Aid for Trade and bilateral trade relations: evidence from a network approach

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Abstract

Purpose – Aid for Trade (AfT) is a major international initiative designed to strengthen the trade capacity and export performance of developing countries. This paper asks whether AfT strengthens bilateral trade relationships between specific donors and recipients, or whether its trade-generating effects are primarily diffuse, benefiting recipient exports to third-country markets rather than to donors themselves.

Design/methodology/approach – This paper examines the effect of AfT on bilateral trade relationships using the Additive and Multiplicative Effects (AME) network model applied to a directed network of 29 Organisation for Economic Co-operation and Development donor countries and 150 recipient countries across the full AfT period, 2004–2021.

Findings – We find that the posterior mean coefficients for AfT sent range from 0.159 to 0.291 and those for AfT received range from 0.109 to 0.249. Coefficients are stable across the period, with a dip in 2009 consistent with the effects of the global financial crisis. Empirical network analysis reveals persistent structural asymmetry in bilateral trade flows, with weighted reciprocity of 0.64–0.73, indicating that 36% of trade volume is not matched by a counter flow. Global transitivity is also positive and statistically significant but declines over time. The estimated elasticity implies a descriptive scaling of roughly 11–22 dollars of bilateral trade per dollar of AfT.

Originality/value – Standard gravity model analyses have produced mixed evidence and cannot capture structural network properties and core–periphery organization that characterize the world trade network. This paper addresses that gap as the first comprehensive analysis of bilateral trade for both donor-to-recipient and recipient-to-donor flows, using a fully directed network analysis.

Keywords Aid for Trade, Bilateral trade, Network analysis, AME model, Dyadic relations, Complex networks, World Trade Network

Paper type Research article

1. Introduction

The Aid for Trade (AfT) initiative, formally established at the 2005 World Trade Organization (WTO) Ministerial Conference in Hong Kong, channels billions of dollars annually into trade-related infrastructure, productive capacity building and trade policy reform in developing countries [23]. Over two decades, total AfT disbursements have grown from approximately USD 4.5 billion in 2002 to nearly USD 19 billion in 2021, involving 29 Organisation for Economic Co-operation and Development (OECD) donor countries and over 150 recipient nations.

A central empirical question is whether AfT strengthens bilateral trade relationships between specific donors and recipients, or whether its trade-generating effects are primarily diffuse, benefiting recipient exports to third-country markets rather than to donors themselves

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(Hühne *et al.*, 2014). Standard gravity model analyses have produced mixed evidence (Cali and te Velde, 2011; Pettersson and Johansson, 2013), partly because they treat dyadic observations as independent and cannot capture structural network properties such as transitivity, reciprocity and core–periphery organization that characterize the World Trade Network (WTN) (Fagiolo *et al.*, 2009).

This paper addresses that gap by applying the Additive and Multiplicative Effects (AME) network model (Hoff *et al.*, 2002; Hoff, 2005; Ward *et al.*, 2013) to the complete 2002–2021 AfT era, the first comprehensive analysis across this full period. Our data set captures bilateral trade in *both* directions: donor-to-recipient (D2R) and recipient-to-donor (R2D), enabling a fully directed network analysis.

2. Related work

2.1 Origins and rationale for Aid for Trade

The AfT initiative emerged from a fundamental recognition within the multilateral trading system: that trade liberalization alone is insufficient to guarantee that developing countries benefit from greater global integration (Hoekstra and Koopmann, 2010). The Sixth WTO Ministerial Conference in Hong Kong in 2005 formally established AfT and charged the OECD and WTO with joint monitoring of financial flows and trade outcomes. The initiative rests on two foundational premises. First, low-income countries face severe supply-side constraints, weak infrastructure, limited productive capacity, inadequate customs administration and underdeveloped financial markets, which prevent them from translating improved market access into actual export gains. Second, multilateral trade liberalization itself generates adjustment costs that disproportionately burden developing countries, particularly those reliant on trade preferences that erode as most-favored-nation tariffs fall.

Cadot *et al.* (2014) identify four broad AfT categories that map directly onto the 19 OECD Creditor Reporting System (CRS) purpose codes used in this study: (1) technical assistance for trade policy and regulations, designed to build institutional capacity for WTO compliance and tariff administration; (2) trade-related infrastructure investment, primarily ports, roads, energy and communications, which reduces trade logistics costs; (3) productive capacity building in agriculture, banking, industry, mining and tourism, which strengthens the supply base for export goods; and (4) trade-related adjustment support, which compensates for preference erosion and terms-of-trade losses. Infrastructure consistently accounts for the largest share of disbursements, approximately 40–60% of total AfT flows, on the hypothesis that logistics cost reduction generates the most direct impact on export competitiveness.

