Covered to Compete: How Export Credit Insurance Shapes Firm Trade*

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Abstract

We estimate the causal effect of short-term export credit insurance (ECI) on firm-level exports using administrative data from China's export credit agency merged with customs and tax records. Exploiting quasi-random variation in ECI approval from buyer-level credit ceilings and a first-come-first-served allocation rule, combined with propensity score matching and two-stage least squares, we find that a 10% increase in insured coverage raises firm-destination exports by approximately 2.3%. ECI expands exports along both intensive and extensive margins, raising product scope and destination entry, while leaving unit values unchanged. Effects are largest for smaller and private firms, financially constrained exporters, and shipments to riskier destinations, and were amplified during the 2008 financial crisis. Balance-sheet evidence points to two channels: insured receivables become more pledgeable, relaxing short-term liquidity constraints, and payment risk is mitigated. Back-of-the-envelope calculations show that each insured dollar generates roughly $0.11 in fiscal revenue, exceeding plausible program costs and implying that the program is fiscally self-financing with substantial social returns.

Keywords: Firm exports, export credit insurance, trade finance, financial constraints, trade policy

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1 Introduction

Export-led growth has transformed some developing economies, yet many that adopt outward-oriented strategies struggle to sustain export expansion. One central impediment is access to trade finance in settings where domestic financial systems are shallow and information about firms and foreign buyers is scarce. Local banks often view exporters as opaque and risky and therefore underprovide working capital, especially to small and privately owned firms (Feenstra et al., 2014; Stiglitz and Weiss, 1981). Importer-side instruments such as letters of credit can reduce buyer credit risk, but they are arranged by foreign banks, rely on information about the importer, and are best documented for large firms and advanced economies (Antràs and Foley, 2015). By contrast, export credit insurance (ECI) allows exporters to sell on open-account terms while transferring foreign-buyer default risk to insurers, making it particularly relevant in financially shallow environments.

Export credit agencies (ECAs) are the primary public providers of this insurance, especially in developing countries. Globally, the scale of export credit insurance is comparable to buyer-side bank instruments such as letters of credit, which account for roughly 10–20% of world trade.[1] Successful export-led growth episodes, including in East Asia, have typically been associated with active ECAs that provide short-term ECI for working-capital-intensive exports. Trade credit insurance underpins about 15–20% of exports in China and Korea, but it remains scarce in many developing countries. For example, penetration is estimated at less than 1% of exports in Egypt and about 2% in Jordan (Dornel et al., 2021).

These contrasts suggest that limited exporter-side risk coverage can be a first-order constraint on sustaining export expansion precisely where financial frictions are most severe. This paper estimates the causal effect of short-term ECI on firm-level exports and evaluates its social returns as a public instrument. We focus on short-term ECI because it accounts for the bulk of insured export transactions, with about USD 2.2 trillion in annual cross-border coverage, far exceeding medium- and long-term segments.[2] We ask three questions. First, what is the causal elasticity of firm-level exports with respect to short-term ECI coverage? Second, through which margins does this response operate, including export scale, product

[1] Members of the Berne Union provide around USD 2.6 trillion of annual export credit and investment risk protection, amounting to about 12% of global cross-border trade (Berne Union, 2024). Within this market, short-term export credit insurance is dominant. WTO data based on Berne Union reporting indicate that short-term insured export credit flows were about USD 2.2 trillion in 2019, and roughly one quarter of this short-term segment was supported by official export credit agencies (ECAs) (Auboin and Engemann, 2014). This implies that ECA-provided short-term export credit insurance alone accounted for on the order of USD 0.5 trillion in annual cross-border coverage.

[2] WTO data based on Berne Union reporting indicate that short-term insured export credit flows were approximately USD 2.2 trillion in 2019 and constitute the dominant share of export credit insurance activity (Auboin and Engemann, 2014; Berne Union, 2024).

scope, and entry into new destination markets? Third, what are the implied social returns to ECI when it is provided as a public policy instrument by an export credit agency?

Answering these questions is challenging because insurance coverage is endogenous. Firms that obtain ECI may have an incentive to trade with riskier buyers and destinations, and insurers may prefer safer firms. Naive comparisons between insured and uninsured exporters would conflate the effect of insurance with differences in firm quality, destination risk, and unobserved demand. Moreover, coverage is mechanically related to exports because the insured amount is a subset of total export value, which generates simultaneity concerns.

We tackle these challenges using a novel administrative dataset from China's state-owned export credit insurer. The insurer is a policy-oriented institution that prices short-term coverage at actuarially fair rates and has become one of the world's largest ECAs, insuring more than one-fifth of China's exports in recent years. Short-term ECI, defined as policies with payment terms below two years, accounts for over 90% of its portfolio and is the primary instrument supporting working capital needs. We observe application-level records for exporter-buyer pairs from 2001 to 2019, including requested and approved credit limits, as well as the realized value of insured shipments. These records are merged with customs data on firm-product-destination exports and tax registry information on firm balance sheets and ownership.

Our identification strategy exploits how the insurer allocates risk across foreign buyers. For each buyer, the insurer sets an aggregate credit ceiling and processes applications on a first-come, first-served (FCFS) basis. Multiple exporters' approvals draw down this common ceiling. The insurer does not disclose the ceiling level, the cumulative approvals already granted, or any updates to remaining capacity. Firms therefore apply without knowing how close the ceiling is to being exhausted. When cumulative approved exposure reaches the ceiling, the next applicant is rejected purely because of where the crossing happened to fall in the unobservable application queue, not because of the applicant's characteristics. Conditional on applying for insurance with a given buyer, the position of any individual firm relative to the ceiling crossing is plausibly quasi-random. We exploit this variation, combined with propensity score matching (PSM) on lagged firm financials, to instrument the amount of ECI coverage at the firm-destination-year level. The approval shock is buyer-specific, but our outcome is the firm's total exports to a destination-year, not only shipments to the insured buyer. We therefore interpret the estimated elasticity as the net destination-level export response to marginal insured exposure, which can include within-destination reallocation across buyers.

The empirical analysis delivers three main sets of results. First, short-term export credit insurance has a sizable effect on exports. Our preferred IV estimates on the PSM-matched

sample imply that a 1% increase in ECI coverage raises total exports by about 0.225%. ECI coverage is the insured value of shipments, while exports are total firm-destination exports, so the baseline estimate captures a firm-destination aggregate that blends higher shipments to existing buyers with potential entry into additional products or buyers within the same country. Within a destination, the within-destination intensive margin dominates: conditional on positive exports, a 10% increase in ECI coverage raises export value by 1.09%. ECI also operates along the within-destination extensive margin, with a 10% increase in coverage raising the number of HS6 product varieties exported to a given destination by about 0.5%, while unit values are unaffected. Beyond these within-destination effects, ECI modestly raises entry into new destination markets. The product diversification and new-market effects are particularly important for development because sustained export growth often comes from entry into new products and destinations, which are precisely the margins most sensitive to fixed costs and information frictions (Martincus and Carballo, 2008; Manova, 2013; Feenstra et al., 2014). We also find positive effects on firms' uninsured exports within the same destinations, consistent with ECI building broader export capacity within the firm-destination relationship that extends beyond the directly covered transactions.

Second, the results point to two complementary mechanisms, easing financial constraints and reducing buyer default risk. At the firm level, balance-sheet evidence shows that higher ECI coverage raises interest expenses (reflecting larger borrowing volumes), accounts receivable, and cash working capital, while reducing operating cash-flow shortfalls. These responses indicate that insurance makes receivables more pledgeable and helps exporters finance production while offering deferred-payment terms. The export response is also concentrated in riskier destination countries and rises sharply during the global financial crisis, with yearly elasticities reaching about 0.34 in 2008, supporting a risk-mitigation and countercyclical role. The two channels reinforce each other. Firms in cities with lower credit access respond more strongly, consistent with financial constraints, while the concentration of effects among smaller and private firms is consistent with both channels, as these firms face tighter financing frictions and greater exposure to arm's-length buyer default risk. The export gains are front-loaded, persisting through one to two years after approval before fading, consistent with the per-transaction nature of short-term coverage.

Third, scaling the micro estimates implies substantial aggregate and fiscal returns. With short-term ECI covering about 26.9% of China's goods exports in recent official statistics, the preferred elasticity implies that each insured dollar generates roughly \$0.84 in additional exports[3] and about \$0.55 in GDP under a conservative value-added share of 0.65, yielding

[3]Because insured shipments represent only a share s of total exports, the implied marginal export gain per insured dollar is $dX/dI = (d\ln X/d\ln I)\cdot(X/I) = e/s$, so \$0.84 is computed as $0.225/0.269 \approx 0.84$.

$0.11 in fiscal revenue at a 19.5% tax-to-GDP ratio. This fiscal revenue exceeds plausible program costs, defined as administrative expenses plus expected claim payouts net of premium income, implying that the program is fiscally self-financing.[4] The implied GDP return of $0.55 per insured dollar suggests substantial social returns from short-term ECI.

This paper contributes to three strands of literature. First, we provide, to our knowledge, the first *causal* estimate of the elasticity of exports with respect to the amount of short-term ECI coverage. Existing work on government-backed export credit support has shown that such support matters but typically asks a binary question of whether supported firms export more than unsupported ones, rather than how export outcomes scale with the *amount* insured. For example, Agarwal et al. (2023) exploit a fuzzy regression discontinuity design around Swedish firm size thresholds to show that guarantees raise both the probability and value of exporting to covered destinations, and Matray et al. (2024) use the 2015–19 shutdown of the US EXIM Bank as a natural experiment to document large real effects of withdrawing trade finance on sales, exports, investment, and employment for mostly long-term ECI. These studies identify important presence/absence effects of short-term guarantees and long-term project finance in advanced economies, but they do not recover an elasticity of exports with respect to the level of coverage. Closer to our setting, Choi and Kim (2021) use Korean firm-product-destination data to relate short-term ECI coverage to exports with a Poisson estimator and rich fixed effects, finding positive correlations between insurance and export performance but not exploiting quasi-experimental variation in coverage. Our design, based on buyer credit ceilings and FCFS allocation, delivers quasi-random variation in the amount of short-term ECI that exporters receive. This allows us to estimate how export value and product scope respond to marginal changes in insured exposure, conditional on applying for coverage, thereby pinning down an elasticity that has not been causally identified in the prior literature.

Second, we use this elasticity to construct the first benefit-cost analysis of a large ECA in a major developing economy. Prior micro evidence on ECAs comes primarily from high-income settings. Agarwal et al. (2023) study Sweden, a small open economy with mature financial markets, while Matray et al. (2024) analyze the US EXIM Bank, whose clientele is skewed toward large, capital-intensive exporters and medium- to long-term deals. These results confirm that export credit guarantees or insurances have real effects in high-income

[4] Matray et al. (2024) show that the US EXIM Bank earned total profits exceeding $480 million during 2010–19, driven by low default rates of 0.3% and premium income that more than covered claims and administrative costs. Private-sector benchmarks point in the same direction. The three largest publicly listed trade credit insurers, Allianz Trade, Atradius, and Coface, reported combined ratios (claims plus administrative expenses as a share of premium income) of 64–79% in 2023 (Coface SA, 2024; Atradius N.V., 2024), indicating that market-rate premiums comfortably cover all costs.

settings but leave open whether ECAs can overcome the more severe financial and informational frictions that constrain exporters in developing countries, where domestic credit discrimination and high information costs are well documented (Poncet et al., 2010; Manova, 2013; Feenstra et al., 2014). By combining Chinese administrative data on short-term ECI with customs and tax records, we show that expanding buyer-based insurance has large effects on exports for smaller and private firms, which are most financially constrained, and we translate our elasticity into a benefit-cost ratio that substantially exceeds one. These results suggest that ECAs can ease the financing constraints and information barriers that private credit markets underprovide in developing economies.

Third, we contribute to the trade finance literature by identifying how reducing payment risk exposure, while holding exporter risk constant, affects firms' export behavior. Prior research on trade finance emphasized exporters' access to credit and bank-intermediated liquidity (Schmidt-Eisenlohr, 2013; Niepmann and Schmidt-Eisenlohr, 2017a; Paravisini et al., 2015; Demir and Javorcik, 2018), while a parallel literature has studied how letters of credit and bank guarantees allocate preexisting cross-border risk across exporters, importers, and banks (Amiti and Weinstein, 2011; Niepmann and Schmidt-Eisenlohr, 2017b; Auboin, 2009; Antràs and Foley, 2015). This body of work treats the probability that a foreign buyer defaults as an environmental characteristic that is captured through country risk indexes, distance, or sector dummies, rather than as a margin shaped by a policy instrument. Although ECI contracts rely on both exporter-side and buyer-side risk assessments, all firms in our sample have already passed the insurer's underwriting screen on exporter risk. Conditional on this screening, the quasi-random rejection of applications arises solely from the exhaustion of buyer credit ceilings. We therefore isolate how exogenous limitations on insurable exposure to a particular buyer affect exporters' ability to ship, diversify products, and enter new markets. This approach complements the existing literature by showing that exogenous limits on insurable buyer exposure, determined by portfolio ceiling rules rather than firm choices, materially raise exports, particularly for financially constrained firms trading with riskier destinations.

The remainder of the paper is organized as follows. Section 2 describes the institutional background of China's ECI system and the *FCFS* allocation rule underlying our identification strategy. Section 3 introduces the data sources and the construction of the matched firm-destination-year panel. Section 4 presents our empirical identification strategy. Section 5 reports the baseline empirical findings, followed by Section 6, which explores the underlying mechanisms related to financial constraints and risk mitigation. Section 7 provides robustness checks. Section 8 concludes.

2 Background

Export-led growth and trade finance China's rapid post-reform growth is widely understood through an export-led growth lens, with export expansion central to industrialization, structural transformation, and technology upgrading (Felipe and Lanzafame, 2020; Xue, 1995). To sustain this strategy, the central government and local authorities have combined reductions in trade barriers with extensive trade facilitation, including the creation of special economic zones, export processing zones, and large-scale investments in ports and logistics (Zeng, 2011; Lu et al., 2019).

However, reducing border and logistics frictions is only one part of enabling export transactions. In modern international commerce, most trade is conducted under some form of credit, insurance, or guarantee, reflecting the time lag between production, shipment, and final payment, as well as the importer's preference to pay after delivery.[5] These payment terms are therefore competitively necessary. Firms seeking to enter and expand in global markets must often match internationally standard contracting practices (e.g., deferred-payment terms) rather than rely exclusively on cash-in-advance or bank-intermediated settlement. Yet selling on credit creates a working capital gap and raises exposure to both commercial default risk and destination country political risk. ECI provides an additional source of financing, as insured receivables are pledgeable as collateral, easing short-term liquidity constraints and supporting the scale-up of export operations. It also reduces the risk of extending trade credit, increasing exporters' willingness to serve new and riskier markets.

Short-term ECI and ECA Export credit insurance products are typically divided into short-term and medium- and long-term business based on maturity structure and the nature of the underlying transaction (Berne Union, 2026). Short-term ECI usually covers export receivables with maturities of up to one or two years and is closely tied to ordinary merchandise trade conducted on open-account or deferred payment terms. It primarily insures against commercial and political risks associated with buyer nonpayment and relies on risk pooling across a large number of transactions. In contrast, medium- and long-term ECI generally supports capital goods exports, infrastructure projects, and buyer-credit arrangements with maturities exceeding two years. Medium- and long-term business is typically project-based, involves larger ticket sizes, and is more directly linked to state-backed financing and industrial policy objectives. Our focus is short-term ECI, which accounts for over 90% of the portfolio of the Chinese ECA and is the primary instrument supporting working capital needs.

[5] World Trade Organization (2025) report that roughly 80%–90% of world trade depends on credit, insurance, or guarantees provided by banks and other financial institutions.

