estimate the impact of search frictions on trade flows without needing extensive data and estimation. Using this approach, we estimate that search frictions reduce international trade by about 40%. Furthermore, the model suggests that public information can increase the export share of the top four exporters by 15 percentage points. These results highlight the importance of policies that promote public access to public information for the economy.

Extrapolating from the specific context of foreign buyer information, our findings offer insights for today's data-driven economies. In an environment where large firms often monopolize various types of data (e.g., big data on language usage and customer behavior), policies facilitating public access to data and information have the potential to significantly benefit the economy. Such policies equip firms, especially small and medium-sized ones, with crucial information and data, fostering growth and reducing overall economic concentration.

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Appendix

A. Data

A.1. Data Processing for New Buyer Information

For each inquiry, we extract the information on countries and inquired items from the sampled pages and match it to country codes and SITC 2nd revision codes at the 4-digit level to merge the extracted new buyer information data with bilateral trade flow data. There are two main difficulties in digitizing the buyer information from the magazine. The first is for a machine to recognize the table structure. While recent developments in Computer Vision (and its application in Economics, such as Layout Parser, e.g., Shen, Zhang, Dell, Lee, Carlson and Li 2021) can facilitate this process with higher accuracy, they did not perform well for the tables in my sample. So instead, we manually label table regions for all the sampled magazines.

We extract items in each row and column from the labeled tables using a heuristic algorithm that distinguishes rows and columns. The next problem arises from the step of matching inquired items to the known SITC codes. For instance, the inquired items from the first row in Figure 2, "Shovels, Locks, Padloocks", should be matched to the SITC 4-digit code 6951 (Interchangeable tools for hand or machine tools (tips, blades, etc.), 6991 (Locksmiths wares, safes, etc, and hardware, nes, of base metal), and 6991, respectively.[26][27] To do so, we calculate the text-based similarity between each inquired item and the description for each SITC code from UNSD. we pick the SITC code with the highest similarity score to be the matched industry for the inquired item. To be specific, we use a keyword search method after normalizing words.[28] For instance, after the normalization, the example items become shovel, lock, and padlock, respectively. Then, we count the number of occurrences for each normalized word in each SITC 4-digit description.[29] Since the word "padlock" is only used by two SITC codes, 6991 and 69911 (Padlocks and locks (key, combination, etc.), clasps and frames with clasps and locks, of base metal; keys for the foregoing articles, of base metal; which is a subcategory of 6991), the calculated similarity is the highest for 6991. In case an inquired item consists of more than one word, we use weights from the TF-IDF (Term Frequency-Inverse Document Frequency) method, which is essentially a system that gives higher weights to words that have higher power at distinguishing different SITC codes. Also, when an inquired item has the same similarity score for more than one SITC code, we use a cosine similarity measure calculated

[26] Note that some of the inquired items contain typographical errors. For instance, "Padloocks" is a typographical error of padlock. we use multiple spelling checker Python packages to correct them.

[27] In this case, we add one to the buyer information count at the corresponding level (Kenya, 1981, 6951) and two to (Kenya, 1981, 6991). Alternatively, we also try a different counting method (set method). When a buyer inquired N products (N>1) from the same SITC-4digit code in the same year, the set method converts buyer information count to be one instead of N. For instance, the set method adds one to (Kenya, 1981, 6991) instead of two, in this case.

[28] To be specific, we delete stop words, correct potentially misspelled words, and use lemmatization.

[29] Each SITC 4-digit description contains the descriptions of 5-digit SITC codes that belong to the same 4-digit STIC code, so that the description has a bigger number of keywords relevant to the 4-digit industry.

from word embedding to break the tie.[30]

A.2. Bilateral trade data

We use the NBER-United Nations Trade Data from the Center for International Data (Feenstra et al., 2005). The data contains bilateral trade flows by commodity (SITC 4-digit, second revision) between 1962 and 2000, with values greater than $100,000. The dataset prioritizes the trade flows reported by importers.

A.3. Data merge process

We create the final dataset by merging trade flow data with buyer information collected by KOTRA. The result is an unbalanced panel that includes South Korea's export values and collected buyer information counts for each destination industry (SITC 4-digit) from 1977 to 1990. We begin with a balanced panel that includes all possible destination-SITC-year observations.[31] We then merge the trade and buyer information data into this panel.

However, for some destinations, the trade flow data is missing for entire years. For instance, Afghanistan does not have any 4-digit SITC observations on imports from South Korea between 1982 and 1983. We drop these country-year observations because it is unclear whether they represent missing data or actual zero trade flows. Apart from such cases, we fill missing observations for both trade flow and buyer information with zeros, interpreting them as zero trade flows and no collected buyer information from KOTRA. As a result, the final dataset has 1,374,714 observations, with most values being zeros for trade flow (92.3%) or buyer information (98.7%) over the sample years.

[30] We used the word embedding provided by spaCy, which is an open-source software library for advanced natural language processing (Honnibal and Montani 2017). In this specific setup, we find that a keyword search method works better at pinning down a more detailed industry level, while word embedding can be better at distinguishing among broadly defined industries by considering the semantic similarity of all words used in each SITC code description, not just a keyword alone. In the economics literature, Hoberg and Phillips (2016) used word count based cosine similarity to measure similarity between products.

[31] There are 188 countries that have reported import values from South Korea for at least one year, and there are 786 4-digit industries. Therefore, the total number of possible destination-industry-year combinations is 2,068,752 ($= 188 \times 786 \times 14$)

B. Formal Analysis on New Buyer Information

To formally investigate these relationships, we regress the collected information on standard variables in the gravity equation of trade literature. The gravity equation highlights that bilateral trade flows increase with market sizes and decrease with geographic distance. Table A.1 compares how these variables are correlated with the collected information and South Korea's exports. We utilize destination j's variables such as GDP growth ($\ln \texttt{GDP}_{j,t}$), the first difference in the GDP deflator ($\Delta \ln \texttt{Deflator}_{j,t}$), distance from Korea ($\ln \texttt{Distance}_{j,t}$) in logs, and the sum of log imports from the rest of the world excluding South Korea ($\texttt{ImportSize}^k_{j,t} = 0.01 \times \sum_{i \neq \text{Korea}} \ln \texttt{EX}^k_{j,t}(i)$) for each destination-industry-year triple as independent variables.

Table A.1: Gravity Regressions For the New Buyer Information and Exports

Dep. Variable	(1) New Buyer Info	(2)	(3) IHS(New Buyer Info)	(4) Export	(5)	(6) IHS(Export)
$\ln \texttt{GDP}_{j,t}$	0.216***			0.577***		
	(0.047)			(0.099)		
$\Delta \ln \texttt{Deflator}_{j,t}$	0.337			-2.035		
	(0.218)			(1.607)		
$\ln \texttt{Distance}_j$	0.065			-0.689***		
	(0.215)			(0.155)		
$\texttt{ImportSize}^k_{j,t}$	0.260***	0.096	0.003	0.553***	0.606***	1.648***
	(0.098)	(0.093)	(0.005)	(0.083)	(0.112)	(0.111)
Regression	PPML	PPML	OLS	PPML	PPML	OLS
Observations	461,587	45,833	455,757	461,587	155,042	455,757
(Pseudo) R-squared	0.115	0.384	0.423	0.539	0.968	0.781
Other controls	✓			✓		
Year FE	✓			✓		
Country-Industry FE		✓	✓		✓	✓
Year-Country FE		✓	✓		✓	✓
Year-Industry FE		✓	✓		✓	✓

Notes: The table examines the correlation of standard gravity equation variables with both the collected information and exports. The dependent variables are the collected buyer information (Columns 1 and 2) and its inverse hyperbolic sine (IHS) transformed value (Column 3), as well as export values (Columns 4 and 5) and their IHS transformed values at the Country-Industry (4-digit SITC) year level. The explanatory variables include log GDP ($\ln \texttt{GDP}_{j,t}$), inflation measured by the first difference of the GDP deflator ($\Delta \ln \texttt{Deflator}_{j,t}$), and the log distance from South Korea ($\ln \texttt{Distance}_j$). Other controls consist of indicators for each language and product classification as outlined in Rauch (1999). The GDP and GDP deflator data are sourced from World Bank Data. For the PPML specification, pseudo R-squared values are reported. *p<0.1, **p<0.05, ***p<0.01. The standard errors in parentheses are adjusted for arbitrary correlation within country and industry.

