JOURNAL OF SUSTAINABLE COMPETITIVE INTELLIGENCE

DOI: https://doi.org/10.37497/eagleSustainable.v17i.1346

ARTICLE

Competitive Intelligence in China–Japan–Asean Relations: A Comparative Analysis of Strategic Cooperation in Southeast Asia, 2022–2025

Inteligência Competitiva nas Relações China–Japão–Asean: Uma Análise Comparativa da Cooperação Estratégica no Sudeste Asiático, 2022–2025

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ABSTRACT | Purpose: This study operationalizes Competitive Intelligence (CI) in two empirical domains: as a reproducible intelligence cycle for strategic trade monitoring and as a formative organizational-system construct measuring observable CI capability in public statistical organizations. **Methodology/Approach:** Official JETRO and Japan Customs trade data for 2022–2025 were analyzed using a pooled log-linear model with HC3 robust inference. Monthly 2022–2024 data provided robustness checks through Newey–West HAC models, correlations, seasonal controls, and lag specifications. Organizational CI capability was measured using the 12-item formative Observed Organizational Competitive Intelligence Capability Index (OOCICI), covering planning, collection, analysis, dissemination, utilization/feedback, and governance. **Originality/Relevance:** The study distinguishes intelligence-analysis outputs from organizational CI capability by observing formal mandates, collection systems, analytical architectures, dissemination channels, decision-support mechanisms, feedback, and governance controls. It converts official open data into a reproducible CI framework for trade-promotion agencies, policy units, and research organizations. **Key Findings:** From 2022–2025, Japan's exports to ASEAN increased annually by 0.88% and imports by 0.29%, while exports to China decreased by 0.40% and imports increased by 2.42%. However, China-versus-ASEAN trend differences were not statistically significant for exports ($\beta = -.0098$, $p = .828$) or imports ($\beta = .0182$, $p = .609$). Monthly robustness analyses confirmed no statistically detectable partner-specific divergence. OOCICI scores were 100.0 for Japan Customs/MOF and ASEANstats and 83.3 for JETRO and World Bank WDI. **Theoretical/Methodological Contributions:** The study integrates classical CI, organizational intelligence capability, intelligence governance, information asymmetry, dynamic capabilities, and the resource-based view. It separates econometric trade monitoring from organizational CI capability measurement through an empirically audited formative index.

Keywords | Competitive Intelligence. Organizational intelligence capability. Intelligence planning. Intelligence utilization. Intelligence Governance. China–Japan–ASEAN. Strategic trade monitoring.

Qualis B1 CAPES 2021-2024

Indexed by Scopus ELSEVIER

Received: 03 Jun. 2026
Revised: 17 Aug. 2026
Accepted: 23 Aug. 2026
e-ISSN: 3085-7813

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Editor in chief: Altieres de Oliveira Silva – Alumni.In Editors

How to cite this article: Liang, T., & Liu, S. (2027). Competitive Intelligence in China–Japan–Asean Relations: A Comparative Analysis of Strategic Cooperation in Southeast Asia, 2022–2025. *Journal of Sustainable Competitive Intelligence*, 17, e01346. https://doi.org/10.37497/eagleSustainable.v17i.1346

RESUMO | Objetivo: Este estudo operacionaliza a Inteligência Competitiva (IC) em dois domínios empíricos: como um ciclo de inteligência reproduzível para o monitoramento estratégico do comércio e como um construto formativo de sistema organizacional que mensura a capacidade observável de IC em organizações públicas de estatística. **Metodologia/Abordagem:** Dados oficiais de comércio da JETRO e da Japan Customs referentes ao período de 2022–2025 foram analisados utilizando um modelo log-linear agrupado (*pooled*) com inferência robusta HC3. Dados mensais de 2022–2024 foram utilizados para verificações de robustez por meio de modelos Newey–West HAC, correlações, controles sazonais e especificações com defasagens. A capacidade organizacional de IC foi mensurada por meio do índice formativo de 12 itens Observed Organizational Competitive Intelligence Capability Index (OOCICI), abrangendo planejamento, coleta, análise, disseminação, utilização/feedback e governança. **Originalidade/Relevância:** O estudo distingue os resultados da análise de inteligência da capacidade organizacional de IC por meio da observação de mandatos formais, sistemas de coleta, arquiteturas analíticas, canais de disseminação, mecanismos de apoio à decisão, feedback e controles de governança. Dessa forma, converte dados oficiais abertos em um framework reproduzível de IC para agências de promoção comercial, unidades de políticas públicas e organizações de pesquisa. **Principais Resultados:** Entre 2022 e 2025, as exportações do Japão para a ASEAN aumentaram 0,88% ao ano e as importações cresceram 0,29%, enquanto as exportações para a China diminuíram 0,40% e as importações aumentaram 2,42%. Entretanto, as diferenças nas tendências China-versus-ASEAN não foram estatisticamente significativas para as exportações ($\beta = -0{,}0098$; $p = 0{,}828$) nem para as importações ($\beta = 0{,}0182$; $p = 0{,}609$). As análises mensais de robustez confirmaram a ausência de divergência estatisticamente detectável específica entre os parceiros. Os escores do OOCICI foram de 100,0 para Japan Customs/MOF e ASEANstats e de 83,3 para JETRO e World Bank WDI. **Contribuições Teóricas/Metodológicas:** O estudo integra a IC clássica, capacidade de inteligência organizacional, governança da inteligência, assimetria informacional, capacidades dinâmicas e visão baseada em recursos. Além disso, separa o monitoramento econométrico do comércio da mensuração da capacidade organizacional de IC por meio de um índice formativo empiricamente auditado.

Palavras-chave | Inteligência Competitiva. Capacidade de inteligência organizacional. Planejamento da inteligência. Utilização da inteligência. Governança da inteligência. China–Japão–ASEAN. Monitoramento estratégico do comércio.

1 INTRODUCTION

The post-pandemic political economy of East and Southeast Asia has made strategic trade monitoring a central problem for organizations that must interpret competitive environments. China remains a dominant external economic actor for ASEAN, while Japan continues to operate a mature institutional infrastructure for trade information through JETRO and Ministry of Finance customs statistics. For Competitive Intelligence (CI), this setting is not merely a regional-trade case. It is a setting in which planning, environmental scanning, intelligence collection, analysis, dissemination, and feedback can be operationalized with public transactional data rather than invoked only as background terminology.

The research problem is that many studies of China–ASEAN or Japan–ASEAN relations describe strategic competition, digital order, public diplomacy, Belt and Road cooperation, or supply-chain diversification without converting those descriptions into a measured intelligence process. Classical CI is a process for identifying intelligence needs, collecting and validating signals, analyzing them in relation to decision problems, disseminating results, and feeding learning back into subsequent monitoring cycles (Herring, 1999; Prescott, 1999; Calof & Wright, 2008; Fleisher & Bensoussan, 2015). When CI is treated only as an interpretive vocabulary, information asymmetry remains unresolved: decision makers receive narratives but not auditable intelligence outputs.

This article responds to that gap by distinguishing two empirical domains and two analytical frequencies. The first domain concerns trade-signal analysis. Within this domain, the complete 2022–2025 annual series constitutes the primary econometric layer, while the January 2022–December 2024 monthly series provides a secondary high-frequency robustness layer. The second domain concerns organizational Competitive Intelligence capability. It is measured through the Observed Organizational Competitive Intelligence Capability Index (OOCICI), whose indicators directly record organizational routines manifested in mandates, collection cycles, analytical architectures, dissemination mechanisms, recurring decision-support products, feedback channels, and governance controls. This structure prevents CAGR, HHI, correlations, regression coefficients, and JSTEI scores from being misrepresented as organizational capability measures. Figure 1 presents the CI cycle, whereas Figure 2 presents the integrated empirical design.

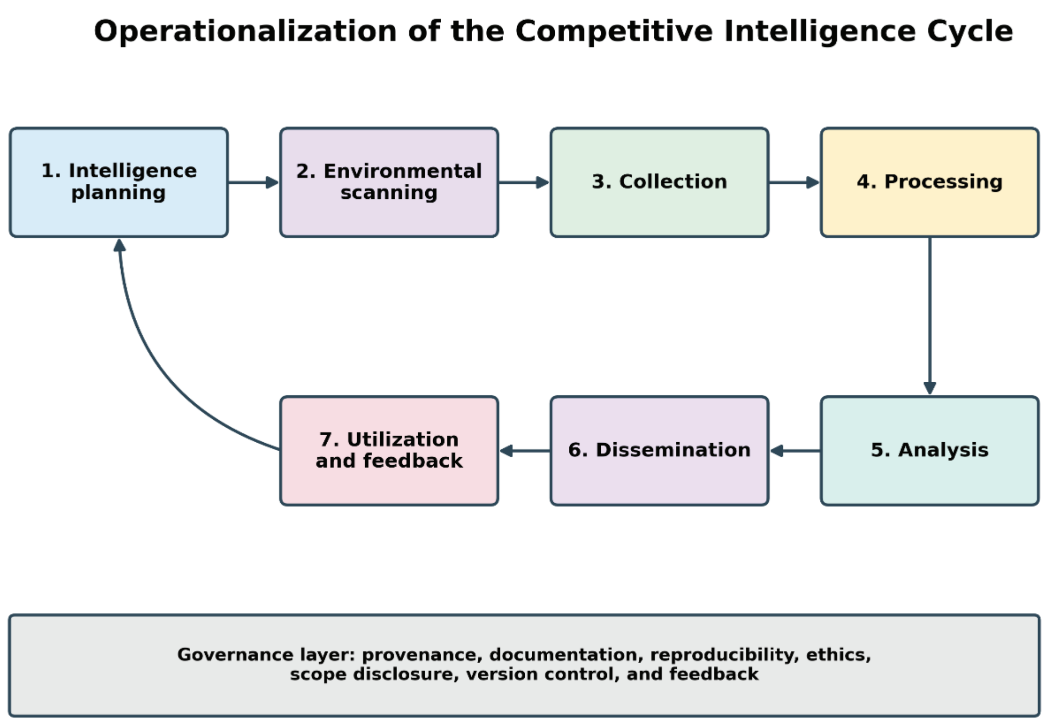


Figure 1. Operationalization of the Competitive Intelligence cycle used in the study.