Given these motivations for AfT, we hypothesize that

H1. AfT sent is positively associated with bilateral trade flows.

H2. AfT received is positively associated with bilateral trade flows.

These hypotheses are not novel in the literature, but results from models testing them have been mixed and thus warrant further investigation.

2.2 Empirical evidence on AfT and export performance

The empirical record on AfT effectiveness is broadly positive but exhibits important heterogeneity across recipient countries, aid categories and estimation approaches. Gravity model studies represent the dominant methodological tradition.

Cali and te Velde (2011) provide the most widely cited gravity model analysis, showing that a 10% increase in infrastructure AfT is associated with approximately 1.5% higher recipient exports, while trade policy and regulatory assistance show weaker and less consistent effects. Their identification strategy relies on cross-country variation in AfT composition, controlling for standard gravity determinants, including GDP, geographic distance, colonial history and common language. The result is robust across multiple subsamples and holds when instrumenting AfT using donor fixed effects, though the instrument strength is debated.

Pettersson and Johansson (2013) extend this analysis to the bilateral setting, finding positive effects of AfT on bilateral trade flows between specific donor–recipient pairs while noting sensitivity to model specification and the inclusion of recipient fixed effects. Their bilateral focus is methodologically close to the present study but stops short of modeling network-level dependencies between dyads.

Hühne *et al.* (2014) introduced a crucial asymmetry finding: AfT tends to enhance recipient exports to *third-country* markets rather than specifically to the donor country providing the aid. This suggests that AfT's trade-generating effects are diffuse and multilateral rather than concentrated on the bilateral donor–recipient channel. The authors interpret this as evidence that AfT improves general export capacity (logistics, customs and financial services) rather than creating preferential commercial ties with specific donors. This finding directly motivates the bilateral focus of the present study and raises the question of whether dyadic AfT coefficients in a directed network model capture something that the standard gravity approach misses.

Bearce *et al.* (2013) analyze US AfT allocations from 1999 to 2008 and confirmed positive export effects concentrated in sectors directly targeted by AfT investment, particularly infrastructure-intensive industries. Their identification exploits variation in US congressional appropriations cycles as a source of exogenous variation in AfT levels. Ghimire *et al.* (2016) provide a comprehensive review of the post-2006 AfT literature, confirming positive average effects while documenting important heterogeneity. Institutional quality in recipient countries emerges consistently as a moderator: AfT is most effective where recipient governments have adequate absorptive capacity to deploy aid productively. Disaggregation by AfT category remains essential as infrastructure AfT consistently outperforms trade policy assistance in generating export gains.

A critical limitation of the existing gravity model literature, noted by multiple authors, is the treatment of dyadic observations as statistically independent. Standard gravity models with dyadic-clustered standard errors account for within-dyad correlation across time but cannot model the dependence of one dyad on other dyads sharing a common node, precisely the structural property that makes international trade a network phenomenon rather than a collection of independent bilateral transactions.

2.3 Network approaches to international trade

The WTN has attracted growing attention from complex network scholars. Fagiolo *et al.* (2009) provide a systematic characterization of WTN topology using data from 1981 to 2000, documenting three key structural features: heterogeneous degree distributions following approximate power laws, high global clustering coefficients indicating triadic closure among core economies and a pronounced core–periphery organization in which a small set of highly interconnected hub countries account for a disproportionate share of world trade links. These structural properties are remarkably stable over time and across commodity classifications, suggesting that they reflect deep institutional and geographic forces rather than conjunctural trade patterns.

De Benedictis and Tajoli (2011) systematically survey the WTN literature, distinguishing between binary network analysis (whether a trade link exists) and weighted network analysis (the volume of trade flows). They show that the network's topology is highly unequal in both dimensions: core economies are deeply embedded in dense reciprocal networks, while peripheral economies maintain primarily vertical, asymmetric ties directed toward core importers. This asymmetry has direct implications for AfT research: if AfT donors are core economies and recipients are peripheral, any bilateral trade effects of AfT must overcome the structural tendency of peripheral countries toward sparse, nonreciprocal trade integration.

Wallerstein's world-systems theory (Wallerstein, 1974) provides the theoretical backdrop for this structural asymmetry. In the world-system framework, the global economy is organized hierarchically, with core economies connected by dense horizontal linkages and peripheral economies linked to the core primarily through vertical, extractive relationships. Aid flows, including AfT, may reinforce this hierarchy by increasing peripheral dependence on core donors, even while providing developmental benefits.

