Public Information on Overseas Buyers for Export Promotion

Chan Kim* Daisoon Kim†

June 2026

Abstract

Expanding access to foreign markets is central to economic development, and governments widely use trade promotion organizations (TPOs) to help firms overcome export-market frictions. Yet less is known about which TPO services promote exports and the mechanisms through which they operate. Using newly digitized historical data from South Korea's trade promotion agency, KOTRA, we study a core intervention: the public dissemination of foreign buyer information. We exploit plausibly exogenous variation in the timing and intensity of buyer information provision and find that access to foreign buyer information significantly and persistently increases exports to targeted destination-industries. We interpret these effects through a search-and-matching model in which exporters differ in productivity and endogenously search for overseas buyers. In the model, publicly provided buyer registries reduce foreign buyer search costs, with especially large predicted gains for information-constrained smaller exporters. Consistent with this mechanism, the aggregate export response is significantly weaker in industries where exports are concentrated among a few large firms. Our results highlight the quantitative importance of buyer-search frictions and suggest that public information provision can support export promotion in economies where foreign market access is central to growth.

JEL Classification: D83; F13; F14.
Keywords: Buyer search; Export promotion; Non-tariff barrier; Public information.

* International Monetary Fund
E-mail: chankimecon@gmail.com. Webpage: https://sites.google.com/view/chankimecon.
† Andersen Institute of Finance and Economics; NC State University
E-mail: dkim29@ncsu.edu. Webpage: https://daisoonkim.github.io.

The authors would like to thank Jose Asturias, Ruben Gaetani, Jay Hyun, Eunhee Lee, Nuno Limão, Luca David Opromolla, and Theodore Papageorgiou, as well as seminar/conference participants at the University of Maryland, Empirical Investigations in International Trade XXXI Conference (Purdue University), Fall 2024 Midwest International Trade Conference (University of Rochester), 18th North American Meeting of the Urban Economics Association (Georgetown University), and Fall 2022 Midwest International Trade Conference (University of Notre Dame), for useful comments.

1. Introduction

Expanding firms' participation in export markets is a central objective for developing economies. With decades of trade liberalization having eroded traditional tariff protections, non-tariff barriers have emerged as the critical impediments to cross-border commerce. Among these, informational frictions—firms' limited knowledge about foreign demand, regulations, networks, and prospective buyers—pose a particularly significant hurdle (Anderson and Van Wincoop 2004; Head and Mayer 2013). In response, governments worldwide have established trade promotion organizations (TPOs) to offer a suite of services, including market intelligence and trade-show coordination, that aim to bridge these informational gaps. While a growing literature finds that TPO support can be a cost-effective tool to boost export volumes (e.g.,Volpe Martincus and Carballo 2008; Munch and Schaur 2018; Buus, Munch, Rodrigue and Schaur 2025), most studies treat this assistance as a single "black-box" intervention, leaving the underlying mechanisms unclear and raising the question of which specific TPO activities alleviate particular barriers.

In this paper, we fill this gap by investigating one of the most binding non-tariff barriers—buyer search frictions—and the corresponding TPO intervention: the public dissemination of foreign buyer contacts. These frictions are especially acute for small and medium-sized enterprises (SMEs), which typically lack the internal resources and international networks of larger firms (Leonidou 2004; Secretariat 2016). By isolating the task of buyer identification, we move from broad assessments of "any TPO support" to a granular evaluation of how targeted information provision drives export performance. Our approach complements—and refines—the few existing studies that disaggregate TPO activities into broader categories like counseling, trade agendas, or fairs.[1]

Our empirical setting is South Korea (hereafter Korea) around its export-led development period, when access to foreign demand was central to growth and pre-internet information frictions made overseas buyer discovery costly for many firms. We study a unique historical archive from the Korea Trade-Investment Promotion Agency (KOTRA), a central institution in this strategy. From its founding in 1962 until 2001, KOTRA published the Daily KOTRA Overseas Market, which systematically compiled and distributed contact information for foreign buyers. The archive provides unusually detailed visibility into the timing and content of a large-scale public information policy before the internet reshaped global commerce. Linking these buyer listings to destination-industry export flows allows

[1]For instance, Volpe Martincus and Carballo (2010a) offer a valuable disaggregation of services, but their 'trade agenda' category bundles direct buyer-matching with other commercial assistance. Our focus on the raw provision of buyer contacts allows for a cleaner identification of the pure information channel.

us to study how public information provision promotes exports in a developing-country context.

We digitize and analyze a representative sample of this publication covering 1977–1990, resulting in 43,239 importer listings at the destination-industry-year level. Descriptive evidence from a heterogeneous difference-in-differences design shows that the provision of buyer information is followed by a significant and persistent increase in Korean exports to the corresponding destination-industry pairs. Specifically, we estimate average treatment effects on the treated (ATET) by event time, defined relative to the first year of buyer information provision. Treated pairs experience an export increase of approximately 40 percent relative to untreated pairs.

To illuminate the underlying mechanisms, we extend a canonical search-and-matching trade model (e.g., Arkolakis 2010; Antràs and Costinot 2011; Allen 2014; Benguria 2021; Eaton, Jinkins, Tybout and Xu 2022) by explicitly incorporating the role of TPO-provided public information. This theoretical framework helps to understand how firms of varying sizes might differentially benefit from such information. While all firms face search frictions in accessing foreign buyers, more productive (i.e., larger) firms can afford to exert greater search effort due to higher profits per match. Publicly provided buyer information helps alleviate these frictions by expanding firms' access to potential importers. The model predicts that although all firms benefit from such information, the gains are proportionately larger for smaller exporters. As a result, the export-promoting effects of TPO-provided information are expected to be stronger in industries with low export concentration, that is, industries not dominated by a small number of large firms.

A key challenge in identifying the causal effect of (public) information on exports is the potential for reverse causality. As emphasized in the literature on information frictions and trade, information flows are often endogenous to trade activity, responding to changes in the trade environment (e.g., Steinwender 2018). In our context, destinations with rising trade volumes may receive increased attention from KOTRA, making local buyers more likely to be featured in its publications. Consequently, the estimated effect of public information may capture this underlying correlation, rather than a true causal influence on export outcomes.

To address this concern, we first demonstrate that a substantial share of the variation in the timing and intensity of information provision is not systematically correlated with destination-specific market conditions. This pattern reflects the discretionary and decentralized nature of KOTRA's operations: buyer information was collected by local office staff, typically general administrative personnel rather than trained market analysts, as part of their routine responsibilities (KOTRA 2012). Variation in staff capacity, experience,

and judgment likely introduced considerable noise into both the quantity and quality of information flows.[2] Moreover, geopolitical considerations, such as Korea's foreign policy priorities, also shaped the allocation of search effort.[3]

We use this idiosyncratic variation to estimate plausibly causal effects on Korean exports. The identifying assumption is that, conditional on controls and fixed effects, residual variation in KOTRA's information provision is uncorrelated with unobserved export-demand shocks. We implement this strategy by extending the standard gravity framework to include KOTRA's provision of buyer information at the destination-industry-year level and estimate the model using Poisson pseudo-maximum likelihood (PPML). Our empirical strategy aims to reduce the scope for confounding by systematic trade determinants through detailed bilateral and time-varying fixed effects, along with controls for import demand. To further address concerns about reverse causality, we complement the baseline analysis with an event-study design based on the local projection difference-in-differences (LP-DiD) method of Dube, Girardi and Taylor (2023). This approach enables us to assess the dynamic export response to buyer information and examine whether treated and comparison cells exhibit differential pre-period export changes conditional on controls. In addition, it mitigates bias from heterogeneous treatment effects across destinations and industries over time.

Our empirical results yield two main findings that align closely with the theoretical framework. First, we find that the provision of new buyer information by KOTRA is followed by significant and persistent growth in Korean exports at the destination-industry-year level. Specifically, a doubling of buyer listings in the KOTRA magazine is associated with a roughly 10% increase in exports in the following year and an 8.2% increase over a five-year horizon. These effects underscore the importance of search frictions in shaping trade outcomes: if firms already had perfect information about potential buyers, the provision of public information would have no effect on exports.

Second, we document substantial heterogeneity in the effectiveness of public information across industries. Consistent with the model, the export response is significantly weaker in industries with high export concentration, where exports are dominated by large firms, than in industries with a greater presence of smaller exporters. This pattern suggests that public information plays a more prominent role for smaller, more information-constrained firms. Larger firms, by contrast, are likely to be less reliant

[2] Barteska and Lee (2026) document that the quality of KOTRA's market reports varied substantially with the professional background and prior overseas experience of individual Korean bureaucrats.

[3] For example, in 1981, KOTRA devoted more coverage to Ghana and Nigeria than to the considerably larger U.S. market, reflecting South Korea's diplomatic engagement with oil-producing countries in West Africa amid strategic competition with North Korea.

on publicly provided information because they are more productive and have better-developed information networks. This interpretation is consistent with prior research on endogenous information acquisition and buyer search. For instance, Dickstein and Morales (2018) show that larger firms invest more in gathering overseas market information, while Blum, Claro and Horstmann (2010) and Bernard, Moxnes and Ulltveit-Moe (2018) document that larger exporters engage with a broader set of foreign buyers. This result complements findings from the related literature on export promotion programs. Volpe Martincus and Carballo (2010b) and Munch and Schaur (2018) find size-dependent impacts of such programs, with larger effects observed for SMEs.

These findings are robust to a range of empirical checks. A remaining concern is that our extended gravity specification may not fully capture Korea-specific shocks, such as bilateral tariffs or destination-specific demand fluctuations for Korean goods, which are not directly observed. To address this, we incorporate lagged Korean exports and introduce more granular fixed effects that absorb persistent bilateral trade conditions and correlated industry-level shocks. We further conduct placebo tests using export data from Japan and Taiwan—two economies with export structures broadly comparable to Korea's. If unobserved destination-level trade shocks were driving our results, we would expect to find similar export responses to buyer information in these countries; however, no such effects are observed. This supports the interpretation that the estimates are not driven solely by common destination-industry demand shocks. Finally, our event-study analysis using the LP-DiD framework reveals a significant increase in exports following the receipt of buyer information, with no evidence of differential pre-period export changes after conditioning on controls. This further mitigates concerns about reverse causality.

The paper first contributes to the development literature on export-led growth by identifying a concrete institutional mechanism through which public policy can expand firms' access to foreign demand. Exports are especially important for developing economies with limited domestic markets, where foreign demand can support scale expansion, learning from buyers, and upgrading in tradable sectors (Hausmann, Hwang and Rodrik 2007; Atkin, Khandelwal and Osman 2017). Korea provides a useful setting for studying this process because its industrialization was closely tied to export-oriented policy and public TPOs, including KOTRA (Amsden 1989; Westphal 1990; KOTRA 2012). We show that one concrete service provided by such institutions, disseminating foreign buyer contacts, is associated with persistent export growth in targeted destination-industries.

Second, the paper contributes to the literature on export promotion programs by isolating a specific service within the broader bundle of TPO activities. Existing studies show that export promotion agencies and related support programs can increase exports (Volpe

Martincus and Carballo 2008, 2010b; Lederman, Olarreaga and Payton 2010; Van Biesebroeck, Yu and Chen 2015; Munch and Schaur 2018; Buus et al. 2025), but many evaluations combine multiple services such as counseling, trade fairs, and buyer matching. Closest to our institutional setting, Barteska and Lee (2026) show that the effectiveness of Korea's overseas export-promotion offices depended strongly on bureaucrat ability, consistent with market-information transmission as a central channel. We contribute to this literature by measuring the buyer contacts disseminated by KOTRA and estimating how this specific information service affected destination-industry exports.

Third, the paper contributes to the empirical literature on information and search frictions in trade, which has often grappled with the unobservable and endogenous nature of information. Prior studies have typically relied on proxies for information flows, such as ethnic networks (Rauch and Trindade 2002), the adoption of mobile phone services (Sreekumar 2011; Allen 2014), or internet penetration (Kneller and Timmis 2016; Akerman, Leuven and Mogstad 2022).[4] This paper leverages a more direct measure: a digitized archive of international buyer contacts systematically collected and published by a TPO. This unique dataset allows us to provide more direct evidence on how public information provision shapes export activities across a wide range of industries.

The remainder of this paper is organized as follows: Section 2 describes the historical context, data construction, and preliminary descriptive analysis. Section 3 presents our theoretical model. Section 4 discusses empirical specification issues and identification challenges. Section 5 documents the benchmark regression results. Section 6 introduces an alternative event-study specification and discusses its results. The final section concludes.

2. Institutional Context and Data

The Korean government established the Korea Trade-Investment Promotion Agency (KOTRA) to support its export-led growth strategy. A central component of KOTRA's activities was identifying and providing overseas buyer information to domestic exporters. But did this effort actually succeed in promoting exports? This section introduces the institutional and historical context of KOTRA's information provision efforts, focusing on the period covered by our empirical analysis. We then describe how we construct our measure of buyer information and present descriptive patterns that illustrate its relationship with Korea's export dynamics.

[4]While some recent studies, such as Steinwender (2018) and Juhász and Steinwender (2018), analyze observable information flows, their focus is often on a single industry (e.g., textiles) to establish plausible exogenous information shocks. Our study broadens this scope by examining variations across multiple industries.

2.1. Institutional and Historical Context

Established in 1962, KOTRA was tasked with supporting Korea's export-oriented development by providing essential export-related services to domestic firms. A key function of the agency was to mitigate information frictions between Korean producers and foreign markets. Specifically, KOTRA dedicated substantial resources to improving access to international buyers, thereby addressing a common challenge for firms in developing economies: the difficulty of identifying and connecting with potential trading partners (Secretariat 2016).