The central research question is: How can official trade statistics and directly observable organizational routines be combined into a governed Competitive Intelligence system for monitoring China–Japan–ASEAN relations during 2022–2025? Six empirical questions follow: (1) how did Japan's nominal trade with ASEAN and China change between 2022 and 2025; (2) did partner identity produce statistically distinguishable annual trade trends across the complete 2022–2025 period; (3) were the annual conclusions supported by the January 2022–December 2024 monthly high-frequency models; (4) to what extent did Japan–ASEAN and Japan–China monthly trade changes co-move; (5) how concentrated and heterogeneous was Japan's trade engagement across ASEAN-10 member states; and (6) what level of observable organizational CI capability was demonstrated by the information systems supporting the monitoring process?

The empirical lens has both methodological and substantive rationales. Methodologically, the annual Japan–ASEAN and Japan–China export and import series provide four comparable trade-flow trajectories for the complete 2022–2025 period. These 16 flow-year observations are used in the principal Time × Partner × Flow model with HC3 small-sample robust inference. The monthly January 2022–December 2024 observations remain analytically valuable but are repositioned as a secondary high-frequency robustness layer rather than the sole inferential basis of the article. Substantively, the Japanese trade-statistics infrastructure is an organizational intelligence system because it operates through formal statistical mandates, repeated collection and processing routines, standardized analytical classifications, public dissemination, correction channels, and documented governance controls.

The article makes five contributions. First, it operationalizes the complete CI cycle as a traceable organizational process rather than using CI as an interpretive label. Second, it measures observable organizational-system CI capability through a formative index whose dimensions are theoretically specified and supported by item-level documentary evidence. Third, it fully incorporates 2025 into the principal econometric estimation rather than treating the year only as a descriptive update. Fourth, it separates annual primary inference, monthly high-frequency robustness, trade-analysis outputs, and organizational capability measurement. Fifth, it connects intelligence governance with evidence provenance, revision control, reproducibility, decision-support utilization, feedback, and the reduction of information asymmetry.

2 THEORETICAL FRAMEWORK

2.1 Competitive Intelligence as a Decision-Oriented Cycle

Competitive Intelligence has evolved from environmental scanning, strategic planning, marketing intelligence and information-management traditions. The environmental-scanning foundation of CI can be traced to Aguilar's (1967) systematic treatment of how organizations monitor external environments. The core argument of this literature is not that organisations require information but that the information must be turned into intelligence relevant to decision making and subject to a disciplined process. Herring (1999) identified key intelligence topics as the starting point of intelligence work; Prescott (1999) traced the evolution of CI from a more informal level of competitive awareness to a more organized level of intelligence capability for the organization; Calof and Wright (2008) validated CI as a field of practice, academia, and interdisciplinary research; and Fleisher and Bensoussan (2015) provided analytical techniques for turning competitive information into strategic insight.

The process approach followed in the present study is in line with these traditions. The decision problem is defined by intelligence planning, the signals that can be observed are the result of environmental scanning, heterogeneity of files is overcome through intelligence collection, processing transforms the files into uniform units, analysis performs statistical tests, dissemination communicates the outputs that are interpretable, intelligence is used to connect findings to relevant strategic decision needs, and governance documents the limits of the evidence and diminishes information asymmetry. This cycle is essential since CI loses its scientific specificity if it is used in a general sense.

2.2 Intelligence Governance, Information Asymmetry, and Sustainability

Intelligence governance deals with the rules, documentation, accountability and feedback mechanisms in use to produce and use intelligence. It is particularly relevant for cross-border trade analysis, as lack of data can lead to information asymmetry among analysts, policy makers, business and regional institutions. Some actors might see good and bad trade signals quicker, while others may see them later; strategic decisions may be based on asymmetric information rather than competitive strengths. These governance problems are also connected to the institutional control of digital information and the allocation of authority across overlapping governance forums (Han, 2024; Hofmann & Pawlak, 2023).

In the current one, governance is carried out via transparency of sources, harmonization of units, explicit reporting of temporal scope, reproducing code, cautious reporting of statistical conclusions and separation between data products and policy stories. The concept of sustainability is introduced into the framework in two ways. An initial requirement for sustainable competitive advantage is that it must be maintained until it is possible to sense change and reconfigure resources in a durable manner (Teece et al., 1997; Barney, 1991). Second, public and open intelligence systems allow for lower cost monitoring by universities, agencies and smaller intelligence providers who have access to intelligence systems but don't have proprietary subscriptions. The ability to constantly refresh public intelligence signals is thus also an organizational sustainable ability.

2.3 Organizational Competitive Intelligence Capability as a Formative Construct

Implementation of a Competitive Intelligence process and measurement of organizational CI capability are related but analytically distinct. Organizational CI capability refers to the institutionalized capacity through which an organization defines intelligence requirements, repeatedly obtains and validates relevant information, applies standardized analytical procedures, distributes intelligence to intended users, incorporates feedback, and governs the process through documented responsibilities and controls (Dishman & Calof, 2008; Madureira et al., 2021, 2026; Wright et al., 2009).

The unit of analysis in the present capability assessment is the organizational information system maintained by each institution: Japan Customs/MOF, JETRO, ASEANstats, and World Bank WDI. Organizational capability is therefore observed through formal and recurrent routines rather than inferred from national trade performance or individual employee attitudes. An advance release calendar represents planning routinization; repeated and disaggregated data production represents collection capability; standardized classifications, metadata, historical series, and revision architectures represent analytical capability; open and machine-readable outputs represent dissemination capability; recurring analytical products and correction or feedback mechanisms represent utilization and organizational learning; and provenance, methodological documentation, and version controls represent intelligence governance.

The OOCICI is specified as a formative rather than reflective construct. Its indicators are non-interchangeable organizational components that jointly constitute capability; they are not assumed to be correlated manifestations of a single psychological trait. Consequently, internal-consistency coefficients such as Cronbach's alpha are not appropriate validity criteria for the index (Diamantopoulos & Winklhofer, 2001; Jarvis et al., 2003). Construct-validation evidence instead rests on theoretical content specification, direct observation of organizational routines, item-level documentary triangulation, transparent coding rules, complete auditability, and sensitivity of the total score to alternative dimension compositions.

The utilization dimension requires observable organizational action rather than the mere availability of data. It records whether the institution repeatedly transforms data into analytical or monitoring products directed to policy, market, research, or operational users and whether it maintains a documented correction, inquiry, or feedback mechanism capable of altering subsequent outputs. The construct therefore measures an organizationally enacted information-system capability. It does not claim to measure employee personality, informal managerial cognition, or the causal effectiveness of a particular decision.

2.4 Classical CI Literature and the Present Study

Theoretical support was enhanced by situating the article in the context of the classical CI scholarship. Dishman and Calof (2008) explain that CI is a multiphasic phenomenon that precedes the application of marketing strategy, and that intelligence is not just about collecting data but also about interpreting and applying data strategically. Wright et al. (2009) demonstrate the diversity of CI practice in different organizations and its assessment through the actual practices. Pellissier and Nenzhelele (2013) suggest a universal model for CI process and Du Toit (2003) associates CI with competitiveness in knowledge economy. The materials presented in this article are complementary to each other and to the central design decision of using CI as a workflow of stages and audit trails.

This approach also sets this study apart from studies of the China–ASEAN relationship in the fields of international relations, public diplomacy, development finance and digital-governance narratives. This kind of work is still useful and can still be considered CI but it does not automatically qualify as CI if the intelligence cycle is not visible. This study uses one measurable part of the regional economic environment—the trade and macro-structural data—to illustrate the implementation of CI using public data.

2.5 Strategic Trade Monitoring in China-Japan-ASEAN Relations

The China–Japan–ASEAN relationship exists in a larger regional context of diversification of supply chains, the digital economy, industrial policy, and geopolitical competition. The broader literature associates these dynamics with China's economic rise, digital-order formation, China–ASEAN cooperation, and the continuing evolution of ASEAN regionalism (Brühl, 2025; Chang, 2023; Chen et al., 2023; Velasco, 2023). The strategic impacts of the digital economy in Asia, the shift in the digital trade regime and the varied reactions of Southeast Asian states to technological competition have already been captured with previous scholarship (Li et al., 2020; Tung et al., 2023; Gao & Chen, 2025; Zhao, 2025). The present study analyzes the complete 2022–2025 annual period as the primary econometric window and retains the January 2022–December 2024 monthly series as a secondary high-frequency robustness layer.

The ASEAN bloc should not be treated as a homogeneous unit. Member states differ in market size, industrial structure, logistics roles, and political-economic risks. A CI system that reports only aggregate ASEAN statistics may hide strategically important differences across Singapore, Thailand, Viet Nam, Malaysia, Indonesia, the Philippines, Cambodia, Laos, Brunei, and Myanmar. The JSTEI addresses this problem by producing a transparent ranking of Japan-centric bilateral trade engagement for all ten members.

2.6 Synthesis of the Theoretical Model

The theoretical model combines Competitive Intelligence, dynamic capabilities, and the resource-based view (RBV). CI structures the transformation of environmental information into decision-relevant intelligence. Dynamic-capabilities theory explains why repeatable monitoring supports sensing, seizing, and resource reconfiguration, while the RBV clarifies how durable relational and informational resources can support strategic positioning. The framework does not treat sustainable competitive advantage as an observed empirical outcome; instead, these theories provide the strategic logic for designing a repeatable monitoring capability.

3 METHOD

3.1 Research Design

This study adopts an integrated longitudinal descriptive-comparative design comprising two empirical domains and three analytical components. The first component is the primary annual econometric analysis. It includes Japan's exports to ASEAN, imports from ASEAN, exports to China, and imports from China for 2022, 2023, 2024, and 2025, producing 16 flow-year observations. These data are used to estimate annual partner, flow, time, and interaction effects with the complete 2022–2025 period incorporated into the principal model.