Comparing Column (1) of Table A.1 with Column (4), the collected buyer information increases with market size, similar to exports. However, the adverse effects of distance are less clear, confirming that market size was the primary determinant of the amount of collected information, aligning with findings from Figure 1.[32] Nevertheless, two notable differences emerge in how these variables correlate with the collected information and exports. First, the correlation between market size and collected information becomes unclear after controlling for detailed fixed effects (Columns 2 and 3), while it remains clear for exports (Columns 5 and 6). Second, even after adding high-dimensional fixed effects, these variables can explain less than half of the variation in collected information, in contrast to exports, where their variation is well-explained by these factors. These results are robust to using the Poisson pseudo-maximum likelihood (PPML) estimator or using the inverse hyperbolic sine (IHS) transformed values with OLS. These differences suggest that the search was not highly responsive to changes in market conditions and further support the notion that the search was more of an untargeted process.

[32]This provides additional validation for our buyer information construction process, including digitization and the assignment of SITC industry classifications, especially as the market size of each industry ($\texttt{ImportSize}^{k}_{j,t}$) exhibits a clear correlation with the collected information.

C. Mechanisms of the Effects of Section 3

In this section, we discuss additional empirical findings that shed light on the mechanisms behind the observed effects. First, we distinguish between the intensive and extensive margins. The estimated effects from the baseline models in the main text include both the intensive margin and the extensive margin. To analyze these margins separately, we repeat the baseline specifications in Section 3 in the following ways.

To explore the intensive margin, we restrict the samples to those with positive trade flows and use the same baseline specifications as in equation (3). For the extensive margin, we define $\mathbb{1}_{\{\texttt{EX}^k_{j,t}>0\}}$ as an indicator variable that takes the value of one when the export value of industry k to destination country j in year t is positive. We use the following linear probability model to examine whether public information helped South Korean firms export new products to new destinations:

$$\mathbb{1}_{\{\texttt{EX}^k_{j,t}>0\}} = \alpha^{ext} \times \texttt{NewBuyerInfo}^k_{j,t-l} + \gamma^{ext} \times \texttt{ImportSize}^k_{j,t-l} + \delta^k_j + \delta_{j,t} + \delta^k_t + \epsilon^k_{j,t}. \tag{A1}$$

Additionally, we investigate the dynamic effects of public information on the extensive margin by replacing the dependent variable in the main text specification with this indicator:

$$\mathbb{1}_{\{\texttt{EX}^k_{j,t}>0\}} = \sum_{l=0}^{5} \alpha^{ext}_l \times \texttt{NewBuyerInfo}^k_{j,t-l} + \sum_{l=0}^{5} \gamma^{ext}_l \times \texttt{ImportSize}^k_{j,t-l} + \delta^k_j + \delta_{j,t} + \delta^k_t + \epsilon^k_{j,t}. \tag{A2}$$

The parameters of interest are α^{ext}_l, which represent the effect of the l-th lagged new buyer information count on the extensive margin.

Table A.2 shows the estimated effects on both the intensive and extensive margins. We observe clear effects on the intensive margin but not on the extensive margin. The first two columns present the intensive margin effects from the PPML and OLS estimators, showing clear positive effects. The first column, which uses the same baseline specification as the main text, shows that the estimated coefficient for the intensive margin is very close to the estimated coefficient for total effects in Table 1. In contrast, column (3) shows that public information did not have economically or statistically significant effects on the extensive margin.

Table A.3 shows the dynamic effects on the intensive and extensive margins. The first column shows clear positive dynamic effects on the intensive margin. In contrast, the dynamic effects on the extensive margin in Column (2) are small and statistically insignificant. However, we observe some positive effects on the extensive margin for homogeneous products. The last three columns repeat equation (A2), but split the samples into three groups: homogeneous, reference-priced, and differentiated goods, using the product classification by Rauch (1999). For homogeneous products, we observe positive dynamic effects on the extensive margin. These effects seem to peak later than those on the intensive margin.

Similarly, Carballo et al. (2022) find that buyer information provided by internet platforms increases firm-level exports. However, there are some differences in the mechanisms of the effect.

Table A.2: Impacts of Buyer Information on Exports (Intensive and Extensive Margin)

	(1)	(2)	(3)
Method	PPML	OLS	OLS
Dep. Variable	Export	ln(Export)	$\mathbb{1}_{[\text{Export}>0]}$
$\texttt{NewBuyerInfo}^k_{j,t-1}$	0.044***	0.028***	-0.000
	(0.006)	(0.008)	(0.002)
$\texttt{ImportSize}^k_{j,t}$	0.508***	1.040***	0.226***
	(0.088)	(0.086)	(0.014)
Samples	Export>0	Export>0	All
Observations	99,265	99,265	707,985
R-squared		0.877	0.671
Country-Industry FE	✓	✓	✓
Year-Country FE	✓	✓	✓
Year-Industry FE	✓	✓	✓

Notes: The dependent variables in Columns (1)–(3) are the export value at the Country-Industry (4-digit SITC)-Year level, its log value, and an indicator for positive trade, respectively. The explanatory variables are the one-period lagged buyer information count ($\texttt{NewBuyerInfo}^k_{j,t-1}$) and the sum of log imports from countries other than South Korea at Destination Country-Industry (4-digit SITC)-Year ($\texttt{ImportSize}^k_{j,t}$). *p<0.1, **p<0.05, ***p<0.01. Standard errors in parenthesis are corrected for arbitrary correlation within country and industry.

Unlike our findings, Carballo et al. (2022) find that the effects are stronger at the extensive margin (i.e., an increase in the number of products and destinations). Several factors may explain these differences. First, some firm-level extensive margins could be captured as intensive margins in this paper since products within the same SITC 4-digit industry and buyers in the same destination are not distinguishable in our trade data. Additionally, since Carballo et al. (2022) use data from the 2010s, advancements in communication technology, such as the Internet, may have made it easier for exporters to reach new destinations and export new products. Lastly, the trade data in this paper omits trade flows below $100,000, potentially underestimating the extensive margin effect. If an exporter manages to export a new product to a new destination but the export value is below this threshold, the data may not capture this change.

Carballo et al. (2022) also find that the effects of informational internet platforms are stronger for differentiated products. One interpretation of this discrepancy is that exporting a new product to a new destination requires significant information exchange. Exporting new differentiated products typically requires more information than just buyer contacts, since they can vary among multiple dimensions such as style and function. While internet platforms facilitate the exchange of detailed information, our medium, a relatively short description of import demand, may not be flexible or fast enough to exchange detailed information. Therefore, the effects might be stronger for homogeneous products, which require less product customization but benefit more from knowing foreign buyers. This result suggests that the medium of information may also be important in affecting trade flows.