To achieve this, KOTRA built an extensive network of overseas offices responsible for gathering and disseminating buyer and market intelligence. By 2000, KOTRA operated 138 offices across 87 countries, many located in emerging markets. Local staff regularly engaged with firms in host countries to gauge their interest in importing Korean products. The information gathered—including firm names, product interests, and contact details—was published in the *Daily KOTRA Overseas Market*, a publicly accessible magazine. This publication enabled Korean firms, especially small and medium-sized enterprises (SMEs) lacking the resources for independent overseas market research, to identify and approach potential buyers.

Our empirical analysis focuses on the 1980s to assess the impact of publicly provided buyer information on exports. This period is chosen for two primary reasons. First, during the pre-internet era, the costs associated with acquiring foreign market information were exceptionally high, particularly for SMEs. Expenses for international phone calls, telexes, and business travel were significant (see Figure A.4), rendering KOTRA's publicly available buyer information particularly valuable. Second, the institutional and policy landscape of the 1980s facilitates credible identification. Domestically, Korea was transitioning from a state-led industrial policy under authoritarian rule towards a more liberalized, market-oriented economy, concurrent with its democratic reforms. This shift diminished direct government intervention in targeting specific industries and fostered more balanced economic development across sectors and firms (Kim 1991; Lee 2013). Concurrently, global trade policy remained relatively stable. The major wave of multilateral tariff reductions, often termed the "Great Liberalization," predominantly occurred in the 1990s, after our sample period (Coelli, Moxnes and Ulltveit-Moe 2022).[5] Consequently, the 1980s provide a comparatively stable policy environment for examining the effects of buyer information on export performance.

[5]The 1990s saw widespread trade liberalization in both developed and developing nations. While this liberalization is a frequent subject of empirical trade studies, the associated policy shocks would confound efforts to isolate the specific impact of information provision.

2.2. Measurement of Variables

New Buyer information. Our primary measure of public information is $\texttt{NewBuyerInfo}^k_{j,t}$. This variable quantifies the number of new buyer contacts listed in KOTRA's magazine for a specific SITC 4-digit industry k, destination country j, and year t. Each instance where KOTRA's magazine features information about a buyer interested in products from a particular SITC 4-digit industry in a given year is counted as one unit of buyer information for that industry-country-year triplet.

KOTRA's magazine dedicated a section to foreign buyer information. We randomly selected one issue per week from the period 1977 to 1990, 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 Figure A.1). 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.

Instances where KOTRA reported no buyer information for a specific country-industry pair in a given year lead to zero values for $\texttt{NewBuyerInfo}^k_{j,t}$. As the logarithmic transformation is undefined for zero, we employ the inverse hyperbolic sine (IHS) transformation: $\text{asinh}(x) \equiv \ln(x + \sqrt{1 + x^2})$.

Korea's exports and destination market sizes. 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. Our primary dependent variable, destination-industry level exports from Korea, is denoted as $\texttt{EX}^k_{j,t} \equiv \texttt{EX}^k_{j,t}(\text{Korea})$.

We also construct a measure of market size for each industry-destination pair, defined as the sum of log imports from the rest of the world (excluding Korea):

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

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.

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.

2.3. Descriptive Analysis: Buyer Information and Exports

To explore the impact of KOTRA's buyer information provision on export promotion, we employ a heterogeneous difference-in-differences (DiD) framework. This approach compares industry-destination pairs that received buyer information from KOTRA (treated group) with those that did not (control group). Our treatment variable is defined as an indicator for whether an industry-destination pair has ever received buyer information up to a given year:

$$\text{Treatment}^k_{j,t} = \mathbb{1}_{\left\{\sum_{l=t_0}^{t} \texttt{NewBuyerInfo}^k_{j,l} > 0\right\}} \tag{2}$$

where $t_0 = 1977$ represents the initial period of our sample.

In this staggered adoption setup, different industry-destination pairs (treatment cohorts) begin receiving buyer information in different years, and once treated, they remain exposed to the treatment. Untreated industry-destination pairs are those that never receive buyer information from KOTRA during the sample period. We acknowledge that treatment effects (Average Treatment Effect on the Treated, ATET) may vary over time since treatment and across different treatment cohorts. To address this, we implement the doubly robust DiD estimators for longitudinal data developed by Sant'Anna and Zhao (2020), specifically the augmented inverse-probability weighting estimators, into a balanced panel (175,080 observations).

Figure 1 plots the estimated ATETs against years relative to the initial provision of KOTRA buyer information (event time). The horizontal axis denotes event time, where year 0 is the year KOTRA first provided buyer information for a specific industry k in destination j. The vertical axis measures the ATET in terms of the IHS transformed export volume, $\text{asinh}(\texttt{EX}^k_{j,t})$. The estimates indicate no significant pre-treatment differential trends

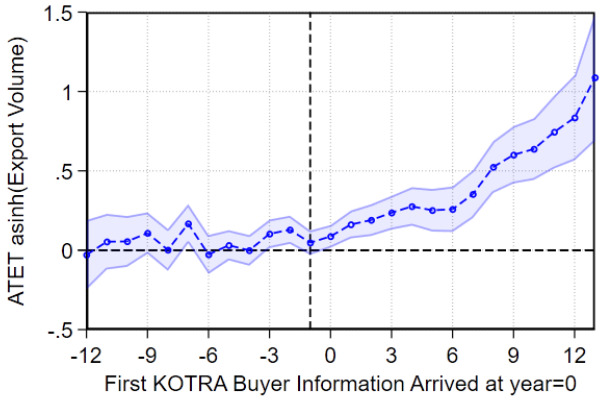

Figure 1: Impact of KOTRA Information Provision on Exports

Notes: This figure presents the estimated average treatment effects on the treated (ATETs) using the doubly robust heterogeneous difference-in-differences (DiD) estimator with staggered adoption (Sant'Anna and Zhao 2020). The analysis is based on a balanced panel of 175,080 observations at the industry-country-year level. An industry-country pair is defined as treated if it has received any KOTRA buyer information by year t (i.e., $\mathbb{1}_{\{\sum_{l=t_0}^{t} \texttt{NewBuyerInfo}_{j,l}^{k}>0\}}$). The x-axis represents years relative to the first year KOTRA provided buyer information for a given industry-destination pair (year=0). The y-axis shows the ATET on the IHS transformed Korean export volume, $\text{asinh}(\texttt{EX}_{j,t}^{k})$. The shaded area represents 95% confidence intervals, calculated using standard errors robust to arbitrary correlation within country and industry.

in export volumes between the subsequently treated and control groups, lending credibility to the common trends assumption underlying the DiD design.

Following the initial provision of buyer information (year 0), Korean exports to the treated industry-destination pairs exhibit a marked and sustained increase relative to untreated pairs. Overall ATET is 0.33, with treated group exports being over 39%($\approx 100 \times [\exp(0.33) - 1]$) higher. The impact appears to grow over time. For instance, five years after the initial information provision, exports to the treated industry-destinations are approximately 32% higher (ATET 0.28). After ten years, this effect grows substantially. The point estimate suggests that exports are over 90% higher (ATET 0.64) compared to what they would have been without the KOTRA information. The widening confidence intervals at longer horizons reflect the decreasing number of cohorts observed for many years post-treatment.

These treatment effects, presented in Figure 1, offer compelling preliminary evidence that KOTRA's provision of new buyer information is associated with a significant increase in Korean exports. The distinct divergence in export trajectories between industry-destination pairs that received buyer information and those that did not supports the hypothesis that alleviating information frictions effectively promotes exports.

3. Theoretical Motivation

To build intuition about the role of public information on overseas buyer contracts, we extend the conventional market penetration model (e.g., Arkolakis 2010) by incorporating public information provided by a trade promotion organization (TPO). This framework can also be interpreted within the search-and-matching trade literature (e.g., Antràs and Costinot 2011; Eaton et al. 2022). Exporters are heterogeneous in productivity and must incur search or outreach costs to reach overseas buyers. We model this process using an advertising technology, which provides a tractable reduced-form representation of costly buyer search. High-productivity exporters reach a larger pool of homogeneous (potential) importers by investing more in advertising efforts. When a TPO provides importer contacts, exporters can expand their reach and boost export volumes. Importantly, these benefits are relatively larger for smaller exporters, thereby reducing export concentration.

3.1. Environment

Export Market Penetration (Importer Search). We consider an advertising technology inspired by the theory of informative advertising (Butters 1977; Grossman and Shapiro 1984) and closely related to search-and-matching frameworks in trade (Antràs and Costinot 2011; Eaton et al. 2022).

Suppose that a market is populated by a mass L of potential importers whom potential exporters seek to contact through advertising efforts.[6] Potential exporters can advertise on a set of platforms represented by a mass $M \geq 1$. Each potential exporter undertakes an advertising campaign consisting of a total mass S of advertisements distributed evenly across these platforms. We assume that an importer's exposure to advertisements across the different platforms is independent. With a uniform exposure probability, each unit of advertisement reaches potential importers with probability $S/(L \times M)$. In effect, the total advertising effort S is evenly allocated over M platforms and across the L importers.

Consequently, the probability that a specific importer is exposed to an advertisement on a single platform is $[S/(M \times L)]$. With M independent platforms, the probability that an potential importer sees none of the advertisements is $\{1 - [S/(M \times L)]\}^M$. Thus, the total mass of importers who see at least one advertisement (i.e., matched importers) is the

[6] Arkolakis (2010) allows the number of potential importers reached by each ad to be $L^{1-\alpha}$ with $\alpha \in [0, 1]$, while here we set $\alpha = 1$ as in Dukes (2004). Allowing $\alpha \neq 1$ would not affect our qualitative results.

following.[7]

$$b(S) = \left[1 - \left(1 - \frac{S}{M \times L}\right)^{M} \times \mathbb{1}_{\{S \leq M \times L\}}\right] L, \tag{3}$$

where $\mathbb{1}\{\cdot\}$ is an indicator function. If $S > M \times L$, the exporter reaches all potential importers, so $b(S) = L$. Advertising effort incurs a constant marginal cost, with each unit of effort requiring $1/\psi$ units of labor. Rearranging equation (3), the labor required to reach $b \in [0, L]$ importers is

$$f_X(b) = \frac{M}{\psi}\left[1 - \left(1 - \frac{b}{L}\right)^{\frac{1}{M}}\right] L. \tag{4}$$

Information Intermediary and Public Information. A TPO collects and publicly provides the contacts of $I \in [0, L]$ potential importers (henceforth, *informed importers*). For these informed importers, the marginal labor cost to reach an additional informed importer is $1/\psi$; that is, we set the lowest number of advertisement platforms ($M = 1$, single platform) in equations (3) and (4). Note that when $M > 1$, the labor cost $f_X(b)$ exceeds b/ψ. Hence, exporters first contact the informed importers (with mass I) at low cost before expanding their search to the remaining $L - I$ potential importers.

Given L and I, the labor required to reach $b \in [0, L]$ importers is

$$f_X(b, I) = \begin{cases} \dfrac{M}{\psi}\left[1 - \left(\dfrac{L-b}{L-I}\right)^{\frac{1}{M}}\right](L - I) + \dfrac{1}{\psi}I & \text{if } b \in (I, L] \\ \dfrac{1}{\psi}b & \text{if } b \in [0, I] \end{cases} \tag{5}$$

The search cost function is increasing and convex in the number of matched importers, meaning that the marginal productivity of additional importer contacts decreases. Public information thus reduces the advertising/search cost for any given level of b, i.e., $f_X(b, I) \geq f_X(b, I')$ for all I and I' satisfying $0 \leq I \leq I' \leq L$.

Production Technology. Production follows the standard trade model with constant marginal costs. Each potential exporter φ produces a unique variety using labor as the sole input, paid at wage w. Exporter φ requires $1/\varphi$ units of labor to produce one unit of

[7] This matched importer equation (3) can be derived from the differential equation as in Dukes (2004) and Arkolakis (2010): the marginal change in the mass of matched importers through new ads, $b'(S)L = L[1 - b(S)]^M$ with the initial condition $b(0) = 0$, in which $[1 - b(S)]^M$ is the probability that a new ad is seen by a importer for the first time.

its product. In addition, iceberg trade costs $\tau > 1$ imply that delivering one unit abroad requires producing τ units. The productivity distribution of exporters follows a Pareto law with cumulative distribution $G(\varphi) = 1 - (\underline{\varphi}/\varphi)^{\theta}$ and density $g(\varphi) = \theta(\underline{\varphi}/\varphi)^{\theta}/\varphi$ where $\underline{\varphi}$ is the minimum productivity level.

Preference and Demand. All firms (potential exporters and domestic firms) compete monopolistically in each market. The market demand for an individual exporter's product depends on its price p and the mass of importers reached, b, as well as on the destination market's aggregate demand Q and price index P:

$$pq = b\frac{Q}{L}\left(\frac{p}{P}\right)^{1-\sigma}, \tag{6}$$

with the elasticity of substitution across varieties $\sigma > 1$. We assume that the importing country is large relative to the exporting country so that P and Q are exogenous. This assumption is appropriate for exporters in small open economies such as Korea.