The second component is a secondary high-frequency robustness analysis based on the January 2022–December 2024 monthly partner-flow series. These 144 series-month observations are used for seasonally controlled Newey–West HAC regressions, partner-trend contrasts, co-movement analysis, and alternative-lag sensitivity checks. The monthly results are not presented as substitutes for the complete annual analysis; they assess whether conclusions derived from the annual model depend on temporal frequency or short-run volatility.

The third component measures organizational Competitive Intelligence capability in four organizational information systems: Japan Customs/MOF, JETRO, ASEANstats, and World Bank WDI. The unit of analysis is the information-producing organizational system. Capability is coded through the 12-item OOCICI and evaluated through theoretical content mapping, direct documentary evidence, leave-one-dimension-out sensitivity, and dimension-resampling stability analysis. No individual-level records, interviews, employee surveys, experimental interventions, or personally identifiable information were used. Figure 2 shows how the three analytical components contribute separately to governed decision support.

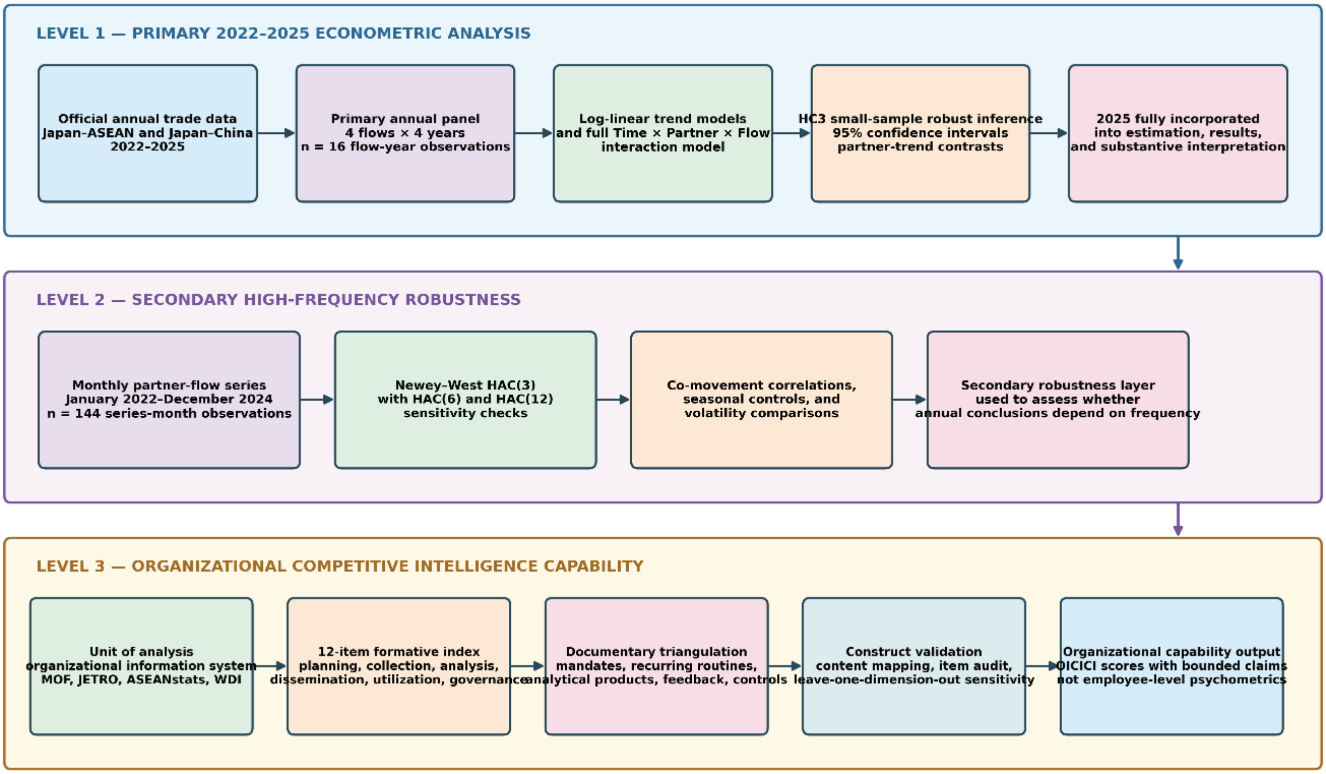


Figure 2. Integrated empirical design linking the primary 2022–2025 annual econometric analysis, secondary monthly robustness analysis, and organizational Competitive Intelligence capability measurement.

Table 1. Operationalization of the Competitive Intelligence Cycle

CI stage	Operationalization in the study	Decision relevance
Intelligence planning	Define China–Japan–ASEAN strategic trade-monitoring questions	Clarifies intelligence needs before analysis
Environmental scanning	Identify public JETRO/MOF, World Bank, and ASEAN Secretariat sources	Reduces ad hoc source selection
Collection	Retrieve annual and monthly trade tables and macro indicators	Creates documented evidence base
Processing	Harmonize units, construct monthly and annual panels, check missing values	Improves comparability and auditability
Analysis	Compute CAGR, HHI, co-movement, HAC trends, pooled interaction, and JSTEI	Transforms data into intelligence signals
Dissemination	Report tables, figures, and interpretable findings in the manuscript	Supports communication to decision users
Utilization and feedback	Use JSTEI and trend results as rolling monitoring outputs	Enables future updating and governance review

Note. Each classical Competitive Intelligence stage is linked to a concrete analytical action and decision-support function.

3.2 Direct Operationalization of Observable Organizational-System CI Capability

The Observed Organizational Competitive Intelligence Capability Index (OOCICI) measures enacted organizational routines in the information systems maintained by Japan Customs/MOF, JETRO, ASEANstats, and World Bank WDI. The index contains 12 binary indicators grouped into six dimensions. Planning covers a formal statistical or monitoring mandate and an advance release calendar. Collection covers recurring data acquisition and partner- or country-level disaggregation. Analysis covers standardized metadata or classifications and a historical time-series or revision architecture. Dissemination covers open public access and machine-readable download or API access. Utilization/feedback covers recurring analytical or monitoring products directed to identifiable decision-user communities and a correction, inquiry, or feedback channel capable of informing later outputs. Governance covers provenance or methodological documentation and explicit version, provisional, revised, or fixed-status controls. Each indicator receives a score of 1 when the organizational routine is explicitly evidenced in the audited materials and 0 when direct evidence is not identified. Each dimension contains two indicators and receives a score of 0, 50, or 100. The total OOCICI score is the arithmetic mean of the six dimension scores. The formative specification means that the dimensions jointly constitute organizational CI capability and are not treated as interchangeable reflections of a latent psychological characteristic. Construct-validation evidence was evaluated in four stages. First, content validity was established by mapping every indicator to a classical CI-cycle or intelligence-governance function. Second, empirical content was confirmed through a complete item-level documentary audit covering 48 institution-by-indicator coding decisions. Third, leave-one-dimension-out analysis assessed whether organizational rankings depended on any single dimension. Fourth, 10,000 resamples of the six dimensions with replacement were used as a compositional-stability assessment. These resampling ranges describe index stability under alternative dimension compositions and are not population confidence intervals.

Table 2. Observed Organizational Competitive Intelligence Capability Index (OOCICI) Scores

Organizational system	Planning	Collection	Analysis	Dissemination	Utilization/ feedback	Governance	OOCICI	Leave-one-dimension-out range	Dimension-resampling interval
Japan Customs/ MOF	100	100	100	100	100	100	100.0	100.0–100.0	100.0–100.0
JETRO	50	100	100	100	100	50	83.3	80.0–90.0	66.7–100.0
ASEANstats	100	100	100	100	100	100	100.0	100.0–100.0	100.0–100.0
World Bank WDI	50	100	100	100	100	50	83.3	80.0–90.0	66.7–100.0
Mean across systems	75.0	100.0	100.0	100.0	100.0	75.0	91.7	—	—

Note. Each dimension contains two binary indicators and receives a score of 0, 50, or 100. OOCICI is the arithmetic mean of the six formative dimension scores. The leave-one-dimension-out range shows the total score obtained when each dimension is removed in turn. The dimension-resampling interval is based on 10,000 resamples of the six dimensions with replacement and represents compositional stability rather than population sampling uncertainty.

Japan Customs/MOF and ASEANstats retained scores of 100.0 under every leave-one-dimension-out specification. JETRO and World Bank WDI remained between 80.0 and 90.0, indicating that their lower organizational capability scores were not produced by a single isolated dimension. The wider dimension-resampling intervals for these two systems reflect their two documented capability gaps. The organizational ordering is therefore stable, although the four-system sample is intentionally bounded and does not support population-wide institutional rankings.

3.3 Data Sources and Sample

The primary trade source is the Trade Statistics of Japan system maintained by the Ministry of Finance/Japan Customs and the corresponding JETRO annual and monthly files (Japan External Trade Organization & Ministry of Finance Japan, 2025). Annual observations cover calendar years 2022–2025. The 2022–2024 annual observations use fixed vintages, and 2025 uses the current revised time-series vintage. Monthly observations used in the HAC and co-movement models cover January 2022–December 2024. Annual values are retained in nominal current yen and reported in JPY trillions. Monthly values are reported in nominal USD billions, following the JETRO/MOF partner-month series. The annual and monthly layers are analyzed separately and are not pooled as directly comparable level observations.

World Bank World Development Indicators provide descriptive macro-context indicators, while ASEANstats provides regional trade, investment, metadata, release-calendar, and governance documentation. These contextual variables are not entered as regression explanatory variables because the monthly models are designed to compare partner-flow trajectories rather than estimate a macro-causal structure (ASEAN Secretariat, 2024, 2025; World Bank, 2025).

Timor-Leste became ASEAN's eleventh member on 26 October 2025. To preserve a constant longitudinal composition, the member-state HHI and JSTEI calculations retain ASEAN-10—Brunei Darussalam, Cambodia, Indonesia, Lao PDR, Malaysia, Myanmar, the Philippines, Singapore, Thailand, and Viet Nam. Timor-Leste is excluded from those calculations because it was not an ASEAN member during the baseline years and a comparable four-year member-state series is not used. The 2025 aggregate ASEAN totals remain included in the annual monitoring layer.

Table 3. Data Sources, Variables, and Analytical Roles.