China has experimented with ECI since the late 1980s, but the current system dates from the establishment of the state-funded, policy-oriented export and credit insurance corporation (hereafter "the insurance company"), which was created in December 2001, shortly after China's WTO accession (World Trade Organization, 2006; Organisation for Economic Co-operation and Development, 2015; China Export & Credit Insurance Corporation, 2024). Article 53 of the 2004 Foreign Trade Law subsequently designated ECI as one of the three main policy instruments to support foreign trade.[6] Since then, the insurance company has been the dominant ECI provider, especially for medium- and long-term business with higher-risk markets. Commercial insurers have only gradually entered parts of the short-term segment. By the mid-2010s, the insurer had already achieved substantial domestic coverage: by 2013, its short-term ECI covered around 15% of China's total exports, with coverage continuing to expand in subsequent years (Organisation for Economic Co-operation and Development, 2015; China Export & Credit Insurance Corporation, 2024). Reflecting this rapid expansion, by the end of 2024 the company had cumulatively supported more than USD 9 trillion of trade and investment and had consistently ranked among the top Berne Union members worldwide in terms of newly insured amounts since 2015 (China Export & Credit Insurance Corporation, 2024).

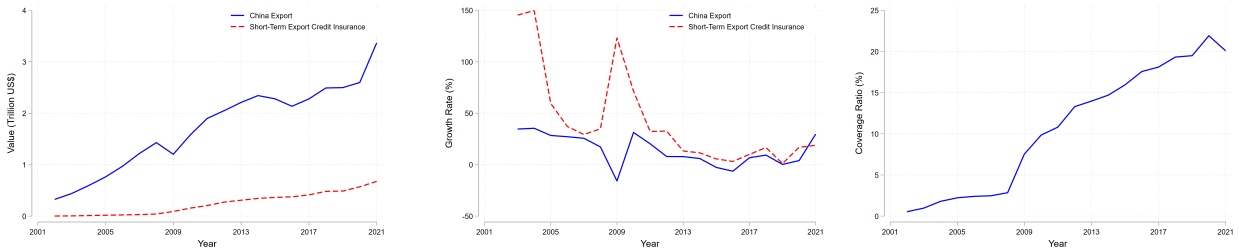
Figure 1 plots the joint evolution of China's exports and short-term ECI from 2002 to 2021. Both increase substantially over the period. The growth rates are largely in line after the 2008 financial crisis. Notably, during the downturns in 2008-09, while export growth slowed sharply, insured volumes continued to expand, suggesting a countercyclical policy role for ECI in stabilizing trade. The share of trade covered by short-term ECI rises from zero to about 20% by the end of the period, which is large compared to developed countries such as the US, where the coverage ratio is only about 0.8% (Matray et al., 2024).

Buyer Credit Ceilings For each foreign buyer, the insurer sets an aggregate credit ceiling that caps its total exposure across all exporters trading with that buyer. This ceiling is determined by the insurer's internal risk-control assessment, drawing on the buyer's financial indicators, industry characteristics, country conditions, and past repayment history.

Individual credit limits approved for different exporters draw down this common ceiling and are released when coverage lapses or expires, functioning as a revolving facility. The limit granted to a given exporter represents the maximum insured exposure it may hold for that buyer over the specified payment term.

The insurance company operates a continuous open-application system: exporters may submit an application for any foreign buyer at any time after receiving a purchase order,

[6] See the 2004 *Foreign Trade Law of the People's Republic of China*, Art. 53, and discussion in World Trade Organization (2006).



(a) Exports and short-term ECI volume

(b) Growth rate of exports and short-term ECI

(c) Coverage ratio of short-term ECI to exports

Figure 1: Trends in China's exports and short-term ECI (2002–21).

Source: Calculations based on annual statistical reports of the insurance company.

specifying the buyer, expected shipment value, and expected payment terms.[7] The insurer evaluates the buyer's risk and determines whether to approve coverage and at what limit. Once approved, the exporter may offer open-account or delayed payment terms to the buyer: shipments within the approved limit are insured, while any excess remains at the exporter's risk. Exporters may also pledge insured accounts receivable as collateral to obtain trade finance from banks, and in the event of buyer default the insurer compensates the exporter or lender up to the approved limit.

Because multiple exporters may sell to the same foreign buyer, the insurer allocates credit on an FCFS basis, processing applications in chronological order. Once the buyer-level ceiling is exhausted, subsequent applications are rejected regardless of exporter size, ownership, or performance. This rationing rule helps the insurer manage concentration risk while maintaining a simple and transparent allocation mechanism. Section 4.2 exploits this feature for identification.

The aggregate coverage data reveal two stylized facts about ECI usage. First, exporters typically seek insurance for a small number of buyers per destination: the median number of buyer applications per exporter-destination-year is one, and over 80% of exporters apply for fewer than three buyers (Appendix Figure B4). Second, insured export values and coverage ratios have risen steadily since the early 2000s, with accelerated growth after 2008 (Appendix Figures B5–B8). While insured exports are concentrated in advanced economies in absolute terms, coverage ratios are higher toward emerging and developing economies, and insured exports to riskier destinations have expanded disproportionately over time.[8]

[7] Prior to submitting an application, exporters must pass a qualification review verifying their legal registration, operational status, and basic credit standing. Application records in our data therefore correspond to exporters that have already met the insurer's eligibility criteria.

[8] Because our data are restricted to buyers with at least one rejected application, reported insured amounts

3 Data

To estimate the effect of ECI on firms' export performance, we construct a firm-destination-level dataset by merging four administrative sources. These are (1) exporter-importer-level short-term ECI application records and firm-country level ECI coverage data from the insurance company, (2) firm-product-country-level exports data from China Customs, (3) firm financial characteristics from the China Tax Survey, and (4) firm registration information from Chinese firm business registration data.

ECI data The insurance company is China's dominant provider of short-term export credit insurance, covering approximately 95% of national short-term ECI volume in 2022. Our data span 2001–19 and cover the company's full operational period.

The application-level data record firm name and Unified Social Credit Code (USCC), buyer name and country, approval date, and both requested and approved credit limits. We construct two key variables from these records. *ECI coverage* measures the total insured export value at the firm-destination-year level, drawn from an aggregated exporter-destination-year file provided by the insurer.[9] *ECI dummy*, the binary treatment indicator, is defined at the firm-buyer level and aggregated to the firm-destination-year level following the PSM sample-construction procedure described in Section 4.3 and Appendix C. The raw ECI data contain approximately 600,000 application records covering 9,104 exporters and 221,408 buyers across 203 destination countries.

Customs data The Customs data, obtained from China's General Administration of Customs, record all export transactions at the firm-product-destination-month level for the universe of Chinese trading firms from 2000–16. Each record reports the exporter's firm name and a unique 10-digit customs identification number, along with export value (in US dollars), quantity, and destination country.

The data are reported at the HS 8-digit level and monthly frequency. We aggregate to the firm-country-year level to match the annual frequency of the ECI and Tax Survey data.[10] Each merged observation captures a firm's annual export performance to a given destination, including export value, product scope (number of HS 6-digit product lines), and average unit values (the weighted average of HS 6-digit unit values using each product's export value share).

represent lower bounds of true national ECI coverage.

[9] The credit limit represents the maximum indemnifiable amount in the event of buyer default and may revolve multiple times within a policy year depending on the exporter's underlying sales contracts and payment terms.

[10] A concordance table of the USCC and customs identification number provided by the insurance company is used to match the export data with the insurance data.

Tax Survey data The National Tax Survey, administered by the State Taxation Administration of China, provides annual firm-level income tax filings and detailed financial statements from 2007 to 2016, covering approximately 700,000 firms per year across China. The survey includes key enterprises as well as medium-sized and small firms, and spans all major ownership types, making it highly representative at the national level.[11] The dataset includes both basic identifiers, such as the taxpayer identification number, organization code, ownership type, location, and industry, and more than 300 financial and operational variables. These variables capture firm assets, liabilities, accounts receivable, profits, employment, output, and total operating income across a wide range of industries, although some indicators are missing.[12]

We merge the Tax Survey with the ECI dataset using firms' USCC, which incorporates the organization code according to the State Council's unified identification system introduced in 2015.[13] We use firm financial characteristics lagged by one year, such as total assets, accounts receivable, return on assets (ROA), and leverage, to perform PSM between firms with approved and rejected insurance applications.

China Business Registration data The China Business Registration database covers the universe of firm registrations in China and includes firm-level information such as firm name, establishment year, detailed registration address, and industry classification. Industry codes are harmonized to the 2017 national classification at the 2-digit level.[14] We focus on firms that registered before 2016.

We merge the business registration data with the ECI records using firms' unique USCC and achieve a 97% match rate. The merged data provide information on firms' registered industry, ownership type, geographic location at county-level, and year of establishment. We use this database to identify firms' industry classification and geographic location, which are essential for examining heterogeneity across locations and within industries.

Merged sample We link the ECI records to the Customs data at the firm-country-year level using the concordance table provided by the insurance company.[15] Among ECI records,

[11] The sample includes roughly 300,000 firms in 2007 and between 600,000 and 700,000 firms for each year from 2008 to 2016.

[12] We complement the Tax Survey with the Business Registration dataset to obtain firm location, ownership, and industry information, given its broader coverage.

[13] See State Council Document No. 33 (2015): "General Plan for the Unified Social Credit Code System for Legal Persons and Other Organizations." The USCC's fourth component (digits 9-17) corresponds to the organization code as defined in the national standard GB 11714-1997.

[14] Industry classifications are harmonized to the 2017 revision of the Chinese national industry standard at the 2-digit level. Where the same USCC is associated with multiple firm names due to name changes, we retain the USCC as the unique firm identifier.

[15] We retain all application records for a firm if it appears at least once in all three databases. Where a Customs match is not found, exports and insured values are set to zero. Firms that never appear in both

66% are matched to firm-country-year export observations; the remainder reflect canceled orders, deferred shipments, or identifier inconsistencies. The resulting ECI–Customs panel (Sample A) contains more than 40,000 firm-destination-year observations for 6,542 exporters across 125 destination countries and 68 two-digit industries from 2002–16, representing approximately 1.4% of exporting firms and 4.4% of total export value over the period.

We further merge financial and operational variables from the Tax Survey using the organization code component of the USCC, achieving a 55% match rate, consistent with the survey's stratified sampling design. The ECI–Customs–Tax Survey panel (Sample B) contains more than 16,000 firm-destination-year observations for 3,399 exporters across 192 destination countries and 81 industries from 2008–16. We exclude firms with accounting anomalies, such as zero reported assets or net profits exceeding total revenue.

Table 1 reports summary statistics for the two main estimation samples. Panel A covers the ECI–Customs merged sample (2002–16, 125 destinations, 68 industries); Panel B adds Tax Survey data (2008–16, 192 destinations, 81 industries). The median firm exports approximately $1.7 million annually to a given destination, of which roughly $0.3 million is insured.[16] Both export and insured amounts exhibit large variation across firms and destinations, motivating the use of firm fixed effects and heterogeneity analysis by firm size and financial access. Appendix Figure B2 shows that ECI exporters are larger in export value than the full Customs universe. Panel C reports summary statistics for the post-PSM matched sample used in the baseline regressions, described in Section 4.3.

the insured and Customs data are dropped.

[16] Appendix Figure B1 shows that $\ln(\text{Export})_{ict}$ follows an approximately normal distribution for positive values.

Table 1: Summary statistics of exporters applying for ECI

	N	Mean	Median	S.D.
Panel A: Sample A (ECI + Customs, 2002–2016)				
ln(Export)	41,080	11.852	13.583	5.377
ln(ECI coverage)	41,080	7.372	10.610	6.753
Panel B: Sample B (ECI + Customs + Tax Survey, 2008–2016)				
ln(Export)	16,321	12.339	13.986	5.385
ln(ECI coverage)	16,321	8.383	11.790	6.900
Panel C: Sample C (after PSM, main sample for analysis)				
	Firm–country–year level			
Export (mil US$)	6,757	11.325	1.783	34.713
ECI coverage (mil US$)	6,757	4.403	0.298	16.483
ECI dummy	6,757	0.727	1.000	0.445
ECI credit limit (mil US$)	6,757	0.648	0.200	2.535
HS6 count	6,075	19.360	5.000	41.324
HS8 count	6,075	20.721	6.000	45.027
Export status (dummy)	6,757	0.899	1.000	0.301
ln(Export)	6,757	13.116	14.394	4.819
ln(ECI coverage)	6,757	9.570	12.604	6.617
ln(ECI credit limit)	6,757	9.274	12.206	5.784
	Firm–year level			
Lag ln(assets)	4,225	12.538	12.510	1.684
Lag ln(account receivables)	4,225	10.362	10.612	2.357
Lag ROA	4,225	0.034	0.020	0.081
Lag leverage	4,225	0.667	0.666	0.280
	Firm level			
SOE (dummy)	2,042	0.017	0.000	0.128
Foreign (dummy)	2,042	0.207	0.000	0.405
Private (dummy)	2,042	0.776	1.000	0.417

Notes: This table reports summary statistics for three datasets. Panel A reports summary statistics for the ECI-Customs merged sample (2002–16). Panel B further merges Tax Survey data for 2008–16. Panel C reports the post–PSM matched sample from Sample B. Sample C is used in baseline regressions. All samples only include applications for buyers with both rejection and approval ECI application records, and approvals that are earlier than rejections within three years. All monetary values (mil US$) are in millions of US dollars. Sample A has 125 destination countries and 68 2-digit industries; Sample B has 192 destination countries and 81 2-digit industries, and after merging the Tax Survey data; Sample C has 182 destination countries and 77 2-digit industries.

4 Methods

Estimating the causal effect of ECI on exports is complicated by self-selection: firms with stronger export prospects are more likely to apply for and receive insurance, and time-varying shocks can simultaneously affect both coverage and export outcomes. Our identification strategy exploits quasi-random variation in approval outcomes generated by the insurer's first-come, first-served (FCFS) buyer credit ceiling. Conditional on applying to a given

buyer, whether a firm's application arrives just before or just after the ceiling is exhausted is plausibly unrelated to firm characteristics, as documented in Section 4.2. We exploit this variation in two stages. We first use propensity score matching to construct a sample of approved and rejected applicants competing for the same buyer's credit limit, balanced on observable financial characteristics. This matched sample delivers a reduced-form binary treatment effect of ECI approval on exports. We then instrument the continuous intensity of ECI coverage with the binary approval indicator in a two-stage least squares (2SLS) specification on the matched sample, recovering the causal elasticity of exports to insured coverage. We begin with a baseline OLS specification that documents the raw correlations and motivates the need for causal identification.

4.1 Baseline OLS Specification

We first estimate a standard panel data OLS model to document the correlation between ECI coverage and firm export performance at the firm-destination-year level. Our baseline specification is

$$\ln(Export)_{ict} = \beta_0 + \beta_1 \ln(ECI\ coverage)_{ict} + \lambda_i + \gamma_{ct} + \eta_{st} + \phi_{cs} + \epsilon_{ict}, \tag{1}$$

where i indexes firms, c destination countries, s industries, and t years. $\ln(Export)_{ict}$ denotes the log of total exports of firm i to destination c in year t.[17] The key regressor $\ln(ECI\ coverage)_{ict}$ measures the insured export value at the firm-destination-year level, as defined in Section 3.

The specification includes firm fixed effects λ_i for time-invariant firm characteristics, destination-year fixed effects γ_{ct} for market-level demand shocks, industry-year fixed effects η_{st} for sector-specific trends, and country-industry fixed effects ϕ_{cs} for time-invariant bilateral frictions within sectors. The remaining variation in equation (1) therefore comes from within-firm changes over time in ECI coverage, net of common shocks at the destination, industry, and destination-industry levels. As discussed below, this variation alone does not support a causal interpretation. Standard errors are clustered at the destination country level.