Smith and Sarabi (2022) apply the Exponential Random Graph Model (ERGM) to examine how core and periphery countries differ in their product-specific export and import patterns. Their key finding is that import patterns, rather than export patterns, most clearly distinguish product groups and reveal the hierarchical structure of global trade, suggesting that demand-side factors at the core drive the overall architecture of the WTN. For AfT researchers, this implies that donor countries' import absorption capacity may be a binding constraint on how much AfT-induced export capacity recipients can actually utilize.

Additional network approaches include studies of WTN resilience (Fagiolo *et al.*, 2009), community detection in trade networks (Barigozzi *et al.*, 2011) and the relationship between network centrality and economic development (Hidalgo and Hausmann, 2009). The common finding across these approaches is that network position, not just bilateral characteristics, is a fundamental determinant of trade performance, yet this dimension is absent from standard gravity model analyses of AfT.

Given these characteristics of the trade and AfT network, we further hypothesize that

H3. AfT flows are associated with positive transitivity in the bilateral trade network.

H4. AfT flows are associated with positive reciprocity effects, reflecting growing trade.

2.4 Statistical models for directed trade networks

Statistical modeling of directed relational data requires methods that explicitly account for the nonindependence of dyadic observations. Three families of models have been applied to international trade networks.

The first model family, Quadratic Assignment Procedure (QAP) regression (Krackhardt, 1988), corrects standard errors for dyadic dependence using permutation tests, providing a computationally simple robustness check for gravity model coefficients. However, QAP does not model structural network dependencies; it only corrects inference and cannot decompose outcomes into sender, receiver and latent clustering components, making it insufficient for estimating the structural relationships we are interested in.

The second family of models is the ERGMs, which treat the entire network adjacency matrix as the unit of analysis and model the probability of each configuration (edge, triad, k-star) as a function of network statistics (Smith and Sarabi, 2022). ERGMs excel at modeling binary tie formation and testing hypotheses about specific structural tendencies (transitivity, reciprocity, degree heterogeneity). However, ERGMs are computationally challenging for large weighted directed networks and do not readily incorporate continuous outcome variables such as log trade flows. The best option for making use of ERGMs in our case is count models, which require logging and rounding the values to whole numbers for convergence and computational feasibility (Schoeneman *et al.*, 2022). However, in addition to losing information from rounding, it is limited to assuming a Poisson reference distribution.

The AME model (Hoff *et al.*, 2002; Hoff, 2005) provides the most flexible framework for continuous directed relational outcomes, which we are interested in. The AME model decomposes the linear predictor for each dyadic outcome into additive row effects (sender heterogeneity), additive column effects (receiver heterogeneity) and a multiplicative bilinear term $u_i^T \Lambda u_j$ capturing latent clustering and homophily in the network. This decomposition allows the model to separate direct covariate effects, the AfT coefficients of primary interest, from unobserved network structure, preventing omitted-variable bias that would arise if latent clustering were absorbed into the coefficient estimates.

Furthermore, Ward *et al.* (2013) demonstrated that AME substantially outperforms standard gravity models in fitting bilateral trade data and in revealing latent structural features, including bloc-like regional clustering, that are not captured by observed covariates. The Bayesian Markov Chain Monte Carlo (MCMC) estimation framework produces full posterior distributions for all parameters, enabling credible interval (CI) inference that properly propagates estimation uncertainty. The AME model also includes estimates for the structural terms we are interested in, reciprocity and transitivity, making it comparable to ERGMs for testing the type of structural dependence.

2.5 Gaps in the literature and contributions of this study

Despite the methodological advances reviewed earlier, three significant gaps remain at the intersection of AfT research and network analysis.

First, the temporal scope of AME analyses has been limited. No existing study applies AME to the complete 2002–2021 AfT era, the period over which AfT disbursements grew fourfold and reached their contemporary scale.

Second, bilateral trade directionality has been underexplored. The present study models *both* directions simultaneously, donor-to-recipient exports (D2R) and recipient-to-donor exports (R2D), within a single directed network framework, capturing the full commercial relationship between donor and recipient.

Third, network-level structural statistics, transitivity and reciprocity, have not been systematically examined across the full AfT period. Whether AfT generates triadic closure (H3) or mutual trade reciprocity (H4) over time is an open empirical question with direct policy implications.

3. Data and methods

3.1 Data sources and sample

AfT disbursement data are drawn from the OECD-CRS, covering 19 purpose-code categories:

(1) Trade policy and regulations

(2) Economic infrastructure: transport, energy, communications

(3) Productive capacity building: agriculture, banking, industry, mining, tourism

(4) Trade-related adjustment support

Bilateral trade flows in both directions, D2R and R2D, are obtained from a harmonized bilateral trade database and merged with AfT data by donor, recipient and year. The merged data set covers 29 OECD donor countries and 150 developing-country recipients across 20 years (2002–2021), with the AME estimation sample covering 18 years (2004–2021) due to the two-year AfT lag, yielding 1,754–2,642 complete dyadic observations per estimation year.