Construct or component	Operational indicator	Source/unit	Coverage
Organizational CI capability	OOCICI based on 12 formative documentary indicators	Official organizational webpages, mandates, statistical products, methodological documents, and governance records	Four organizational systems; 2026 audit
Annual bilateral trade	Nominal exports and imports for Japan–ASEAN and Japan–China	Japan Customs/MOF and JETRO; JPY trillion	2022–2025
Primary econometric panel	Log annual trade value by partner, flow, and year	Constructed from annual bilateral trade values	Four series × four years; n = 16
Secondary monthly robustness	Monthly partner-flow export and import values	JETRO/MOF; nominal USD billion	January 2022–December 2024; n = 144

Construct or component	Operational indicator	Source/unit	Coverage
Annual trade trajectory	Log-linear time coefficient and CAGR	Derived	2022–2025
Partner identity	China = 1; ASEAN = 0	Constructed	Time invariant
Flow direction	Import = 1; export = 0	Constructed	Time invariant
Annual interactions	Time × Partner; Time × Flow; Partner × Flow; Time × Partner × Flow	Constructed	Primary annual model
Monthly seasonality	Calendar-month indicators; January reference	Constructed	Eleven indicators
Monthly serial dependence	Newey–West HAC(3), HAC(6), and HAC(12)	Derived	Secondary monthly models
Trade concentration	HHI based on constant ASEAN-10 member-state shares	JETRO/MOF fixed member-state tables	2022–2024
Co-movement	Pearson correlation of paired month-on-month log changes	Derived monthly series	February 2022–December 2024; n = 35 paired changes per flow
JSTEI	Mean of standardized export CAGR, export share, and normalized balance	Constructed; ASEAN-10 member state	2024 fixed cross-section; n = 10
Macro context	GDP growth, trade openness, and high-technology export share	World Bank WDI; descriptive	Latest common vintage
External regional benchmark	ASEAN trade and investment indicators	ASEANstats; descriptive	2022–2025 where available

Note. The complete 2022–2025 annual panel forms the primary econometric analysis. The 2022–2024 monthly series form a secondary high-frequency robustness layer and are not presented as the sole inferential basis of the study.

3.4 Analytical Procedures

Annual descriptive growth is evaluated over three complete intervals using CAGR = (V2025/V2022)^(1/3) – 1. The 2025 year-on-year change is calculated as (V2025/V2024) – 1. ASEAN and China shares are calculated relative to Japan's total exports or imports, and ASEAN/China ratios are calculated separately for each flow. Trade concentration within the constant ASEAN-10 composition is calculated as HHI = Σsi^2, where si denotes each member state's share of Japan's ASEAN trade in a given flow and year (Rhoades, 1993).

The primary econometric specification uses the complete annual 2022–2025 panel:

$$\ln(\text{Valuepft}) = \alpha + \beta 1\text{Timet} + \beta 2\text{Chinap} + \beta 3\text{Importf} + \beta 4(\text{Timet} \times \text{Chinap}) + \beta 5(\text{Timet} \times \text{Importf}) + \beta 6(\text{Chinap} \times \text{Importf}) + \beta 7(\text{Timet} \times \text{Chinap} \times \text{Importf}) + \varepsilon\text{pft}.$$

Valuepft is the nominal annual trade value for partner p, flow f, and year t. Time is coded 0, 1, 2, and 3 for 2022–2025; China equals 1 for the China series and 0 for ASEAN; and Import equals 1 for imports and 0 for exports. ASEAN exports constitute the reference trajectory. Because the model contains 16 observations and eight residual degrees of freedom, HC3 heteroskedasticity-robust standard errors and t-based confidence intervals are used. Derived partner-flow trends are obtained through linear combinations of the estimated coefficients. Percentage changes associated with log-trend coefficients are reported as 100[exp(β) – 1]. The interaction terms are interpreted as comparative trend contrasts and not as causal policy effects.

The secondary monthly analysis estimates seasonally controlled log-linear trends for January 2022–December 2024. Series-level models include a linear time term and calendar-month indicators with Newey–West HAC standard errors. HAC(3) is the principal monthly specification, while HAC(6) and HAC(12) assess sensitivity to alternative serial-dependence assumptions. A pooled monthly model estimates partner, flow, time, and interaction effects. Pearson correlations between paired month-on-month log changes assess export and import co-movement.

OOCICI construct stability is evaluated through theoretical item mapping, complete documentary evidence reporting, leave-one-dimension-out analysis, and 10,000 dimension resamples. Because OOCICI is formative, internal-consistency coefficients are not used. The JSTEI remains the arithmetic mean of three standardized Japan-centric engagement indicators and is analyzed separately from organizational CI capability.

3.5 Reliability, Validity, Ethics, and Governance

Reliability of the trade analysis is supported through official source provenance, explicit data-vintage labels, consistent flow definitions, unit harmonization, complete temporal coverage, reproducible transformations, HC3 small-sample inference for the annual model, and HAC sensitivity checks for the monthly models. Annual and monthly values are analyzed in separate models because they use different frequencies and reporting units. OOCICI construct validation follows formative-index principles. Content validity is supported by mapping the 12 indicators to planning, collection, analysis, dissemination, utilization/feedback, and governance functions established in CI theory. Empirical content validity is supported by direct organizational evidence for every coded item. Auditability is provided through the complete coding matrix, documentary source, coding rationale, and access date in Appendix A. Leave-one-dimension-out and dimension-resampling analyses assess whether conclusions depend disproportionately on a single capability dimension. Cronbach's alpha is not reported because correlation among non-interchangeable formative components is not a requirement of construct validity.

The apabilityy construct is bounded to organizational information systems and directly documented routines. It does not measure employee attitudes, informal cognition, or the causal effectiveness of individual management decisions. The documentary coding was performed under explicit binary rules; because an independent second coder was not used, no inter-rater reliability coefficient is claimed. This limitation is retained transparently rather than replaced by an unsupported statistic. The study uses public, aggregate, and non-personal evidence. It includes no human participants, private records, interviews, or personally identifiable information. Governance safeguards include provenance reporting, revision-status disclosure, separation of analytical frequencies, constant ASEAN-10 composition for member-state comparisons, explicit Japan-centric scope, reproducible scoring rules, and separation of trade-performance indicators from organizational capability scores.

4 RESULTS AND DISCUSSION

4.1 Organizational Competitive Intelligence Capability

The OOCICI results measure observable organizational routines in the four information-producing systems and are analytically independent of trade performance. Japan Customs/MOF and ASEANstats each scored 100.0, while JETRO and World Bank WDI each scored 83.3; the cross-system mean was 91.7. The two lower scores reflect one documented planning gap and one documented governance gap in each system. They do not arise from trade levels, national competitiveness, or subjective assessments of institutional reputation. All four systems demonstrated recurring collection, standardized analytical architecture, open dissemination, and organizational utilization/feedback routines. Utilization is evidenced by the recurring production of statistical, analytical, or monitoring outputs for identifiable policy, market, research, or operational user communities, together with mechanisms through which corrections, inquiries, or feedback can affect later releases. The construct therefore captures organizationally enacted information-system capability rather than only the technical availability of public files. The capability ordering was stable under alternative dimension compositions. Japan Customs/MOF and ASEANstats remained at 100.0 in every leave-one-dimension-out specification. JETRO and World Bank WDI remained between 80.0 and 90.0. These results support the robustness of the observed organizational differences while preserving the bounded interpretation appropriate to a four-system audit.

4.2 Descriptive Trade and Macro-Contextual Signals

Table 4. Japan's Annual Nominal Merchandise Trade with ASEAN and China, 2022–2025

Indicator	2022	2023	2024	2025	CAGR 2022–2025 (%/yr)
Exports to ASEAN (JPY tn)	15.544	14.717	15.354	15.960	+0.88
Imports from ASEAN (JPY tn)	17.715	16.914	17.647	17.871	+0.29
Exports to P.R. China (JPY tn)	19.004	17.764	18.862	18.778	−0.40
Imports from P.R. China (JPY tn)	24.850	24.424	25.313	26.695	+2.42
ASEAN share of total Japanese exports (%)	15.833	14.590	14.338	14.451	—
China share of total Japanese exports (%)	19.357	17.610	17.614	17.002	—
ASEAN share of total Japanese imports (%)	14.949	15.321	15.656	15.802	—
China share of total Japanese imports (%)	20.970	22.124	22.458	23.605	—
Export ratio, ASEAN/China	0.818	0.829	0.814	0.850	—
Import ratio, ASEAN/China	0.713	0.693	0.697	0.669	—

Note. Values are nominal current yen and are reported in trillions of yen. CAGR is calculated over three complete annual intervals. The 2025 column uses the current revised annual time-series vintage.

Japan's annual trade signals changed materially when the 2025 observation was added. From 2022 to 2025, exports to ASEAN increased from JPY 15.544 trillion to JPY 15.960 trillion, corresponding to a CAGR of 0.88% per year. Imports from ASEAN increased from JPY 17.715 trillion to JPY 17.871

trillion, a CAGR of 0.29%. Exports to China decreased from JPY 19.004 trillion to JPY 18.778 trillion, a CAGR of −0.40%, while imports from China increased from JPY 24.850 trillion to JPY 26.695 trillion, a CAGR of 2.42%.

The 2025 annual observation provides a more differentiated intelligence signal within the complete 2022–2025 primary analysis. Relative to 2024, Japan's exports to ASEAN increased by 3.95% and imports from ASEAN increased by 1.27%. Exports to China decreased by 0.45%, whereas imports from China increased by 5.46%. Consequently, the ASEAN/China export ratio increased from 0.814 to 0.850, while the import ratio decreased from 0.697 to 0.669. The update therefore does not support a single-direction diversification narrative: export engagement moved relatively toward ASEAN, but import dependence moved relatively toward China. A monthly series, underlying the descriptive patterns presented above, is shown in Figure 4.