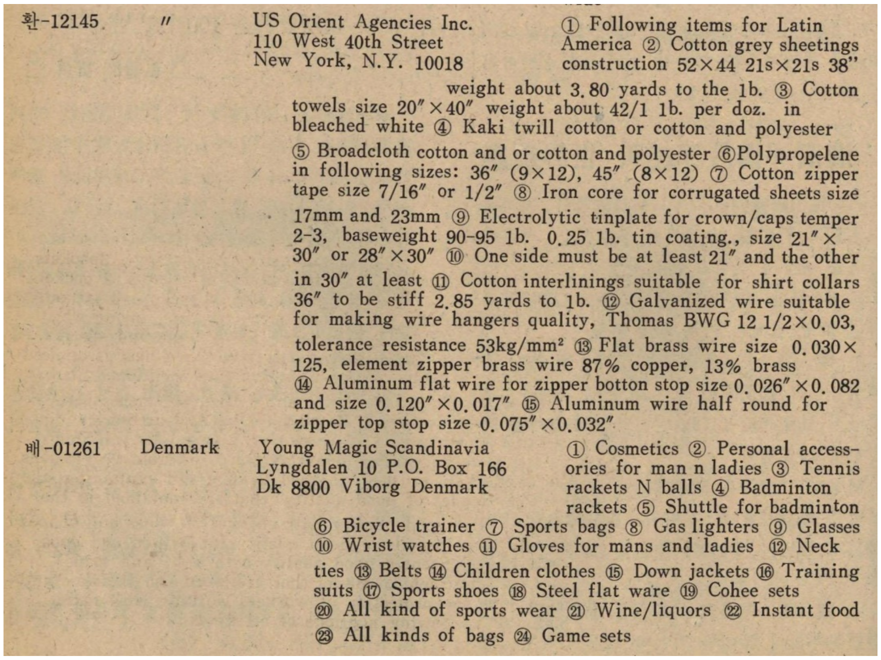
Table A.3: Dynamic Impacts New Buyer Information on Exports

	(1)	(2)	(3)	(4)	(5)
Method	PPML	OLS	OLS	OLS	OLS
Dep. Variable	Export	$\mathbb{1}_{\{\text{Export}>0\}}$	$\mathbb{1}_{\{\text{Export}>0\}}$	$\mathbb{1}_{\{\text{Export}>0\}}$	$\mathbb{1}_{\{\text{Export}>0\}}$
$\texttt{NewBuyerInfo}^k_{j,t}$	0.015**	-0.002	-0.015	-0.015	-0.001
	(0.007)	(0.003)	(0.013)	(0.010)	(0.003)
$\texttt{NewBuyerInfo}^k_{j,t-1}$	0.043***	0.001	0.004	-0.003	0.001
	(0.013)	(0.003)	(0.015)	(0.011)	(0.003)
$\texttt{NewBuyerInfo}^k_{j,t-2}$	0.041***	0.004	0.012	-0.008	0.003
	(0.013)	(0.003)	(0.011)	(0.012)	(0.002)
$\texttt{NewBuyerInfo}^k_{j,t-3}$	0.033***	0.002	0.033**	0.001	0.000
	(0.010)	(0.003)	(0.015)	(0.006)	(0.003)
$\texttt{NewBuyerInfo}^k_{j,t-4}$	0.027***	0.005	0.030*	-0.001	0.005
	(0.005)	(0.004)	(0.018)	(0.007)	(0.004)
$\texttt{NewBuyerInfo}^k_{j,t-5}$	0.026***	0.002	0.012	-0.008*	0.003
	(0.008)	(0.004)	(0.015)	(0.005)	(0.004)
Samples	Export>0	All	Homogeneous	Ref. Priced	Differentiated
Observations	34,998	189,007	18,445	51,246	103,813
R-squared		0.777	0.653	0.766	0.782
Country-Industry FE	✓	✓	✓	✓	✓
Year-Country FE	✓	✓	✓	✓	✓
Year-Industry FE	✓	✓	✓	✓	✓

Notes: The table reports PPML estimates of equation (3) with lagged values using samples with positive trade flows (Column 1) and OLS estimates of equation (A2) (Columns 2–5). The dependent variables are the export value at the Country-Industry (4-digit SITC)-Year level (Column 1) and an indicator for positive trade flows (Columns 2–5). The explanatory variables are the counts of new buyer contacts (`NewBuyerInfo`) and their lagged values up to 5 years. The control variables are the sum of log imports from the rest of the world for each Destination Country-Industry (4-digit SITC) Year (`ImportSize`) and their lagged values up to 5 years. The estimated coefficients on these controls are omitted to save space. Columns (3)–(5) report OLS estimates of equation (A2) with samples restricted to homogeneous, reference-priced, and differentiated products, following the product classification by Rauch (1999). *p<0.1, **p<0.05, ***p<0.01. Standard errors in parenthesis are corrected for arbitrary correlation within country and product.

Motivated by this, we explore a slightly different dimension of product type as well. Juhász and Steinwender (2018) argue that the effects of information and communication technology on trade depend on the technology-specific codifiability of the product. They show that the telegraph network had a larger effect on the trade of products that were more codifiable with words, using the 19th-century cotton textile industry. Since KOTRA's buyer information also took the form of text-based information, the effect of buyer information could be greater for products that are more codifiable with words and numbers.

For instance, in Figure A.1, the first inquiry is from a buyer in the US who wanted to import standardized goods such as cotton and wires, which can be more easily described with words and numbers. Compared to the first inquiry, the items from the second inquiry are much harder to describe in text format since they are differentiated in multiple dimensions, such as design and function. Upon receiving the buyer information, it would be quicker and easier for an exporter to handle the inquired products from the first inquiry. Even among the goods classified as


환-12145 〃 US Orient Agencies Inc. 110 West 40th Street New York, N.Y. 10018 ① Following items for Latin America ② Cotton grey sheetings construction 52×44 21s×21s 38" weight about 3.80 yards to the 1b. ③ Cotton towels size 20″×40″ weight about 42/1 1b. per doz. in bleached white ④ Kaki twill cotton or cotton and polyester ⑤ Broadcloth cotton and or cotton and polyester ⑥Polypropelene in following sizes: 36″ (9×12), 45″ (8×12) ⑦ Cotton zipper tape size 7/16″ or 1/2″ ⑧ Iron core for corrugated sheets size 17mm and 23mm ⑨ Electrolytic tinplate for crown/caps temper 2-3, baseweight 90-95 1b. 0.25 1b. tin coating., size 21″× 30″ or 28″×30″ ⑩ One side must be at least 21″ and the other in 30″ at least ⑪ Cotton interlinings suitable for shirt collars 36″ to be stiff 2.85 yards to 1b. ⑫ Galvanized wire suitable for making wire hangers quality, Thomas BWG 12 1/2×0.03, tolerance resistance 53kg/mm² ⑬ Flat brass wire size 0.030× 125, element zipper brass wire 87% copper, 13% brass ⑭ Aluminum flat wire for zipper botton stop size 0.026″×0.082 and size 0.120″×0.017″ ⑮ Aluminum wire half round for zipper top stop size 0.075″×0.032″

배-01261 Denmark Young Magic Scandinavia Lyngdalen 10 P.O. Box 166 Dk 8800 Viborg Denmark ① Cosmetics ② Personal accessories for man n ladies ③ Tennis rackets N balls ④ Badminton rackets ⑤ Shuttle for badminton ⑥ Bicycle trainer ⑦ Sports bags ⑧ Gas lighters ⑨ Glasses ⑩ Wrist watches ⑪ Gloves for mans and ladies ⑫ Neck ties ⑬ Belts ⑭ Children clothes ⑮ Down jackets ⑯ Training suits ⑰ Sports shoes ⑱ Steel flat ware ⑲ Cohee sets ⑳ All kind of sports wear ㉑ Wine/liquors ㉒ Instant food ㉓ All kinds of bags ㉔ Game sets

Figure A.1: An Example of Inquiries on Homogeneous and Differentiated Goods

differentiated in Rauch's classification, there might be heterogeneity in their level of codifiability.