Figure 1 provides an overview of AfT allocation across donors. Japan is the largest donor in the sample (USD 107.5 billion cumulative), followed by the United States (USD 48.7 billion) and Germany (USD 41.2 billion). Donor reach ranges from 146 countries (Japan) to 19 (Slovenia). The implications of this donor concentration for the structural findings reported below are discussed in Section 5. AfT values are lagged two years relative to the bilateral trade outcome variable, following Cali and te Velde (2011), to allow infrastructure investments time to materialize in trade outcomes. We adopt this two-year lag and verify that it is not consequential: estimating the model at lags of zero, one, two and three years yields AfT-sent coefficients stable across all four specifications (posterior means 0.210–0.216), each positive with posterior probability one. In-sample fit improves only marginally and monotonically with lag length (mean residual variance 0.887, 0.839, 0.823 and 0.817 for lags zero through three), so no single lag is clearly preferred on fit grounds; the two-year lag lies on the flat portion of this curve and matches the infrastructure-maturation rationale. Full results appear in Table 1.

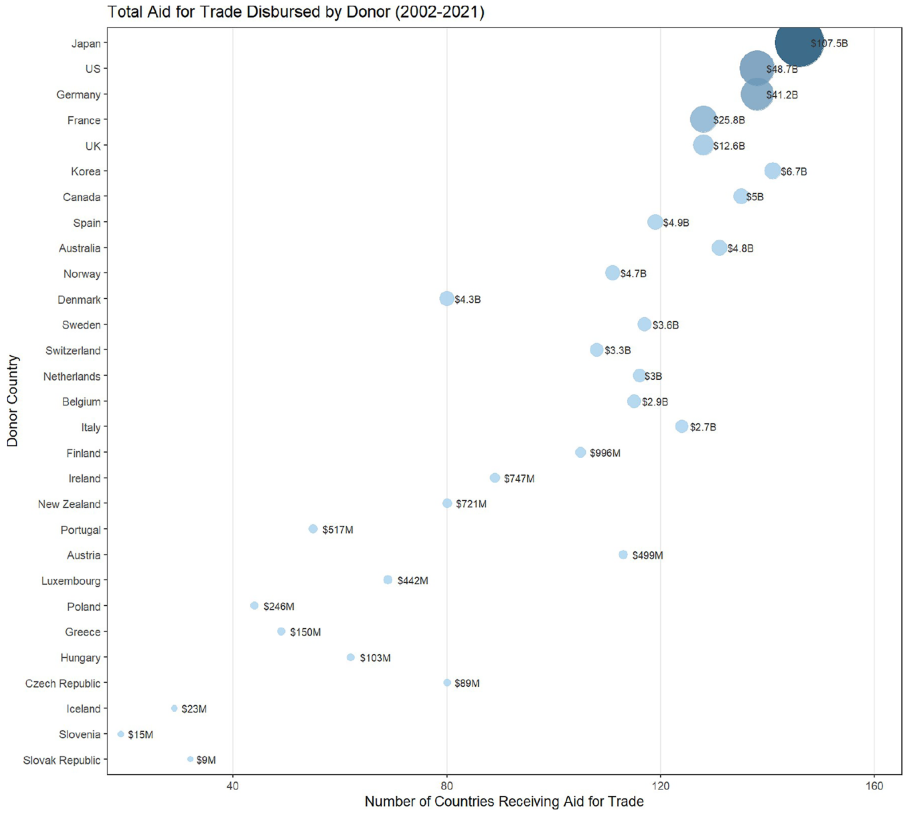

Figure 1. Total Aid for Trade (AfT) by donor country, 2002–2021. Bubble size and color represent total AfT disbursed (USD million). Japan dominates with USD 107.5 billion across 146 recipients

Table 1. Lag-selection check: AME re-estimated at AfT lags of zero to three years. Mean AfT-sent coefficient and mean residual variance across estimation years

Lag (years)	Mean AfT sent	Mean resid. Var
0	0.216	0.887
1	0.212	0.839
2	0.210	0.823
3	0.213	0.817

3.2 The AME network model

The AME model specifies the directed relational outcome y_{ij} (log bilateral trade from country i to country j) as

$$y_{ij} = x_{ij}^T\beta + a_i + b_j + u_i^T \Lambda u_j + \varepsilon_{ij} \tag{1}$$

where x_{ij} contains dyadic covariates (log lagged AfT sent, log lagged AfT received); β is the vector of regression coefficients; a_i and b_j are additive sender and receiver random effects capturing unobserved country-level heterogeneity in exporting and importing propensity, respectively; $u_i^T \Lambda u_j$ is a bilinear latent factor term with $K = 2$ dimensions capturing network clustering and homophily and ε_{ij} is residual error under a Gaussian family.