Exporters' Problem and Productivity Cutoff. Given the public information on importer contacts provided by the TPO, a potential exporter with productivity φ maximizes profit by choosing its price p, quantity q, and the number of importers b to contact:

$$\max_{p,q,b} pq - w\left(\frac{\tau q}{\varphi}\right) - wf_X(b, I),$$

subject to equations (5) and (6). The first-order condition with respect to price yields the standard markup rule, $\mu = \sigma/(\sigma - 1)$, so that the optimal price is $p(\varphi) = \mu\tau w/\varphi$ to the reached importers.

The optimal choice of b satisfies the first-order condition:

$$\frac{1}{\sigma}\left(\frac{\mu\tau w}{\varphi P}\right)^{1-\sigma}\frac{Q}{L} = \begin{cases} \dfrac{w}{\psi}\left(\dfrac{L-b}{L-I}\right)^{\frac{1}{M}-1} & \text{if} \quad \varphi \in (\varphi^*, \infty) \;\Leftrightarrow\; b \in (I, L) \\ \dfrac{w}{\psi} & \text{if} \quad \varphi \in [\underline{\varphi}, \varphi^*] \;\Leftrightarrow\; b \in [0, I] \end{cases} \tag{7}$$

where the cutoff productivity φ^* is determined by equating the marginal benefit of search to its marginal cost w/ψ when $b = I$. Exporters with $\varphi > \varphi^*$ expand their search beyond the informed importers, while those with $\varphi \leq \varphi^*$ do not search further. In the latter case, profits are non-positive—attaining zero profit only at $\varphi = \varphi^*$. In other words, potential exporters with lower productivity will opt not to search. The cutoff serves as the export

market entry cutoff. Note that the cutoff, $\varphi^* = [(\sigma w L)/(\psi Q)]^{1/(\sigma-1)}[(\mu\tau w)/P]$, does not depend on the provided information I. Thus, in our partial equilibrium framework the public information does not induce additional market entry.

3.2. Optimal Search and Export Behaviors

We next analyze how public information affects exporters' decisions. Access to public information influences both the intensity of importer search and export performance.

Matched Importers. For a given level of public information I, the optimal mass of importers reached by an exporter with productivity φ is

$$b(\varphi, I) = \big[L - (L - I) \times \lambda(\varphi)\big] \times \mathbb{1}_{\{\varphi > \varphi^*\}}, \quad \text{where} \quad \lambda(\varphi) = (\varphi/\varphi^*)^{-(\sigma-1)/(1-1/M)}. \quad (8)$$

For all active exporters, $\varphi > \varphi^*$, the share of unmatched buyers is less than one, $\lambda(\varphi) < 1$, and decreases with exporter productivity, $\lambda'(\varphi) < 0$. The matched-importer equation in (8) can also be written as $b(\varphi, I) = I + [1 - \lambda(\varphi)] \times (L - I)$. This expression has a natural interpretation. An exporter reaches the mass I of informed importers with certainty and searches among the remaining mass $L - I$ of uninformed importers, matching with each of them with probability $1 - \lambda(\varphi)$.

For active exporters ($\varphi > \varphi^*$) given informed importers ($I < L$), higher productivity leads to a larger mass of matched importers because they can generate more profits from each importer they reach:

$$\frac{\partial b(\varphi, I)}{\partial \varphi} = -(L - I)\lambda'(\varphi) > 0.$$

Furthermore, while public information expands the pool of matched importers for all exporters, the incremental benefit, $\lambda(\varphi) \times I$, is larger for less productive exporters. The responsiveness of matched importers to public information is given by $\lambda(\varphi)$, which decreases with productivity:

$$\frac{\partial b(\varphi, I)}{\partial I} = \lambda(\varphi) > 0 \quad \text{and} \quad \frac{\partial}{\partial \varphi}\left[\frac{\partial b(\varphi, I)}{\partial I}\right] = \lambda'(\varphi) < 0,$$

where the entry cutoff (φ^*) is independent of the public information (I, informed importers). The impact of public information is less pronounced for highly productive exporters since they would have likely reached these importers anyway due to their higher buyer search intensity.

Export Sales. Exporters' export sales in the presence of public information are $\text{ex}(\varphi, I) = b(\varphi, I)[p(\varphi)/P]^{1-\sigma}(Q/L)$. Using equation (8), we can write

$$\text{ex}(\varphi, I) = \left[1 - (1 - I/L)\lambda(\varphi)\right] \times \overline{\text{ex}}(\varphi) \times \mathbb{1}_{\{\varphi > \varphi^*\}}, \tag{9}$$

where $\overline{\text{ex}}(\varphi)$ represents export sales under full information (i.e., when $I = L$). The full information provision scenario aligns with the conventional trade model described in Melitz (2003). Notice that the increase in exports due to public information stems solely from reaching more importers, not from increasing per-importer sales. For $\varphi > \varphi^*$, the percentage change in exports with respect to $I \in (0, L)$ is

$$\frac{\partial \ln \text{ex}(\varphi, I)}{\partial \ln I} = \frac{\lambda(\varphi)}{1 - (1 - I/L)\lambda(\varphi)} \times \frac{I}{L} > 0,$$

while the elasticity with respect to I declines with productivity:

$$\frac{\partial}{\partial \varphi}\left[\frac{\partial \ln \text{ex}(\varphi, I)}{\partial \ln I}\right] = \frac{\lambda'(\varphi)}{[1 - (1 - I/L)\lambda(\varphi)]^2} \times \frac{I}{L} < 0.$$

Thus, although all exporters benefit from public information, the relative gains are smaller for higher-productivity (larger) exporters.[8] This result implies that if exporters must pay a fee to access the public information, highly productive exporters may opt out of purchasing the information because of their relatively smaller gains—a prediction consistent with empirical findings that smaller exporters are more likely to rely on intermediary services (e.g., Ahn, Khandelwal and Wei 2011).

3.3. Aggregate Exports

We now examine how exporter-level decisions aggregate to affect total exports and the distribution of export sales across exporters. Our analysis, which is particularly relevant for small open economies like Korea, assumes that the TPO's public information does not affect the destination market's overall price and quantity.

In equilibrium, total industry exports to a given market are the sum of sales from all exporters, $\text{EX}(I) = J \times \int_{\varphi^*}^{\infty} \text{ex}(\varphi, I)\text{d}G(\varphi)$ where J denotes the mass of potential exporters.

[8] In absolute terms, the marginal increase in export sales, given by $\partial \text{ex}(\varphi, I)/\partial \iota = \lambda(\varphi)\overline{\text{ex}}(\varphi) > 0$, also declines with productivity because the fraction of unmatched buyers from an exporter's search, $\lambda(\varphi)$, decreases with productivity at a higher rate ($(\sigma - 1)(1 + 1/M)$) than the rate of increase in per-buyer exports ($\sigma - 1$). Therefore, the increases in exporter-level exports in the absolute term, which is a product of the fraction of unmatched importers and per-importer exports, are smaller for larger exporters than smaller exporters.

We can express aggregate exports as follows.[9]

$$\mathrm{EX}(I) = [1 - (1 - I/L)\Lambda]\,\overline{\mathrm{EX}}, \quad \text{where} \quad \Lambda = \frac{\theta - (\sigma - 1)}{\theta + (\sigma - 1)/M} > 0. \tag{10}$$

Here, $\overline{\mathrm{EX}}$ represents total exports in the frictionless case (i.e., when $I = L$), following the standard trade model in Melitz (2003). When the TPO connects exporters with all importers, the frictionless export level is attained ($\mathrm{EX}(L) = \overline{\mathrm{EX}}$).

Public information mitigates the export losses induced by search frictions. The elasticity of aggregate exports with respect to public information $I \in (0, L)$ is

$$\frac{\partial \ln \mathrm{EX}(I)}{\partial \ln I} = \frac{\Lambda}{1 - (1 - I/L)\Lambda} \times \frac{I}{L} > 0.$$

As shown in our exporter-level analysis, the effects of public information vary across exporters, more pronounced in smaller exporters than bigger exporters. These heterogeneous effects can translate that the aggregate effects depend on the size distribution of exporters. In particular, more concentrated export distributions dampen the aggregate export gains from public information.

In our model, there are two key supply- and demand-side parameters shaping the export sales distribution. First, this export promotion effect is amplified by a larger shape parameter θ (indicating a thinner right tail in the productivity distribution):

$$\frac{\partial}{\partial \theta}\left[\frac{\partial \ln \mathrm{EX}(I)}{\partial \ln I}\right] = \frac{I/L}{[1 - (1 - I/L)\Lambda]^2} \times \frac{\partial \Lambda}{\partial \theta} > 0,$$

where $\partial\Lambda/\partial\theta > 0$. However, it weakened by a higher elasticity of substitution σ (implying less product differentiation):

$$\frac{\partial}{\partial(\sigma - 1)}\left[\frac{\partial \ln \mathrm{EX}(I)}{\partial \ln I}\right] = \frac{I/L}{[1 - (1 - I/L)\Lambda]^2} \times \frac{\partial \Lambda}{\partial(\sigma - 1)} < 0,$$

where $\partial\Lambda/\partial(\sigma - 1) < 0$. Because a smaller shape parameter and a higher elasticity of substitution imply a more concentrated sales distribution, these model predictions indicate that exporter concentration dampens the export gains from TPO-provided public information.

[9] In equation (10), Λ captures how search frictions reduce aggregate exports: $\Lambda = \overline{\mathrm{EX}}/\mathrm{EX}(0) - 1$. This ratio reflects the total percentage decrease in exports due to overseas buyer search frictions when no public information is available ($I = 0$), compared to the frictionless case.

4. Empirical Specification and Issues

Our theoretical framework predicts that buyer information provided by TPOs can alleviate search frictions and facilitate export growth. But did the buyer information collected and disseminated by KOTRA actually achieve this goal, particularly for small and medium-sized enterprises?

Empirically identifying the causal impact of such information poses several challenges. Most notably, reverse causality and omitted variable bias may confound the relationship: countries with more active trade may attract greater information collection, and favorable market conditions, such as stronger import demand, may simultaneously increase both exports and the supply of buyer information. These concerns are well recognized in the literature on trade and information frictions (e.g., Steinwender 2018).

To address these challenges, we examine the properties of KOTRA's buyer information and find that a substantial share of the collection process does not systematically respond to contemporaneous destination market conditions. This results in considerable idiosyncratic variation in the timing and intensity of information provision. In the remainder of this section, we document this variation and describe our empirical strategy, which exploits it to identify the causal effect of buyer information on export performance.

4.1. KOTRA's Buyer Information Collection

At an aggregate level, market size appears to be an important driver of KOTRA's information collection. As shown in Figure 2, destination countries with larger economies and industries with greater global trade volumes (excluding Korea) received more buyer information on average. This pattern supports the validity of our digitization and suggests that KOTRA's search efforts were partially responsive to global trade patterns. Several mechanisms could underlie this correlation: locating buyers is likely easier in active markets, and KOTRA may have allocated more resources to high-potential destinations. For instance, in 1980, KOTRA operated 12 offices in the United States, compared to just 3 in Canada and 1 in Mexico, reflecting differences in market size.

At a more granular level, however, KOTRA's information collection exhibits substantial variation that is uncorrelated with contemporaneous market conditions. Figure 3's Panels (a) and (b) present binned scatter plots of import demand and buyer information at the country-industry-year level. While a positive correlation is evident in the raw data (Panel a), the relationship disappears after controlling for detailed fixed effects, including country-year, product-year, and country-industry (Panel b). This suggests that, after accounting

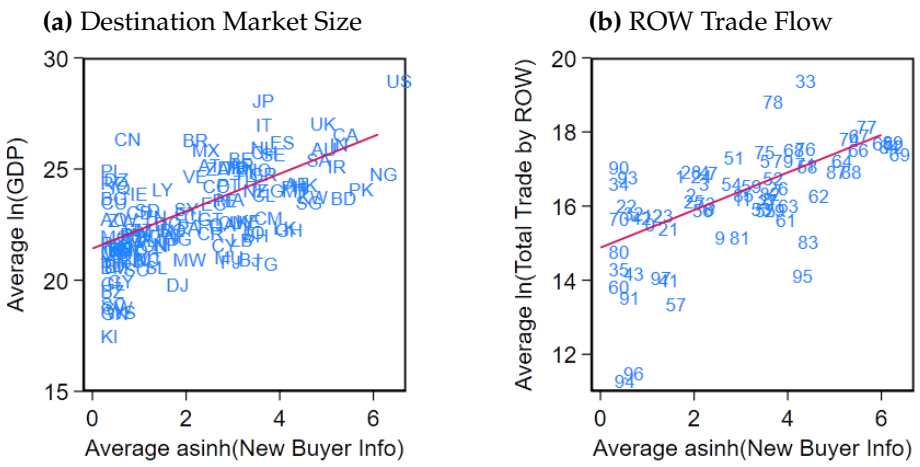

Figure 2: Average New Buyer Information and Market Size

Notes: The left panel plots the average IHS transformed new buyer information against the average log GDP for each destination country. The right panel shows the relationship between the average IHS-transformed buyer information and the average log total trade flows (excluding Korea) for each SITC 2-digit industry. All averages are computed over the sample period.

for systematic components of information collection, such as the number and location of KOTRA offices, much of the variation in buyer information remains unexplained by observable trade fundamentals.

This pattern is specific to buyer information and stands in contrast to Korea's export flows. As shown in Figure 3's Panel (c) and (d), Korean exports remain strongly correlated with market size, even after controlling for the same set of fixed effects. To quantify this contrast, we estimate gravity-style regressions for both buyer information and exports (see Appendix C for details). While market size and fixed effects account for a large share of the variation in Korea's exports ($R^2 = 0.78$), they explain less than half of the variation in buyer information ($R^2 = 0.42$). Moreover, the coefficient on market size becomes statistically insignificant and near zero for buyer information once fixed effects are included, whereas it remains large and highly significant for exports.