[17] Throughout the paper, variables in logarithmic form are transformed as $\ln(1+x)$. Approximately 9% of firm-destination-year observations feature zero exports, and positive values are typically in the thousands of dollars, so the unit offset is negligible for the vast majority of observations. As Chen and Roth (2024) note, this transformation can in principle alter the estimand when zeros are prevalent. As a robustness check, we re-estimate the main specifications using Poisson pseudo-maximum likelihood (PPML) with a control function (Correia et al., 2020), which naturally accommodates zeros and yields consistent estimates under multiplicative heteroskedasticity. The PPML estimates are quantitatively similar (Tables A6–A7, columns 7–8).

Endogeneity concerns Although equation (1) is saturated with fixed effects, three endogeneity concerns prevent a causal interpretation of β_1.

First, and most importantly, firms self-select into the ECI system along two margins. At the extensive margin, exporters facing riskier buyers or tighter financial constraints have stronger incentives to apply for insurance. Since equation (1) is estimated on applicants only, this margin does not generate an internal validity concern. Our estimates speak to firms that sought ECI, which are the population the program is designed to serve. At the intensive margin, conditional on applying, approved firms may be systematically stronger exporters than rejected firms. For instance, firms with stronger export exposure or riskier buyer portfolios may apply to more buyers or for larger credit amounts, increasing their probability of securing at least one approval and generating upward bias even within the applicant pool. Firm fixed effects absorb time-invariant differences between firms but leave within-firm selection over time unaddressed.

Second, unobserved time-varying firm-level shocks may jointly determine both ECI coverage and export outcomes. A positive liquidity shock, an improvement in managerial quality, or the acquisition of private information about a buyer's creditworthiness could simultaneously induce a firm to increase insurance take-up and to expand exports. Such confounders are not absorbed by the rich set of fixed effects in equation (1), since they vary within firm over time.

Third, $ECI\ coverage_{ict}$ is mechanically constructed as a sub-component of $Export_{ict}$. Because $\ln C_{ict} = \ln s_{ict} + \ln X_{ict}$, where s_{ict} is the insured share, the regressor in equation (1) contains the dependent variable, creating upward simultaneous-equations bias even if s_{ict} is entirely exogenous.[18] The IV strategy described below resolves this bias. The quasi-randomly assigned approval dummy Z_{ict} satisfies $\text{Cov}(Z_{ict}, \varepsilon_{ict}) = 0$, so the predicted $\widehat{\ln C}_{ict}$ from the first stage is free of the mechanical contamination from ε_{ict}, and β_1 is consistently estimated.

For these reasons, the OLS estimates in equation (1) are best interpreted as descriptive correlations. Our identification strategy below exploits institutional features of the insurer's FCFS allocation rule to generate quasi-random variation in approval outcomes and address

[18] Write $C_{ict} = s_{ict} \cdot X_{ict}$, where C_{ict} denotes ECI coverage, X_{ict} denotes total exports, and $s_{ict} \in [0, 1]$ is the insured share. Substituting $\ln C_{ict} = \ln s_{ict} + \ln X_{ict}$ into equation (1) yields $\ln X_{ict} = \beta_0 + \beta_1(\ln s_{ict} + \ln X_{ict}) + \text{FE} + \varepsilon_{ict}$, a simultaneous equation in $\ln X_{ict}$. Any shock ε_{ict} that raises $\ln X_{ict}$ also raises $\ln C_{ict}$ through the shared $\ln X$ component, guaranteeing $\text{Cov}(\ln C_{ict}, \varepsilon_{ict}) > 0$. In OLS, the simultaneity runs in both directions: higher C may raise X (the causal effect) and higher X mechanically raises C (the reverse feedback through $C = sX$). The IV breaks the reverse channel. Because the quasi-randomly assigned approval dummy Z_{ict} is orthogonal to ε_{ict}, instrument-induced variation in $\ln C$ operates only through the forward causal chain ($Z \to s \to X$), not through the reverse feedback ($\varepsilon \to X \to C$). The IV-Wald ratio $\beta_1^{IV} = (d \ln X/dZ)/(d \ln C/dZ)$ is therefore free of the simultaneity bias, and β_1 is consistently estimated. In most cases in our data, $ECI\ coverage_{ict} < Export_{ict}$.

these endogeneity concerns.

4.2 Identification Strategy Using Quasi-Experimental Variation

FCFS allocation The identifying variation in our design is the buyer credit ceiling crossing event. The insurer assigns each foreign buyer a fixed maximum exposure limit but does not disclose the level of this ceiling, the cumulative approvals already granted, or any updates to remaining capacity. Firms therefore apply without knowing how much of the buyer's ceiling has been consumed by earlier applicants. When cumulative approved exposure reaches the ceiling, the next applicant is rejected purely because of where the crossing happened to fall in the unobservable application queue, not because of the applicant's characteristics. Conditional on applying to a given buyer, the position of any individual firm relative to the ceiling crossing is plausibly quasi-random. Rejected firms are not weaker exporters but simply later applicants in a queue they cannot observe.[19]

Figure 2 provides a simple illustration of this mechanism for a representative buyer S. Four exporters, A, B, C, and D, apply for ECI coverage at different times. Exporters A, B, and C apply earlier and receive approvals that cumulatively exhaust the buyer's ceiling (red horizontal line). Exporter D applies after the ceiling has been reached and is therefore rejected.[20]

Validity of quasi-random rejection The FCFS mechanism identifies quasi-random variation only if approval outcomes are unrelated to firm characteristics at the time of application, whether through deliberate strategic timing or through systematic differences in application patterns across firm types. We therefore test whether application timing or approval probability varies with firm characteristics around rejection events.

We find no evidence of strategic application timing. Figure 3 summarizes two tests. Panel (a) plots the monthly distribution of approved and rejected applications. The two series track each other closely across months, with no clustering of rejections at particular

[19]Buyer ceilings may on occasion be partially relaxed when a prior approval lapses unused or when the insurer revises its risk assessment of the buyer. Such revisions are infrequent, typically occurring on an annual basis. Importantly, because the insurer does not disclose ceiling states or updates, firms cannot observe when a release has occurred, for exactly the same reason they cannot observe the original ceiling level. Strategic timing to exploit a quota release is therefore no more feasible than strategic timing to avoid the original ceiling crossing. The application-timing evidence in Figure 3, which shows no clustering of applications at particular calendar periods, is consistent with firms being unable to anticipate ceiling states in either direction.

[20]If the cumulative approved limits for A, B, and C did not fully exhaust the ceiling, the application of D could be partially approved up to the residual balance. In the data, we cannot distinguish whether approved credit amounts below the requested amounts reflect buyer-level ceiling constraints or insurer prudence. We provide robustness checks by dropping approved firms immediately preceding a rejection (Table A6, column 4).

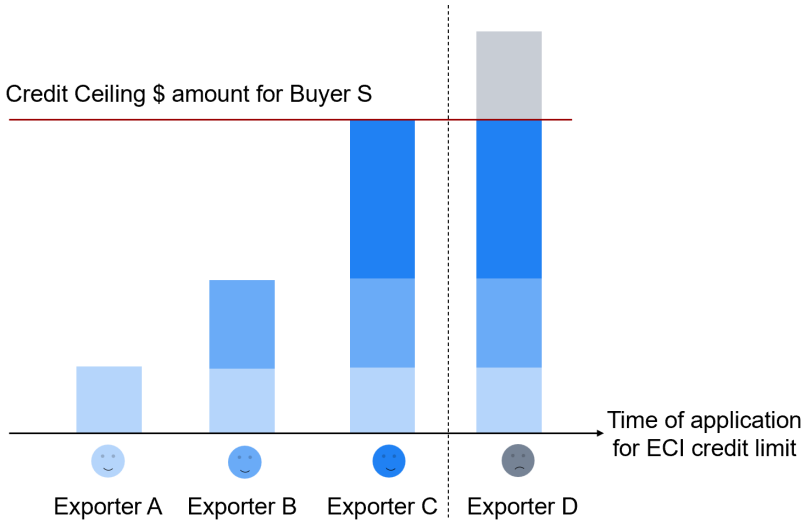
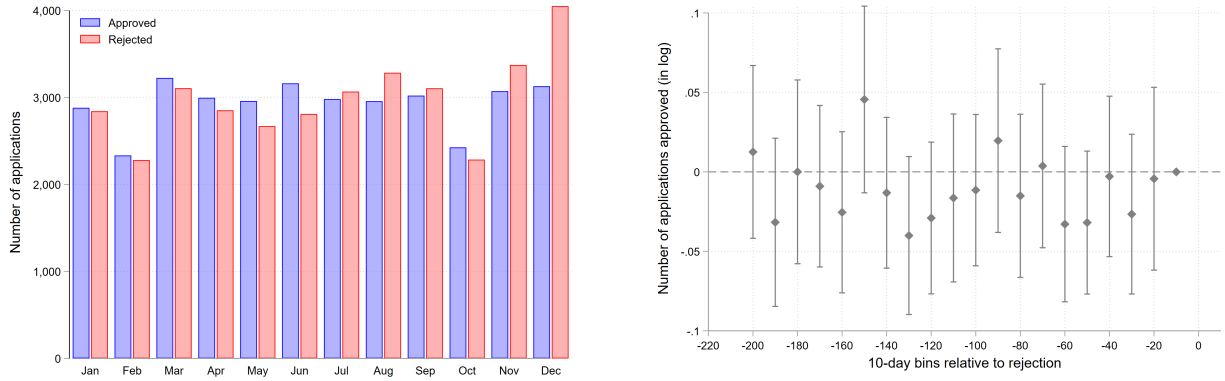


Figure 2: Illustrative example: Approval and rejection timeline

Notes: The figure illustrates the FCFS allocation rule applied to the buyer credit ceiling. Exporters A, B, and C apply sequentially for credit limits under the same buyer S and receive approvals until the cumulative insured exposure reaches the buyer's credit ceiling (red line). Exporter D applies afterward and is rejected because the remaining ceiling is zero. The horizontal axis represents the time of application, and the vertical bars indicate the approved ECI credit limit per exporter.



(a) Number of applications **(b)** LPM

Figure 3: Distribution and pre-rejection probability of application approvals

Notes: Panel (a) shows the monthly distribution of approved (blue) and rejected (red) applications. Panel (b) shows event study estimates of pre-rejection approval probabilities using a linear probability model (LPM) with buyer fixed effects, and Appendix Figure B3a shows similar results using PPML estimation. Approvals are grouped into 10-day bins over the 200 days preceding rejection, and 95% confidence intervals are reported.

times of the year. Panel (b) estimates a linear probability model of approval with buyer fixed effects and 10-day-bin indicators over the 200 days preceding each buyer's first rejection; all pre-rejection coefficients are close to zero and statistically insignificant, and a PPML specification yields similar results (Appendix Figure B3a). The distribution of approvals within 200 days prior to a rejection is also nearly uniform (Appendix Figure B3b). Importantly, the uniformly flat approval probability throughout the pre-rejection window rules out not only deliberate strategic timing but also systematic selection by firm type. If higher-quality or more-frequent applicants disproportionately secured early approvals, approval rates would decline monotonically as the ceiling approached exhaustion. The evidence provides no support for this pattern.

Taken together, the FCFS rule, the inability of firms to observe buyer ceilings, the underwriting screen, and the application-timing evidence support the assumption that approval or rejection for a given buyer is as good as random with respect to firm-level export shocks.

4.3 Propensity Score Matching

Propensity score matching serves three purposes in our design. First, it restricts the comparison to firms that applied to the same buyer within a three-year window, so that approved and rejected firms share the same buyer risk profile, credit quality, and market conditions. In equation (1), the contrast between approved and rejected firms partly reflects which buyer a firm happened to apply to, and within-buyer matching removes this confound so the contrast reflects variation in ECI access within a common buyer environment. Second, matching further balances approved and rejected firms on observable financial characteristics, ensuring that within-buyer differences in approval status are not confounded by firm quality. Third, the matched sample produces a reduced-form binary treatment effect that benchmarks our IV elasticity against the binary treatment effects estimated in the export credit and insurance guarantee literature (Agarwal et al., 2023; Matray et al., 2024).

Sample construction and treatment indicator We construct the matched sample and define the treatment indicator in four steps. First, we anchor the sample on rejections: for each rejected ECI application to buyer b in year t, we record the rejecting firm as the control unit ($ECI\ dummy = 0$). Second, for each such rejection, we identify all exporters who received an approved ECI application for the same buyer b in year t, $t-1$, or $t-2$, ensuring that approved and rejected firms face the same buyer-level credit ceiling and FCFS allocation environment. Buyers with no approvals within this three-year window are excluded. Third, within each buyer, we perform propensity score matching to pair each rejected firm with observationally similar approved firms on lagged financial covariates (total assets, accounts

receivable, ROA, leverage), as detailed in Appendix C. The matching is implemented using nearest-neighbor matching with replacement, pairing each rejected firm with five approved firms within the common support (1:5 matching). As a robustness check, we also implement a 1:3 matching ratio, and the results remain qualitatively unchanged. Fourth, we aggregate to the firm-destination-year level: *ECI dummy* equals one if the firm holds an approved application for its matched representative buyer in destination c ($ECI\ dummy = 1$), and zero if it holds a rejected application. Firm-destination-year cells in which the same exporter holds both an approved and a rejected application for the same destination are dropped, so that *ECI dummy* is uniquely defined at the unit of analysis. We refer to the buyers that survive these restrictions as *representative buyers*, which form the basis of the post-PSM analysis sample (Panel C in Table 1). Figure 4 confirms that, after matching, approved and rejected firms are statistically indistinguishable on all covariates, with point estimates close to zero and confidence intervals spanning zero across total assets, accounts receivable, total debt, leverage, operating income, ROA, interest expenses, cash working capital, and cash-flow shortfall. We further verify in the pre-trend placebo (Appendix Table A8) that approved and rejected firms exhibit no differential export growth in the four years preceding application, directly ruling out the concern that higher export momentum drives selection into approval.

Estimation based on the PSM sample On the matched sample, we estimate the effect of ECI approval on export outcomes at the firm-destination-year level

$$\ln(Export)_{ict} = \delta_0 + \delta_1 ECI\ dummy_{ibt} + X'_{it-1}\delta + \lambda_i + \gamma_{ct} + \eta_{st} + \phi_{cs} + \nu_{ict}, \tag{2}$$

where $ECI\ dummy_{ibt}$ indicates whether firm i has an approved application for its representative buyer in destination country c, X'_{it-1} collects lagged firm-level financial controls, and the fixed effects are as in equation (1). The coefficient δ_1 measures the average difference in exports between approved and rejected firms that are similar in observables and that applied to the same buyers.

The coefficient δ_1 identifies a reduced-form effect of ECI approval on exports, but our parameter of interest is the elasticity of exports with respect to the continuous intensity of ECI coverage. Because realized coverage is subject to the endogeneity concerns identified in Section 4.1, including intensive-margin selection, time-varying confounders, and the mechanical overlap between coverage and exports, we instrument $\ln(\text{ECI coverage})_{ict}$ with the approval dummy in a 2SLS specification on the matched sample, as described next.