The outcome matrix Y is populated with log D2R exports at Y [donor, recipient] and log R2D exports at Y [recipient, donor], capturing the full directed bilateral trade relationship. The dyadic covariate array X_d encodes the AfT relationship: X_d $[i, j,$ AfT_sent] receives the log lagged AfT disbursed from donor i to recipient j, and X_d $[i, j,$ AfT_recv] receives the same value from the perspective of the recipient.

The model is estimated via MCMC using the amen package in R (Hoff *et al.*, 2002), with 50,000 iterations, a 10,000 burn-in and a thinning factor of 25, yielding 1,600 posterior draws per year. Models are estimated separately for each of the 18 cross-sectional years to allow network structure to evolve. Posterior means and 95% CIs are reported for all parameters of interest.

3.3 Network statistics

Empirical network statistics, global transitivity (clustering coefficient) and bilateral reciprocity, are computed annually using igraph (Csardi and Nepusz, 2006) on the directed bilateral trade network, providing structural context for the AME coefficient estimates independent of the MCMC estimation. In addition to binary reciprocity, we report the weighted reciprocity measure of Squartini *et al.* (2013) defined as the share of total trade volume matched by a counter flow, $r_w = \left\{\sum_{i \neq j} \min(w_{ij}, w_{ji})\right\} / \left\{\sum_{i \neq j} w_{ij}\right\}$, which better captures the flow asymmetry characteristic of donor–recipient relationships than does binary edge reciprocity.

Betweenness centrality identifies nodes that occupy structurally unique positions as brokers along the shortest paths connecting other pairs of countries in the network. In the AfT–trade context, brokerage has a specific theoretical meaning: a country with high betweenness sits on indirect channels through which aid and trade flows propagate across the system, rather than merely receiving or sending large volumes itself. This distinction matters because the world-systems perspective (Wallerstein, 1974) and the core–periphery network literature (De Benedictis and Tajoli, 2011; Smith and Sarabi, 2022) predict that structural position, not flow volume, determines whether a country can translate integration into durable trade advantages. If AfT were to reshape the structural architecture of the global trade network, we would expect AfT-intensive recipients to migrate toward brokerage positions over time. Conversely, if AfT operates primarily through bilateral donor–recipient channels without generating indirect network spillovers, betweenness rankings should remain dominated by established core economies regardless of AfT receipt. Betweenness is computed on a combined network incorporating AfT edges, D2R trade edges and R2D trade edges, enabling the identification of structural broker countries in the integrated AfT–trade system.

4. Results

4.1 Descriptive network properties

Figure 2 shows the hub network for Japan, the largest AfT donor and its top 20 recipients by AfT received. Orange edges represent D2R trade flows ,and green edges represent R2D trade flows. The bidirectionality of trade is evident for nearly all recipient nodes, confirming high empirical reciprocity. However, D2R flows generally exceed R2D flows, consistent with the structural trade asymmetry inherent in donor–recipient relationships.

4.2 AME dyad coefficients

Figure 3 displays the full time series of AfT dyad coefficients with 95% CI ribbons across all 18 estimation years. The full numerical results are presented in Table 2.