These findings indicate that KOTRA's information collection contains considerable idiosyncratic variation that is orthogonal to trade flows. We attribute this variation to the human-driven nature of the search process, which relied more on individual discretion than on standardized or algorithmic assessments of market potential. Local KOTRA staff, typically general administrative personnel rather than trained market analysts, conducted information-gathering as part of their routine assignments (KOTRA 2012). As a result, variation in capacity, experience, and judgment likely introduced significant noise into the

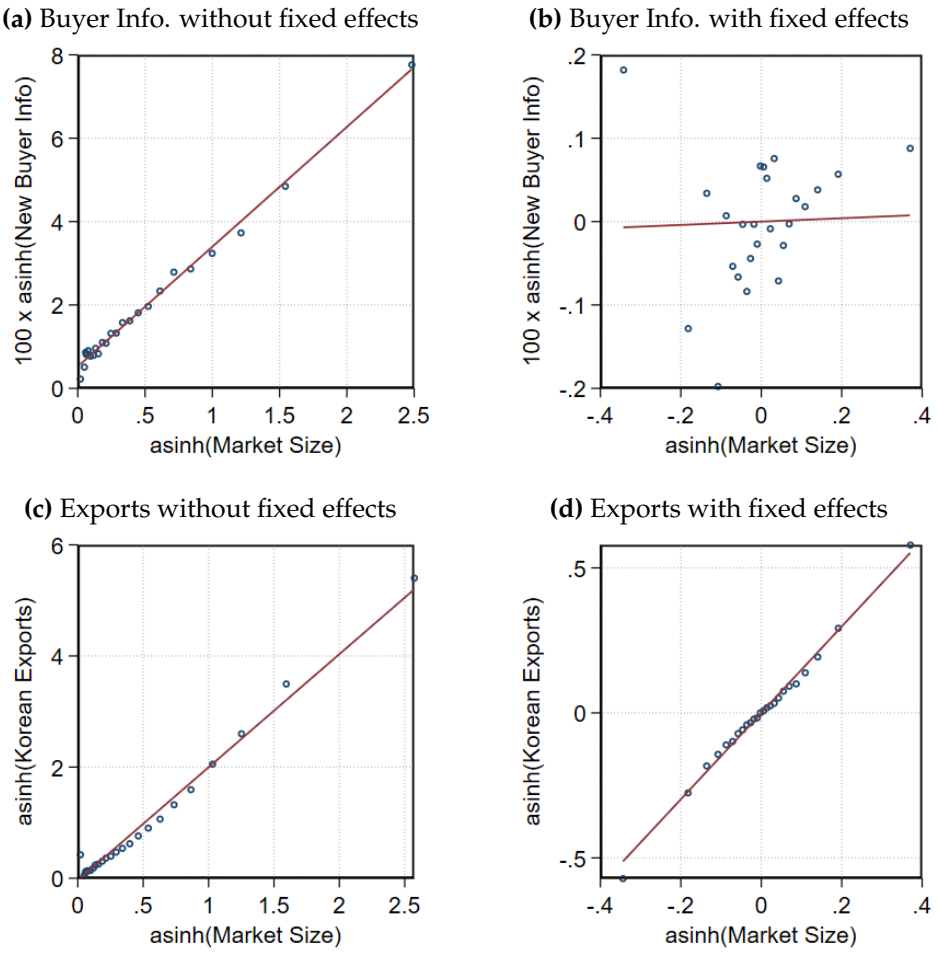

Figure 3: Binned Scatter Plot of Buyer Information, Korean Exports, and Market Size

Notes: The first row (Panels a and b) presents a binned scatterplot of inverse hyperbolic sine (IHS) transformed new buyer information ($\texttt{NewBuyerInfo}^k_{j,t}$) against market size ($\texttt{ImportSize}^k_{j,t}$), measured as the sum of IHS-transformed imports, at the country-industry-year level. The second row (Panels c and d) presents a binned scatterplot of inverse hyperbolic sine (IHS) transformed Korean exports ($\texttt{EX}^k_{j,t}$) against market size ($\texttt{ImportSize}^k_{j,t}$), at the country-industry-year level. The left column (Panels a and c) illustrates the raw relationship between the two variables. The right column (Panels b and d) depict the residualized relationship after controlling for country-year, industry-year, and country-industry fixed effects, using the covariate adjustment method developed by Cattaneo, Crump, Farrell and Feng (2019).

quantity of collected information.[10]

Beyond these personnel-driven sources of heterogeneity, non-economic considerations also influenced the direction and intensity of KOTRA's buyer search. For example, Figure A.3 shows that in 1981, smaller economies such as Ghana and Nigeria received more buyer coverage than the much larger U.S. market. This reflects Korea's foreign policy priorities in the wake of the 1970s oil shocks, during which the government sought to strengthen diplomatic and economic ties with oil-producing countries in West Africa, in part to counter North Korea's influence in the region.

Finally, the data indicate that the vast majority of collected entries correspond to distinct buyers. For example, in the United States, which had the highest number of reported contacts, only six out of 98 firms appeared more than once in 1981, and only nine out of 255 firms were recorded in both 1981 and 1982. Given this low rate of repetition, we interpret the collected buyer contacts as representing new buyer information.

4.2. Effect of Buyer Information on Exports

The preceding analysis suggests that KOTRA's buyer information contains substantial idiosyncratic variation that is not explained by standard trade determinants. Our baseline empirical specification exploits this variation by controlling for systematic determinants of trade flows using detailed fixed effects and destination-industry level demand measures:

$$\texttt{EX}^k_{j,t} = \exp\left[\alpha \times \text{asinh}(\texttt{NewBuyerInfo}^k_{j,t-1}) + \gamma \times \texttt{ImportSize}^k_{j,t} + \delta^k_j + \delta_{j,t} + \delta^k_t + \epsilon^k_{j,t}\right], \quad (11)$$

where $\texttt{EX}^k_{j,t}$ denotes Korea's exports in SITC 4-digit industry k to country j in year t, and $\texttt{NewBuyerInfo}^k_{j,t}$ is the number of new buyer contacts collected by KOTRA. The variable $\texttt{ImportSize}^k_{j,t}$ captures destination-level market size, measured as the sum of IHS-transformed imports from the rest of the world. Fixed effects δ^k_j, $\delta_{j,t}$, and δ^k_t control for destination-industry, destination-year, and industry-year factors, respectively.

The baseline specification uses the annual flow of newly listed buyer contacts because the KOTRA archive records new information arrivals, but not whether previously listed buyers remained active or relevant. We therefore use $\text{asinh}(\texttt{NewBuyerInfo}^k_{j,t-1})$ to capture exposure to newly available buyer information, and in Section 5.1 we also consider a decaying stock measure to connect the empirical specification more directly to the stock variable in the model.

[10] Consistent with this interpretation, Barteska and Lee (2026) finds that the individual capacity and prior experience of Korean bureaucrats posted to KOTRA's overseas offices significantly influenced the quality and effectiveness of market research.

The coefficient of interest, α, measures the export response to newly available buyer information. If the variation in $\texttt{NewBuyerInfo}^k_{j,t-1}$ is orthogonal to the error term $\epsilon^k_{j,t}$, meaning it is uncorrelated with unobserved determinants of trade flows conditional on import demand and fixed effects, then α can be interpreted as the causal effect of new buyer-information arrivals. A positive estimate of α would imply that increases in buyer contacts lead to higher export values, consistent with the presence of search frictions.[11]

Identification relies on the ability of the fixed effects and the import demand control to isolate exogenous variation in buyer information from other determinants of Korean exports. The fixed effects in equation (11) absorb a broad set of potential confounders: δ^k_j captures time-invariant heterogeneity across destination-industry pairs, such as average market size, which is positively correlated with buyer information (see Figure 2); $\delta_{j,t}$ controls for time-varying destination-specific factors, including ethnic Korean networks (immigration) and their changes as well as market expansion or changes in trade policy; and δ^k_t accounts for industry-specific shocks over time, such as domestic policies targeting particular sectors. In addition, $\texttt{ImportSize}^k_{j,t}$ captures fluctuations in import demand or trade conditions at the destination-industry-year level, such as a surge in U.S. demand for shoes or a general reduction in tariffs on those products in the U.S.

Specification issues. The baseline specification exploits variation in KOTRA's buyer information that is plausibly exogenous to the determinants of Korean exports, controlling for destination-industry-year import demand and incorporating a rich set of fixed effects. These controls are effective in absorbing shocks that influence trade flows across all exporters to a given destination-industry pair. However, they may not fully account for shocks specific to Korean exports, potentially inducing spurious correlation between KOTRA's information provision and export outcomes. For example, Korea may face distinct tariff schedules or destination-specific demand shocks that are not experienced by other countries. Although our earlier analysis suggests that KOTRA's search activities were not systematically responsive to general market conditions, it remains possible that these efforts were influenced by Korea-specific trade policies or demand conditions.

Ideally, we would directly control for such Korea-specific factors. However, the lack of bilateral country-industry-year data on tariffs, transport costs, or destination-specific demand in the 1980s makes this infeasible. To address this limitation, we implement several robustness checks. First, we include Korea's lagged exports to the same destination-industry pair, $\text{asinh}(\texttt{EX}^k_{j,t-1})$, to account for persistent bilateral trade determinants such as

[11] Given the high incidence of zero trade flows in the dataset, we primarily rely on Poisson pseudo-maximum likelihood (PPML) estimation, following Silva and Tenreyro (2006). For robustness, we also report OLS estimates in the appendix, restricting the sample to positive trade flows to focus on the intensive margin.

tariff schedules. Second, we introduce finer-grained fixed effects at the country-SITC 2-digit-year and country-SITC 3-digit-year levels to absorb Korea-specific shocks operating at broader industry aggregates. Third, we conduct a placebo analysis using export data from Japan and Taiwan, two countries with export structures broadly comparable to Korea's. If the estimated effect of buyer information merely reflects unobserved destination-level conditions, we would expect to find similar effects for these countries. The absence of such patterns would lend support to the interpretation that the observed impact for Korea operates through the buyer information channel. Finally, in Section 6, we present an event-study analysis using a local projection difference-in-differences (LP-DiD) framework, which further assesses whether the export response is preceded by differential export dynamics.

5. Regression Results

5.1. Public Information Promotes Exports

The baseline regression equation (11) assumes that firms require time (one year) to absorb the information, establish contact with potential buyers, and complete transactions. We explore alternative timing structures of the buyer information variable. In Table 1, we incorporate its contemporaneous information or more lags, $\texttt{NewBuyerInfo}^k_{j,t-l}$, $l = 0, 1, 2, \cdots, 5$.

Table 1 presents the estimated impact of buyer information on exports (α) from regression equation (11). Columns (1) and (2) show that contemporaneous buyer information has a limited impact on exports. In contrast, Columns (3), (4), and (5) indicate that lagged information exerts a statistically significant and economically meaningful effect, suggesting that firms act on newly acquired buyer information with a delay. Moreover, comparing Columns (1) and (3) with Columns (2) and (4) shows that including the control variable $\texttt{ImportSize}^k_{j,t}$ has little effect on the estimates. This suggests that our empirical strategy—leveraging rich fixed effects—helps isolate residual variation in buyer information that is uncorrelated with market demand potential, thereby reinforcing the credibility of our identification approach.

Given the robust evidence of lagged effects, we focus on new buyer information from the previous period in the remainder of the analysis. The coefficient in Column (4) indicates that a doubling of publicly available buyer information leads to a 5.7% increase in exports in the subsequent year. In practical terms, a one standard deviation increase in new buyer information translates into a 1.3% rise in exports.

Table 1: Impacts of New Buyer Information on Exports

Dep. Variable	(1) Export	(2) Export	(3) Export	(4) Export	(5) Export	(6) Export	(7) Export
$\text{asinh}(\texttt{NewBuyerInfo}^k_{j,t})$	–0.015	0.009			0.011	–0.018	0.028
	(0.033)	(0.026)			(0.027)	(0.043)	(0.030)
$\text{asinh}(\texttt{NewBuyerInfo}^k_{j,t-1})$			0.042**	0.057**	0.059**	0.076**	0.101***
			(0.019)	(0.022)	(0.025)	(0.032)	(0.023)
$\text{asinh}(\texttt{NewBuyerInfo}^k_{j,t-2})$						0.057**	0.090***
						(0.029)	(0.025)
$\text{asinh}(\texttt{NewBuyerInfo}^k_{j,t-3})$						0.037	0.060**
						(0.030)	(0.029)
$\text{asinh}(\texttt{NewBuyerInfo}^k_{j,t-4})$						0.049**	0.071***
						(0.024)	(0.020)
$\text{asinh}(\texttt{NewBuyerInfo}^k_{j,t-5})$						0.062**	0.082***
						(0.025)	(0.026)
$\texttt{ImportSize}^k_{j,t}$		0.547***		0.566***	0.536***		0.494***
		(0.093)		(0.093)	(0.092)		(0.091)
Observations	241,565	241,565	236,570	236,570	210,077	99,322	90,041
Country-Industry FE	✓	✓	✓	✓	✓	✓	✓
Year-Country FE	✓	✓	✓	✓	✓	✓	✓
Year-Industry FE	✓	✓	✓	✓	✓	✓	✓

Notes: The table reports estimates of PPML regression equation (11). The dependent variable is export at the Country-Industry(4-digit SITC)-Year level. Explanatory variables include the inverse hyperbolic sine transformation of the count of newly collected buyer contacts, $\text{asinh}(\texttt{NewBuyerInfo}^k_{j,t})$, and its l lagged value, $\text{asinh}(\texttt{NewBuyerInfo}^k_{j,t-l})$; and the sum of IHS-transformed imports from the rest of the world, $\texttt{ImportSize}^k_{j,t}$. *p<0.1, **p<0.05, ***p<0.01. Standard errors in parentheses are two-way clustered within country and within industry.