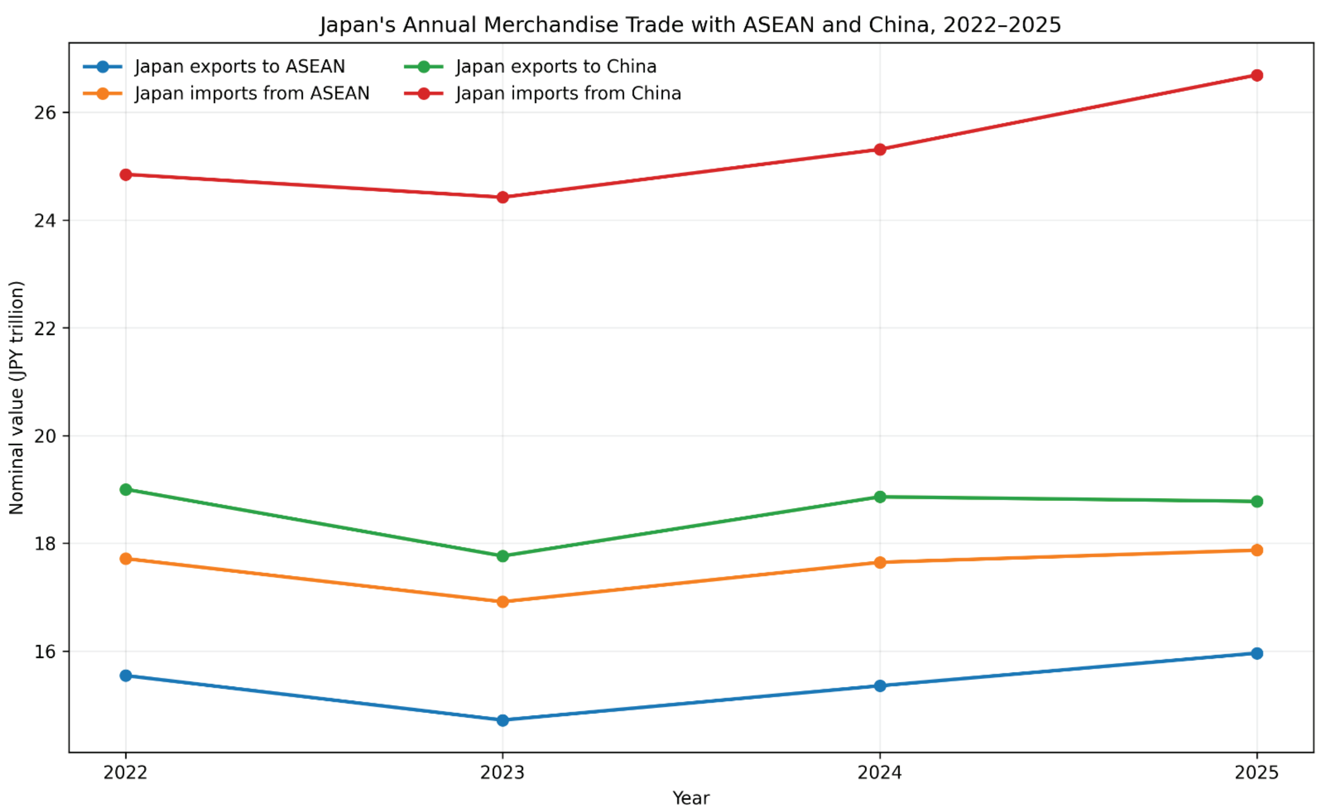


Figure 3. Japan's annual nominal merchandise exports and imports with ASEAN and China, 2022–2025 (JPY trillion).

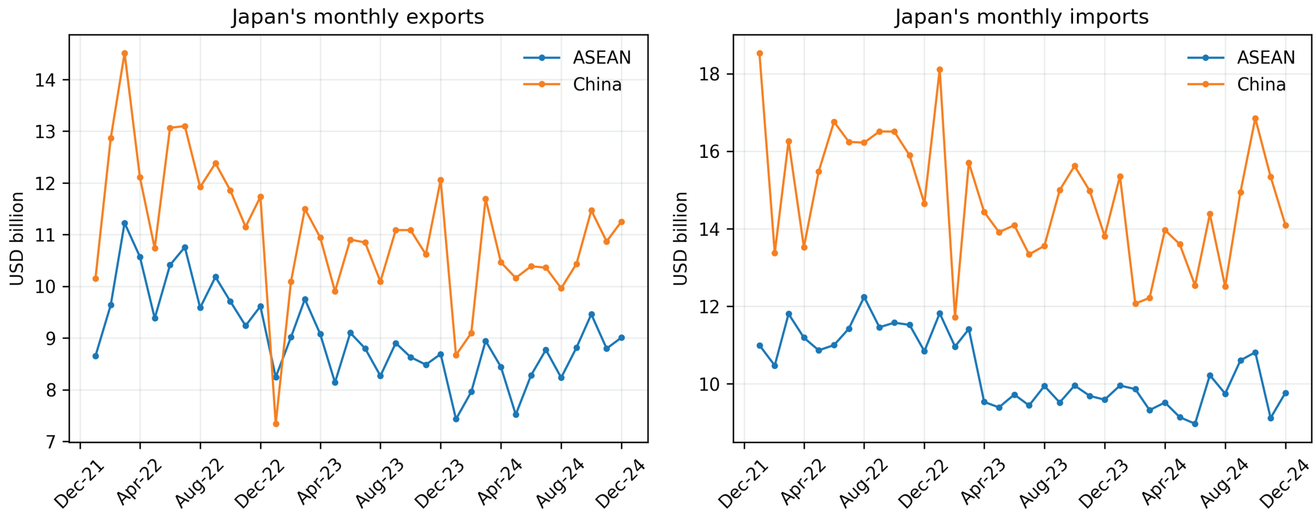


Figure 4. Monthly nominal merchandise exports and imports between Japan and ASEAN and between Japan and China, January 2022–December 2024 (USD billion; pre-specified estimation window).

4.3 Concentration, Co-Movement, and Intelligence Interpretation

The concentration analysis uses the latest fully fixed ASEAN-10 member-state vintage, 2022–2024. The 2025 aggregate update is reported separately because the member-state ranking layer is held constant for comparability and Timor-Leste entered ASEAN only in October 2025.

Table 5. HHI of Japan's Trade Concentration within ASEAN, 2022–2024

Year	HHI—exports	HHI—imports
2022	0.1822	0.1728
2023	0.1832	0.1733
2024	0.1803	0.1762

Note. HHI values are computed from ten ASEAN member-state shares expressed as proportions on a 0–1 scale.

Japan's trade concentration across ASEAN member states remained stable. Export HHI values were .1822 in 2022, .1832 in 2023, and .1803 in 2024. Import HHI values were .1728, .1733, and .1762. Because an equal distribution across ten member states would produce an HHI of .1000, the observed values indicate moderate concentration, but not a sharp reallocation during the period. Figure 5 confirms that the composition of ASEAN-bound exports changed only modestly.

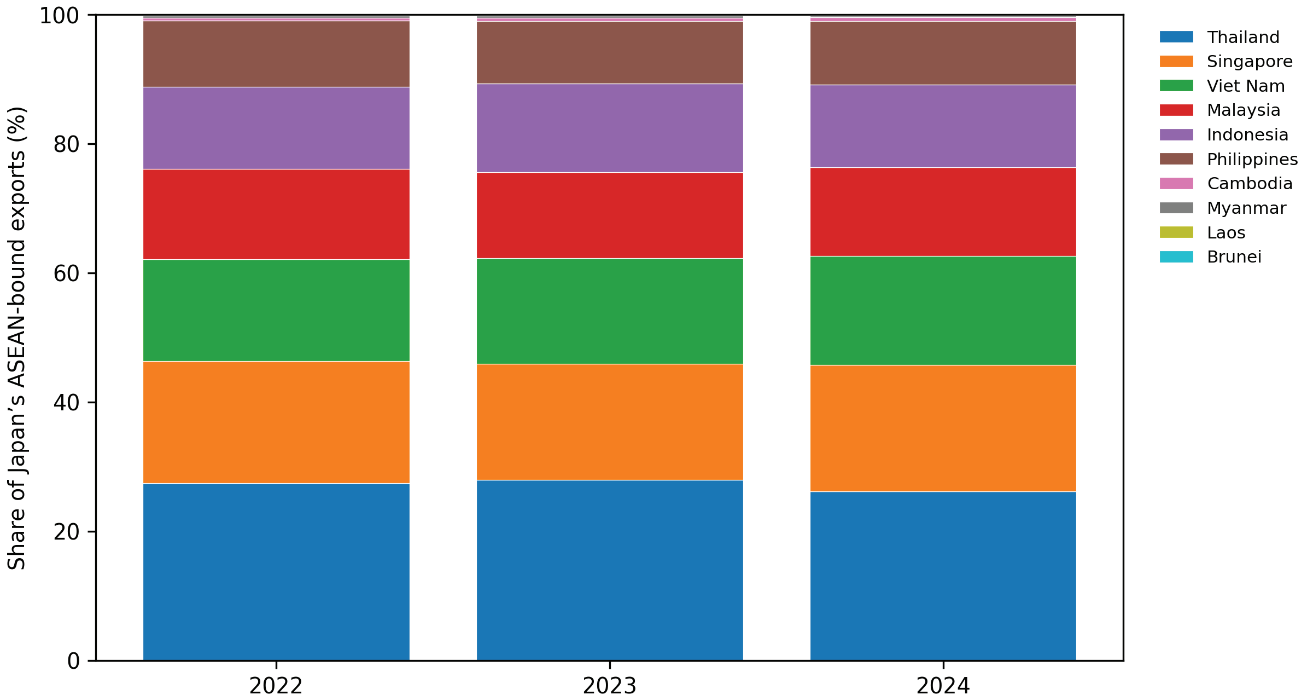


Figure 5. Composition of Japan's ASEAN-bound exports by ASEAN member state, 2022–2024.

Tables 7 and 8 report the primary 2022–2025 annual econometric model, whereas Tables 9 and 10 report the secondary January 2022–December 2024 monthly robustness analyses. Accordingly, 2025 is incorporated directly into the principal econometric estimation, while the monthly layer is retained to assess whether the annual conclusions are robust to higher-frequency variation.