Therefore, we measure codifiability for each buyer contact based on whether a description of the inquired item contains units, such as inches or kilograms, and numbers. To investigate whether more codifiable buyer information has larger effects on trade flows, we estimate the following specification:

$$\mathtt{EX}^k_{j,t} = \exp\Bigg[\sum_{l=0,1}\alpha^{NQ}_l \times \mathtt{NewBuyerInfo}^k_{j,t-l} + \sum_{l=0,1}\alpha^{Q}_l \times \mathtt{QuantNewBuyerInfo}^k_{j,t-l} + \sum_{l=0,1}\gamma_l \times \mathtt{ImportSize}^k_{j,t-l} + \delta^k_j + \delta_{j,t} + \delta^k_t + \epsilon^k_{j,t}\Bigg], \tag{A3}$$

where $\mathtt{QuantNewBuyerInfo}^k_{j,t}$ is the number of new buyer contacts whose descriptions contain units or have numbers making up more than 5% of the total characters. If α^Q_l is positive, it indicates that buyer information on more codifiable products has an additional effect on exports compared to other products. Additionally, a positive α^Q_0 suggests that buyer information on codifiable products also increased exports more quickly.

The results from Table A.4 support this idea. Column (1) shows that the effects of buyer information that contains units or more numbers are quicker and bigger. Column (2) shows that these differences are larger and statistically more significant for differentiated goods. This suggests that among differentiated goods, those described with numbers and extra information are more likely to result in quicker exports. One potential explanation is that since differentiated goods are less codifiable on average, the codifiability or additional numerical information has more

Table A.4: Codifiability and Impacts of Buyer Information on Exports

Dep. Variable	(1) Export	(2) Export
$\texttt{NewBuyerInfo}^k_{j,t}$	0.029***	0.027***
	(0.008)	(0.007)
$\texttt{NewBuyerInfo}^k_{j,t-1}$	0.046***	0.050***
	(0.009)	(0.010)
$\texttt{QuantNewBuyerInfo}^k_{j,t}$	0.048*	0.076***
	(0.025)	(0.027)
$\texttt{QuantNewBuyerInfo}^k_{j,t-1}$	0.035*	0.057**
	(0.019)	(0.026)
$\texttt{ImportSize}^k_{j,t}$	0.544***	0.443***
	(0.082)	(0.081)
$\texttt{ImportSize}^k_{j,t-1}$	0.011	0.004
	(0.0053)	(0.052)
Observations	198,374	128,758
Samples	All	Differentiated
Country-Industry FE	✓	✓
Year-Country FE	✓	✓
Year-Industry FE	✓	✓

Notes: The table reports PPML estimates of equation (A3). The first column shows the estimated coefficients from the full sample, while the second column restricts the samples to differentiated goods, following the product classification by Rauch (1999). The dependent variable is the export value at the Country-Industry (4-digit SITC) Year level. The explanatory variables are the count of collected buyer information (NewBuyerInfo), its lagged value, and the number of buyer information contacts whose descriptions contain units or have numbers making up more than 5% of the total characters (QuantNewBuyerInfo), and its lagged value. Control variables are the sum of log imports from the rest of the world for each Destination Country-Industry (4-digit SITC) Year ($\texttt{ImportSize}^k_{j,t}$) and their lagged values. *p<0.1, **p<0.05, ***p<0.01. Standard errors in parenthesis are corrected for arbitrary correlation within country and product.

informational value.

Lastly, we explore whether the effect of buyer information depends on the destination characteristics such as the distance from South Korea and official language with the following specification:

$$\begin{aligned}\texttt{EX}^k_{j,t} = \exp\Bigg[\Bigg(\alpha_0 + \alpha_D \times \ln(\texttt{Distance}_j) + \sum_{l\in L}\alpha_l \times \mathbb{1}_{\{\texttt{Language}_j = l\}}\Bigg) \times \texttt{NewBuyerInfo}^k_{j,t-1} \\ + \gamma \times \texttt{ImportSize}^k_{j,t} + \delta^k_j + \delta_{j,t} + \delta^k_t + \epsilon^k_{j,t}\Bigg], \qquad \text{(A4)}\end{aligned}$$

where $\ln(\texttt{Distance}_i)$ is a distance of destination country i from South Korea, which uses a weighted distance calculated by CEPII (Mayer and Zignago 2011), and $\mathbb{1}_{\{\texttt{Language}_j = l\}}$ is an indicator that takes the value of one if country j's official language is l, where L is the set of languages: English, Spanish, German, and French.

Table A.5 suggests that the effects of buyer information can be different depending on the destination characteristics. For instance, the impact of buyer information is greater for those

Table A.5: Heterogeneous Impacts of New Buyer Information on Exports (Destination features)

Dep. Variable	(1) Export	(2) Export
$\texttt{NewBuyerInfo}^k_{j,t-1}$	0.435**	0.380**
	(0.170)	(0.178)
$\texttt{NewBuyerInfo}^k_{j,t-1} \times \ln(\texttt{Distance}_j)$	-0.055**	-0.049**
	(0.022)	(0.023)
$\texttt{NewBuyerInfo}^k_{j,t-1} \times \mathbb{1}_{\{\text{Language}_j=\text{English}\}}$	0.135***	0.137***
	(0.040)	(0.051)
$\texttt{NewBuyerInfo}^k_{j,t-1} \times \mathbb{1}_{\{\text{Language}_j=\text{Spanish}\}}$	0.137**	0.106
	(0.062)	(0.066)
$\texttt{NewBuyerInfo}^k_{j,t-1} \times \mathbb{1}_{\{\text{Language}_j=\text{German}\}}$	0.031	0.018
	(0.038)	(0.046)
$\texttt{NewBuyerInfo}^k_{j,t-1} \times \mathbb{1}_{\{\text{Language}_j=\text{French}\}}$	0.073**	0.106**
	(0.033)	(0.047)
$\texttt{ImportSize}^k_{j,t}$	0.643***	0.568***
	(0.108)	(0.085)
$\text{IHS}(\texttt{EX}^k_{j,t-1})$		0.140***
		(0.013)
Observations	216,084	216,084
Country-Industry FE	✓	✓
Year-Country FE	✓	✓
Year-Industry FE	✓	✓

Notes: The table reports PPML estimates of equation (A4). The dependent variable is export at the Country-Industry (4-digit SITC)-Year level. The explanatory variables are the one-period lagged new buyer contacts ($\texttt{NewBuyerInfo}^k_{j,t-1}$) and its interaction with distance and language dummies. Each language dummy has a value of one if the destination country uses the corresponding language as the official language. The distance measure uses a weighted distance measure provided by CEPII (Mayer and Zignago 2011). Standard errors clustered by country and product are reported in parentheses below the estimated coefficients. *p<0.1, **p<0.05, ***p<0.01. Standard errors in parenthesis are corrected for arbitrary correlation within country and product.

countries whose official language is one of the languages commonly taught in South Korea (e.g., English and French). Also, distance from South Korea to a destination country decreases the buyer information effects.

D. Export Promotion Policy Decision

In this appendix section, we examine the optimization problem of a TPO. This will highlight the factors that determine the optimal information collection efforts by the TPO. Additionally, it can offer an alternative approach to infer the number of buyers in each destination country, which can be used in the quantification section 6 of the main text.