Long-term effects of buyer information. Beyond short-term effects, public information may also have persistent impacts through learning and dynamic mechanisms (e.g., Atkin et al. 2017; Eaton, Eslava, Jinkins, Krizan and Tybout 2021, and Eaton et al. 2022). Although not all buyer matches result in successful transactions, those that do can lead to enduring trade relationships that expand over time. The magnitude of both initial and long-run effects ultimately determines the dynamic contribution of buyer information to trade performance. To empirically examine this, we extend our baseline specification by including up to five annual lags of new buyer information.

The estimation results of Column (6) in Table 1 show that the effect of new buyer information peaks one year after the information is received, but remains positive and statistically significant in subsequent years. This confirms that the information takes time to be absorbed and suggests that its impact persists beyond the initial period. Notably, these dynamics are consistent with the long-term exporter-importer relationship patterns

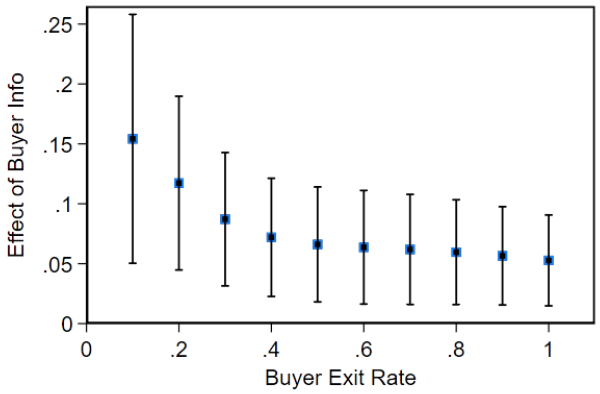

Figure 4: Impacts of Buyer Information Stock on Exports with Various Exit Rates

Notes: This figure reports estimates from the PPML regression in equation (11), using the lagged IHS-transformed value of informed buyers from public information, $\text{asinh}(\texttt{BuyerInfo}^k_{j,t-1})$, constructed under different assumptions about the buyer exit rate (ϱ) in equation (12). The 95% confidence intervals are based on standard errors two-way clustered within country and within industry. The dependent variable is export value at the country-industry (4-digit SITC)-year level. Control variables include the sum of IHS-transformed imports from the rest of the world, $\texttt{ImportSize}^k_{j,t}$, and fixed effects.

documented by Eaton et al. (2021).[12]

To incorporate the effects of previously available buyer information, we alternatively use the stock of informed active buyers, rather than the flow of new buyer contacts, as the main regressor. Although our dataset includes newly collected buyer contacts, it does not provide information on whether previously identified buyers remain active. To address this, we apply an exogenous buyer exit rate $\varrho \in [0, 1]$ to construct a decaying stock of informed buyers over time, defined as:

$$\texttt{BuyerInfo}^k_{j,t} = \texttt{NewBuyerInfo}^k_{j,t} + \sum_{l=1}^{t-1977} (1-\varrho)^l \times \texttt{NewBuyerInfo}^k_{j,t-l}, \tag{12}$$

where $(1-\varrho)^l$ represents the survival rate l years after being listed. Because our public information records begin in 1977, we exclude the first five years of data to minimize bias in constructing lagged buyer information stocks during the early years of the sample.

Figure 4 presents the estimated effects of buyer information when the main regressor in equation (11) is replaced with the one-year lagged stock of buyers, $\text{asinh}(\texttt{BuyerInfo}^k_{j,t-1})$, under various assumptions about the exit rate. When $\varrho = 1$, the stock measure collapses to our baseline regressor, $\text{asinh}(\texttt{NewBuyerInfo}^k_{j,t-1})$. Across specifications, we find posi-

[12]Including lags of market size variables to Column (6) does not qualitatively alter the estimated effect of buyer information. Notably, the influence of market size on exports diminishes quickly over time, reinforcing the interpretation that our estimates reflect the persistent value of information rather than coincidental fluctuations in market demand.

tive and statistically significant effects of buyer information. Notably, lower exit rates lead to larger estimated impacts, further underscoring the persistent influence of buyer information over time.

Robustness. Our baseline specification assumes that fixed effects and market size effectively address destination-industry-year specific confounding factors. Appendix Table A.2 tests this assumption. To control for Korean exporter-specific potential confounders, Column (1) includes the lagged 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. Column (4) further shows that the positive relationship is not driven by the IHS transformation of buyer information: using the untransformed lagged count of new buyer contacts yields a similar qualitative conclusion. Moreover, our results are robust to the choice of standard errors: clustered standard errors within country-industry pairs and robust standard errors are reported in Columns (5) and (6), respectively.

Placebo test. Appendix Table A.4 shows that our buyer information measure is not positively associated with exports from Japan or Taiwan. Since these countries have export portfolios similar to Korea's, they are likely subject to comparable destination-industry-year demand shocks. The absence of a positive relationship in this placebo test reinforces the interpretation that our findings are not driven by unobserved confounding factors. Taken together, these robustness checks and placebo tests provide strong evidence supporting the validity of our empirical strategy and results.

Extensive and intensive margins. Appendix D provides additional evidence on the mechanisms underlying the observed effects. We find that the impact of buyer information operates primarily through the intensive margin, with limited effects on the extensive margin—that is, whether Korea begins exporting in a given country-industry pair following the provision of public information.[13] Tables A.6 and A.7 show that PPML and OLS estimates excluding zero export observations remain statistically significant and are quantitatively similar to the baseline estimates reported in Table 1. By contrast, regressions using export status ($\mathbb{1}_{[\text{Export}>0]}$) as the dependent variable yield statistically insignificant estimates for new buyer information.

[13]This contrasts with Carballo, Chatruc, Santa and Volpe Martincus (2022), who find that information from internet platforms helped Peruvian firms expand exports across destinations and products. Appendix D discusses several possible explanations, including differences in data aggregation and in the role of information and communication technologies.

5.2. Heterogeneous Effects: Export Concentration

In our theoretical model, large and productive firms are more prevalent and already engage in extensive independent search, reducing the marginal value of publicly provided information. Thus, public buyer information generates smaller export gains in industries dominated by a few exporters. To test this prediction, we extend our baseline specification by incorporating interaction terms between buyer information and export concentration.

Concentration measurement. We measure export concentration at the industry level rather than at the more granular destination-industry level, as firm-level export flows by destination are not available. Specifically, we construct industry-level concentration measures for manufacturing sectors using establishment-level export data from the Korean Mining and Manufacturing Census (MMS).[14]

Our first measure of concentration is the export share held by the top N exporters, ranked by export volume, which is commonly used in the literature (e.g., Autor, Dorn, Katz, Patterson and Van Reenen 2020). We define this measure for each 3-digit Korean Standard Industrial Classification (KSIC) manufacturing industry $\tilde{k}$ as $\texttt{Top}N\texttt{ExportShare}_t^{\tilde{k}}$.[15] For our baseline analysis, we focus on $N = 4$ and $N = 8$ to ensure meaningful variation in exporter concentration across industries.[16]

While this measure is informative, it can be mechanically influenced by the total number of exporters in an industry, which may confound comparisons of concentration across industries with differing exporter counts. To mitigate this concern, we adopt a modified measure of top-exporter dominance that is less sensitive to the extensive margin:

$$\texttt{Top}N_1/\texttt{Top}N_2\texttt{Export}_t^{\tilde{k}} \equiv \frac{\ln(\texttt{Top}N_1\texttt{ExportShare}_t^{\tilde{k}}/N_1) - \ln\left(\texttt{Top}N_2\texttt{ExportShare}_t^{\tilde{k}}/N_2\right)}{\ln N_2 - \ln N_1}, \tag{13}$$

where $N_1 < N_2$. This metric compares the average export shares of the top N_1 and top N_2 firms on a log scale, normalized by the log difference in ranks. Higher values indicate a greater concentration of exports among the top-ranked firms. We set $N_1 = 4$ or 8 and $N_2 = 20$ in the baseline analysis.

[14]The Korean Mining and Manufacturing Census covers all Korean manufacturing and mining establishments and provides data on both domestic sales and exports.

[15]There are 29 manufacturing industries at the 3-digit KSIC classification. We map 4-digit SITC industries to these 3-digit KSIC industries using the concordance table between 4-digit SITC and 3-digit ISIC (Revision 2) from Muendler (2009), noting that the 3-digit KSIC codes are identical to the corresponding ISIC codes.

[16]In 1980, the median and average numbers of exporters across KSIC 3-digit industries were 171 and 195, respectively, while the 10th percentile had only 12 exporters. Our results remain robust when using larger thresholds, such as the top 20 exporters.

Table 2: Impacts of Concentration on the New Buyer Information's Effects

Dep. Variable	(1) Export	(2) Export	(3) Export	(4) Export
$\text{asinh}(\texttt{NewBuyerInfo}^{k}_{j,t-1})$	0.175***	0.215***	0.242***	0.334***
	(0.031)	(0.040)	(0.052)	(0.062)
$\text{asinh}(\texttt{NewBuyerInfo}^{k}_{j,t-1})$				
$\times\texttt{Top4ExportShare}^{\tilde{k}(k)}_{1980}$	–0.384***			
	(0.072)			
$\times\texttt{Top8ExportShare}^{\tilde{k}(k)}_{1980}$		–0.366***		
		(0.076)		
$\times\texttt{Top4/Top20Export}^{\tilde{k}(k)}_{1980}$			–0.352***	
			(0.082)	
$\times\texttt{Top8/Top20Export}^{\tilde{k}(k)}_{1980}$				-0.480***
				(0.098)
$\texttt{ImportSize}^{k}_{j,t}$	0.596***	0.598***	0.592***	0.593***
	(0.096)	(0.095)	(0.097)	(0.096)
Observations	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 (14). The dependent variable is export value at the Country-Industry (4-digit SITC)-Year level. The key explanatory variable is the IHS-transformed one-period lagged count of new buyer contacts ($\text{asinh}(\texttt{NewBuyerInfo}^{k}_{j,t-1})$), interacted with the exporter concentration measures. *p<0.1, **p<0.05, ***p<0.01. Standard errors in parentheses are two-way clustered within country and within industry.

Regression specification. To examine whether the benefits of public buyer information are attenuated in industries with higher exporter concentration, we introduce an interaction term between exporter concentration and new buyer information:

$$\begin{aligned}\texttt{EX}^{k}_{j,t} = \exp\big[&(\alpha_0 + \alpha_1 \times \texttt{Concentration}^{\tilde{k}(k)}_{1980}) \times \text{asinh}(\texttt{NewBuyerInfo}^{k}_{j,t-1}) \\ &+ \gamma \times \texttt{ImportSize}^{k}_{j,t} + \delta^{k}_{j} + \delta_{j,t} + \delta^{k}_{t} + \epsilon^{k}_{j,t}\big],\end{aligned} \tag{14}$$

where $\texttt{Concentration}^{\tilde{k}(k)}_{1980}$ denotes the exporter concentration in KSIC 3-digit industry $\tilde{k}$ associated with SITC 4-digit industry k. To mitigate endogeneity concerns, we rely on concentration measured in 1980, which is the earliest year available in the MMS data. The coefficient of interest, α_1, captures how exporter concentration moderates the effect of buyer information. Its negative value indicates that industries with more concentrated exporters derive smaller benefits from public buyer information.

Regression result. Table 2 shows that the export-promoting effect of public buyer information is significantly weaker in more concentrated industries. The estimated coefficients on the interaction term between buyer information and concentration are consistently negative across various measures. This finding aligns with our theoretical model, which predicts that firms in such industries—typically larger and with more established networks—benefit less from public information due to their extensive private search efforts.

A potential concern is that this result could be driven by other industry characteristics correlated with concentration. We therefore test its robustness by including additional interaction terms for variables such as capital intensity, the total number of firms, and product differentiation, which may independently influence the effectiveness of information.[17] As reported in Table A.3, our main finding remains stable and significant, suggesting that the moderating effect of industry concentration is not an artifact of these other factors.

6. Alternative Specification: LP-DiD Approach

Section 5 presented evidence that KOTRA's provision of buyer information significantly increased Korean exports. We exploited plausibly exogenous variation in information provision to identify causal effects, estimating an extended gravity model using the PPML estimator. A series of robustness checks and placebo tests reinforced this finding, alleviating concerns about reverse causality—that rising trade flows might themselves trigger additional information collection and confound the estimates.

To further assess the causal interpretation, we implement a difference-in-differences (DiD) analysis that estimates the dynamic export response to new buyer information and examines whether treated and comparison cells exhibit differential export changes before information arrives. The absence of differential pre-period export changes provides additional support for a causal interpretation and reduces concerns that the estimates are driven by underlying trade dynamics.