Table 6. Co-Movement of Month-on-Month Log Changes, February 2022–December 2024

Flow	n	Pearson r	p	SD: ASEAN leg (%)	SD: China leg (%)
Export	35	0.837	< .001	8.74	15.07
Import	35	0.552	< .001	6.85	14.93

Note. Co-movement is descriptive and does not identify a causal macroeconomic driver.

The co-movement results provide a stronger intelligence signal than a single-series trend would provide. Monthly export log changes were strongly correlated across the ASEAN and China legs ($r = .837$, $p < .001$), while import changes were moderately correlated ($r = .552$, $p < .001$). The China leg was more volatile in both flows. For decision users, this means that a Japan-only or China-only monitoring system could misattribute shared macro-cyclical movement to partner-specific strategic change. The comparative design reduces that risk of information asymmetry.

4.4 Primary 2022–2025 Econometric Results and Monthly Robustness

To incorporate 2025 fully into the econometric analysis, the principal interaction model was re-estimated using all four annual partner-flow series for 2022–2025. The annual panel contains 16 observations and uses HC3 small-sample robust inference. The earlier January 2022–December 2024 monthly HAC models are retained as a secondary high-frequency robustness analysis.

Table 7. Derived Annual Trends from the Primary 2022–2025 Pooled Model

Annual series	Trend β	HC3 SE	95% CI	p	Implied annual change
Japan exports to ASEAN	.012161	.034238	[−.066793, .091114]	.732	+1.22%
Japan exports to China	.002408	.026914	[−.059656, .064473]	.931	+0.24%
Japan imports from ASEAN	.006873	.022921	[−.045983, .059728]	.772	+0.69%
Japan imports from China	.025061	.025310	[−.033303, .083425]	.351	+2.54%

Note. Estimates are derived from the full Time × Partner × Flow model. Percentage changes equal 100[exp(β) − 1]. Confidence intervals and p values use HC3 robust standard errors with t-based inference.

Table 8. Primary 2022–2025 Time × Partner × Flow Model and Derived Contrasts

Term or contrast	Coefficient	HC3 SE	95% CI	p
ASEAN-export annual trend	.012161	.034238	[−.066793, .091114]	.732
China vs ASEAN export trend	−.009752	.043550	[−.110180, .090675]	.828
ASEAN import vs export trend	−.005288	.041202	[−.100301, .089725]	.901
China × Import baseline-level interaction	.135690	.119244	[−.139286, .410666]	.288
Time × China × Import	.027940	.055341	[−.099675, .155556]	.627
China vs ASEAN import trend	.018188	.034146	[−.060552, .096929]	.609

Note. ASEAN exports constitute the reference series. $n = 16$ flow-year observations; residual df = 8. Adjusted $R^2 = .971$. HC3 robust standard errors and t-based confidence intervals are reported.

The complete 2022–2025 model does not identify statistically significant partner-specific trend divergence. The China-versus-ASEAN export contrast was −.009752 ($p = .828$), and the corresponding import contrast was .018188 ($p = .609$). The three-way Time × China × Import interaction was also non-significant ($p = .627$). The point estimates suggest modest positive annual movement in ASEAN exports and China imports, but every annual trend confidence interval includes zero. The appropriate CI conclusion is therefore not that the four series were identical, but that four annual observations per trajectory do not provide sufficiently precise evidence of systematic partner-specific divergence. The series-level models show statistically significant negative trends in all four nominal USD-denominated monthly trade series after controlling for calendar-month seasonality. The implied annualized changes are −7.56% for Japan's exports to ASEAN, −7.37% for exports to China, −7.06% for imports from ASEAN, and −6.06% for imports from China. These estimates refer to nominal values and should not be interpreted as physical trade-volume changes.

The pooled interaction model tests whether partner identity altered the time trend. The China-versus-ASEAN export trend contrast is positive but not statistically significant ($\beta = .001010$, $p = .626$). The corresponding import trend contrast is also non-significant ($\beta = .001478$, $p = .372$), and the Time

× China × Import interaction is non-significant (β = .000468, p = .866). The CI implication is important: the data support a shared decline across the two partner legs rather than a clearly detectable aggregate shift in Japan's trade trajectory away from China and toward ASEAN during 2022–2024.

Table 9. Secondary Monthly Series-Level Trend Sensitivity, January 2022–December 2024

Series	Month FE + HAC(3)	Month FE + HAC(6)	Month FE + HAC(12)	No month FE + HAC(3)
Japan exports to ASEAN	< .001	< .001	< .001	.001
Japan exports to China	< .001	< .001	< .001	.014
Japan imports from ASEAN	< .001	< .001	< .001	< .001
Japan imports from China	< .001	< .001	< .001	.025

Note. These models constitute a secondary high-frequency robustness layer and apply only to January 2022–December 2024.

Table 10. Secondary Monthly Pooled-Model Partner-Trend Sensitivity

Monthly contrast	HAC(3)	HAC(6)	HAC(12)
China vs ASEAN export trend	.626	.648	.625
China vs ASEAN import trend	.372	.331	.291
Time × China × Import	.866	.864	.848

Note. Entries are two-sided p values. All partner-specific monthly trend contrasts remain non-significant under the alternative HAC lag lengths.

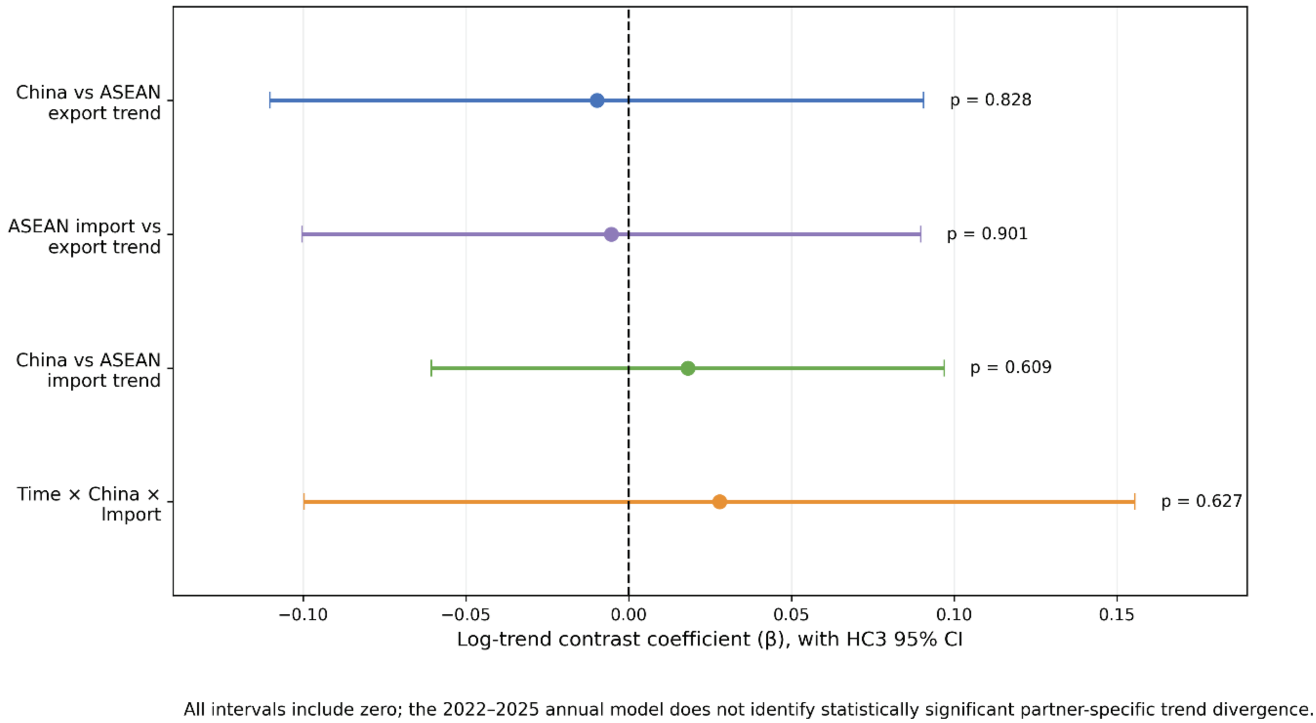


Figure 6. Partner-trend contrasts from the primary 2022–2025 annual interaction model with HC3 95% confidence intervals.