4.4 Instrumental Variables

We instrument $\ln(ECI\ coverage)_{ict}$ with $ECI\ dummy_{ict}$ using two-stage least squares (2SLS) on the propensity-score-matched sample. Running IV on a propensity-score-matched sample is an established approach in the program evaluation literature. Matching first removes selection on observables and creates a covariate-balanced comparison group. The instrument then addresses any residual selection on unobservables, together yielding more credible causal estimates (Ichimura and Taber, 2001; Frölich, 2007, 2015; Baiocchi et al., 2010; Kang et al., 2016). Hence, the PSM reduced-form and IV estimates are jointly informative. The former benchmarks to binary treatment effects in the export credit literature, and the latter recovers the continuous-treatment elasticity. The second-stage equation is

$$\ln(Export)_{ict} = \beta_0 + \beta_1 \ln(ECI\ coverage)_{ict} + X'_{it-1}\beta + \lambda_i + \lambda_{cs} + \lambda_{ct} + \lambda_{st} + \epsilon_{ict}, \quad (3)$$

with the first-stage equation

$$\ln(ECI\ coverage)_{ict} = \alpha_0 + \alpha_1 ECI\ dummy_{ict} + X'_{it-1}\alpha + \sigma_i + \sigma_{cs} + \sigma_{ct} + \sigma_{st} + \mu_{ict}, \quad (4)$$

where X'_{it-1} collects lagged firm-level controls (total assets, accounts receivable, ROA, and leverage), and the fixed effects λ_{cs}, λ_{ct}, and λ_{st} (and their first-stage counterparts σ_{cs}, σ_{ct}, σ_{st}) control for destination-industry, destination-year, and industry-year shocks, respectively, in addition to firm fixed effects.

Relevance Approval for the representative buyer directly raises the insured export volume to destination c. In the data, approved firms are substantially more likely to have positive $ECI\ coverage_{ict}$ and exhibit higher covered export values than otherwise similar rejected firms. Because $ECI\ coverage_{ict}$ is aggregated at the firm-destination-year level and reflects insured shipments to all buyers in country c, approval for the representative buyer shifts but does not mechanically determine total coverage. The first stage therefore captures how approval for one buyer shifts the firm's total insured exports to that destination. The first-stage coefficient is large because most exporters apply for insurance for only one or two buyers per destination (Appendix Figure B4), so approval for the representative buyer accounts for most of the firm's insured coverage in that market. The first-stage F-statistic, reported in the results tables, confirms that the instrument is strong.

Exogeneity The instrument is plausibly exogenous because approval outcomes are driven by buyer-level credit ceilings under FCFS, which exporters cannot observe or manipulate. Conditional on applying to a given buyer and after controlling for firm, destination-year,

industry-year, and country-industry fixed effects, whether a particular application falls just before or just after the ceiling is exhausted is orthogonal to firm-specific export shocks. The timing tests in Section 4.2 support this assumption.

Interpretation Because the instrument is binary, the 2SLS estimate identifies a local average treatment effect (LATE) for firms whose ECI coverage responds to approval of their representative buyer. These compliers are applicants who would use the approved coverage, precisely the population whose access the insurer's capacity allocation directly determines. The estimate therefore speaks to the firms and the margin that any feasible policy intervention would reach.

5 Empirical Results

OLS results Table 2 reports OLS estimates of the correlation between ECI coverage and firm exports. Columns (1)–(3) use the full ECI–Customs sample. Columns (4)–(6) add Tax Survey balance-sheet data at the cost of a smaller sample. The unconditional elasticity is 0.487 in the full sample (column (1)). Adding firm fixed effects reduces it to 0.446 (column (2)), and including the full set of industry-year, destination-year, and industry-destination fixed effects brings it to 0.319 (column (3)). The Tax Survey sample yields a similar preferred estimate of 0.311 after adding fixed effects and lagged firm-level financial controls (column (6)). The steady attenuation as we absorb more sources of unobserved heterogeneity confirms substantial positive selection into ECI coverage but does not resolve reverse causality or residual insurer selection, motivating the matched-sample and IV strategies below. PPML specifications retaining zero export flows show the same attenuation pattern (Appendix Table A1).

Matched-sample estimates Figure 4 confirms that the propensity-score-matched sample is well balanced: approved and rejected firms are statistically indistinguishable on total assets, accounts receivable, total debt, leverage, operating income, and ROA.[21] Differences in subsequent export outcomes therefore reflect the effect of ECI approval rather than pre-existing firm characteristics.

Table 3 reports the matched-sample estimates. Each panel progressively adds fixed effects and controls across columns (1)–(5). In the OLS panel, the elasticity falls from 0.470 in column (1) to 0.271 in column (5), our preferred specification with firm, industry-year,

[21] Firm size ($lnAsset$ = ln(lagged assets)), liquidity exposure ($lnAccountReceivable$ = ln(lagged accounts receivable + 1)), leverage (LEV = lagged debt/lagged assets), profitability (ROA = lagged net profit/lagged assets), and operating profit intensity ($OperatingProfit/Asset$ = lagged operating profit/lagged assets).

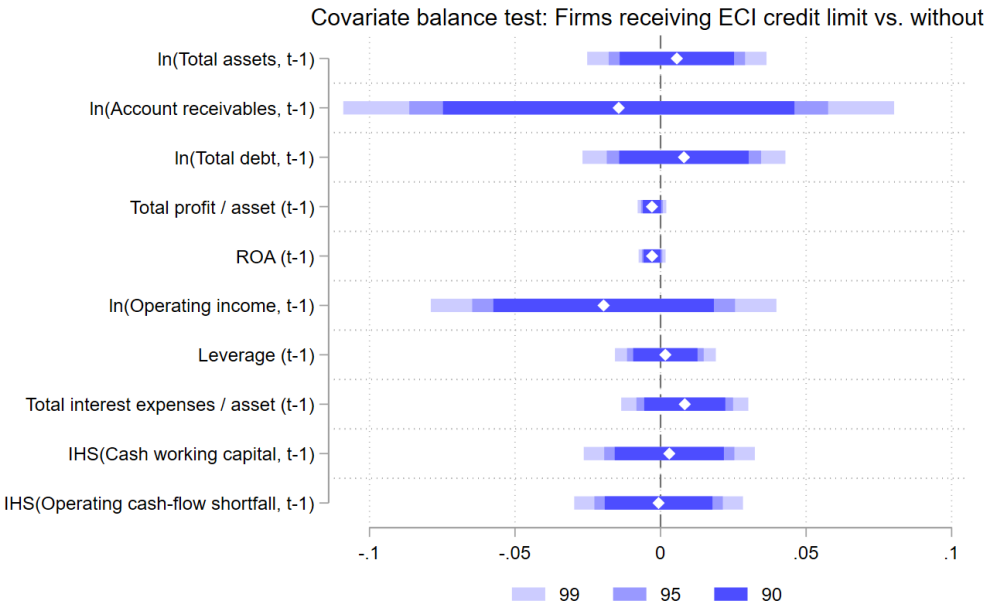


Figure 4: Covariate balance post-matching

Notes: The figure shows the balance test after propensity score matching. All covariates are measured at $t-1$, including total assets (ln(Total assets)), accounts receivable (ln(Account receivables)), total debt (ln(Total debt)), total profit over assets, return on assets (ROA, net profit over assets), operating income (ln(Operating income)), leverage, interest expenses scaled by assets, cash working capital, and cash-flow shortfall. Cash working capital and cash-flow shortfall are scaled by assets and transformed using the inverse hyperbolic sine (IHS). Each covariate is regressed on the ECI approval indicator, controlling for firm, year, destination country, and industry fixed effects. Standard errors are clustered at the firm level. The matched sample is an unbalanced firm-year panel with more than 2,102 firms and about 7,042 observations; therefore, the balance test is assessed conditional on firm fixed effects, that is, after absorbing time-invariant firm heterogeneity. Confidence intervals of 90%, 95%, and 99% are indicated.

Table 2: ECI coverage and exports

	Full Sample			Tax Survey Sample		
	(1) ln(Export)	(2) ln(Export)	(3) ln(Export)	(4) ln(Export)	(5) ln(Export)	(6) ln(Export)
ln(ECI coverage)	0.487***	0.446***	0.319***	0.506***	0.312***	0.311***
	(0.006)	(0.008)	(0.008)	(0.010)	(0.011)	(0.011)
Year FE		✓				
Firm FE		✓	✓		✓	✓
Industry-Year FE			✓		✓	✓
Destination-Year FE			✓		✓	✓
Industry-Destination FE			✓		✓	✓
Controls						✓
Observations	41080	39037	37077	16321	13320	13247
R^2	0.37	0.58	0.72	0.42	0.79	0.79

Notes: The unit of observation is firm-destination-year, where the sample firms are firms applying for ECI for the same buyer and approval is earlier than rejection within three years. The dependent variable is the logarithm of export value. The key regressor is the logarithm of ECI coverage. We use the sample from merging ECI with Customs data. Column (1) estimates OLS without fixed effects, column (2) adds firm fixed effects and year fixed effects, and column (3) adds firm fixed effects and the high-dimensional sets Industry × Year, Destination × Year, and Industry × Destination. Then we use the sample from merging ECI, Customs, and the Tax Survey data. Column (4) estimates OLS without fixed effects, column (5) adds firm fixed effects and the high-dimensional sets Industry × Year, Destination × Year, and Industry × Destination, and column (6) further includes lagged firm-level controls, including log accounts receivable, ROA, leverage, and assets. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

destination-year, and industry-destination fixed effects plus lagged firm controls. Column (5) in the IV panel yields our main result: an elasticity of 0.225, implying that a 10% increase in ECI coverage raises exports by approximately 2.3%. The IV estimate declines from 0.479 without fixed effects to 0.225 in our preferred specification as progressively richer fixed effects absorb correlated industry and destination shocks, confirming that the saturated specification isolates the direct effect of coverage on exports.

The Kleibergen-Paap F-statistic of 73.33 in column (5) confirms the instrument is strong. The first-stage coefficient of 2.173 indicates that approved firms receive more than twice the ECI coverage of their rejected counterparts. The reduced-form estimate in column (5) implies that approved firms export about 63% more than rejected firms ($e^{0.489} - 1$). This magnitude is broadly consistent with the export credit literature. Agarwal et al. (2023) report a factor-of-three effect for Swedish guarantees covering a broader product scope, and Matray et al. (2024) document roughly a 20% decline in U.S. exports when access to export credit agency financing is lost. Differences in program scope account for much of the gap, as their coverage includes longer-term guarantees while we focus on short-term ECI.

Table 3: Instrumented effects of ECI on export value

	Export Value				
	(1)	(2)	(3)	(4)	(5)
OLS					
ln(ECI coverage)	0.470***	0.425***	0.321***	0.270***	0.271***
	(0.012)	(0.015)	(0.016)	(0.017)	(0.017)
First stage					
ECIdummy	4.428***	3.039***	2.282***	2.075***	2.173***
	(0.225)	(0.223)	(0.227)	(0.279)	(0.254)
Reduced-form					
ECIdummy	2.121***	1.268***	0.744***	0.489***	0.489***
	(0.176)	(0.160)	(0.143)	(0.147)	(0.147)
IV estimates					
ln(ECI coverage)	0.479***	0.417***	0.326***	0.225***	0.225***
	(0.029)	(0.041)	(0.053)	(0.061)	(0.061)
Year FE		✓			
Firm FE		✓	✓	✓	✓
Industry-Year FE			✓	✓	✓
Destination-Year FE			✓	✓	✓
Industry-Destination FE				✓	✓
Controls					✓
Observations	6757	5862	5432	4843	4843
R^2	0.42	0.36	0.25	0.20	0.20
KP F-Statistic	388.95	186.20	101.43	73.13	73.33

Notes: This table presents baseline estimation results using OLS, first-stage, reduced-form, and IV regressions. The dependent variable is the logarithm of export value in all columns. Robust standard errors, clustered at the firm level, are reported in parentheses. The sample is restricted to firms in the matched PSM sample. Columns (1)–(5) progressively add fixed effects: year FE (column (2)), firm FE (columns (2)–(5)), industry-year FE (columns (3)–(5)), destination-year FE (columns (3)–(5)), and industry-destination FE (columns (4)–(5)). Column (5) additionally includes lagged firm-level controls. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

The progressive attenuation from the full-sample OLS to the matched-sample IV is informative about the sources of endogeneity identified in Section 4.1. The full-sample OLS with the richest fixed effects yields an elasticity of 0.311 (Table 2, column (6)). Restricting to the PSM matched sample reduces this to 0.271 (Table 3, column (5)). This drop is consistent with the extensive-margin selection concern: in the full sample, firms with stronger export prospects are more likely to apply for and obtain larger coverage, inflating the OLS correlation. PSM restricts the comparison to applicants competing for the same buyer's credit ceiling, removing this positive selection and confirming that extensive-margin sorting biases the full-sample estimates upward.

Within the matched sample, the IV elasticity of 0.225 is smaller still than the OLS estimate of 0.271. This further attenuation is consistent with the three endogeneity concerns identified in Section 4.1, all of which bias OLS upward. Intensive-margin selection, time-varying confounders, and mechanical variable-construction bias are each resolved by the quasi-random FCFS instrument. The pattern of progressive attenuation from full-sample OLS to PSM OLS to IV confirms that each estimation stage addresses a distinct source of bias.

Magnitude and policy-relevant population The IV elasticity of 0.225 implies that a 10% increase in ECI coverage raises firm-destination exports by 2.3%. Equivalently, the reduced-form estimate implies that ECI approval raises exports by about 63% relative to rejection among matched applicants. As discussed in Section 4.4, this is a LATE for compliers whose coverage responds to approval of their representative buyer. Importantly, whether a firm is a complier depends only on whether its application arrives near ceiling exhaustion, and Section 4.2 documents that application timing is quasi-random with respect to firm characteristics. Compliers are therefore representative of the broader applicant population, and the LATE generalizes to the average treatment effect for firms that apply for ECI. We translate this elasticity into aggregate export and fiscal effects in the cost-benefit analysis in Section 5.

Extensive margin, product scope, and export destination Having established the effect on total export value at the firm-destination level, we ask how this aggregate effect is distributed across the margins of trade.[22] The firm-destination aggregate already blends margins at finer levels of disaggregation: it captures both higher shipments to existing buyers and potential entry into additional buyers or products within the same destination country. Table 4 reports IV estimates for seven outcome variables, all using the preferred full-control

[22]The distinction between intensive and extensive margins of trade at the firm level is discussed in Martincus and Carballo (2008) and Besedeš and Prusa (2011).

Table 4: ECI effects across margins of trade

	Total exports	Intensity (exp.>0)	Particip. $D(\text{exp.} > 0)$	New dest.†	HS6 varieties‡	Unit value§	Uninsured exports
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
First stage							
ECI dummy	2.173***	2.074***	2.173***	2.386***	2.074***	1.932***	2.173***
	(0.254)	(0.265)	(0.251)	(0.201)	(0.279)	(0.339)	(0.251)
Reduced form							
ECI dummy	0.489***	0.226***	0.018*	0.014*	0.110***	0.000	0.254*
	(0.147)	(0.070)	(0.010)	(0.008)	(0.034)	(0.054)	(0.145)
2SLS estimates							
ln(ECI coverage)	0.225***	0.109***	0.008*	0.006*	0.053***	0.000	0.117*
	(0.061)	(0.033)	(0.004)	(0.003)	(0.016)	(0.028)	(0.066)
Firm FE	✓	✓	✓	✓	✓	✓	✓
Industry-Year FE	✓	✓	✓		✓	✓	✓
Destination-Year FE	✓	✓	✓		✓	✓	✓
Industry-Destination FE	✓	✓	✓		✓	✓	✓
Year, Dest., Ind. FE†				✓			
Controls	✓	✓	✓	✓	✓	✓	✓
Observations	4843	4326	4843	5124	4326	3123	4843
KP F-Statistic	73.33	61.14	74.93	141.61	55.19	32.54	74.93

Notes: This table reports first-stage, reduced-form, and 2SLS estimates across seven outcome variables, each using the preferred specification with full controls. Column (1) reproduces the baseline export-value result from Table 3, column (5). Columns (2) and (3) decompose the total effect into conditional intensity ($\ln(\text{Export}|\text{Export} > 0)$) and participation ($D(\text{Export} > 0)$). Column (4) reports effects on the probability of entering a new destination country in year t. Column (5) reports effects on the number of HS 6-digit product varieties. Column (6) reports effects on unit values. Column (7) reports effects on uninsured exports, defined as total exports minus ECI-covered exports. All specifications include firm fixed effects and lagged firm-level controls. Columns (1)–(3) and (5)–(7) further include industry-year, destination-year, and industry-destination fixed effects. †Column (4) uses a different sample (all potential firm-destination-year observations, including non-exporting spells) and separate year, destination, and industry fixed effects in place of interaction fixed effects, which accounts for the larger observation count ($N = 5{,}124$). ‡Columns (2) and (5) are estimated on the subsample with positive exports ($N = 4{,}326$); the first-stage coefficient reflects this subsample. §Column (6) is estimated on the subsample with available unit value data ($N = 3{,}123$), which requires reported quantity information; this selected subsample should be kept in mind when interpreting the unit value null result. Robust standard errors, clustered at the firm level, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

specification.