Because the timing of information provision varies across country-industry pairs, standard estimators may produce biased results when treatment effects are heterogeneous across groups (e.g., de Chaisemartin and D'Haultfœuille 2020; Goodman-Bacon 2021). To address this concern, we adopt the local projection difference-in-differences (LP-DiD) method of Dube et al. (2023). In our setting, where buyer information can arrive repeatedly for the same country-industry pair, LP-DiD allows us to focus on information arrivals that are not preceded by recent treatment episodes and to compare them with observations

[17] For instance, Korean industries dominated by large firms often had lower sales and produced more homogeneous products.

that remain untreated through the horizon used to construct the outcome change. This approach ensures cleaner comparisons between treated and control groups.

6.1. LP-DiD Specification

Our baseline LP-DiD specification examines the impact of buyer information on exports from Korean firms to a given destination country j and industry k, measured h periods after the arrival of information:

$$\begin{aligned}\Delta_h \text{asinh}(\texttt{EX}^k_{j,t}) = \beta_h \times \mathbb{1}_{\{\texttt{NewBuyerInfo}^k_{j,t}>0\}} \\ + \gamma_h \times \texttt{ImportSize}^k_{j,t} + \eta_h \times \texttt{PreTrend}^k_{j,t} + \delta^h_{j,t} + \delta^{k,h}_t + \varepsilon^{k,h}_{j,t},\end{aligned} \tag{15}$$

where Δ_h is the time difference operator between $t-1$ and $t+h$, for example, $\Delta_h \text{asinh}(\texttt{EX}^k_{j,t}) = \text{asinh}(\texttt{EX}^k_{j,t+h}) - \text{asinh}(\texttt{EX}^k_{j,t-1})$. The sample is restricted to observations satisfying:

$$\begin{cases} \text{Treatment:} & \mathbb{1}_{\{\texttt{NewBuyerInfo}^k_{j,t}>0\}} = 1 \quad \text{and} \quad \sum_{l=1}^{L} \mathbb{1}_{\{\texttt{NewBuyerInfo}^k_{j,t-l}>0\}} = 0, \\ \text{Clean Control:} & \sum_{l=-h}^{L} \mathbb{1}_{\{\texttt{NewBuyerInfo}^k_{j,t-l}>0\}} = 0. \end{cases} \tag{16}$$

Here, we include country-year and industry-year fixed effects (denoted by $\delta^h_{j,t}$, and $\delta^{k,h}_t$, respectively), and controls for $\texttt{ImportSize}^k_{j,t}$ to account for time-varying market demand conditions that may confound the relationship between exports and buyer information. Notably, to account for the possibility that destination-industry pairs receiving buyer information may already be experiencing differential export growth, we include a pre-trend control $\texttt{PreTrend}^k_{j,t} \equiv \text{asinh}(\texttt{EX}^k_{j,t-1}) - \text{asinh}(\texttt{EX}^k_{j,t-6})$, defined as the change in the outcome variable from $t-6$ to $t-1$.

The treatment variable, $\mathbb{1}_{\{\texttt{NewBuyerInfo}^k_{j,t}>0\}}$, is an indicator equal to one if Korean firms received new buyer contact information for country j and industry k in year t, as published in KOTRA's magazine.[18] The coefficient of primary interest, β_h, captures the dynamic effect of buyer information on exports h years after the information's arrival.

To address potential bias in the estimation of β_h from heterogeneity treatment effects, we follow Dube et al. (2023) and impose sample restrictions in equation (16). These

[18]We adopt a non-absorbing treatment definition to fully exploit the non-persistent, idiosyncratic variation in buyer information described in Section 4. The LP-DiD framework is particularly well-suited to this setting, as it accommodates non-absorbing, repeated treatments. While we use a binary indicator to align with conventions in the difference-in-differences literature, our results are robust to using the count of new buyer contacts instead.

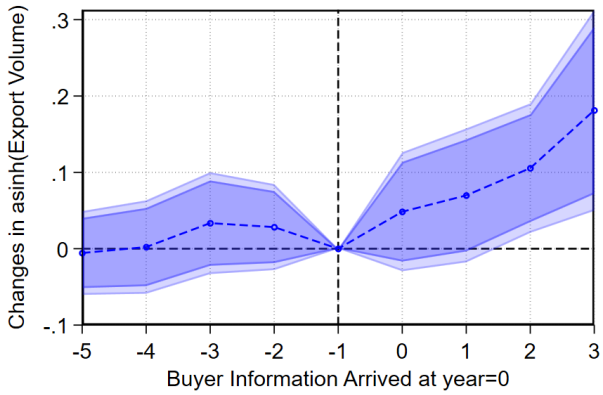

Figure 5: Export Responses to Buyer Information

Notes: This figure presents the estimated coefficients β_h from equation (15) . The y-axis in each panel represents the change in the inverse hyperbolic sine (IHS) transformation of exports relative to period $t-1$. The darker and lighter shaded areas denote the 90% and 95% confidence intervals based on standard errors two-way clustered within country and within industry. The specification includes industry–time and country–time fixed effects, market size controls, and a pre-trend control based on export changes between $t-1$ and $t-6$. The stabilization period is set to five periods.

restrictions ensure that both treated and control groups are unaffected by prior treatments, thereby avoiding contamination from overlapping or residual effects of earlier information shocks. Specifically, we assume that the effects of buyer information are not fully realized or stabilized until L years have passed. Accordingly, clean comparison observations are required to have no buyer-information arrivals during the preceding L years, or before the post-treatment horizon h used to construct the outcome change. In our baseline specification, we set the stabilization period L to five years.

6.2. LP-DiD Results

Figure 5 presents the estimated coefficients β_h from our baseline LP-DiD specification. The results indicate that the arrival of new buyer information is associated with sustained increases in export levels. We find no evidence of differential pre-period export changes between treated and comparison cells after conditioning on the fixed effects, market-size control, and five-year pretrend control. This pattern is consistent with the conditional parallel-trends assumption underlying the LP-DiD design and reduces concerns that the estimates are driven by differential pre-existing export dynamics. The export response grows over time, with an estimated increase of approximately 0.18 in IHS-transformed export values three years after the arrival of buyer information. This corresponds to a 19.9% increase in exports for destination–industry pairs that received new buyer information, relative to those that did not receive such information within the same three-year window.

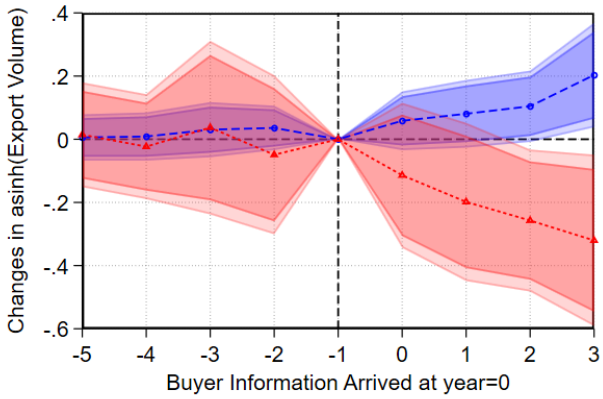

Figure 6: Export Responses to Buyer Information by Level of Exporter Concentration

Notes: This figure plots the estimated coefficients β_h (blue circles) and β_h^{conc} (red triangles) from Equation (17). High-concentration industries are defined as those in the top quartile of the 1980 export concentration measure, $\texttt{Top4/Top20Export}_{1980}^{\tilde{k}(k)}$. The y-axis shows changes in the inverse hyperbolic sine (IHS) transformation of exports relative to period $t-1$. The darker and lighter shaded areas denote the 90% and 95% confidence intervals based on standard errors two-way clustered by country and industry. The specification includes industry–time and country–time fixed effects, market size controls, and a pre-trend control based on export changes between $t-1$ and $t-6$. The stabilization period is set to five years.

Moreover, we do not find statistically significant increases in long-term exports when using Japanese or Taiwanese export data in place of Korean exports, as shown in Figure A.5. This supports the interpretation that the observed effects are not driven by spurious correlations with rising demand in destination countries that received buyer information, as Japan and Taiwan have export compositions similar to Korea's.

6.3. Industry Heterogeneity: Export Concentration

Following Section 5.2, we then examine whether high exporter concentration dampens the export-promoting effects of public buyer information provided by the TPO, as predicted by our model. To test this, we extend the baseline LP-DiD specification (equation 15) by including an interaction term between the treatment and exporter concentration:

$$\begin{aligned}\Delta_h \text{asinh}(\texttt{EX}_{j,t}^k) = &\left(\beta_h + \beta_h^{\text{conc}} \times \mathbb{1}_{\{\texttt{Top4/Top20Export1980}^{\tilde{k}(k)}=\text{Q3}\}}\right) \times \mathbb{1}_{\{\texttt{NewBuyerInfo}_{j,t}^k>0\}} \\ &+ \gamma_h \times \texttt{ImportSize}_{j,t}^k + \eta_h \times \texttt{PreTrend}_{j,t}^k + \delta_{j,t}^h + \delta_t^{k,h} + \varepsilon_{j,t}^{k,h}, \end{aligned} \tag{17}$$

where $\mathbb{1}_{\{\texttt{Top4/Top20Export}_{1980}^{\tilde{k}(k)}=\text{Q3}\}}$ equals one if the KSIC 3-digit industry $\tilde{k}$ corresponding to industry k belongs to the top quartile of export concentration in 1980, based on the measure in equation (13). To account for differences in export growth trends, we include the pre-trend from $t-6$ to $t-1$, $\texttt{PreTrend}_{j,t}^k \equiv \text{asinh}(\texttt{EX}_{j,t-1}^k) - \text{asinh}(\texttt{EX}_{j,t-6}^k)$.

The coefficient β_h^{conc} captures the differential effect of buyer information in industries with high exporter concentration relative to those with lower concentration. A negative value of β_h^{conc} would indicate that the positive impact of buyer information on exports is attenuated in more concentrated industries, consistent with our theoretical prediction.

Figure 6 presents the estimated coefficients β_h and β_h^{conc} from equation (17). The effect of buyer information is weaker in industries where exports are concentrated among a small number of firms. Specifically, the estimated interaction effects β_h^{conc} (red triangles) are negative, indicating that industries in the top quartile of exporter concentration experience smaller increases in exports following the arrival of new buyer information. These results are consistent with our theoretical framework and earlier PPML regression results in Section 5.2.

7. Conclusion

Foreign market access is central to development strategies in many small and export-oriented economies, but firms face significant information frictions when deciding what and where to export. They often lack knowledge about foreign demand, regulations, and distribution networks, making entry into overseas markets costly. These frictions represent substantial, often unmeasured, trade costs (Anderson and Van Wincoop 2004 and Head and Mayer 2013). Policies that reduce these non-tariff barriers can therefore encourage export activity.

In this paper, we examine the role of publicly provided information in promoting exports by helping firms overcome search frictions in international markets. TPOs are designed to mitigate such frictions, yet empirical evidence on their effectiveness and underlying mechanisms remains limited. We address this gap by studying Korea's experience with KOTRA, a public export-promotion institution in a historically export-oriented economy where helping domestic firms reach foreign markets remained an important policy objective.

Our theoretical and empirical analyses show that public buyer information can significantly increase exports. The main identification concern is that KOTRA's buyer-information collection may be correlated with unobserved destination-industry demand. Our empirical specification mitigates this concern by using detailed fixed effects and import-demand controls to isolate residual variation in information provision that is plausibly unrelated to Korea-specific export shocks. The absence of placebo effects for Japan and Taiwan, which had export structures broadly similar to Korea's during this period, further supports the view that the results are not driven by unobserved destination-industry

demand factors. Event-study estimates based on local projection difference-in-differences show no differential pre-period export changes, further reducing concerns about reverse causality.

Furthermore, we provide empirical evidence on substantial heterogeneity in the effectiveness of public information: export gains are considerably smaller in industries where exports are concentrated among a few large firms. This pattern supports the model's prediction that public information is less valuable when exporters already have strong private search capacity. Conversely, it is consistent with larger gains in sectors where smaller, information-constrained exporters are more likely to face binding search frictions.

The findings have implications for export-promotion policy in developing and export-oriented economies. In countries with limited domestic market size, export expansion can be central to firm growth, making policies that reduce foreign-market access costs especially valuable. Public buyer information offers one such tool: by lowering the cost of identifying potential overseas buyers, TPOs can help firms overcome search frictions that may otherwise limit export activity. The weaker response in highly concentrated industries suggests that this channel is most relevant where private search capacity is limited and smaller exporters are more likely to face binding information constraints.

References

Ahn, JaeBin, Amit K Khandelwal, and Shang-Jin Wei, "The role of intermediaries in facilitating trade," *Journal of International Economics*, 2011, *84* (1), 73–85.

Akerman, Anders, Edwin Leuven, and Magne Mogstad, "Information frictions, internet, and the relationship between distance and trade," *American Economic Journal: Applied Economics*, 2022, *14* (1), 133–63.

Allen, Treb, "Information frictions in trade," *Econometrica*, 2014, *82* (6), 2041–2083.

Amsden, Alice H, *Asia's Next Giant: South Korea and Late Industrialization*, Oxford University Press, 1989.

Anderson, James E and Eric Van Wincoop, "Trade costs," *Journal of Economic literature*, 2004, *42* (3), 691–751.

Antràs, Pol and Arnaud Costinot, " Intermediated trade ," *The Quarterly Journal of Economics*, 08 2011, *126* (3), 1319–1374.

Arkolakis, Costas, "Market penetration costs and the new consumers margin in international trade," *Journal of Political Economy*, 2010, *118* (6), 1151–1199.

Atkin, David, Amit K Khandelwal, and Adam Osman, "Exporting and firm performance: Evidence from a randomized experiment," *The Quarterly Journal of Economics*, 2017, *132* (2), 551–615.