Specifically, in the context of our empirical setup, the goal of the TPO is to maximize the total increase in exports across all destinations and products, while operating within a budget for overseas market research (I).[33] Since KOTRA's search for overseas buyers was primarily conducted through its overseas offices, we assume that the TPO sets the level of market research at the destination country level. This means that a common fraction (ι_j) of buyers is identified by the TPO across all industries within the same country j. We assume that the search cost of the KOTRA at the destination country level has a similar functional form as individual exporters, but we allow it to have different values for search frictions, $\tilde{\zeta}$. We further assume that the number of known buyers identified by the TPO prior to the current search is zero to simplify the problem. Given its budget, the TPO determines the optimal level of market research for each destination country j (ι_j) to maximize the sum of increases in exports from the information:

$$\max_{\{\iota_j \geq 0\}} \sum_j \mathrm{EX}_j(\iota_j; \zeta) \quad \text{subject to} \quad \sum_j \frac{1+\tilde{\zeta}}{\psi}\left[1-(1-\iota_j)^{\frac{1}{1+\tilde{\zeta}}}\right] M_j = I,$$

where $M_j \equiv \sum_k M_j^k$ and $\mathrm{EX}_j(\iota_j, \zeta) \equiv \sum_k \mathrm{EX}_j^k(\iota_j, \zeta)$ are the total number of buyers in destination j and the total exports to destination j, respectively. The search friction parameters ζ and $\tilde{\zeta}$ correspond to each firm and the TPO, respectively, and are allowed to be different.[34]

The first order condition of the maximization problem regarding ι_j returns,

$$\mathsf{G}(\zeta) \times \overline{\mathrm{EX}}_j = \frac{\lambda}{\psi} M_j (1-\iota_j)^{-\frac{\tilde{\zeta}}{1+\tilde{\zeta}}} + \delta_j, \tag{A5}$$

where λ is the Lagrangian multiplier and $\delta_j \geq 0$ satisfies $\delta_j \iota_j = 0, \forall j$. Also, $\overline{\mathrm{EX}}_j$ is the total exports to destination j without search frictions. Here, λ represents the amount of exports that can be increased when the intermediary marginally increases the budget for foreign buyer research. By setting $\iota_j = 0$ and $\delta_j = 0$ in equation (A5), we can derive a condition for the set of destinations j

[33] This can be understood as a simplified setup. According to a publication from KOTRA, other goals included specifically helping SMEs export and assisting domestic firms in exporting to unexplored destinations. Additionally, political motives, such as competition with North Korea and securing relationships with West African countries, also influenced KOTRA's overseas buyer search.

[34] One plausible argument for the existence of TPOs (or information agents in general) is that they can benefit from economies of scale. While each exporter focuses on market research specific to their products, information intermediaries conduct broader market research. For this reason, we allow the search friction parameters to differ between individual firms and the TPO.

that the TPO chooses to search for buyers:

$$\iota_j^* > 0 \quad \text{if} \quad \frac{\mathrm{EX}_j(0;\zeta)}{M_j} \geq T, \quad \text{where} \quad T = \left[\frac{1-\mathsf{G}(\zeta)}{\mathsf{G}(\zeta)}\right]\left[\frac{\lambda}{\psi}\right].$$

The left-hand side of the equation is destination-specific, while the right-hand side is common to all destinations. We denote this common threshold as T. If there are more opportunities to increase exports through market research (high λ), the TPO would allocate its budget to countries with high benefits, raising the threshold for market research. If either the exports without any public information to a destination country are small or the mass of buyers is large, the above condition is not satisfied for the given threshold T, and the TPO does not gather any information from the country.

Solving equation (A5) leads to the following solution:

$$\iota_j^* = \left\{1 - \left[\frac{1}{T}\frac{\mathrm{EX}_j(0;\zeta)}{M_j}\right]^{-\frac{\tilde{\zeta}}{1+\tilde{\zeta}}}\right\} \times \mathbb{1}_{\{\mathrm{EX}_j(0;\zeta)\geq M_j\times T\}} \tag{A6}$$

The optimal fraction of buyers reached by the intermediary is larger for destinations where the mass of buyers is small, making the search less costly, and where the export potential is large.

This equation for the optimal fraction of buyers provides an alternative way to estimate the elasticity of buyer mass with respect to the size of the market in equation (32) (η). We start with the assumption that the realized count of the collected information is the product of the optimal level of search by the TPO, the mass of buyers, and an idiosyncratic term, $\xi_{j,t}^k$:

$$\texttt{NewBuyerInfo}_{j,t}^k = \iota_{j,t}^* M_{j,t}^k \xi_{j,t}^k. \tag{A7}$$

Intuitively, the counts of identified buyer contacts increase if the TPO raises the optimal search level or if there are simply more buyers. The idiosyncratic term, $\xi_{j,t}^k$, represents the idiosyncratic variation in realized search outcomes since buyers are discrete and finite, and the search is probabilistic in the real world. By replacing the optimal level of search by the TPO using equation (A6), the collected buyer information counts can be rewritten as:

$$\texttt{NewBuyerInfo}_{j,t}^k = \left\{1 - \left[\frac{\mathrm{EX}_{j,t}(0;\zeta)}{T_t M_{j,t}}\right]^{-\frac{\tilde{\zeta}}{1+\tilde{\zeta}}}\right\} M_{j,t}^k \xi_{j,t}^k \times \mathbb{1}_{\{\mathrm{EX}_{j,t}(0;\zeta)\geq M_{j,t}\times T_t\}}. \tag{A8}$$

We calibrate the parameters by minimizing the sum of squared differences between the realized buyer contact counts (LHS of equation (A8)) and the predicted values from the model (RHS of equation (A8), excluding the idiosyncratic term).

We further apply the same assumption as in the main text and replace the mass of buyers in equation (A6) with the total imports from the rest of the world (equation (32)). Additionally, since the median information count is zero in the data, we use the current level of exports (EX) in place of $\mathrm{EX}(0;\zeta)$. We compute the value of η along with $\tilde{\zeta}$ and $\{T_t\}_{t=1977}^{1990}$, that minimize the following metric:

$$\min_{\eta} \sum_{j,k,t} \left\{ \texttt{NewBuyerInfo}_{j,t}^{k} - \left[1 - \left(\frac{\mathrm{EX}_{j,t}}{T_t M_{j,t}} \right)^{-\frac{\tilde{\zeta}}{1+\tilde{\zeta}}} \right] M_{j,t}^{k} \times \mathbb{1}_{\{\mathrm{EX}_{j,t} \geq M_{j,t} \times T_t\}} \right\}^2 ,$$

$$\text{subject to} \quad M_{j,t} = \left[\sum_{k} \sum_{i \neq \text{Korea}} \mathrm{EX}_{j,t}^{k}(i) \right]^{\eta} \quad \text{and} \quad M_{j,t}^{k} = \left[\sum_{i \neq \text{Korea}} \mathrm{EX}_{j,t}^{k}(i) \right]^{\eta} .$$

Specifically, $\{T_t\}_{t=1977}^{1990}$ can be identified from the variation in the overall level of collected buyer information counts across years. Additionally, $\tilde{\zeta}$ can be identified by how the total imports and South Korea's total exports affect the overall search level for each destination. Finally, the key parameter η is determined by the variation in collected buyer information across SITC 4-digit industries. The calculated value of the elasticity between the mass of buyers and the imports is 0.193, which is similar to the value estimated from EDD in the main text.