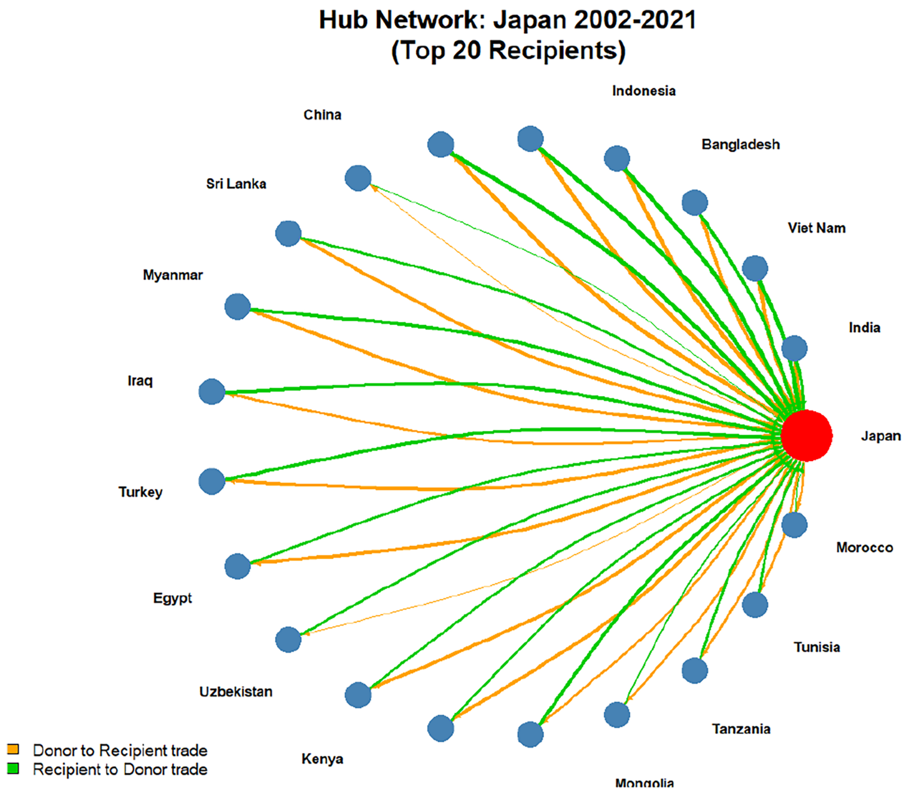

Figure 2. Hub network of Japan (largest AfT donor, 2002–2021) and its top 20 recipients by AfT received. Orange edges = donor-to-recipient trade; green edges = recipient-to-donor trade

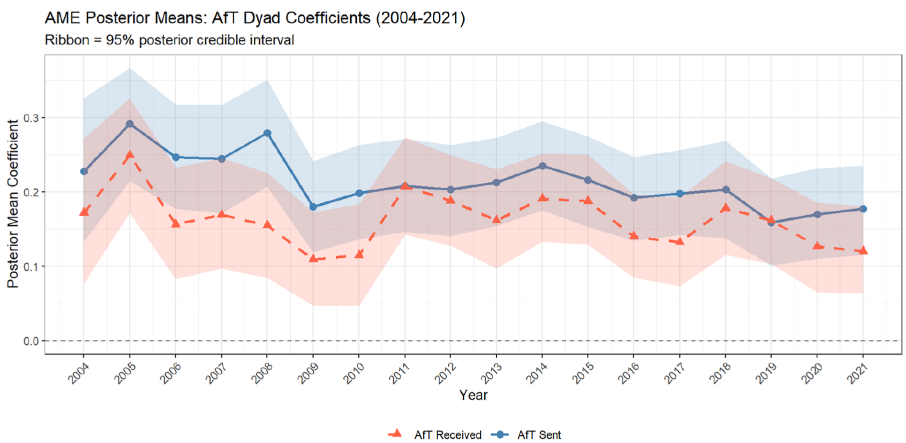

Figure 3. AME posterior means for AfT dyad coefficients, 2004–2021. Blue solid line and ribbon = AfT sent (mean and 95% CI); red dashed line and ribbon = AfT received (mean and 95% CI). All credible intervals exclude zero in every estimation year

Table 2. AME results: AfT dyad coefficients, 2004–2021 (18 estimation years)

Year	AfT sent Mean (95% CI)	AfT received Mean (95% CI)	Snd. Var	Rcv. Var	Res. Var	N
2004	0.228 (0.133, 0.326)	0.172 (0.077, 0.272)	3.37	2.56	0.80	1,754
2005	0.291 (0.215, 0.367)	0.249 (0.172, 0.325)	2.90	2.12	0.74	2,028
2006	0.247 (0.177, 0.318)	0.156 (0.083, 0.233)	2.80	1.80	0.74	2,096
2007	0.244 (0.171, 0.317)	0.169 (0.097, 0.245)	3.07	2.46	0.82	2,188
2008	0.279 (0.207, 0.350)	0.155 (0.084, 0.226)	2.57	1.59	0.90	2,554
2009	0.180 (0.119, 0.241)	0.109 (0.048, 0.172)	2.23	1.18	0.72	2,258
2010	0.199 (0.137, 0.263)	0.115 (0.047, 0.184)	2.58	1.25	0.85	2,616
2011	0.208 (0.146, 0.271)	0.207 (0.143, 0.273)	2.42	1.45	0.89	2,318
2012	0.203 (0.141, 0.263)	0.188 (0.127, 0.249)	2.98	1.76	0.94	2,642
2013	0.213 (0.154, 0.272)	0.162 (0.097, 0.231)	2.38	1.59	0.86	2,534
2014	0.235 (0.175, 0.295)	0.191 (0.133, 0.251)	1.92	1.39	0.83	2,484
2015	0.216 (0.153, 0.275)	0.187 (0.129, 0.250)	1.35	0.92	0.81	2,234
2016	0.193 (0.134, 0.247)	0.140 (0.085, 0.197)	1.89	1.45	0.77	2,374
2017	0.198 (0.142, 0.256)	0.132 (0.073, 0.192)	1.68	1.13	0.78	2,256
2018	0.203 (0.138, 0.268)	0.178 (0.115, 0.242)	1.40	0.97	0.82	2,386
2019	0.159 (0.101, 0.218)	0.162 (0.103, 0.218)	1.29	0.91	0.84	2,558
2020	0.170 (0.110, 0.232)	0.127 (0.065, 0.185)	1.38	0.94	0.87	2,346
2021	0.177 (0.116, 0.235)	0.120 (0.063, 0.181)	1.15	0.81	0.89	2,568