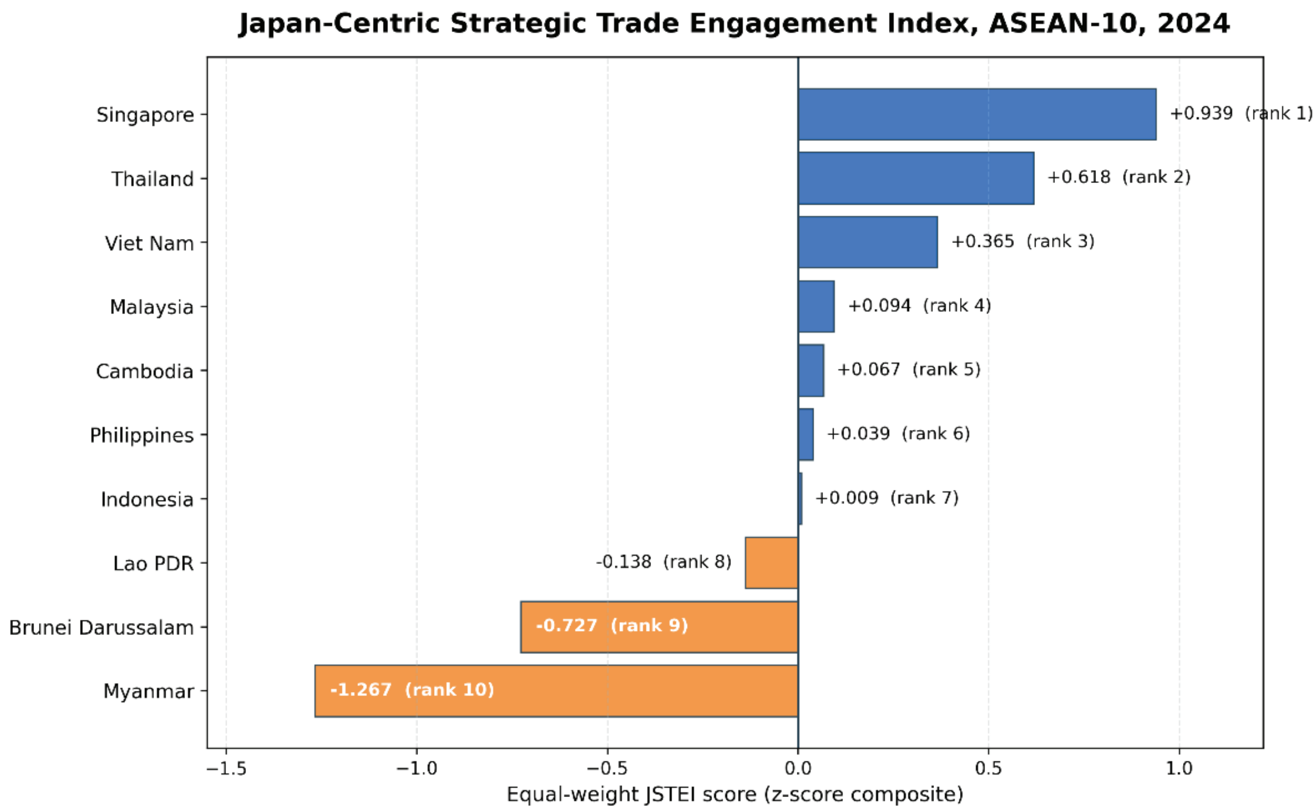
Every confidence interval in Figure 6 crosses zero, confirming the absence of statistically detectable partner-specific annual trend divergence over 2022–2025. The secondary monthly analysis reaches the same comparative conclusion: although the four 2022–2024 monthly series had significant within-series negative fitted trends, none of the partner-specific contrasts was significant under HAC lags of 3, 6, or 12 months. Agreement between the complete annual model and the higher-frequency robustness layer strengthens the conclusion that the available evidence does not establish a systematic aggregate reorientation of Japan's trade trajectory from China toward ASEAN.

4.5 Japan-Centric Strategic Trade Engagement Index

Table 11. Japan-Centric Strategic Trade Engagement Index, 2024

Rank	Country	Within-ASEAN export share	Normalized balance	Equal-weight JSTEI score
1	Singapore	19.55%	.443	.939
2	Thailand	26.21%	.036	.618
3	Viet Nam	16.84%	−.222	.365
4	Malaysia	13.73%	−.156	.094
5	Cambodia	0.57%	−.574	.067
6	Philippines	9.84%	.025	.039
7	Indonesia	12.80%	−.287	.009
8	Laos	0.10%	−.242	−.138
9	Brunei	0.06%	−.941	−.727
10	Myanmar	0.31%	−.638	−1.267

Note. Within-ASEAN export shares sum to approximately 100% apart from rounding. The normalized bilateral balance is $NB_i = (X_i - M_i)/(X_i + M_i)$. The JSTEI is exploratory and Japan-centric; it is not a validated measure of national competitiveness.



Note. Positive and negative scores indicate relative position within this Japan-centric composite. The index is not a measure of national competitiveness or organizational CI capability.

Figure 7. Japan-Centric Strategic Trade Engagement Index scores for ASEAN-10 member states, 2024.

The JSTEI uses the latest fully fixed 2024 ASEAN-10 cross-section and remains an exploratory Japan-centric engagement measure. Singapore ranks first, combining a substantial export share with a strongly positive normalized bilateral balance. Thailand ranks second because it holds the largest within-ASEAN share of Japan's ASEAN-bound exports, and Viet Nam ranks third despite a negative normalized balance. Malaysia, Cambodia, the Philippines, and Indonesia cluster near zero; their small score differences should not be treated as sharply distinct strategic categories. Lao PDR, Brunei Darussalam, and Myanmar occupy the lower positions. The JSTEI is a trade-engagement output rather than an organizational capability measure; organizational Competitive Intelligence capability is measured separately through OOCICI.

The JSTEI does not itself measure intelligence utilization or sustainable competitive advantage. Rather, it is a repeatable analytical output that decision units may use to prioritize subsequent commodity-level, firm-level, or investment-level inquiry. Its value lies in supporting the utilization stage of a CI cycle through transparent and updateable ranking signals. The study observes institutionalized utilization routines and decision-support products but does not estimate the causal effect of those products on individual management decisions.

4.6 Governance Implications and Strategic Decision Making

There are three governance implications of the results. First, there is a need to separate evidence and narrative in Intelligence Governance. The primary 2022–2025 annual model and the secondary 2022–2024 monthly models do not validate a straightforward aggregate shift in Japan's trade trajectory from China toward ASEAN. Second, there is need for source triangulation in governance. Japan-focused trade data provide a bilateral monitoring picture, whereas ASEAN Secretariat statistics provide regional context for China's trade and investment role. Third, scope disclosure is an integral component of intelligence governance. A CI system is viable only when decision users understand what is being monitored, what is not being monitored, and which future evidence could alter the monitoring cycle.

Trade-dominance versus investment-parity is particularly important in strategic decision making. As detailed in the ASEAN Secretariat's reporting, China is playing a major role in ASEAN trade while Japan's position in investment could lie at a closer end than the trade shares would indicate. This is the very kind of signal that CI systems are meant to recognize. Strategic overconfidence can be created by a single indicator family; a governed CI cycle helps to reduce information asymmetry by using multiple indicator families.

4.7 Competitive Intelligence Interpretation of the Findings

It is important to understand that the absence of a detectable partner-specific trend divergence should not be taken as a weak result, but as an important Competitive Intelligence finding. By looking at strategic value from a dynamic-capabilities point of view, strategic value is not just created when there is a clear shift in direction; it is also created when a monitoring system makes it difficult for decision makers to act on unsupported assumptions. The monthly 2022–2024 series showed broadly shared nominal declines, whereas the complete 2022–2025 annual series showed heterogeneous recovery and growth; neither analytical layer identified statistically significant partner-specific trend divergence. This implies that when it comes to the macro-level, pressures might have been more apparent than a clear aggregate reorientation from China to ASEAN over the period observed.

This is an interpretation that enhances the governance function of Competitive Intelligence. A CI system shouldn't just validate prevailing policy narratives; it must separate out what is measured from what may be interpreted and what are questionable claims for the strategy. Findings from the non-significant partner-trend contrasts, the positive co-movement results, and the stability of the ASEAN concentration indicators all suggest that there can be a positive value of intelligence in disciplined caution. This moderation helps minimize information asymmetry, as the decision users will know what is being supported, what is not being supported, and where a finer-grained commodity-level or investment-level monitoring is required.

The results also highlight the importance of not seeing ASEAN as one unified strategic space. The results of the JSTEI ranking show that Singapore, Thailand and Viet Nam have better engagement positions with Japan, while Brunei and Myanmar have lower engagement positions. This ranking can be used by trade-promotion agencies, policy units and research centres to inform the next intelligence cycle by helping them prioritise their actions in terms of commodity-level analysis, firm-level inquiry and investment-flow triangulation. Thus, the study is not limited to reporting the changes in trade but extends to the transformation of public data into a repeatable and decision-support framework.

5 FINAL CONSIDERATIONS

This study reframes China–Japan–ASEAN economic monitoring as an integrated Competitive Intelligence problem. At the process level, official signals move through planning, environmental scanning, collection, processing, analysis, dissemination, utilization, feedback, and governance. At the organizational-capability level, OOCICI directly records formal and recurrent routines in the information systems maintained by Japan Customs/MOF, JETRO, ASEANstats, and World Bank WDI. Trade outcomes and organizational CI capability are consequently measured as separate empirical domains.

The complete 2022–2025 annual period is incorporated into the principal econometric model. Descriptively, Japan's exports to ASEAN grew at 0.88% per year and imports from ASEAN at 0.29%, while exports to China declined at 0.40% and imports from China grew at 2.42%. However, the annual interaction model did not identify statistically significant China-versus-ASEAN trend divergence for exports or imports. The three-way Time × China × Import interaction was also non-significant. The January 2022–December 2024 monthly HAC models, retained as a secondary high-frequency robustness layer, produced the same comparative conclusion.

The OOCICI results show strong observable organizational-system CI capability across the four audited systems. Japan Customs/MOF and ASEANstats scored 100.0, while JETRO and World Bank WDI scored 83.3. These differences remained stable under leave-one-dimension-out analysis. The construct does not rely solely on data availability: it records planning mandates, recurring collection systems, analytical architecture, dissemination mechanisms, recurring decision-support products, feedback or correction channels, and governance controls. It therefore represents a formative organizational capability construct rather than an employee-level psychometric scale.

The theoretical contribution is the integration of classical CI, organizational intelligence capability, intelligence governance, information asymmetry, dynamic capabilities, and the resource-based view. The methodological contribution is a design that fully incorporates 2025 into the principal econometric analysis, preserves monthly evidence as a separate robustness layer, and validates organizational capability through theoretically mapped and empirically auditable formative indicators. The practical contribution is a low-cost monitoring architecture that can be repeatedly updated by trade-promotion agencies, policy units, universities, and research organizations.

Three limitations define the boundaries of the conclusions. First, the annual interaction model contains only four yearly observations per trajectory; HC3 inference reduces small-sample distortion but cannot create information absent from the short series. Second, the monthly robustness layer ends in December 2024 and should be extended when the complete 2025 partner-month file is incorporated into the reproducible dataset. Third, OOCICI observes formal organizational routines and public decision-support products but does not measure confidential managerial deliberation or individual employee cognition. Future research should extend the monthly model through 2025, apply independent multi-rater coding, examine additional organizational information systems, and connect documented CI routines with specific decision outcomes.