Autor, David, David Dorn, Lawrence F Katz, Christina Patterson, and John Van Reenen, "The fall of the labor share and the rise of superstar firms," *The Quarterly Journal of Economics*, 2020, *135* (2), 645–709.

Barteska, Philipp and Jay Euijung Lee, "The implementers of industrial policy: Bureaucrats and the export miracle," Working Paper, Stockholm University 2026.

Benguria, Felipe, "The matching and sorting of exporting and importing firms: Theory and evidence," *Journal of International Economics*, 2021, *131*, 103430.

Bernard, Andrew B, Andreas Moxnes, and Karen Helene Ulltveit-Moe, "Two-sided heterogeneity and trade," *Review of Economics and Statistics*, 2018, *100* (3), 424–439.

Biesebroeck, Johannes Van, Emily Yu, and Shenjie Chen, "The impact of trade promotion services on Canadian exporter performance," *Canadian Journal of Economics/Revue canadienne d'économique*, 2015, *48* (4), 1481–1512.

Blum, Bernardo S, Sebastian Claro, and Ignatius Horstmann, "Facts and figures on intermediated trade," *American Economic Review*, 2010, *100* (2), 419–23.

Butters, Gerard R., "Equilibrium distributions of sales and advertising prices," *The Review of Economic Studies*, 1977, *44* (3), 465–491.

Buus, Magnus T, Jakob R Munch, Joel Rodrigue, and Georg Schaur, "Do export support programs affect prices, quality, markups, and marginal costs? Evidence from a natural policy experiment," *Review of Economics and Statistics*, 2025, *107* (1), 172–187.

Carballo, Jerónimo, Marisol Rodriguez Chatruc, Catalina Salas Santa, and Christian Volpe Martincus, "Online business platforms and international trade," *Journal of International Economics*, 2022, *137*, 103599.

Cattaneo, Matias D, Richard K Crump, Max H Farrell, and Yingjie Feng, "On binscatter," *arXiv preprint arXiv:1902.09608*, 2019.

Coelli, Federica, Andreas Moxnes, and Karen Helene Ulltveit-Moe, "Better, faster, stronger: Global innovation and trade liberalization," *Review of Economics and Statistics*, 2022, *104* (2), 205–216.

de Chaisemartin, Clément and Xavier D'Haultfœuille, "Two-way fixed effects estimators with heterogeneous treatment effects," *American Economic Review*, September 2020, *110* (9), 2964–2996.

Dickstein, Michael J and Eduardo Morales, "What do exporters know?," *The Quarterly Journal of Economics*, 2018, *133* (4), 1753–1801.

Dube, Arindrajit, Daniele Girardi, and Alan M Taylor, "A local projections approach to difference-in-differences event studies," NBER Working Paper 31184 2023.

Dukes, Anthony, "The adverstising market in a product oligopoly," *The Journal of Industrial Economics*, 2004, *52* (3), 327–348.

Eaton, Jonathan, David Jinkins, James R Tybout, and Daniel Xu, "Two-sided search in international markets," Working Paper 29684, National Bureau of Economic Research January 2022.

_ , Marcela Eslava, David Jinkins, C. J Krizan, and James R Tybout, "A search and learning model of export dynamics," Working Paper 29100, National Bureau of Economic Research July 2021.

Feenstra, Robert C, Robert E Lipsey, Haiyan Deng, Alyson C Ma, and Hengyong Mo, "World trade flows: 1962–2000," Working Paper 11040, National Bureau of Economic Research January 2005.

Goodman-Bacon, Andrew, "Difference-in-differences with variation in treatment timing," *Journal of Econometrics*, December 2021, *225* (2), 254–277.

Grossman, Gene M. and Carl Shapiro, "Informative advertising with differentiated products," *The Review of Economic Studies*, 01 1984, *51* (1), 63–81.

Hausmann, Ricardo, Jason Hwang, and Dani Rodrik, "What You Export Matters," *Journal of Economic Growth*, 2007, *12* (1), 1–25.

Head, Keith and Thierry Mayer, "What separates us? Sources of resistance to globalization," *Canadian Journal of Economics/Revue canadienne d'économique*, 2013, *46* (4), 1196–1231.

Hoberg, Gerard and Gordon Phillips, "Text-based network industries and endogenous product differentiation," *Journal of Political Economy*, 2016, *124* (5), 1423–1465.

Honnibal, Matthew and Ines Montani, "spaCy 2: Natural language understanding with Bloom embeddings, convolutional neural networks and incremental parsing," 2017. To appear.

Juhász, Réka and Claudia Steinwender, "Spinning the web: The impact of ICT on trade in intermediates and technology diffusion," Working Paper 24590, National Bureau of Economic Research May 2018.

Kim, Kwan S, *The Korean miracle (1962-1980) revisited: Myths and realities in strategy and development*, Citeseer, 1991.

Kneller, Richard and Jonathan Timmis, "ICT and exporting: The effects of broadband on the extensive margin of business service exports," *Review of International Economics*, 2016, *24* (4), 757–796.

KOTRA, "50 Years of KOTRA Towards the World," Technical Report, KOTRA 2012.

Lederman, Daniel, Marcelo Olarreaga, and Lucy Payton, "Export promotion agencies: Do they work?," *Journal of development economics*, 2010, *91* (2), 257–265.

Lee, Jinsoo, *Foreign capital in economic development: Korean experiences and policies*, Ministry of Strategy and Finance, 2013.

Leonidou, Leonidas C, "An analysis of the barriers hindering small business export development," *Journal of small business management*, 2004, *42* (3), 279–302.

Martincus, Christian Volpe and Jerónimo Carballo, "Export promotion: Bundled services work better," *The World Economy*, 2010, *33* (12), 1718–1756.

Mayer, Thierry and Soledad Zignago, "Notes on CEPII's distances measures: The GeoDist database," 2011.

Melitz, Marc J, "The impact of trade on intra-industry reallocations and aggregate industry productivity," *econometrica*, 2003, *71* (6), 1695–1725.

Muendler, Marc-Andreas, "Converter from SITC to ISIC," *University of California-San Diego, unpublished mimeo*, 2009.

Munch, Jakob and Georg Schaur, "The effect of export promotion on firm-level performance," *American Economic Journal: Economic Policy*, 2018, *10* (1), 357–87.

Rauch, James E, "Networks versus markets in international trade," *Journal of international Economics*, 1999, *48* (1), 7–35.

_ and Vitor Trindade, "Ethnic Chinese networks in international trade," *Review of Economics and Statistics*, 2002, *84* (1), 116–130.

Sant'Anna, Pedro H.C. and Jun Zhao, "Doubly robust difference-in-differences estimators," *Journal of Econometrics*, 2020, *219* (1), 101–122.

Secretariat, WTO, "World trade report 2016: levelling the trading field for SMEs," *WTO, Geneva*, 2016.

Shen, Zejiang, Ruochen Zhang, Melissa Dell, Benjamin Charles Germain Lee, Jacob Carlson, and Weining Li, "LayoutParser: A unified toolkit for deep learning based document image analysis," *arXiv preprint arXiv:2103.15348*, 2021.

Silva, JMC Santos and Silvana Tenreyro, "The log of gravity," *The Review of Economics and statistics*, 2006, *88* (4), 641–658.

Sreekumar, TT, "Mobile phones and the cultural ecology of fishing in Kerala, India," *The Information Society*, 2011, *27* (3), 172–180.

Steinwender, Claudia, "Real effects of information frictions: When the states and the kingdom became united," *American Economic Review*, 2018, *108* (3), 657–96.

Volpe Martincus, Christian and Jerónimo Carballo, "Is export promotion effective in developing countries? Firm-level evidence on the intensive and the extensive margins of exports," *Journal of International Economics*, 2008, *76* (1), 89–106.

_ and _ , "Beyond the average effects: The distributional impacts of export promotion programs in developing countries," *Journal of Development Economics*, 2010, *92* (2), 201–214.

Westphal, Larry E, "Industrial Policy in an Export-Propelled Economy: Lessons from South Korea's Experience," *Journal of Economic Perspectives*, 1990, *4* (3), 41–59.

APPENDIX

A. Details on 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 A.1, "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.[19][20] 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.[21] 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.[22] 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

[19] 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.

[20] 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.

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

[22] 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.

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

Figure A.1: An Example Page of Buyer Information List

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 from word embedding to break the tie.[23]

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.[24] 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.

[23] 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.

[24] 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 ($= 188 \times 786 \times 14$)

A.4. Additional Figures and Tables

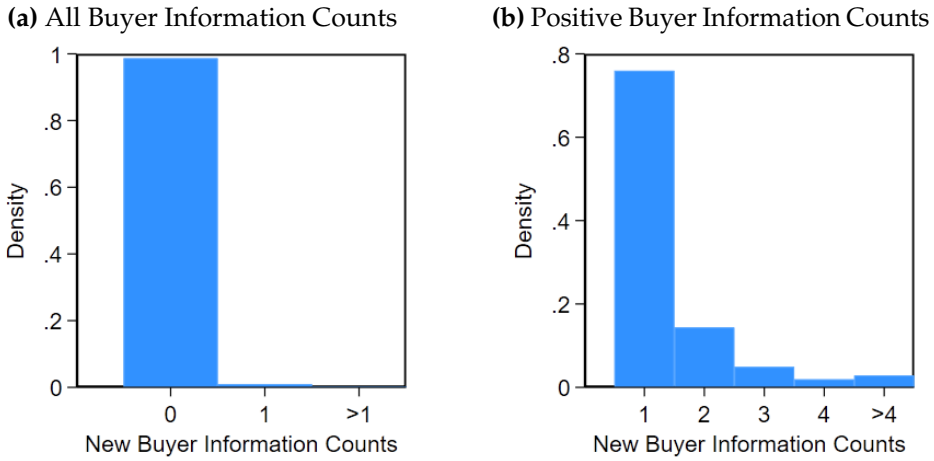

Figure A.2: Buyer Information

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.

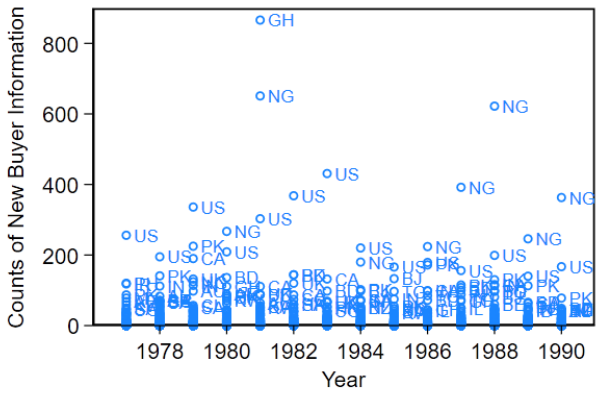

Figure A.3: The Number of New Buyer Information from Each Destination Country

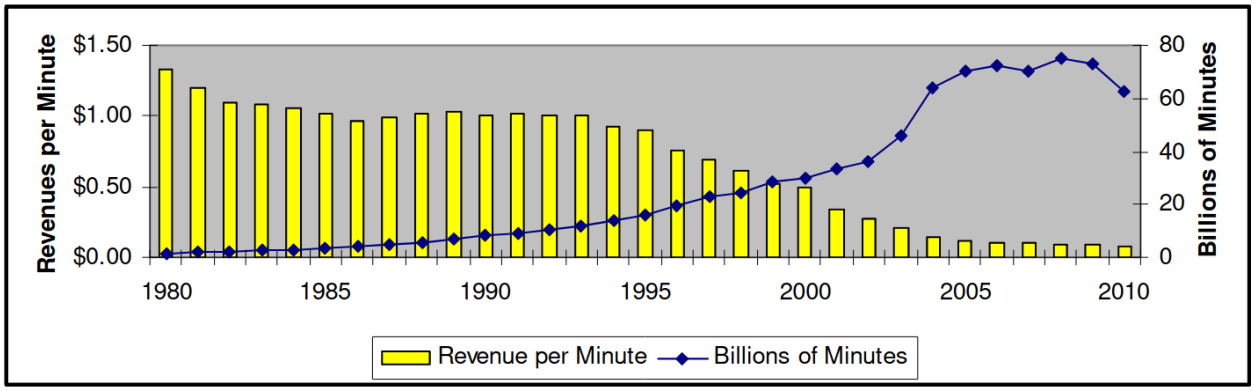

Figure A.4: International Call Rates

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

Table A.1: Heterogeneous Difference-in-Difference with Staggered Adoptions

	(1)	(2)	(3)	(4)	(5)
		Doubly Robust DiD			Synthetic DiD
Dep. Variable	IHS Export	IHS Export	IHS Export	IHS Export	IHS Export
ATET (1 vs 0)	0.220***	0.335***	0.253***	0.362***	0.362***
	(0.032)	(0.048)	(0.032)	(0.049)	(0.046)
Import Size			✓	✓	✓
Sample	Full	Balanced	Full	Balanced	Balanced
Observations	811,329	175,080	811,329	175,080	175,080

Notes: The table reports the aggregation of estimated average treatment effects on the treated (ATETs) that may vary over time and over treatment cohorts. In Columns (3)–(5), regressions include import size ($\texttt{ImportSize}^{k}_{j,t}$; the sum of log imports from the rest of the world) as other covariates. The dependent variable is IHS transformed export at the Country-Industry(4-digit SITC)-Year level. The treatment at the industry-market level is defined as having received buyer information from KOTRA in either the current period or the preceding period. *p<0.1, **p<0.05, ***p<0.01. Standard errors in parentheses are corrected for arbitrary correlation within country and industry in Columns (1)–(4). In Column (5), bootstrap standard error is reported in parentheses.