Note(s): $K = 2$; nscan = 50,000; burn = 10,000; odens = 25 (1,600 draws). $P(\beta > 0) = 1.00$ all years

AfT-sent coefficients ranged from 0.159 (2019) to 0.291 (2005), and AfT-received coefficients ranged from 0.109 (2009) to 0.249 (2005). The 95% posterior CIs exclude zero in *every* estimation year and the posterior probability that each coefficient exceeds zero is 1.00 throughout; not a single posterior draw was negative across the entire 2004–2021 estimation period. These findings provide unambiguous support for Hypotheses 1 and 2.

To isolate the contribution of the network structure, we estimate three nested specifications on the same sample: a Poisson pseudo-maximum likelihood (PPML) gravity baseline with standard controls (log GDP, GDP per capita, population and area), an additive-only AME with sender and receiver effects but no latent term ($K = 0$) and the full AME ($K = 2$). The AfT-sent association is positive throughout and attenuates as network structure is added.

Pooled coefficient is 0.349 under PPML, 0.262 in the additive-only AME and 0.213 in the full model. The decline indicates that part of what a gravity model attributes to AfT is absorbed, in the network model, by the sender, receiver and latent-clustering structure; the AfT effect nonetheless remains positive and well separated from zero once that structure is modeled. This is the dimension on which the gravity baseline is silent, and it is the substantive value added using the network approach. Full results appear in Table 3.

Both coefficients are broadly stable across the period, fluctuating in the range 0.15–0.30 (sent) and 0.12–0.27 (received), with a pronounced dip in 2009 coinciding with the global financial crisis disruption to AfT delivery pipelines, and recovery thereafter. The stability of

Table 3. Incremental contribution of the network model: pooled AfT-sent coefficient under a PPML gravity baseline, an additive-only AME ($K = 0$) and the full AME ($K = 2$)

Specification	AfT-sent coefficient
PPML gravity	0.349
Additive-only AME ($K = 0$)	0.262
Full AME ($K = 2$)	0.213

the coefficients across 18 estimation years indicates that the bilateral AfT–trade relationship is structural rather than driven by any single episode.

The elasticity interpretation is important. Because both the outcome (log bilateral trade) and the covariate (log lagged AfT) are in log scale, the average coefficient $\hat{\beta} \approx 0.21$ implies that a 1% increase in AfT is associated with approximately 0.21% higher bilateral trade. In this sample, average bilateral trade flows are approximately 74 times larger than average AfT disbursements per dyad (USD 738 million versus USD 9.9 million), yielding a return ratio of approximately $0.21 \times 74 \approx 15$ dollars of bilateral trade per dollar of AfT invested. Reported as a range to reflect variation in the coefficient across years (0.159–0.291), this implies an illustrative back-of-envelope figure of roughly 11–22 dollars of bilateral trade associated with each dollar of AfT. We stress that this is a descriptive scaling of a conditional association, not an estimate of the trade generated by an additional dollar of AfT, and it should not be read as a causal multiplier.

Sender and receiver variance components are small and stable (sender: 1.15–3.37; receiver: 0.81–2.56), with residual variance ranging from 0.72 to 0.94. These node-level components capture substantial unobserved donor- and recipient-side heterogeneity in trade propensity, which the AME model estimates jointly with the AfT dyad coefficients rather than absorbing into them. The 2009 trough in both coefficients coincides with the global financial crisis disruption to AfT delivery pipelines, while the progressive decline from 2004 onward suggests diminishing marginal returns as AfT programs mature.