Columns (2) and (3) decompose the total export effect into conditional intensity and participation. A 10% increase in ECI coverage raises the probability of positive exports by 0.08 percentage points (column (3)) and raises export value conditional on exporting by 1.09% (column (2)). The conditional intensity effect is proportionally much larger than the participation effect, indicating that ECI operates primarily by deepening shipments within existing firm-destination relationships rather than by inducing firms to begin exporting to a destination they would otherwise not serve.

Column (4) examines entry into new export markets, where the outcome is a dummy equal to one if the firm exports to a country not served in the previous year. A 10% increase in ECI coverage raises the probability of entering a new destination by 0.06 percentage points, a modest but statistically significant effect. Consistent with the risk-reduction channel, the result points toward insurance lowering the threshold for expanding into unfamiliar markets where buyer default risk is higher.

Column (5) reports IV estimates for the number of exported HS 6-digit product varieties. A 10% increase in ECI coverage raises the number of exported varieties by approximately 0.5%. Column (6) shows a precisely estimated zero effect on unit values. This null result is informative beyond the direct margin decomposition: if ECI approval were correlated with unobserved firm quality, approved firms would tend to export higher-quality goods at higher unit values, and the positive export value effect would partly reflect selection of better exporters into approval rather than a causal effect of insurance access. The absence of any unit value response suggests that the instrument is not proxying for firm quality, and that ECI raises export volumes through liquidity and risk-reduction channels rather than by selecting higher-quality exporters. Taken together, the bulk of the firm-destination-level export gain reflects higher volumes along both the intensive and within-destination extensive margins, with smaller but statistically significant effects on product scope and geographic entry into new countries.

Industry-level analysis As a complementary check, Appendix Table D1 reports regressions at the industry-destination-year level using the pre-PSM full sample. The preferred OLS specification with full fixed effects yields an elasticity of 0.37 (Appendix Table D1, column (4)), which exceeds the firm-level IV estimate of 0.225. The gap reflects endogeneity that cannot be easily resolved at the aggregate level. We therefore do not interpret the industry-level estimates causally. They provide aggregate context and illustrate the magnitude of bias that the IV strategy corrects.[23]

[23]The industry-level OLS elasticity of 0.37 exceeds the estimates reported for South Korea in Choi and Kim (2021), whose sample runs from the first quarter of 2010 through the fourth quarter of 2018. By that

ECI and uninsured exports Does ECI raise only the transactions it directly covers, or does it also raise uninsured exports to the same destination? If ECI relaxes financial or risk constraints that bind on the firm's export activity broadly, the effect should extend beyond insured transactions. Column (7) of Table 4 tests this directly. The outcome is the log of uninsured export value, defined as total firm-destination exports minus ECI-covered exports. The IV estimate of 0.117 implies that a 10% increase in ECI coverage raises uninsured exports by 1.17%, a positive and statistically significant effect. ECI does not merely shift the insured share of a fixed export volume. The uninsured elasticity of 0.117 is roughly half the total export elasticity of 0.225, indicating that ECI's effect on export capacity extends beyond the covered transactions, though with smaller proportional magnitude. We examine the financial constraint and risk reduction mechanisms that underlie this pattern in Section 6.

Dynamic effects Table A2 reports IV estimates of the dynamic export response, with a separate regression for each horizon from the application year through four years after. The export gain is large and precisely estimated at t, persists through $t+1$ and $t+2$ with similarly sized coefficients, and then fades. By $t+3$ and $t+4$ the point estimates are small and statistically insignificant. The export gains from short-term ECI are therefore front-loaded and concentrated within the first two years after approval. The fade-out is not an artifact of a weakening instrument. Because the endogenous variable is always ECI coverage at application year t, the first stage is the same regression across all columns, and the Kleibergen-Paap F-statistics remain well above conventional thresholds throughout, ranging from 37.8 at t to 22.6 at $t+4$. The modest decline reflects sample attrition rather than instrument irrelevance. The near-zero coefficients at $t+3$ and $t+4$ therefore reflect a fading effect rather than instrument weakness. Two interpretations of the fade-out are consistent with the data. First, because most of the baseline export gain accrues on the intensive margin within existing firm-destination relationships (Table 4, column (2)), the dominant mechanism is per-transaction financial relief, with insured receivables serving as pledgeable collateral and the insurer absorbing buyer default risk. These benefits are tied to the period of active coverage, so the effect naturally dissipates as the original insurance lapses. Second, rejected firms may obtain coverage through subsequent applications to the same or different buyers, so the treatment-control contrast converges over time as control firms catch up. Both

period South Korea had long achieved high-income status, with well-developed financial markets and deep trade finance infrastructure. Firms in that setting face fewer binding credit constraints and derive smaller marginal gains from export insurance. This contrast is consistent with ECI generating larger export effects in China, where trade finance constraints are more pervasive. Notably, Choi and Kim (2021) acknowledge that the use of export credit insurance is not random and that such selection may yield endogenous bias, explicitly leaving this issue to future study. Our paper directly addresses this limitation by leveraging the FCFS buyer-ceiling rationing rule that generates quasi-random variation in ECI approval at firm-destination country level.

forces likely contribute, and the current design cannot fully separate them. Regardless of the relative contribution, the persistence of the effect through $t+1$ and $t+2$ confirms that ECI generates export gains extending at least one to two years beyond the initial approval.

Cost-benefit analysis of ECI Prior work has established that ECAs can be profitable on their own balance sheets. Matray et al. (2024) reconstruct EXIM Bank's income statements and find total profits exceeding $480 million during the period surrounding the 2015 shutdown. Their analysis, however, covers EXIM's full portfolio of short-term and long-term trade financing products, and the binary nature of the shutdown precludes recovering the marginal return per dollar of coverage for any individual product line. Because our IV identifies the elasticity of exports with respect to short-term ECI coverage specifically, we can translate the causal export effect into fiscal returns per insured dollar.

Each insured dollar generates roughly $0.11 in fiscal revenue, which exceeds plausible program costs (administrative expenses plus expected claims net of premium income) and implies that China's short-term ECI program is fiscally self-financing. The EXIM Bank profitability evidence discussed above confirms that actual costs fall well below this threshold.[24] We arrive at this figure as follows. The preferred IV elasticity of 0.225 implies that each additional dollar of insured exports generates about $0.84 in additional aggregate exports.[25] Applying a domestic value-added share of exports equal to 0.65, the midpoint of the 0.6–0.7 range estimated for Chinese manufacturing (Kee and Tang, 2016), yields a GDP effect of about $0.55 per insured dollar.[26] At China's tax-to-GDP ratio of approximately 19.5% (OECD, 2023), this yields the $0.11 fiscal revenue figure.[27]

Appendix Table A3 reports break-even thresholds across alternative parameter values, confirming fiscal self-financing across a wide range of scenarios.[28] These calculations extrapolate the LATE estimated on compliers in the PSM sample to the aggregate insured export base, implicitly assuming that the marginal return is representative of the average insured dollar.

[24] Private-sector benchmarks point in the same direction. The three largest publicly listed trade credit insurers, Allianz Trade, Atradius, and Coface, reported combined ratios (claims plus administrative expenses as a share of premium income) of 64–79% in 2023 (Coface SA, 2024; Atradius N.V., 2024).

[25] Let X_a denote insured exports and X denote total goods exports. From the log-log relationship, $dX/dX_a = \beta \cdot (X/X_a) = \beta/(X_a/X)$. Using $\beta = 0.225$ and $X_a/X = 0.269$ yields $dX/dX_a \approx 0.84$. The penetration rate $X_a/X = 0.269$ is based on official statistics reported by China's export credit agency and summarized by Xinhua News Agency (2025).

[26] The implied GDP effect is $dY/dX_a = v \cdot dX/dX_a \approx 0.65 \times 0.84 \approx 0.55$.

[27] The implied fiscal effect is $dT/dX_a = t \cdot dY/dX_a \approx 0.195 \times 0.55 \approx 0.11$.

[28] Using the lower and upper bounds of the domestic value-added share of exports range ($v = 0.6$ and $v = 0.7$) yields GDP effects of about $0.50 and $0.59 per insured dollar, with corresponding fiscal break-even thresholds of roughly $0.10 and $0.12.

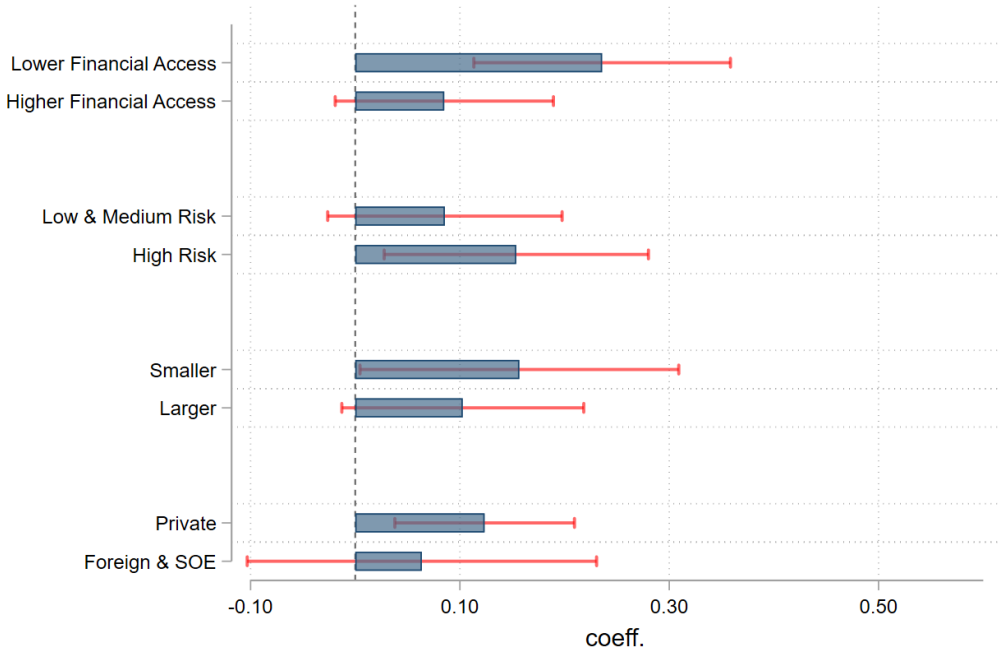


Figure 5: Heterogeneous effects of ECI

Notes: This figure plots the estimated coefficients of ECI on firm-destination-year exports across different subsamples. Each horizontal bar represents the 2SLS point estimate, and the red whiskers indicate 95% confidence intervals. Heterogeneity is examined by city-level financial accessibility (below or above the median total interest divided by total operating income), destination country risk (low, medium, or high, based on the World Uncertainty Index (WUI)), firm output size (smaller or larger, based on the median output value), and firm ownership type (private versus foreign or state-owned). All the regressions include firm, industry-year, destination-year, and industry-destination fixed effects. Standard errors are clustered at the firm level. All observations have positive exports.

6 Mechanisms

Having established that ECI raises firm-destination exports, we now test which channels drive the effect. The trade finance literature points to two leading mechanisms. The *financial constraint* channel operates when ECI relaxes firms' liquidity and borrowing constraints by making insured receivables pledgeable as collateral. The *risk reduction* channel operates when ECI mitigates payment and political risks in foreign markets, lowering the expected cost of default. We examine each in turn, using heterogeneity in firm characteristics and market conditions as reduced-form tests of these mechanisms. Figure 5 summarizes the heterogeneous IV estimates across these dimensions.

6.1 Financial Constraint Channel

We begin with direct evidence on firms' balance-sheet outcomes and then examine heterogeneity across firm characteristics. If ECI operates through the financial constraint channel, coverage should expand firms' access to credit, raise accounts receivable, and ease liquidity constraints. Moreover, the export effect should be most pronounced for firms with limited access to formal credit markets (Xu, 2022).

ECI coverage and firm balance sheets Table 5 examines the effect of ECI on firms' financial outcomes at the firm-year level, estimated on the post-PSM matched sample described in Section 4.3. The key explanatory variable is firm-level ECI coverage, measured as the natural logarithm of the total insured export amount aggregated across all destination countries within a year.

The dependent variables vary across columns to capture different dimensions of firms' financing conditions and liquidity positions. Columns (1)–(2) focus on total interest expenses, which proxy for firms' access to external credit. Columns (3)–(4) examine accounts receivable, which reflect the scale of trade credit extended to buyers. Columns (5)–(6) analyze cash working capital (operating cash inflows minus operating cash outflows plus accounts receivable minus accounts payable), transformed using the inverse hyperbolic sine to accommodate zero and negative values.[29] Finally, columns (7)–(8) consider operating cash-flow shortfalls (operating cash outflows minus operating cash inflows, similarly transformed), which capture short-term liquidity stress.

All specifications are estimated using ordinary least squares. Odd-numbered columns include year fixed effects, while even-numbered columns additionally control for industry fixed effects. Because our baseline IV leverages destination-level variation, aggregating insured exposure to the firm-year level removes the variation required to implement the instrument. Identification instead relies on the quasi-experimental matched-applicant design, which achieves close covariate balance and passes pre-treatment placebo tests (Section 4.3, Figures 3–4, and Table A8).

Across outcomes, the results consistently show that higher ECI coverage improves firms' financing conditions. Firms with greater ECI coverage exhibit significantly higher interest expenses, consistent with larger borrowing volumes facilitated by insured receivables. ECI coverage also raises accounts receivable, reflecting an expansion in trade credit extended to

[29] Because cash working capital and operating cash-flow shortfalls can take zero or negative values, neither $\ln(x)$ nor $\ln(1+x)$ is feasible. We use the inverse hyperbolic sine, $\text{arcsinh}(x) = \ln(x + \sqrt{x^2+1})$, which accommodates the full support. As Chen and Roth (2024) note, the IHS shares the estimand-sensitivity issues of other log-like transformations. Our interpretation therefore focuses on the sign and statistical significance of the coefficients rather than their precise magnitudes.

foreign buyers on deferred-payment terms. Importantly, the liquidity measures move in the same direction. ECI coverage is positively related to cash working capital and significantly reduces operating cash-flow shortfalls, indicating that firms can finance the working-capital gap created by greater receivables without exacerbating short-run cash stress. Taken together, these balance-sheet results provide direct evidence that ECI relaxes firms' financial constraints through the credit-access channel.