E. Additional Tables and Figures

Table A.6: Robustness: Impacts of New Buyer Information on Exports

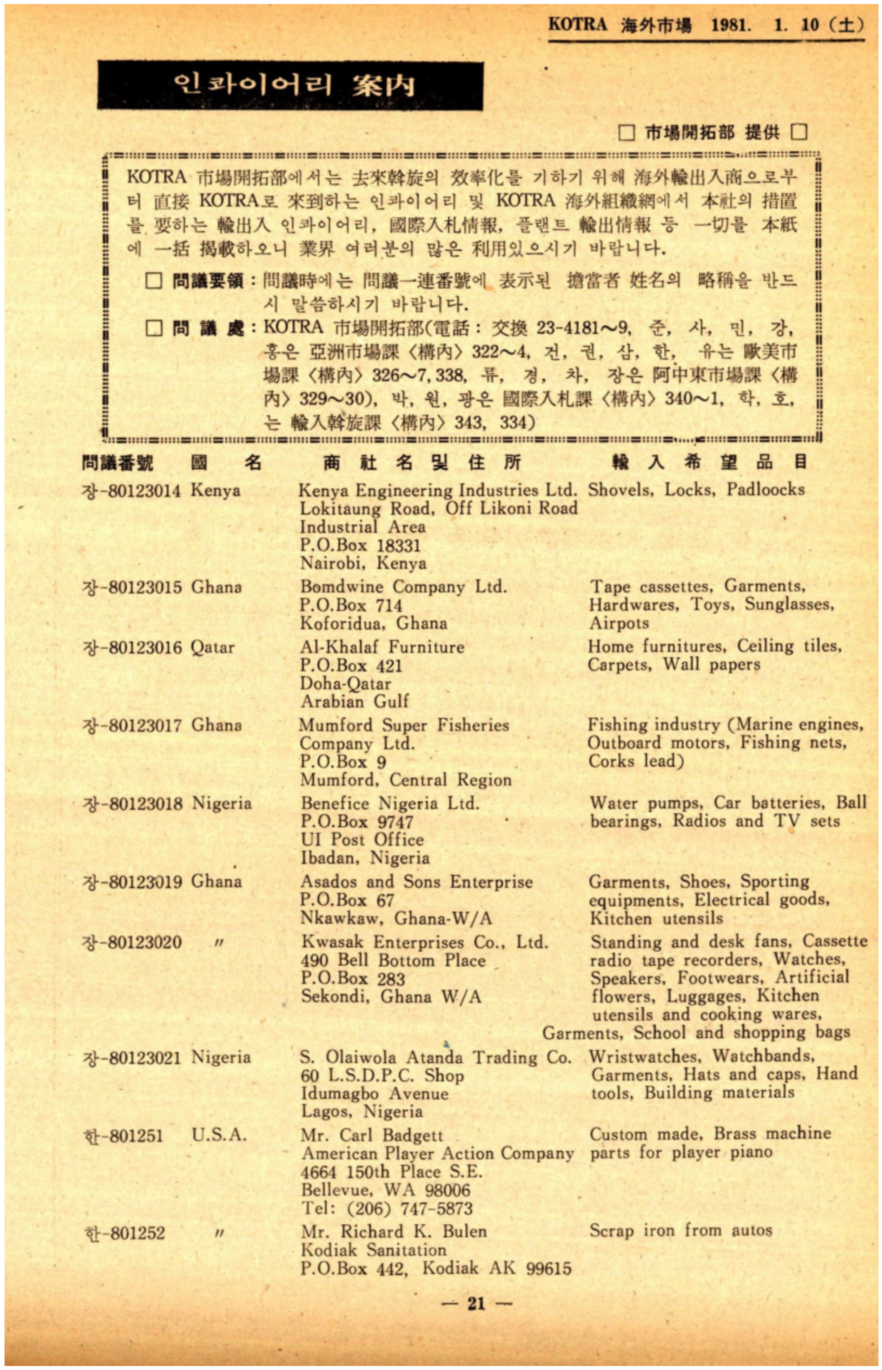
Exporting Country Dep. Variable	(1) Korea Export	(2) Korea Export	(3) Korea Export	(4) Japan Export	(5) Taiwan Export
$\texttt{NewBuyerInfo}^k_{j,t-1}$	0.050***	0.049***	0.040***	-0.021*	0.004
	(0.009)	(0.006)	(0.010)	(0.012)	(0.005)
$\texttt{ImportSize}^k_{j,t}$	0.565***	0.734***	0.894***	0.785***	0.758***
	(0.079)	(0.092)	(0.126)	(0.090)	(0.077)
IHS($\texttt{EX}^k_{j,t-1}$)	0.136***				
	(0.012)				
Observations	236,570	187,722	124,185	551,830	189,734
Country-Industry FE	✓	✓	✓	✓	✓
Year-Country FE	✓			✓	✓
Year-Industry FE	✓	✓	✓	✓	✓
Year-Country-SITC2d FE		✓			
Year-Country-SITC3d FE			✓		

Notes: The table reports PPML estimates of alternative specifications of equation (3). In Columns (1)–(3), the dependent variable is Korean export at the Country-Industry (4-digit SITC)-Year level, but Columns (4) and (5) use Japanese (Column 4) and Taiwanese (Column 5) exports at the Country-Industry (4-digit SITC) Year level. The explanatory variable is the one-period lagged new buyer contacts ($\texttt{NewBuyerInfo}^k_{j,t-1}$). Control variables include the sum of log imports from countries other than South Korea at Destination Country-Industry (4-digit SITC)-Year ($\texttt{ImportSize}^k_{j,t}$). Additionally, the regressions include the IHS transformed lagged export value (IHS($\texttt{EX}^k_{j,t-1}$), Column 1), Year-Country-SITC2d fixed effects (Column 2), and Year-Country-SITC3d fixed effects (Column 3). *p<0.1, **p<0.05, ***p<0.01. Standard errors in parenthesis are corrected for arbitrary correlation within country and industry.

Table A.7: Robustness: Impacts of Concentration on the Buyer Information's Effects

Dep. Variable	(1) Export	(2) Export	(3) Export	(4) Export	(5) Export	(6) Export
$\texttt{NewBuyerInfo}^{k}_{j,t-1}$	0.192	0.154	0.091***	0.098	0.068**	0.075***
	(0.180)	(0.113)	(0.033)	(0.143)	(0.029)	(0.027)
$\texttt{NewBuyerInfo}^{k}_{j,t-1}$						
$\times\texttt{Top20SalesShare}^{\tilde{k}(k)}_{1980}$	-0.300***	-0.296***	-0.303***	-0.255***	-0.205***	-0.238***
	(0.044)	(0.037)	(0.090)	(0.044)	(0.068)	(0.069)
$\times\texttt{ExporterFraction}^{\tilde{k}(k)}_{1980}$	0.389**	0.439***	0.427***	0.420***	0.404***	0.414***
	(0.152)	(0.080)	(0.061)	(0.124)	(0.085)	(0.092)
$\texttt{ImportSize}^{k}_{j,t}$	0.668***	0.668***	0.668***	0.668***	0.682***	0.682***
	(0.101)	(0.101)	(0.101)	(0.101)	(0.103)	(0.103)
Observations	207,804	207,804	207,804	207,804	192,713	192,713
Controls	ln(N)	ln(E)	ln(CI)	ln(Revenue)	Prod (lib)	Prod (con)
Country-Industry FE	✓	✓	✓	✓	✓	✓
Year-Country FE	✓	✓	✓	✓	✓	✓
Year-Industry FE	✓	✓	✓	✓	✓	✓

Notes: The table reports estimates of the PPML regression equation (4) with additional controls for robustness. The dependent variable is export at the Country-Industry (4-digit SITC)-Year level. The explanatory variables are the one-period lagged new buyer contacts ($\texttt{NewBuyerInfo}^{k}_{j,t-1}$), including interactions with a concentration measure based on the sales shares of the top 20 Korean firms in each 3-digit KSIC industry ($\texttt{Top20SalesShare}^{\tilde{k}(k)}_{1980}$) and the exporter share for each KSIC 3-digit manufacturing industry ($\texttt{ExporterFraction}^{\tilde{k}(k)}_{1980}$). Additionally, each column includes an interaction of $\texttt{NewBuyerInfo}^{k}_{j,t-1}$ and an industry characteristic. with an industry characteristic. From column (1) to (7), this industry characteristic is the log number of domestic firms (N), the log number of exporters (E), log capital intensity (total capital over total revenue of each industry) (CI), log total domestic sales (Revenue), and liberal and conservative product classification dummies (Prod(lib) and Prod(con)) from Rauch (1999). The coefficients on these interaction terms are omitted to save space. *p<0.1, **p<0.05, ***p<0.01. Standard errors in parenthesis are corrected for arbitrary correlation within country and industry.



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인콰이어리 案內

☐ 市場開拓部 提供 ☐

KOTRA 市場開拓部에서는 去來斡旋의 效率化를 기하기 위해 海外輸出入商으로부터 直接 KOTRA로 來到하는 인콰이어리 및 KOTRA 海外組織網에서 本社의 措置를 要하는 輸出入 인콰이어리, 國際入札情報, 플랜트 輸出情報 등 一切를 本紙에 一括 揭載하오니 業界 여러분의 많은 利用있으시기 바랍니다.