B. Robustness Check and Placebo Test Results

Table A.2: Robustness: Impacts of New Buyer Information on Exports

	(1)	(2)	(3)	(4)	(5) Alt. Cluster	(6) Robust S.E.
Dep. Variable	Export	Export	Export	Export	Export	Export
$\text{asinh}(\texttt{NewBuyerInfo}^k_{j,t-1})$	0.060***	0.059***	0.041*		0.057***	0.057***
	(0.023)	(0.019)	(0.023)		(0.019)	(0.014)
$\texttt{NewBuyerInfo}^k_{j,t-1}$				0.047***		
				(0.007)		
$\texttt{ImportSize}^k_{j,t}$	0.499***	0.657***	0.804***	0.576***	0.566***	0.566***
	(0.075)	(0.085)	(0.117)	(0.092)	(0.051)	(0.027)
$\text{asinh}(\texttt{EX}^k_{j,t-1})$	0.136***					
	(0.012)					
Observations	236,570	187,722	124,185	236,570	236,570	236,570
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 (11). The dependent variable is Korean exports at the Country-Industry (4-digit SITC)-Year level. Except in Column (4), the main explanatory variable is the IHS-transformed one-period lagged count of new buyer contacts, $\text{asinh}(\texttt{NewBuyerInfo}^k_{j,t-1})$. Column (4) instead uses the untransformed one-period lagged count, $\texttt{NewBuyerInfo}^k_{j,t-1}$. Control variables include the sum of IHS transformed 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, $\text{asinh}(\texttt{EX}^k_{j,t-1})$ (Column 1), fixed effects at the year–country–SITC 2-digit level (Column 2) and year–country–SITC 3-digit level (Column 3). *p<0.1, **p<0.05, ***p<0.01. In Columns (1)–(4), standard errors in parentheses are two-way clustered within country and within industry. In Columns (5) and (6), clustered within country-industry pairs and robust standard errors, respectively, are in parentheses.

Table A.3: Robustness: Impacts of Concentration on the Buyer Information's Effects

Dep. Variable	(1) Export	(2) Export	(3) Export	(4) Export	(5) Export	(6) Export	(7) Export
$\text{asinh}(\texttt{NewBuyerInfo}^{k}_{j,t-1})$	0.066	0.677**	0.225	0.175***	0.436	0.064	0.099
	(0.045)	(0.263)	(0.305)	(0.032)	(0.351)	(0.072)	(0.064)
$\text{asinh}(\texttt{NewBuyerInfo}^{k}_{j,t-1})$							
$\times\texttt{Top4ExportShare}^{\tilde{k}(k)}_{1980}$	–0.437***	–0.648***	–0.414***	–0.452***	–0.387***	–0.263**	–0.299***
	(0.075)	(0.133)	(0.159)	(0.147)	(0.079)	(0.126)	(0.115)
$\times\texttt{Controls}^{\tilde{k}(k)}_{1980}$	0.597***	–0.059*	–0.007	–0.021	–0.020	0.090*	0.056
	(0.148)	(0.032)	(0.047)	(0.028)	(0.028)	(0.053)	(0.046)
$\texttt{ImportSize}^{k}_{j,t}$	0.597***	0.595***	0.596***	0.597***	0.596***	0.609***	0.609***
	(0.095)	(0.096)	(0.095)	(0.095)	(0.096)	(0.098)	(0.098)
Observations	207,804	207,804	207,804	207,804	207,804	192,713	192,713
Controls	ln(E/N)	ln(E)	ln(N)	ln(CI)	ln(Revenue)	Diff(lib)	Diff(con)
Country-Industry FE	✓	✓	✓	✓	✓	✓	✓
Year-Country FE	✓	✓	✓	✓	✓	✓	✓
Year-Industry FE	✓	✓	✓	✓	✓	✓	✓

Notes: The table reports estimates of the PPML regression equation (14) with additional controls for robustness. The dependent variable is export at the Country-Industry (4-digit SITC)-Year level. The explanatory variables are the IHS transformed 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 4 Korean exporters in each 3-digit KSIC industry ($\texttt{Top4ExportsShare}^{\tilde{k}(k)}_{1980}$). Additionally, each column includes an interaction between $\text{asinh}(\texttt{NewBuyerInfo}^{k}_{j,t-1})$ and one additional industry-level characteristic. From Columns (1) to (7), these characteristics include: exporter share, log number of domestic firms (N), log number of exporters (E), log capital intensity (total capital over total revenue; CI), log total domestic sales (Revenue), and product differentiation dummies following the "liberal" and "conservative" classifications from Rauch (1999). *p<0.1, **p<0.05, ***p<0.01. Standard errors in parentheses are two-way clustered within country and within industry.

Table A.4: Placebo Test: Impacts of New Buyer Information on Exports

Exporting Country Dep. Variable	(1) Japan Export	(2) Japan Export	(3) Taiwan Export	(4) Taiwan Export
$\text{asinh}(\texttt{NewBuyerInfo}^k_{j,t-1})$	–0.013		0.010	
	(0.013)		(0.015)	
$\text{asinh}(\texttt{BuyerInfo}^k_{j,t-1})$		0.006		–0.003
		(0.026)		(0.026)
$\texttt{ImportSize}^k_{j,t}$	0.703***	0.703***	0.679***	0.679***
	(0.084)	(0.084)	(0.072)	(0.071)
Observations	551,830	551,830	189,734	189,734
Country-Industry FE	✓	✓	✓	✓
Year-Country FE	✓	✓	✓	✓
Year-Industry FE	✓	✓	✓	✓

Notes: The table reports PPML estimates of alternative specifications of equation (11). In Columns (1) and (2), the dependent variable is Japanese export at the Country-Industry (4-digit SITC)-Year level, but Columns (3) and (4) use Taiwanese exports at the Country-Industry-Year level. The main explanatory variable is either the one-period lagged IHS-transformed number of new buyer contacts, $\text{asinh}(\texttt{NewBuyerInfo}^k_{j,t-1})$, or the lagged IHS-transformed stock of buyer contacts, $\text{asinh}(\texttt{BuyerInfo}^k_{j,t-1})$, as defined in Equation (12) with exit rate $\varrho = 0.1$. Control variables include the sum of IHS-transformed imports from countries other than Japan or Taiwan at the destination Country–Industry–Year level, $\texttt{ImportSize}^k_{j,t}$. *p<0.1, **p<0.05, ***p<0.01. Standard errors in parentheses are two-way clustered within country and within industry.

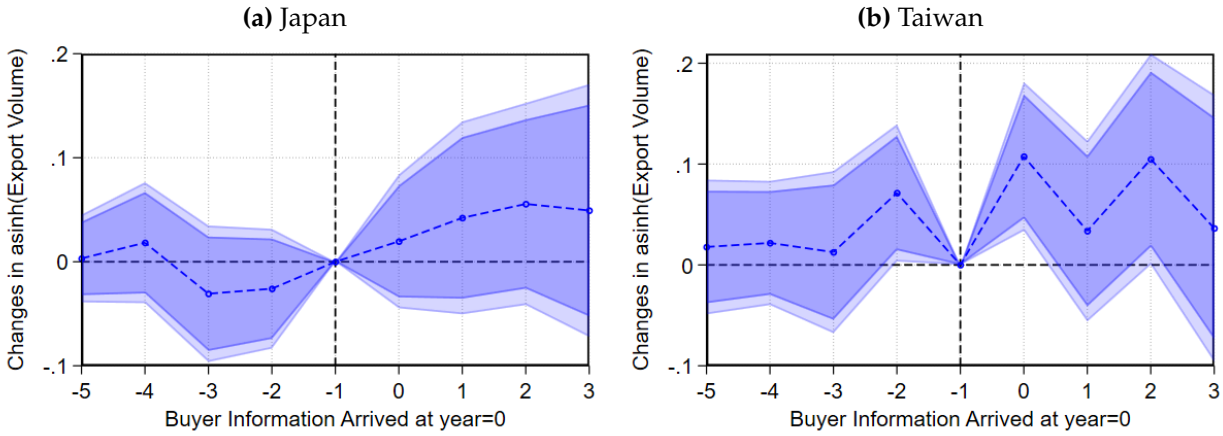

Figure A.5: Impact of Buyer Information on Exports: Placebo Test

Notes: This figure presents the estimated coefficients β_h from equation (15). The y-axis in each panel represents the change in the inverse hyperbolic sine (IHS) transformation of exports relative to period $t-1$. The darker and lighter shaded areas represent the 90% and 95% confidence intervals. The specification includes industry–time and country–time fixed effects, market size controls, and a pre-trend control based on export changes between $t-1$ and $t-6$. The stabilization period is set to five periods.

C. Determinants of New Buyer Information

To formally investigate relationships between new buyer information and economic factors of destination countries, 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.5: Gravity Regressions For the New Buyer Information and Exports

Dep. Variable	(1)	(2)	(3)	(4)	(5)	(6)
	New Buyer Info		IHS(New Buyer Info)	Export		IHS(Export)
$\ln \texttt{GDP}_{j,t}$	0.217***			0.578***		
	(0.047)			(0.099)		
$\Delta \ln \texttt{Deflator}_{j,t}$	0.335			–2.041		
	(0.218)			(1.620)		
$\ln \texttt{Distance}_{j}$	0.067			–0.687***		
	(0.215)			(0.156)		
$\texttt{ImportSize}^{k}_{j,t}$	0.234***	0.091	0.003	0.510***	0.547***	1.458***
	(0.090)	(0.083)	(0.004)	(0.077)	(0.103)	(0.099)
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. Standard errors in parentheses are two-way clustered within country and within industry.

Table A.5 compares how these variables are correlated with the collected information and South Korea's exports. We utilize destination j's variables such as GDP ($\ln \texttt{GDP}_{j,t}$), 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.

Comparing Column (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 2.[25] 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 less clear 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.

D. Mechanisms of the Export Promotion Effects

In this section, we discuss additional empirical findings that shed light on the mechanisms behind the observed effects. In particular, 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 5 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 (11). 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:

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

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 indica-

[25] 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.

tor:

$$\mathbb{1}_{\{\texttt{EX}^k_{j,t}>0\}} = \sum_{l=0}^{5} \alpha_l^{ext} \times \text{asinh}(\texttt{NewBuyerInfo}^k_{j,t-l}) + \sum_{l=0}^{5} \gamma_l^{ext} \times \texttt{ImportSize}^k_{j,t-l} + \delta_j^k + \delta_{j,t} + \delta_t^k + \epsilon_{j,t}^k. \tag{A2}$$

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

Table A.6 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.6: Impacts of Buyer Information on Exports (Intensive and Extensive Margin)

	(1)	(2)	(3)
Method	PPML	OLS	OLS
Dep. Variable	Export	ln(Export)	$\mathbb{1}_{[\text{Export}>0]}$
$\text{asinh}(\texttt{NewBuyerInfo}^k_{j,t-1})$	0.054***	0.043***	–0.000
	(0.020)	(0.014)	(0.003)
$\texttt{ImportSize}^k_{j,t}$	0.447***	0.922***	0.206***
	(0.083)	(0.079)	(0.013)
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 with IHS transformation ($\text{asinh}(\texttt{NewBuyerInfo}^k_{j,t-1})$) and the sum of IHS-transformed 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 parentheses are two-way clustered within country and within industry.

Table A.7 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. 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 some positive dynamic effects on the extensive margin. These effects seem to peak later than those on the intensive margin.

Table A.7: Dynamic Impacts New Buyer Information on Exports

	(1)	(2)	(3)	(4)	(5)
Method	PPML	OLS	OLS	OLS	OLS
Dep. Variable	Export	$\mathbb{1}_{\{\text{Export}>0\}}$	$\mathbb{1}_{\{\text{Export}>0\}}$	$\mathbb{1}_{\{\text{Export}>0\}}$	$\mathbb{1}_{\{\text{Export}>0\}}$
$\text{asinh}(\texttt{NewBuyerInfo}^k_{j,t})$	0.062*	–0.005	–0.022	–0.017	–0.006
	(0.038)	(0.005)	(0.021)	(0.013)	(0.006)
$\text{asinh}(\texttt{NewBuyerInfo}^k_{j,t-1})$	0.124***	–0.003	–0.015	–0.001	–0.002
	(0.037)	(0.005)	(0.021)	(0.017)	(0.006)
$\text{asinh}(\texttt{NewBuyerInfo}^k_{j,t-2})$	0.125***	0.004	0.011	–0.011	0.002
	(0.039)	(0.005)	(0.013)	(0.016)	(0.005)
$\text{asinh}(\texttt{NewBuyerInfo}^k_{j,t-3})$	0.093**	0.003	0.037	0.001	0.002
	(0.036)	(0.005)	(0.023)	(0.010)	(0.005)
$\text{asinh}(\texttt{NewBuyerInfo}^k_{j,t-4})$	0.109***	0.007	0.031	–0.003	0.009
	(0.026)	(0.007)	(0.025)	(0.012)	(0.006)
$\text{asinh}(\texttt{NewBuyerInfo}^k_{j,t-5})$	0.114***	0.003	0.012	–0.010	0.006
	(0.027)	(0.005)	(0.018)	(0.008)	(0.006)
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 (11) 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 IHS transformed counts of new buyer contacts (`NewBuyerInfo`) and their lagged values up to 5 years. The control variables are the sum of IHS transformed 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 parentheses are two-way clustered within country and within industry.

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. 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.