Table 5: The effects of ECI coverage on firms' balance sheets

	Interest Expenses		Account Receivables		Working capital		Cashflow shortfall	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln(ECI coverage)	0.126***	0.127***	0.143***	0.142***	0.090*	0.119**	-0.166***	-0.165***
	(0.017)	(0.016)	(0.013)	(0.013)	(0.050)	(0.050)	(0.038)	(0.038)
Year FE		✓		✓		✓		✓
Industry FE		✓		✓		✓		✓
Observations	2823	2751	2805	2732	2750	2680	2784	2713
R^2	0.03	0.11	0.08	0.19	0.00	0.07	0.01	0.06

Notes: This table examines the effects of export credit insurance (ECI) on firms' balance sheets at the same year at the firm-year level. The sample includes firms retained after propensity score matching. The key explanatory variable is firm-level ECI coverage, measured as the natural logarithm of one plus the total insured export amount aggregated at the firm-year level across all destination countries. The dependent variables differ across columns. Columns (1)-(2) use the logarithm of total interest expenses. Columns (3)-(4) use the logarithm of accounts receivable. Columns (5)-(6) use cash working capital, defined as operating cash inflows minus operating cash outflows plus accounts receivable minus accounts payable, transformed using the inverse hyperbolic sine. Columns (7)-(8) use operating cash flow shortfall, defined as operating cash outflows minus operating cash inflows, also transformed using the inverse hyperbolic sine. All regressions are estimated using ordinary least squares. Specifications progressively include year fixed effects and industry fixed effects, as indicated in the table. Standard errors are clustered at the firm level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Heterogeneity by Financial Accessibility We complement the balance-sheet evidence with a heterogeneity test based on local credit conditions. If ECI mainly operates by easing financing constraints, its effect should be stronger in cities where firms have poorer access to external finance. To proxy for city-level financial accessibility, we use firm-level data from the 2008 China Tax Survey and construct the ratio of total interest expenses to total operating revenue across all reporting firms in each city (Li and Yu, 2009). This measure captures the average reliance on external financing within a city. Cities above the median value are classified as having high financial accessibility, while those below the median are considered financially constrained.[30]

[30]Approximately half the firms in the 2008 Tax Survey do not report interest expenses. These firms are excluded from the calculation. City boundaries are harmonized based on 2008 administrative codes to ensure consistency.

We re-estimate the baseline regression separately for firms located in high- and low-access cities using the PSM sample. As predicted, Figure 5 and Appendix Table A5 show that ECI significantly increases exports for firms in credit-constrained cities, with an estimated elasticity of 0.236. The effect for firms in cities with higher financial accessibility is much smaller, estimated to be 0.085 and marginally statistically significant. These findings indicate that ECI has larger effects in credit-constrained environments, where alternative sources of trade finance are limited. Conversely, firms with better access to credit derive smaller marginal benefits from insurance, consistent with the financial constraint channel.

6.2 Risk Reduction Channel

We now turn to the risk reduction channel. Exporters serving higher-risk or institutionally weak destinations face elevated political, economic, and contract enforcement risks. If ECI operates by mitigating such risks, its export-promoting effects should be stronger in riskier destinations and during periods of heightened aggregate uncertainty such as the global financial crisis.

Destination Country Risk We first study how the effect of ECI varies with destination country risk. We classify destination countries into three groups, low, medium, and high risk, based on the WUI developed by Ahir et al. (2022). This stratification allows us to test whether the export response to ECI is larger in higher-risk markets, consistent with the risk-mitigation channel.

As predicted, Figure 5 and Appendix Table A5 (columns 3–4) show that the effect of ECI is strongest for high-risk destinations, with an estimated elasticity of 0.154. The effects for low- and medium-risk destinations are smaller and statistically insignificant. This finding is in line with Agarwal et al. (2023), who find that export credit guarantees are more effective for trade toward riskier markets.

Time Variation and the Global Financial Crisis Next, we explore how the effect of ECI varies over time, focusing on the global financial crisis as a natural stress test of the risk reduction channel. Figure 6 plots the annual IV (2SLS) coefficients of ECI coverage on firm exports over 2008–16.[31] The coefficients are consistently positive throughout the sample period. They are stable at around 0.22–0.23 in most years, except for 2008, when the estimated elasticity rises to approximately 0.34, roughly 50% above the non-crisis baseline.

The larger effect in 2008 coincides with the global financial crisis, a period of elevated uncertainty, tighter liquidity (Amiti and Weinstein, 2011), and higher default risk in interna-

[31] OLS estimates display a similar pattern and are available upon request.

tional trade. The spike in the elasticity is consistent with ECI playing a countercyclical role by mitigating payment risk and easing access to working capital when private trade finance contracted. This interpretation aligns with the findings of Agarwal et al. (2023), who show that export credit guarantee usage rose sharply during the crisis and helped mitigate the trade downturn.

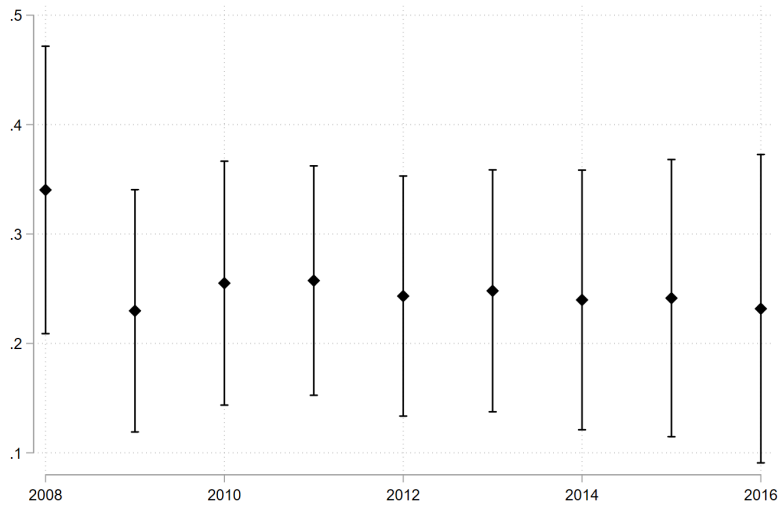


Figure 6: Annual IV coefficients of ECI on firm exports

Notes: This figure plots the annual IV (2SLS) coefficients of log export value on log ECI coverage over 2008–16. The endogenous variable, log ECI coverage, and its interactions with year dummies are instrumented by the ECI approval dummy and its corresponding interactions. The regression absorbs firm and industry–destination fixed effects and clusters standard errors at the destination-country level. Each black diamond represents the estimated coefficient, and the vertical bars denote 95% confidence intervals. The sample is restricted to the PSM-matched firm–destination–year observations.

6.3 Firm and Ownership Heterogeneity

The remaining two dimensions of heterogeneity, firm size and ownership, are consistent with both channels and therefore merit joint discussion rather than attribution to either one alone.

Firm Size Smaller firms face both tighter borrowing constraints and greater vulnerability to buyer default, making them more reliant on government-backed insurance. We classify firms into two groups based on the median of their one-year lagged output value, approximately US$41,400.

Appendix Table A5 (columns 5–6) reports the IV (2SLS) estimates separately for smaller and larger firms on the PSM matched sample. For smaller firms, the estimated elasticity is 0.16 and statistically significant. For larger firms, the corresponding coefficient is 0.10 and

statistically significant only at the 10% level. The size difference is consistent with both channels. Smaller firms face tighter credit access and weaker collateral positions (financial constraint channel) and are also less able to absorb losses from buyer default (risk reduction channel).

Firm Ownership A similar dual interpretation applies to firm ownership. Private firms are typically more credit constrained than state-owned enterprises and foreign-owned firms, which benefit from preferential access to capital (Poncet et al., 2010; Amiti and Weinstein, 2011). Private firms also typically face greater counterparty information asymmetry when transacting with foreign buyers, making default risk more salient.

As shown in Figure 5 and Appendix Table A5 (columns 7–8), ECI coverage significantly increases exports for private firms, with an estimated elasticity of 0.124. The effect for foreign-owned and state-owned firms is half as large and statistically insignificant. This pattern reflects both channels. Private firms face tighter financing frictions (Poncet et al., 2010), and they also transact at arm's length with unfamiliar buyers, making them more exposed to counterparty default risk. State-owned and foreign-invested firms often deal with known counterparties or related parties, reducing the value of insurance on both margins.

Taken together, the evidence from financial accessibility and destination risk provides channel-specific support for the financial constraint and risk reduction mechanisms, respectively. The firm size and ownership results reinforce both channels simultaneously, consistent with ECI addressing a bundle of financial and informational frictions that are jointly more severe for smaller and private exporters.

Heterogeneous selection bias The IV heterogeneity patterns differ from the OLS patterns in ways consistent with heterogeneous selection bias. For firm size and destination risk, the OLS estimates suggest larger effects for larger firms and safer destinations, but the IV reverses both patterns, revealing larger causal effects for smaller firms and riskier destinations. For financial accessibility and ownership, the OLS estimates show near-equal effects across subsamples, but the IV estimates are markedly larger for firms in cities with lower financial accessibility and for private firms.

The three sources of upward OLS bias identified in Section 4.2 (intensive-margin self-selection, correlated time-varying shocks, and mechanical variable construction) all predict that OLS overstates the causal effect. The magnitude of this bias in each subsample depends on how strongly ECI coverage co-moves with unobserved export determinants. For larger firms and safer destinations, export relationships tend to be more stable and predictable, so ECI coverage and unobserved export capacity are likely to co-move more tightly, generating a larger upward bias. For smaller firms and riskier destinations, exports are more volatile and

less predictable, potentially weakening this correlation and reducing the OLS bias. Under this interpretation, the IV correction is largest for the subsamples where the OLS bias is largest (larger firms, safer destinations), and once this differential bias is removed, the true causal effects are concentrated among smaller firms and riskier destinations. For financial accessibility and ownership, the OLS bias appears roughly equal across subsamples, so the IV uncovers a true gap that the common bias masked.

Importantly, both the IV and the PPML control function correction (Appendix Table A9) independently move all four heterogeneity comparisons in the direction predicted by the financial constraint and risk reduction channels.[32] These heterogeneity tests are reduced-form in nature and do not separately identify the contribution of each channel. Nonetheless, the coherence across multiple dimensions of firm and market heterogeneity provides evidence that both channels contribute to the overall effect of ECI on exports.

7 Robustness Checks

Tables A6 and A7 summarize the results across alternative instruments, samples, matching windows, and estimators. We discuss each test in turn.

Same-year matching sample Column (3) of Table A6 re-estimates the baseline IV using a more restrictive sample in which approved and rejected ECI applications are matched within the same year. The IV elasticity of 0.263 is similar to the baseline, suggesting that the findings are not driven by temporal mismatch or intertemporal selection. Full results across all outcome variables are in the Supplementary Online Appendix.

Excluding approved cases immediately preceding a rejection We remove, for each buyer, the most recent approved ECI case immediately preceding a rejection. These "borderline" approvals may reflect situations in which the buyer-level credit ceiling had been nearly exhausted, leading approved coverage to be mechanically smaller than the application amount. Column (4) of Table A6 reports the IV estimates after dropping these cases. The elasticities remain stable and become modestly larger, suggesting that including borderline approvals, if anything, attenuates the baseline estimates.

Post-crisis sample, 2010 and later We restrict the sample to 2010–16 to assess whether the effect of ECI persists outside the global financial crisis period. Column (5) of Table A6 presents the IV estimate. The estimated elasticity of 0.236 remains positive, statistically

[32] The direction of the overall bias correction differs between the linear and PPML specifications (OLS > IV, but naive PPML < PPML+CF), which is expected given that the two functional forms weight observations differently and have different sensitivities to measurement error and selection.

significant, and similar in magnitude to the baseline, confirming that the results are not driven by crisis-era dynamics.

Alternative instrument, approved credit limit We re-estimate the IV specification using the log of the ECI credit limit approved by the insurer at the firm-country-year level as an alternative instrument. The approved limit is set prior to contract issuance based on internal risk assessment and portfolio considerations, and is therefore plausibly orthogonal to unobserved export shocks. Column (6) of Table A6 reports the results. The first-stage F-statistic is 93.67, and the IV elasticity of 0.282 confirms the baseline finding. Full results are in the Supplementary Online Appendix.[33]

Alternative estimator, PPML Since around 9% of observations in the post-PSM sample feature zero exports, we re-estimate the baseline specifications using the PPML estimator with a control function to address endogeneity. Column (7) of Table A6 and column (8) of Table A7 report the preferred PPML estimates for the baseline and drop-nearest samples, respectively. The control function elasticities of 0.170 and 0.216 are positive, statistically significant, and economically close to the linear IV estimates. Full PPML results across all specifications and outcome variables are in the Supplementary Online Appendix.

Appendix Table A9 extends the PPML analysis to heterogeneous effects. As discussed in Section 6, the PPML+CF heterogeneity patterns confirm the IV results across all four dimensions. Our preferred specification remains 2SLS, where the exclusion restriction and first stage are directly visible, whereas the control function approach embeds the identification in a two-step procedure. The consistency across estimators reinforces the baseline findings.

Placebo test for pre-application exports Appendix Table A8 reports placebo regressions that examine whether ECI coverage in the application year predicts export outcomes in the years prior to application. Using the baseline IV strategy, we regress lagged export outcomes ($t-4$ to $t-1$) on $\ln(\text{ECI coverage}_t)$. Across all pre-application horizons, the IV coefficients are small and statistically indistinguishable from zero. Reassuringly, there is no evidence of differential pre-trends, anticipatory behavior, or reverse causality.

Alternative clustering of standard errors Our baseline inference clusters standard errors at the firm level. Columns (9) and (10) of Table A7 replicate the baseline with standard errors clustered at the destination-country and province levels, respectively. The point estimates are unchanged and remain statistically significant under both alternatives (see the Supplementary Online Appendix for full results).

[33]The Supplementary Online Appendix is available at https://github.com/cpenglse/Covered-to-Compete-How-Export-Credit-Insurance-Shapes-Firm-Trade.

Firm-specific year trends Our baseline specification absorbs firm, industry-year, destination-year, and industry-destination fixed effects. Column (11) of Table A7 adds firm-specific linear year trends and month fixed effects, allowing each firm's export trajectory to follow an individual slope. The IV estimate rises to 0.271 (SE = 0.079), larger than the baseline of 0.225, confirming that the baseline is conservative. The Kleibergen-Paap F-statistic remains well above conventional thresholds at 40.68. This result also matches the contemporaneous ($t = 0$) coefficient in the dynamic specification (Table A2, column 1), which controls for the same set of fixed effects and trends.

Alternative treatment of mixed-status cells The PSM matching procedure drops firm-destination-year cells in which the same firm has both approved and rejected applications to different buyers within the same destination-year. Column (12) of Table A7 retains these mixed-status cells by redefining the ECI indicator to equal one whenever any matched application is approved, increasing the sample from 4,843 to 5,401 observations. The IV estimate of 0.258 remains close to the baseline of 0.225. Column (13) goes further by replacing the binary instrument with the approved ECI credit-limit share, defined as the approved credit limit divided by the applied credit limit, on the full sample of 5,760 observations. The IV estimate of 0.243 is again similar. Both specifications yield first-stage F-statistics well above conventional thresholds (50.04 and 30.57, respectively). These results confirm that the baseline findings are not driven by the exclusion of mixed-status cells.

8 Conclusions

This paper estimates the causal effect of short-term export credit insurance (ECI) on firm exports in a developing economy. Exploiting quasi-random variation in insurance approval generated by a first-come-first-served allocation rule among otherwise similar applicants, we find that a 10% increase in ECI coverage raises firm-destination exports by approximately 2.3%.

First, ECI raises exports through multiple margins. It expands quantities, product scope, market participation, and destination entry, while leaving prices largely unchanged. Second, the effects operate through two reinforcing channels. Balance-sheet evidence confirms that ECI eases financial constraints by making insured receivables more pledgeable. At the same time, the concentration of export gains in riskier destinations and during the global financial crisis points to a buyer-risk mitigation channel that is distinctive to ECI relative to other trade finance instruments. Unlike bank credit lines or export subsidies, ECI directly transfers foreign-buyer default risk from the exporter to the insurer, enabling firms to serve markets

they would otherwise avoid. Smaller and private firms benefit most, consistent with both channels, as these firms face tighter credit access and greater exposure to arm's-length buyer default. Third, when scaled to the aggregate level, the estimated elasticities imply a benefit-cost ratio of approximately 2.7, consistent with short-term ECI serving as an effective and countercyclical complement to bank-based trade finance. These findings suggest that well-designed public export insurance can be a cost-effective trade facilitation tool, particularly when targeted toward financially constrained firms trading with higher-risk destinations.