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APPENDIX A. OOCICI ORGANIZATIONAL CAPABILITY AUDIT

Table A1. Binary Coding Matrix for the Observed Organizational Competitive Intelligence Capability Index

System	P1	P2	C1	C2	A1	A2	D1	D2	U1	U2	G1	G2	Total	OOCICI
Japan Customs/MOF	1	1	1	1	1	1	1	1	1	1	1	1	12	100.0
JETRO	1	0	1	1	1	1	1	1	1	1	0	1	10	83.3
ASEANstats	1	1	1	1	1	1	1	1	1	1	1	1	12	100.0
World Bank WDI	1	0	1	1	1	1	1	1	1	1	1	0	10	83.3

Table A2. Operational Definitions of OOCICI Documentary Indicators

Code	Binary documentary indicator
P1	Explicit statistical or monitoring mandate
P2	Advance release calendar
C1	Recurring annual or monthly data acquisition
C2	Country-, member-, or partner-level disaggregation
A1	Standardized metadata or classifications
A2	Historical time series and revision architecture
D1	Open public access
D2	Machine-readable download or API access
U1	Recurring production of analytical or monitoring outputs directed to identifiable policy, market, research, or operational users
U2	Documented correction, inquiry, or feedback mechanism capable of informing subsequent releases or analytical outputs
G1	Provenance, methodology, or governance documentation
G2	Explicit provisional, revised, fixed, or version-status labels

Scoring rule. A score of 1 requires direct documentary evidence that the organizational routine is formally or recurrently enacted; 0 indicates that explicit evidence was not identified in the audited materials. Dimension score = 50 × the sum of the two dimension items. OOCICI = arithmetic mean of the six formative dimension scores.

Table A3. Documentary Evidence and Coding Rationale for OOCICI Indicators

Institutional system	Code	Score	Documentary source	Coding rationale	Access date
Japan Customs/MOF	P1	1	Trade Statistics of Japan homepage and "About Trade Statistics of Japan"	The Ministry of Finance maintains an explicit institutional system for producing and disseminating Japanese trade statistics.	13 July 2026
Japan Customs/MOF	P2	1	Calendar of Release Dates—Trade Statistics of Japan	An advance calendar specifies provisional, detailed, revised, and fixed release dates.	13 July 2026
Japan Customs/MOF	C1	1	Trade Statistics Press Release archive	Monthly, annual, first-10-day, and first-20-day trade observations are collected and released recurrently.	13 July 2026
Japan Customs/MOF	C2	1	Trade Statistics Search and Data Download	Data are disaggregated by country, geographic area, commodity, export, and import flow.	13 July 2026
Japan Customs/MOF	A1	1	Trade Statistics Code Lists and Glossary	Standard country, commodity, statistical-code, unit, and classification documentation is publicly available.	13 July 2026

Institutional system	Code	Score	Documentary source	Coding rationale	Access date
Japan Customs/MOF	A2	1	Time Series Data and Trade Statistics Glossary	Historical series and a documented provisional–detailed–revised–fixed revision architecture are maintained.	13 July 2026
Japan Customs/MOF	D1	1	Trade Statistics of Japan homepage	Statistical outputs can be accessed publicly without institutional subscription.	13 July 2026
Japan Customs/MOF	D2	1	Data Download and Press Release files	Machine-readable XML files and downloadable statistical tables are provided.	13 July 2026
Japan Customs/MOF	U1	1	Trade Statistics Press Releases, monthly and annual summary outputs	The organization repeatedly transforms collected trade data into scheduled statistical and analytical outputs intended for government, market, and research users.	13 July 2026
Japan Customs/MOF	U2	1	Contact, Corrigendum, and revision pages	Public correction and contact mechanisms permit errors and user inquiries to inform revised or subsequent statistical releases.	13 July 2026
Japan Customs/MOF	G1	1	Glossary, Code Lists, and About Trade Statistics	Provenance, classifications, correction procedures, and methodological documentation are publicly available.	13 July 2026
Japan Customs/MOF	G2	1	Calendar of Release Dates and Glossary	Outputs are explicitly labelled provisional, detailed, revised, or fixed.	13 July 2026
JETRO	P1	1	Japanese Trade and Investment Statistics	JETRO explicitly provides facts and figures covering the Japanese economy and international trade.	13 July 2026
JETRO	P2	0	Japanese Trade and Investment Statistics	No separate advance release calendar was identified on the audited statistics page.	13 July 2026
JETRO	C1	1	Japan's International Trade in Goods—Monthly and Yearly	Recurring monthly and annual trade files are published.	13 July 2026
JETRO	C2	1	Japanese Trade and Investment Statistics files	Published statistical tables contain country-, region-, partner-, and flow-level breakdowns.	13 July 2026
JETRO	A1	1	Japanese Trade and Investment Statistics files and source notes	Tables apply standardized trade categories, units, periods, and institutional-source descriptions.	13 July 2026
JETRO	A2	1	Monthly and Yearly Time Series	Archived annual and monthly time-series files are available across multiple years.	13 July 2026
JETRO	D1	1	Japanese Trade and Investment Statistics	Statistical reports and files are openly accessible.	13 July 2026
JETRO	D2	1	Downloadable monthly, yearly, FDI, and related statistical files	Public downloadable spreadsheet and report files are provided.	13 July 2026
JETRO	U1	1	Japanese Trade and Investment Statistics and recurring monthly/yearly analytical releases	JETRO repeatedly converts trade data into monitoring and analytical products intended for firms, policymakers, and research users.	13 July 2026
JETRO	U2	1	FAQs/Inquiry Form and JETRO Worldwide Offices	Formal inquiry channels allow users to request clarification, provide feedback, and identify issues relevant to subsequent information products.	13 July 2026
JETRO	G1	0	Japanese Trade and Investment Statistics	No dedicated trade-statistics governance or comprehensive methodological document was identified on the audited page.	13 July 2026
JETRO	G2	1	Japanese Trade and Investment Statistics	Dated time-series vintages and explicit annual-revision or preliminary labels are displayed for relevant statistical series.	13 July 2026

Institutional system	Code	Score	Documentary source	Coding rationale	Access date
ASEANstats	P1	1	Policies and Guidelines on Data Sharing, Confidentiality and Dissemination of ASEAN Statistics, Version 3.0	The policy establishes explicit statistical production, accessibility, credibility, harmonization, and decision-support objectives.	13 July 2026
ASEANstats	P2	1	ASEANstats Advance Release Calendar and dissemination policy	ASEANstats is required to maintain and publish a release calendar for ASEAN statistics.	13 July 2026
ASEANstats	C1	1	ASEANstats Data Portal	Member-state data are submitted and updated recurrently using agreed statistical templates.	13 July 2026
ASEANstats	C2	1	ASEAN Trade in Goods Data Query	Data can be queried by reporter, partner, period, frequency, classification, and commodity.	13 July 2026
ASEANstats	A1	1	ASEANstats Metadata and AHTN/ IMTS classifications	Standard classifications, definitions, indicator codes, sources, and country metadata are provided.	13 July 2026
ASEANstats	A2	1	ASEANstats historical data query and revision policy	Historical time series, update dates, preliminary-data notes, and revision procedures are documented.	13 July 2026
ASEANstats	D1	1	ASEANstats Data Portal	Data and metadata are publicly accessible under an open-data licence.	13 July 2026
ASEANstats	D2	1	ASEANstats download and API functions	Exportable data, downloads, and API-based indicator access are available.	13 July 2026
ASEANstats	U1	1	ASEAN Statistical Highlights, ASEAN Key Figures, and Data Portal analytical products	ASEANstats recurrently converts member-state submissions into regional monitoring products intended for ASEAN policy and research communities.	13 July 2026
ASEANstats	U2	1	ASEANstats Contact Us and portal-feedback functions	Contact and feedback channels support clarification, correction, and improvement of later portal and statistical outputs.	13 July 2026
ASEANstats	G1	1	ASEAN statistical dissemination and confidentiality policy	Governance documentation covers accessibility, confidentiality, metadata, accountability, and correction procedures.	13 July 2026
ASEANstats	G2	1	ASEANstats revision policy and indicator notes	Preliminary, rebased, revised, and updated observations must be clearly identified.	13 July 2026
World Bank WDI	P1	1	User Guide to WDI Resources	WDI is explicitly identified as the World Bank's principal compilation of cross-country development indicators.	13 July 2026
World Bank WDI	P2	0	WDI User Guide and DataBank	No consolidated advance release calendar was identified for the complete WDI database.	13 July 2026
World Bank WDI	C1	1	World Development Indicators DataBank	WDI recurrently compiles and updates internationally recognized development indicators.	13 July 2026
World Bank WDI	C2	1	WDI DataBank country and indicator selection	Data are available at country, regional, and global levels.	13 July 2026
World Bank WDI	A1	1	DataBank Metadata and Metadata API	Standard indicator definitions, source notes, country metadata, and methodological descriptions are available.	13 July 2026
World Bank WDI	A2	1	WDI archives and historical time-series resources	Historical series and archived database versions extending back to 1989 are available.	13 July 2026
World Bank WDI	D1	1	World Bank Open Data and WDI DataBank	WDI observations and metadata are publicly accessible.	13 July 2026
World Bank WDI	D2	1	Indicators API and DataBank download options	Data and metadata can be downloaded in Excel, CSV, text, and API formats.	13 July 2026

Institutional system	Code	Score	Documentary source	Coding rationale	Access date
World Bank WDI	U1	1	WDI analytical resources, country/ indicator profiles, and recurring data products	WDI repeatedly organizes development indicators into monitoring and analytical products used by policy, development, and research communities.	13 July 2026
World Bank WDI	U2	1	World Bank Data Help Desk, Data Updates and Errata, and WDI contact channels	Questions, correction requests, and user feedback can inform database corrections and subsequent releases.	13 July 2026
World Bank WDI	G1	1	WDI User Guide, Sources and Methods, and Data Help Desk	Compilation methodology, indicator metadata, archives, and data-governance information are documented.	13 July 2026
World Bank WDI	G2	0	WDI DataBank and User Guide	No uniform dataset-wide provisional, revised, or fixed status label was identified for every WDI observation.	13 July 2026

Note. A score of 1 indicates that an organizational capability routine was directly evidenced in the audited materials. A score of 0 indicates that explicit evidence was not identified; it does not prove that an undocumented internal routine is absent. OOCICI measures formal and organizational Competitive Intelligence capability. It does not measure individual employee attitudes or the causal effectiveness of a specific management decision.