☐ **問議要領**: 問議時에는 問議一連番號에 表示된 擔當者 姓名의 略稱을 반드시 말씀하시기 바랍니다.

☐ **問 議 處**: KOTRA 市場開拓部(電話: 交換 23-4181～9, 준, 사, 민, 강, 홍은 亞洲市場課 〈構內〉 322～4, 건, 권, 삼, 한, 유는 歐美市場課 〈構內〉 326～7, 338, 류, 경, 차, 장은 阿中東市場課 〈構內〉 329～30), 박, 원, 광은 國際入札課 〈構內〉 340～1, 학, 호, 는 輸入斡旋課 〈構內〉 343, 334)

問議番號	國名	商社名및住所	輸入希望品目
장-80123014	Kenya	Kenya Engineering Industries Ltd. Lokitaung Road, Off Likoni Road Industrial Area P.O.Box 18331 Nairobi, Kenya	Shovels, Locks, Padloocks
장-80123015	Ghana	Bomdwine Company Ltd. P.O.Box 714 Koforidua, Ghana	Tape cassettes, Garments, Hardwares, Toys, Sunglasses, Airpots
장-80123016	Qatar	Al-Khalaf Furniture P.O.Box 421 Doha-Qatar Arabian Gulf	Home furnitures, Ceiling tiles, Carpets, Wall papers
장-80123017	Ghana	Mumford Super Fisheries Company Ltd. P.O.Box 9 Mumford, Central Region	Fishing industry (Marine engines, Outboard motors, Fishing nets, Corks lead)
장-80123018	Nigeria	Benefice Nigeria Ltd. P.O.Box 9747 UI Post Office Ibadan, Nigeria	Water pumps, Car batteries, Ball bearings, Radios and TV sets
장-80123019	Ghana	Asados and Sons Enterprise P.O.Box 67 Nkawkaw, Ghana-W/A	Garments, Shoes, Sporting equipments, Electrical goods, Kitchen utensils
장-80123020	〃	Kwasak Enterprises Co., Ltd. 490 Bell Bottom Place P.O.Box 283 Sekondi, Ghana W/A	Standing and desk fans, Cassette radio tape recorders, Watches, Speakers, Footwears, Artificial flowers, Luggages, Kitchen utensils and cooking wares, Garments, School and shopping bags
장-80123021	Nigeria	S. Olaiwola Atanda Trading Co. 60 L.S.D.P.C. Shop Idumagbo Avenue Lagos, Nigeria	Wristwatches, Watchbands, Garments, Hats and caps, Hand tools, Building materials
한-801251	U.S.A.	Mr. Carl Badgett American Player Action Company 4664 150th Place S.E. Bellevue, WA 98006 Tel: (206) 747-5873	Custom made, Brass machine parts for player piano
한-801252	〃	Mr. Richard K. Bulen Kodiak Sanitation P.O.Box 442, Kodiak AK 99615	Scrap iron from autos

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Figure A.2: An Example Page of Buyer Information List

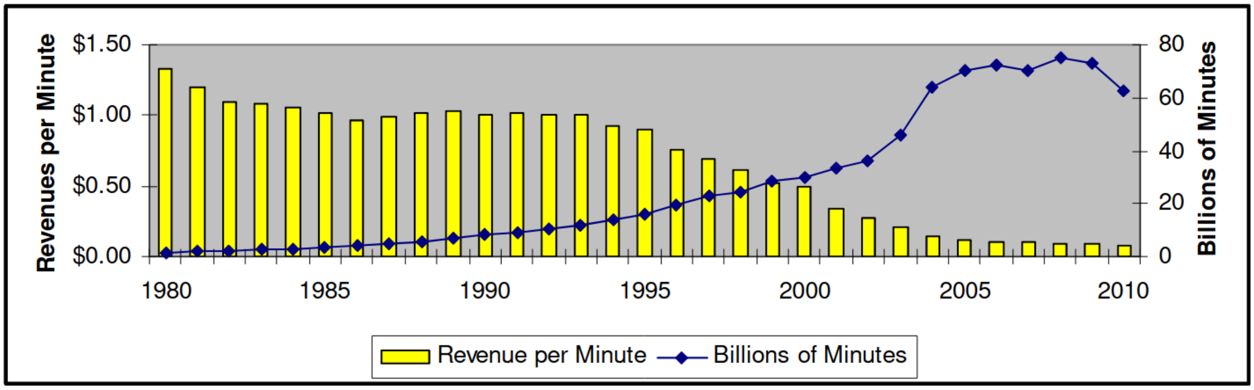
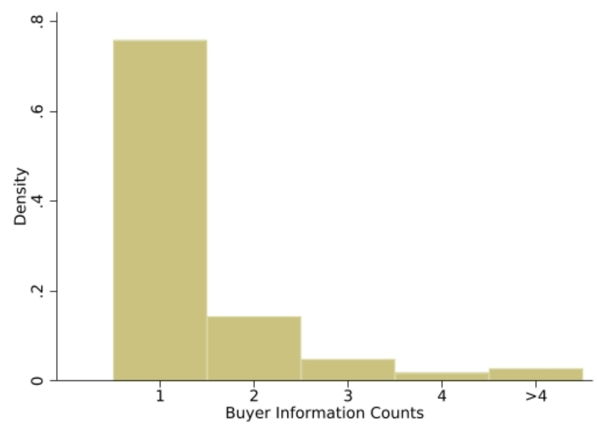


Figure A.3: International Call Rates

Notes: The data comes from FCC report (Table 2) "Trends in the international telecommunications industry: summary through 2010, 2012".

(a) Histogram of All Buyer Information Counts



(b) Histogram of Positive Buyer Information Counts

Figure A.4: Histograms of Buyer Information

Notes: The left panel plots a histogram of buyer information at the destination-STIC4digit-year level over the sample years. The right panel repeats the same histogram of buyer information counts restricting to the observations with positive buyer information counts.