Our identification relies on applicants to the ECI program and thus speaks to marginal expansions of coverage among firms that actively seek insurance, so the estimates may not extend to large, persistent expansions of public insurance where general-equilibrium effects become relevant. The analysis focuses on short- to medium-run responses, and the dynamic estimates indicate attenuation over time, leaving open questions about long-run effects on firm growth. A natural next step is to embed ECI into a general-equilibrium trade framework to quantify welfare, reallocation, and spillover effects across firms and destinations.

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A Tables

Table A1: ECI coverage and export PPML estimates

	Full Sample			Tax Survey Sample		
	(1) Export	(2) Export	(3) Export	(4) Export	(5) Export	(6) Export
ln(ECI coverage)	0.217***	0.203***	0.094***	0.186*	0.108***	0.107***
	(0.078)	(0.011)	(0.005)	(0.108)	(0.009)	(0.009)
Year FE		✓				
Firm FE		✓	✓		✓	✓
Industry-Year FE			✓		✓	✓
Destination-Year FE			✓		✓	✓
Industry-Destination FE			✓		✓	✓
Controls						✓
Observations	41080	38536	36013	16321	12755	12638
Pseudo R^2	0.24	0.74	0.92	0.18	0.94	0.94

Notes: The unit of observation is firm-destination-year, where the sample firms are applying for ECI for the same buyer and approval is earlier than rejection within three years. The dependent variable is export value in levels. The key regressor is the logarithm of ECI coverage. We use the sample from merging ECI with Customs data. Column (1) estimates PPML without fixed effects, column (2) adds firm fixed effects and year fixed effects, and column (3) adds firm fixed effects and the high-dimensional sets Industry × Year, Destination × Year, and Industry × Destination. Then we use the sample from merging ECI, Customs, and Tax Survey data. Column (4) estimates PPML without fixed effects, column (5) adds firm fixed effects and the high-dimensional sets Industry × Year, Destination × Year, and Industry × Destination, and column (6) further includes lagged firm-level controls, including log accounts receivable, ROA, leverage, and assets. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A2: Dynamic effects of export credit insurance on firm exports

	t	t+1	t+2	t+3	t+4
	(1)	(2)	(3)	(4)	(5)
IV estimates					
ln(ECI coverage)	0.271***	0.182*	0.271**	0.114	-0.018
	(0.083)	(0.110)	(0.115)	(0.112)	(0.164)
Firm Year Trend	✓	✓	✓	✓	✓
Industry-Year FE	✓	✓	✓	✓	✓
Destination-Year FE	✓	✓	✓	✓	✓
Industry-Destination FE	✓	✓	✓	✓	✓
Month FE	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓
Observations	4843	4673	4236	3435	2410
KP F-Statistic	37.82	33.74	34.11	34.81	22.62

Notes: This table evaluates the dynamic effects of export credit insurance on firm-level exports from the treatment year (t) through subsequent years ($t+1$ to $t+4$). The dependent variable consists of leads of log exports, and the main explanatory variable is the log of ECI coverage in year t. The instrumental variable is the dummy variable *ECIdummy*. All regressions include controls for lagged accounts receivable, return on assets, leverage, and lagged assets. Fixed effects include application-month, industry-year, destination-year, industry-destination, and firm-level linear time trends. The Kleibergen-Paap F-statistics are reported to assess instrument strength. Robust standard errors are clustered at the firm level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A3: Sensitivity of back-of-the-envelope cost–benefit calculations

	dX/dX_a	dY/dX_a	Break-even k
Panel A: Penetration $s = X_a/X$ (holding $\beta = 0.225$, $v = 0.65$, $t = 0.195$)			
Baseline ($s = 0.269$)	0.836	0.544	0.106
$s = 0.207$ (2022)	1.087	0.707	0.138
$s \approx 0.15$ (2013)	1.500	0.975	0.190
Panel B: Export elasticity β (holding $s = 0.269$, $v = 0.65$, $t = 0.195$)			
Lower 95% CI ($\beta = 0.105$)	0.392	0.255	0.050
Upper 95% CI ($\beta = 0.345$)	1.281	0.833	0.162
Panel C: Domestic value-added share v (holding $\beta = 0.225$, $s = 0.269$, $t = 0.195$)			
$v = 0.60$	0.836	0.502	0.098
$v = 0.70$	0.836	0.586	0.114

Notes: Each row reports implied marginal effects per additional dollar of insured exports X_a. Export multipliers are computed as $dX/dX_a = \beta/(X_a/X)$, with GDP effects given by $dY/dX_a = v \cdot dX/dX_a$. The break-even cost k is the maximum net fiscal cost per insured dollar (administrative expenses plus expected claims net of premium income) at which the program remains fiscally self-financing, computed as $dT/dX_a = t \cdot dY/dX_a$ with $t = 0.195$.

Table A4: Sources for assumption values in the cost-benefit analysis

Symbol	Value(s) used	Meaning	Source
β	0.225	Export elasticity w.r.t. insured exports	Estimated in this paper (Table 3).
$s = X_a/X$	0.269	Short-term ECI penetration (recent)	Xinhua News Agency (2025).
$s = X_a/X$	0.207	Short-term ECI penetration (2022)	SINOSURE Annual Report (2022).
$s = X_a/X$	≈ 0.15	Historical penetration benchmark	OECD (2015).
v	0.60–0.70	Domestic value-added share in exports	Kee and Tang (2016).
t	0.195–0.204	Tax-to-GDP ratio	OECD Revenue Statistics.

Notes: This table documents the data sources and parameter values used in the cost-benefit calculations in Section 5. See Appendix Table A3 for sensitivity analysis across alternative parameter combinations.

Table A5: Heterogeneous effects of ECI

	Financial Accessibility		Destination Country Risk		Firm Size		Firm Ownership Type	
	(1) Lower	(2) Higher	(3) Low & Medium	(4) High	(5) Smaller	(6) Larger	(7) Private	(8) Foreign/SOE
OLS								
ln(ECI coverage)	0.110***	0.108***	0.131***	0.091***	0.094***	0.124***	0.121***	0.111***
	(0.016)	(0.010)	(0.010)	(0.018)	(0.013)	(0.014)	(0.009)	(0.023)
First stage								
ECI dummy	2.958***	1.642***	1.902***	2.032***	1.920***	2.180***	1.828***	2.342***
	(0.651)	(0.375)	(0.418)	(0.560)	(0.605)	(0.546)	(0.334)	(0.594)
Reduced-form								
ECI dummy	0.698***	0.140	0.163	0.313**	0.301**	0.224	0.226***	0.149
	(0.173)	(0.092)	(0.110)	(0.131)	(0.143)	(0.145)	(0.084)	(0.205)
2SLS estimates								
ln(ECI coverage)	0.236***	0.085*	0.086	0.154***	0.157**	0.103*	0.124***	0.064
	(0.063)	(0.051)	(0.053)	(0.059)	(0.066)	(0.056)	(0.044)	(0.082)
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
Industry-Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Destination-Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Industry-Destination FE	✓	✓	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Observations	1087	2790	2431	930	1271	1690	3176	761
KP F-Statistic	20.63	19.16	20.72	13.14	10.07	15.95	29.93	15.55

Notes: This table presents heterogeneous effects based on firm and destination characteristics. The dependent variable is the logarithm of firm-destination-year export value. The main explanatory variable is the logarithm of ECI coverage, instrumented by an indicator for ECI application approval (ECI dummy). The columns report heterogeneous effects across subsamples defined by four dimensions: financial accessibility (columns (1) and (2)), destination country risk (columns (3) and (4)), firm size (columns (5) and (6)), and ownership type (columns (7) and (8)). Financial accessibility: Cities are classified as having lower or higher accessibility based on the sample median of the city-level ratio of total interest expenses to total operating revenue in 2008. Destination country risk: Countries are classified into low and medium or high risk groups based on the tertiles of the World Uncertainty Index Ahir et al. (2022). Firm size: Firms are classified as smaller or larger based on whether their one-year lagged output value is below or above the sample median. Ownership type: Private refers to domestic private firms, and foreign/SOE combines foreign-invested and state-owned enterprises. All regressions include firm, industry-year, destination-year, and industry-destination fixed effects, as well as firm-level controls (lagged accounts receivable, return on assets, leverage, and total assets). Robust standard errors, clustered at the firm level, are reported in parentheses. The Kleibergen-Paap F-statistic for weak instruments is reported at the bottom. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A6: Summary of robustness checks: IV and PPML estimates of the effect of ECI on exports

	(1) Baseline (1:5 match)	(2) 1:3 match	(3) Same-year match	(4) Drop-nearest approvals	(5) Post-2010 sample	(6) Alt. IV (credit limit)	(7) PPML+CF (baseline)
Panel A: IV / PPML+CF estimates							
ln(ECI coverage)	0.225***	0.224***	0.263***	0.366***	0.236***	0.282***	0.170***
	(0.061)	(0.061)	(0.097)	(0.083)	(0.067)	(0.055)	(0.026)
Panel B: First stage							
ECI dummy	2.173***	2.173***	1.797***	2.054***	2.153***		2.173***
	(0.254)	(0.254)	(0.398)	(0.339)	(0.273)		(0.254)
ln(ECI credit limit)						0.189***	
						(0.019)	
Panel C: Reduced form							
ECI dummy	0.489***	0.487***	0.473**	0.751***	0.507***	0.053***	
	(0.147)	(0.147)	(0.204)	(0.181)	(0.158)	(0.011)	
KP F-statistic	73.33	73.17	20.37	36.61	62.35	93.67	
Observations	4,843	4,840	1,411	3,467	4,190	4,843	4,326
Estimator	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	PPML+CF

Notes: This table summarizes robustness checks for the effect of ECI coverage on firm exports. The dependent variable is the logarithm of export value in columns (1)–(6) and export value in levels in column (7). All specifications include firm, industry-year, destination-year, and industry-destination fixed effects, plus firm-level controls (lagged accounts receivable, ROA, leverage, and total assets). Column (1) reproduces the baseline IV estimate from Table 3 using 1:5 nearest-neighbor matching. Column (2) uses a 1:3 PSM matching ratio. Column (3) restricts matched pairs to the same year. Column (4) drops the most recently approved application before each rejection. Column (5) restricts the sample to 2010–16. Column (6) uses the approved credit limit as an alternative instrument. Column (7) uses PPML with a control function on the baseline sample. The reduced-form row is blank for the PPML column, which uses a control function rather than a standard two-stage procedure. Standard errors clustered at the firm level in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

Table A7: Summary of robustness checks (continued)

	(8) PPML+CF (drop-nearest)	(9) Cluster: destination	(10) Cluster: province	(11) Firm-year trend	(12) Any approval	(13) Alt. IV (ECI share)
Panel A: IV / PPML+CF estimates						
ln(ECI coverage)	0.216***	0.225***	0.225***	0.271***	0.258***	0.243***
	(0.039)	(0.065)	(0.060)	(0.079)	(0.071)	(0.084)
Panel B: First stage						
ECI dummy	2.054***	2.173***	2.173***	2.172***	2.264***	
	(0.340)	(0.267)	(0.195)	(0.341)	(0.320)	
ECI share						1.618***
						(0.293)
Panel C: Reduced form						
ECI dummy		0.489***	0.489***	0.588***	0.583***	
		(0.159)	(0.159)	(0.185)	(0.178)	
ECI share						0.393**
						(0.154)
KP F-statistic		66.14	123.67	40.68	50.04	30.57
Observations	3,137	4,843	4,843	4,843	5,401	5,760
Estimator	PPML+CF	2SLS	2SLS	2SLS	2SLS	2SLS

Notes: Continued from the previous page. Column (8) uses PPML with a control function on the drop-nearest sample. Columns (9) and (10) replicate the baseline specification with standard errors clustered at the destination-country and province levels, respectively. Column (11) adds firm-specific linear year trends and month fixed effects to the baseline specification. Column (12) redefines the instrument after PSM such that, within the same exporter-country-year, the ECI indicator equals one if any matched application is approved. Column (13) replaces the ECI dummy with the approved ECI credit-limit share, defined as the approved credit limit divided by the applied credit limit. The reduced-form row is blank for the PPML column, which uses a control function rather than a standard two-stage procedure. Standard errors clustered at the firm level in parentheses unless otherwise noted. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

Table A8: Placebo test using lags of export outcomes

	t-4	t-3	t-2	t-1
	(1)	(2)	(3)	(4)
IV estimates				
ln(ECI coverage)	0.051	0.107	0.149	0.089
	(0.118)	(0.106)	(0.093)	(0.092)
Firm Year Trend	✓	✓	✓	✓
Industry-Year FE	✓	✓	✓	✓
Destination-Year FE	✓	✓	✓	✓
Industry-Destination FE	✓	✓	✓	✓
Month FE	✓	✓	✓	✓
Controls	✓	✓	✓	✓
Observations	4843	4843	4843	4843
KP F-Statistic	39.74	38.61	36.83	34.71

Notes: This table reports placebo regressions using lagged export outcomes ($t-1$ through $t-4$) as the dependent variable. The explanatory variable is the logarithm of ECI coverage in year t, instrumented with an indicator for accidental approval (*ECI dummy*). All regressions include one additional lag of exports as a control, firm balance sheet controls (accounts receivable, ROA, leverage, asset size), and fixed effects: firm-by-year trend, industry-by-year, destination-by-year, industry-by-destination, and application month. KP F-statistics are reported to assess instrument relevance. Robust standard errors are clustered at the firm level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A9: Heterogeneous effects (PPML)

	Financial Accessibility		Destination Country Risk		Firm Size		Firm Ownership Type	
	(1) Lower	(2) Higher	(3) Low & Medium	(4) High	(5) Smaller	(6) Larger	(7) Private	(8) Foreign/SOE
PPML								
ln(ECI coverage)	0.114***	0.097***	0.128***	0.080***	0.087***	0.117***	0.107***	0.125***
	(0.025)	(0.014)	(0.015)	(0.016)	(0.015)	(0.018)	(0.013)	(0.033)
First stage								
ECI dummy	2.958***	1.642***	1.902***	2.032***	1.920***	2.180***	1.828***	2.342***
	(0.652)	(0.375)	(0.418)	(0.561)	(0.606)	(0.546)	(0.334)	(0.595)
PPML + Control Function								
ln(ECI coverage)	0.185***	0.151***	0.171***	0.196***	0.205***	0.188***	0.207***	0.150***
	(0.046)	(0.038)	(0.047)	(0.049)	(0.054)	(0.042)	(0.034)	(0.050)
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
Industry-Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Destination-Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Industry-Destination FE	✓	✓	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Observations	1087	2790	2431	930	1271	1690	3176	761
Pseudo R^2	0.96	0.95	0.92	0.97	0.96	0.95	0.93	0.98

Notes: This table uses PPML to estimate the heterogeneous effects of ECI based on firm and destination characteristics, as a robustness check for Table A5. The dependent variable is firm-destination-year export value (in levels). The main explanatory variable is the logarithm of ECI coverage, instrumented by an indicator for ECI application approval (ECI dummy). The columns report heterogeneous effects estimated via Poisson pseudo maximum likelihood (PPML) across subsamples defined by four dimensions: financial accessibility (columns (1) and (2)), destination country risk (columns (3) and (4)), firm size (columns (5) and (6)), and ownership type (columns (7) and (8)). Financial accessibility: Cities are classified as having lower or higher accessibility based on the sample median of the city-level ratio of total interest expenses to total operating revenue in 2008. Destination country risk: Countries are classified into low and medium or high risk groups based on the tertiles of the World Uncertainty Index Ahir et al. (2022). Firm size: Firms are classified as smaller or larger based on whether their one-year lagged output value is below or above the sample median. Ownership type: Private refers to domestic private firms, and foreign/SOE combines foreign-invested and state-owned enterprises. Panel A reports PPML estimates, Panel B the first-stage estimates, and Panel C the PPML estimates augmented with a control function. All regressions include firm, industry-year, destination-year, and industry-destination fixed effects, as well as firm-level controls (lagged accounts receivable, return on assets, leverage, and total assets). Robust standard errors, clustered at the firm level, are reported in parentheses. Pseudo R-squared values are reported for the PPML models. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

B Figures

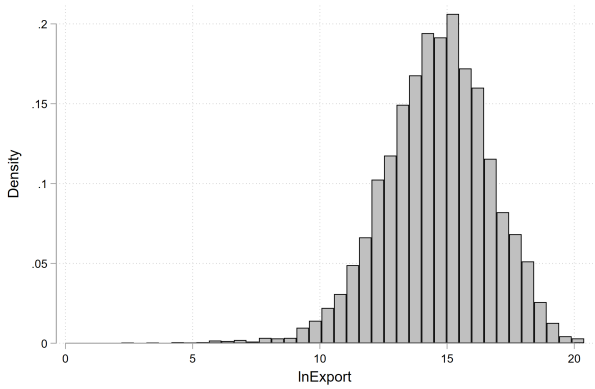


Figure B1: Distribution of $\ln(\text{Export})_{ict}$ in the post-PSM sample

Notes: The figure shows the distribution of $\ln(\text{Export})_{ict}$ using the post-PSM matched sample. The histogram includes only positive export values at the firm-destination-year level. The distribution is approximately normal after log transformation.