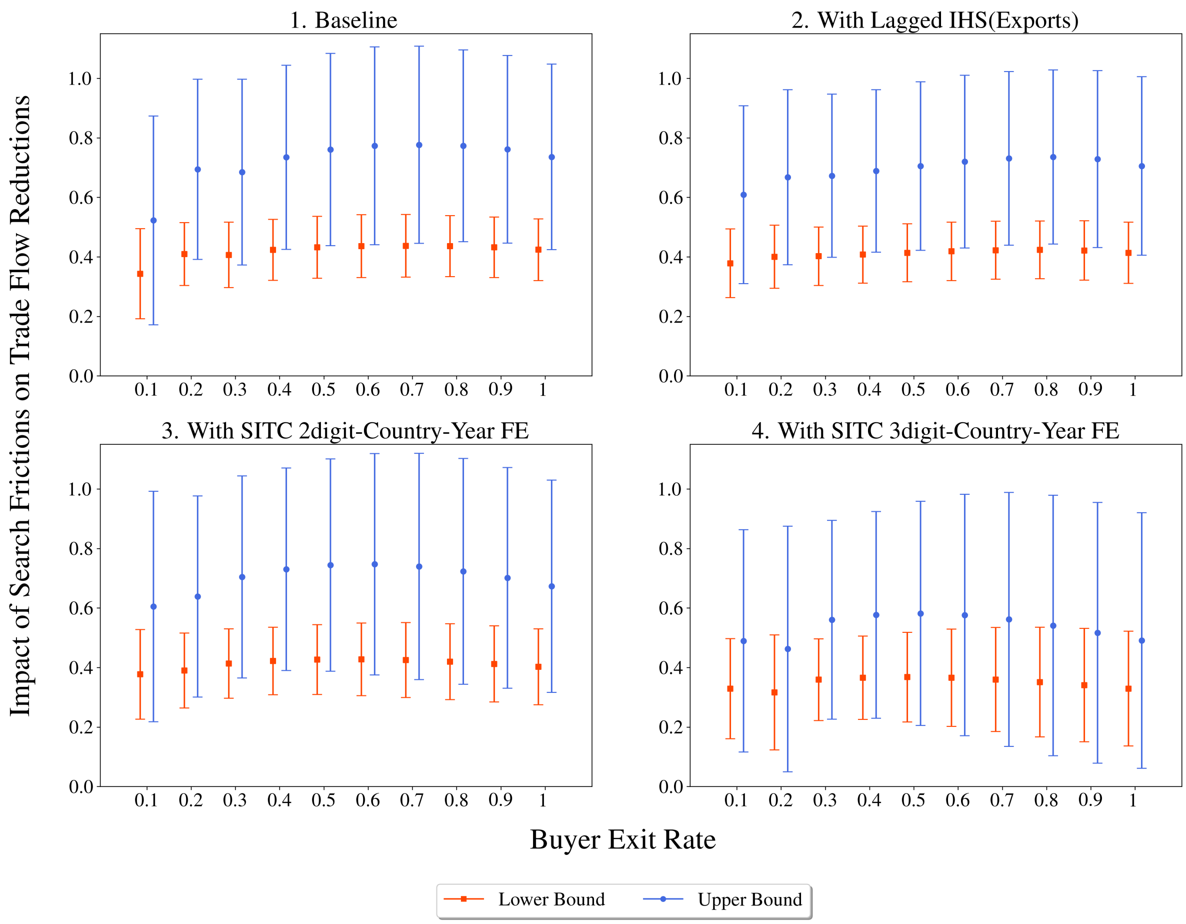


Figure A.5: Impact of Search Frictions on Trade Flow Reductions

Notes: Each panel reports estimates of the lower bound ($\beta/(1+\beta)$) and upper bound (β) of the reduction in trade from search frictions relative to the frictionless case ($\mathtt{G}$) along with their 95% confidence intervals. These are derived from PPML regression estimates of β from PPML regression based on equation (31). Standard errors in parenthesis are corrected for arbitrary correlation within country and industry. The dependent variable in this analysis is the export value at the Country-Industry (4-digit SITC)-Year level. The explanatory variable is the lagged fraction of known buyers from public information ($\iota^k_{j,t-1}$). All panels include $\mathtt{ImportSize}^k_{j,t}$ and fixed effects as specified in equation (31). Panels 2-4 additionally incorporate the IHS-transformed lagged export value of South Korea (IHS($\mathtt{EX}^k_{j,t-1}$)), Country-Industry (2-digit SITC)-Year fixed effects, and Country-Industry (3-digit SITC)-Year fixed effects, respectively.

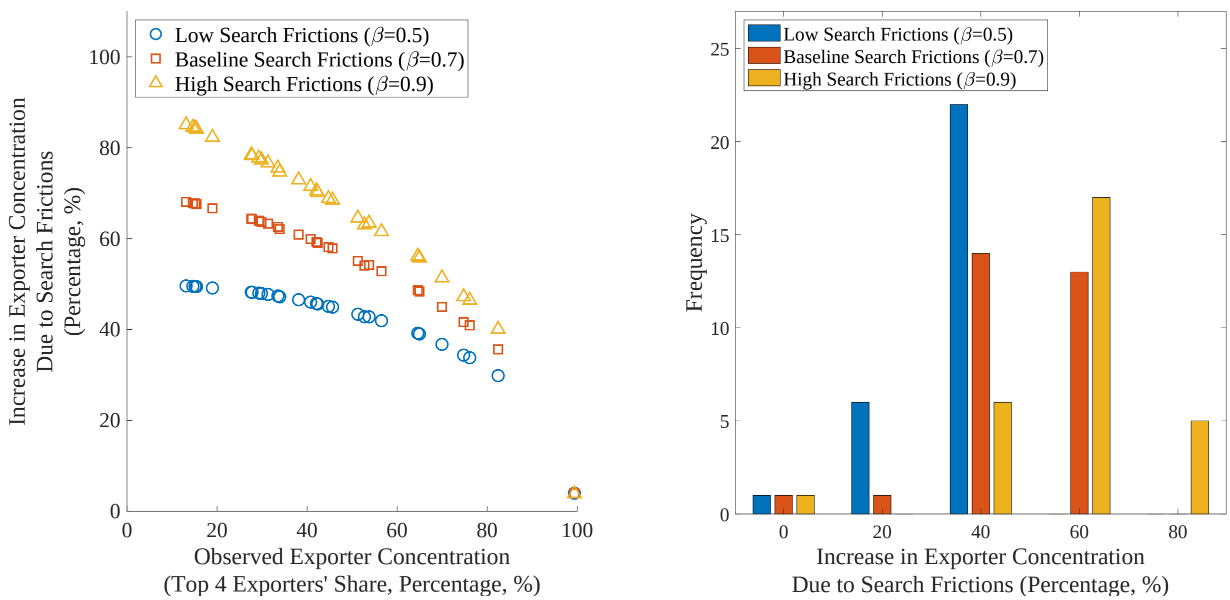


Figure A.6: Impact of Search Frictions on Exporters' Concentration

Note: The figure illustrates the effects of search frictions on the export share of the top-4 exporters. The percentage increase in exporters' concentration is calculated as $\left(C\left(4|0;\zeta\right)-\bar{C}(4)\right)/\bar{C}(4)\times 100$ using equation (28) for each KSIC 3-digit industry. For each industry, the observed top-4 exporters' export share and the fraction of known buyers, averaged over the sample period (1983–1990), are used for the calculation. The left panel shows a histogram of this increase in exporters' concentration, measured in percentage points, across 29 manufacturing KSIC 3-digit industries. The right panel presents a scatter plot of the increase in exporter concentration against the observed level of concentration. Each point represents a KSIC 3-digit manufacturing industry. Blue, red, and yellow indicate calculations assuming low, baseline, and high search frictions, respectively, with semi-elasticity parameter β values of 0.5, 0.7, and 0.9.

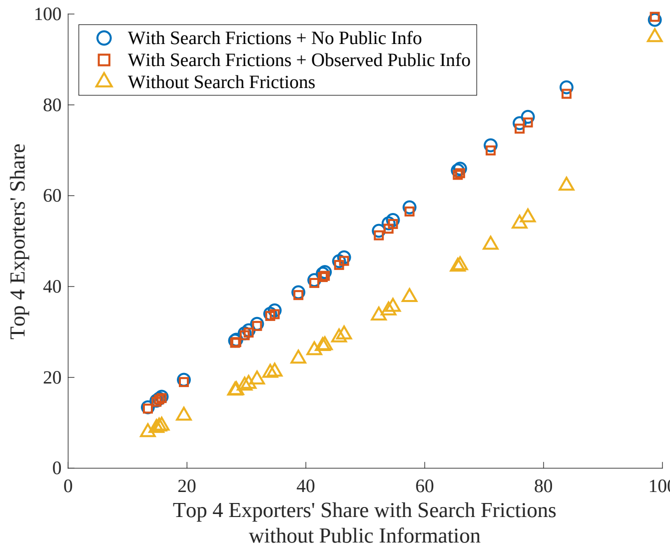


Figure A.7: Impact of Search Frictions and Public Information on Exporters' Concentration

Notes: The figure illustrates the effects of search frictions and public information on the export share of the top-4 exporters. Blue circles represent the level of the top-4 exporters' share with search frictions but without any public information ($C\,(4|0;\zeta)$). Yellow triangles represent the level of the top-4 exporters' share without search frictions ($\bar{C}(4)$). Red squares represent the observed level of concentration ($C\,(4|\bar{\iota};\zeta)$), where $\bar{\iota}$ represents the average ι for each KSIC 3-digit industry during the sample period (1983–1990).