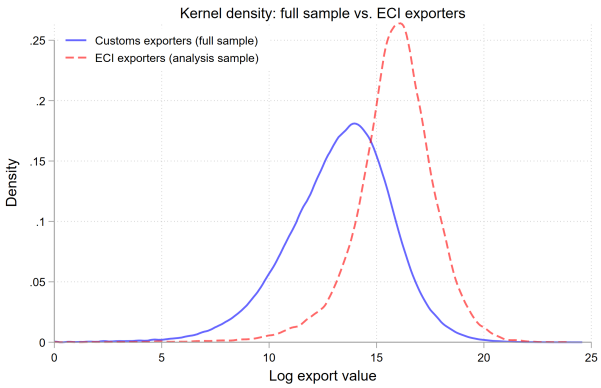
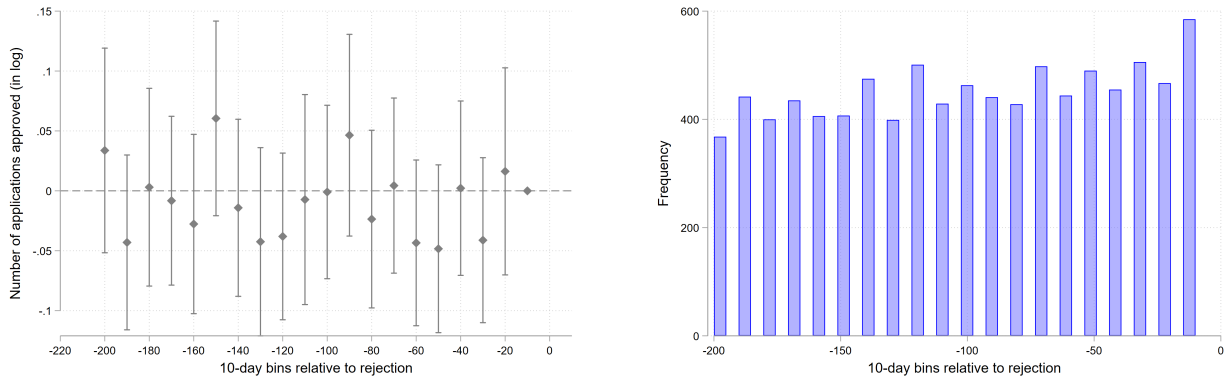


Figure B2: Distribution of $\ln(Export)_{ict}$ in the full sample of Customs data versus the ECI-Customs merged sample (2008–16)

Notes: The figure compares the kernel density of $\ln(\text{Export})_{ict}$ between the full sample of Chinese exporters in the Customs data and the subset of exporters included in the merged ECI-Customs dataset over 2008–16. Export values are measured at the firm-destination-year level in US dollars. The distribution for ECI exporters (red dashed line) lies to the right of that for all customs exporters (blue solid line).



(a) Event study PPML **(b)** Number of applications approved

Figure B3: Distribution and pre-rejection probability of application approvals

Notes: Panel (a) reports event study estimates of pre-rejection approval probabilities using PPML estimation. Panel (b) shows the histogram of approvals relative to rejection dates. Approvals are grouped into 10-day bins over the 200 days preceding rejection, and 95% confidence intervals are reported.

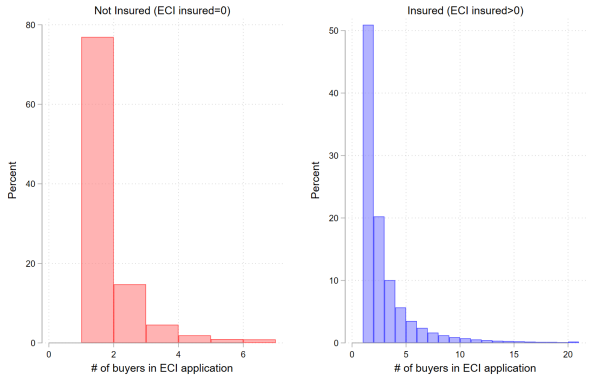


Figure B4: Distribution of buyer counts per exporter-destination by ECI coverage status

Notes: The figure shows the distribution of the number of foreign buyers per exporter-destination-year between insured (right panel) and non-insured (left panel) exporter-destination-year observations in the ECI coverage data. Observations in which the number of buyers for a given exporter-destination exceeds the 99th percentile are excluded. Most exporters apply for insurance for only one or two buyers in a given destination.

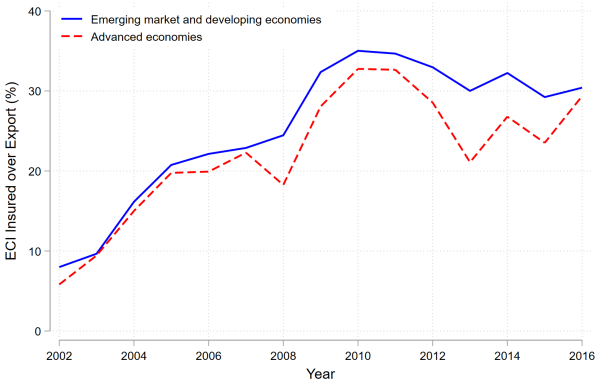


Figure B5: Ratio of ECI insurance over exports by destination country group

Notes: The figure plots the ratio of insured exports (ECI coverage) to total exports by destination country group using the merged ECI-Customs sample for 2002–16. Because our dataset only includes foreign buyers who have at least one rejected ECI application, buyers with exclusively approved records are not observed. As a result, the coverage ratio shown here represents a lower bound of the true national ECI coverage rate. Country classification into advanced economies and emerging markets and developing economies follows the IMF World Economic Outlook classification, and the number of developed countries is 41.

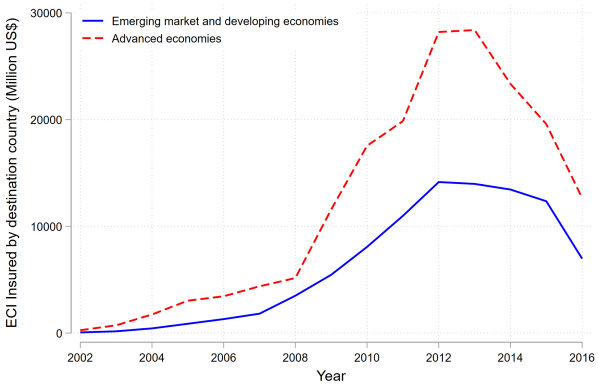


Figure B6: Short-term ECI coverage by destination-country income group

Notes: The figure plots the total value of exports insured by short-term ECI by destination country group over 2002–16, based on the merged ECI-Customs dataset. Advanced economies and emerging markets and developing economies are classified following the IMF World Economic Outlook classification, and the number of developed countries is 41. Because our data include only buyers with at least one rejected ECI application, buyers with exclusively approved records are unobserved, implying that the total insured amount shown here is a lower bound of the true national total.

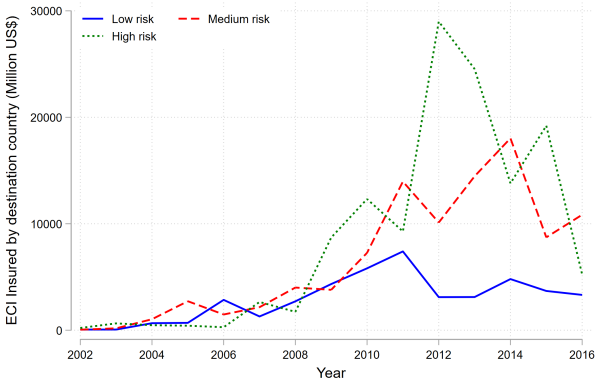


Figure B7: Short-term ECI coverage by destination-country risk category

Notes: The figure shows the total value of exports insured by short-term ECI by destination country risk category (low, medium, and high risk) from 2002 to 2016. We classify countries into three groups, low, medium, and high risk, based on the World Uncertainty Index (WUI) developed by Ahir et al. (2022). The data are from the merged ECI-Customs sample and cover only buyers with at least one rejected application, so the insured values represent a lower bound of the true insured amounts.

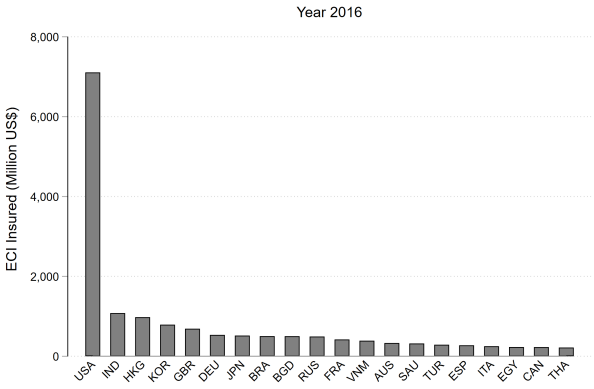


Figure B8: Top 20 destination countries: ECI coverage (2016)

Notes: The figure ranks the top 20 destination countries by the total value of exports insured by short-term ECI in 2016, based on the merged ECI-Customs dataset. Values are measured in millions of US dollars.

C Construction of Representative Buyers in the PSM Sample

This appendix provides technical detail on the construction of the PSM sample summarized in Section 4.3. The four steps below correspond directly to those described in the main text.

Step 1: Anchor on rejected applications We begin with all rejected ECI applications in the merged ECI–Customs dataset. Each rejected application to buyer b in year t defines one potential control observation. Buyers for which *no* rejection is observed are excluded from the analysis, as they provide no control units.

Step 2: Construct the pre-PSM candidate pool for each rejected application For each rejected application to buyer b in year t, we identify all exporters under the same buyer whose ECI applications were *approved* before the rejection date. To keep matches temporally comparable, we restrict approved applications to occur within the same year as the rejection or up to two years prior (i.e., in t, $t-1$, or $t-2$). Buyers for which no approved application is found within this three-year window are dropped.

Step 3: Propensity score matching within buyer Within the pre-PSM pool defined above, we estimate a logit model for treatment status using firm-level covariates measured one year prior to the application year: firm size ($\ln \text{Asset}_{t-1}$), order size ($\ln \text{AccountReceivables}_{t-1}$), profitability ($ROA_{t-1}$), and leverage (average debt-to-asset ratio). We then apply nearest-neighbor matching with replacement, pairing each rejected exporter with the five nearest approved exporters (1:5 matching) under a common support requirement, allowing ties when multiple candidates share the same propensity score.

Step 4: Post-matching restrictions and representative buyers After matching, we retain only buyer cells in which both approved and rejected exporters are observed. Buyer cells containing only one treatment status after matching are dropped. Because regressions are conducted at the exporter–country–year level, we further drop exporter–country–year cells that contain both an approved and a rejected application, so that *ECI dummy* is uniquely defined at the unit of analysis. The buyers that survive these restrictions are the *representative buyers* that form the post-PSM analysis sample (Panel C in Table 1).

D Additional Results

Industry-Level Aggregation To gauge the aggregate relevance of these firm-level patterns, we next re-estimate the relationship between ECI coverage and exports at the industry-destination level using the pre-PSM full sample. Specifically, we collapse firm-destination observations to the industry-destination-year level and estimate

$$\ln(\text{Export})_{sct} = \beta_0 + \beta_1 \ln(\text{ECI coverage})_{sct} + \lambda_{st} + \phi_{ct} + \gamma_{cs} + \varepsilon_{sct}, \tag{5}$$

where $\ln(\text{Export})_{sct}$ denotes the (log) export value of industry s to destination country c in year t, and $\ln(\text{ECI coverage})_{sct}$ is the log of total approved ECI coverage aggregated across all firms in that industry-destination pair. The specification includes industry-year fixed effects λ_{st} and destination-year fixed effects ϕ_{ct}, which absorb sector-specific shocks and destination-specific macro and political risks. The term γ_{cs} denotes time-invariant industry-destination fixed effects that capture long-run comparative advantage and persistent bilateral relationships within sectors. Standard errors are clustered at the destination country level. Industries are defined at the 2-digit Chinese industry classification, yielding 86 distinct industries in our sample.

Table D1: ECI coverage and exports at the industry level

	ln(Export), OLS+FE			
	(1)	(2)	(3)	(4)
ln(ECI coverage)	0.567***	0.490***	0.438***	0.368***
	(0.012)	(0.008)	(0.009)	(0.009)
Destination-Year FE		✓	✓	✓
Industry-Year FE			✓	✓
Industry-Destination FE				✓
Observations	44717	44506	43884	42410
R^2	0.52	0.61	0.66	0.75

Notes: The unit of observation is industry-destination-year. Both export values and insured export coverage are aggregated across firms within each industry and destination. The dependent variable is log export value in both columns. Column (1) includes no fixed effects; column (2) adds industry-year, destination-year, and industry-destination fixed effects. All specifications use the pre-PSM full sample, constructed by merging ECI data with business registration data and Chinese Customs data. Standard errors are clustered at the destination country level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table D1 reports the estimates. The coefficients are positive and highly significant across all specifications. Without fixed effects, column (1) yields an elasticity of 0.57. Adding industry-year, destination-year, and industry-destination fixed effects in column (2) reduces this to 0.37, the preferred OLS specification; the attenuation reflects absorption of industry-level demand trends and destination-level macro conditions rather than any change in the underlying causal parameter.

The preferred OLS elasticity of 0.37 exceeds the firm-level IV estimate of 0.225 by roughly 64 percent. This gap reflects endogeneity bias that cannot be resolved at the industry level:

no exogenous instrument for aggregate ECI penetration is available, so the self-selection of high-performing firms into insurance and the mechanical link between coverage and exports remain unaddressed in the industry-level OLS. For comparison, firm-level OLS on the matched sample yields 0.271 and on the full sample yields 0.311 (Tables 3 and 2), both above the IV but below the industry OLS, consistent with endogeneity biases persisting and potentially compounding under industry-level aggregation. The FCFS quasi-random design at the firm level is what allows recovery of the causal estimate of 0.225.