4.3 Network statistics: transitivity and reciprocity

Figure 4 presents two complementary network statistics across the full 2002–2021 period. Binary reciprocity under the log (trade $+1$) specification is 1.000 in every year, a mechanical consequence of retaining all dyads (a pair with zero exports in one direction still contributes $\log(0+1) = 0$, treated as a present edge). To address this artifact, we additionally computed the weighted reciprocity measure of Squartini *et al.* (2013) defined as the share of total trade volume matched by a counter-flow. Weighted reciprocity averages 0.68 across the period (range: 0.64–0.73), with a visible dip during 2006–2008 and again in 2020, revealing that 27–36% of bilateral trade volume is *not* matched by a reverse flow. Global transitivity is exactly

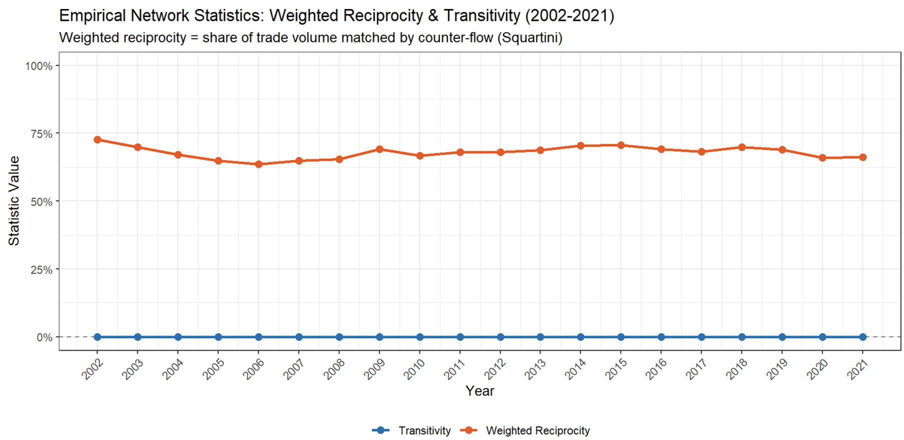

Figure 4. Empirical network statistics: weighted reciprocity (Squartini *et al.*, 2013) and global transitivity, 2002–2021. Weighted reciprocity (orange) ranges from 0.64–0.73, indicating that 27–36% of bilateral trade volume is not matched by a counter flow, with a pronounced dip during the 2008–2009 global financial crisis. Global transitivity (blue) is zero throughout, reflecting the bipartite donor–recipient structure of the network

zero throughout the sample, indicating that no triangular trade relationships exist in this donor–recipient directed network. Full numerical values are provided in Table 4.

Global transitivity is identically zero in every year. This is a structural property of the bipartite donor–recipient network rather than a substantive result: the network contains only D2R and R2D edges, so no triangles can form and the clustering coefficient is zero by construction. Hypothesis 3, which concerns triadic closure, therefore cannot be tested within this design, and we do not interpret the zero as evidence about whether AfT promotes structural integration. Assessing closure directly would require an expanded network incorporating recipient-to-recipient (South–South) and donor-to-donor trade, which the present data set does not contain; we leave this to future work. Hypothesis 4 is likewise not directly testable here, though for a different reason: reciprocity is a property of the empirical trade network rather than a coefficient of AfT, and the weighted measure shows persistent structural asymmetry with no AfT-linked trend.

4.4 Network centrality

Figure 5 shows betweenness centrality for the combined AfT and bilateral trade network. Iraq and Afghanistan rank highest among recipients, reflecting concentrated AfT flows from multiple donors that create bridge paths in the network. The dominance of post-conflict and fragile states among high-betweenness recipients supports the interpretation that AfT allocation follows political and diplomatic logics rather than commercial integration objectives.

A notable finding is that New Zealand and Norway exhibit disproportionate betweenness centrality relative to their total AfT volume, substantially outranking much larger donors such as the United States and Japan. This counterintuitive result reflects a fundamental property of

Table 4. Empirical network statistics: binary reciprocity, weight reciprocity (Squartini), transitivity and edge count, 2002–2021. All dyads retained via log (trade +1) transformation

Year	Bin. Recip	Wtd. Recip	Transitivity	*N* edges
2002	1.000	0.727	0.000	2,242
2003	1.000	0.698	0.000	2,518
2004	1.000	0.670	0.000	2,434
2005	1.000	0.648	0.000	2,538
2006	1.000	0.636	0.000	2,946
2007	1.000	0.650	0.000	2,974
2008	1.000	0.655	0.000	3,088
2009	1.000	0.691	0.000	2,764
2010	1.000	0.668	0.000	3,182
2011	1.000	0.680	0.000	3,214
2012	1.000	0.680	0.000	3,144
2013	1.000	0.687	0.000	2,970
2014	1.000	0.704	0.000	2,934
2015	1.000	0.707	0.000	2,672
2016	1.000	0.691	0.000	2,966
2017	1.000	0.681	0.000	3,154
2018	1.000	0.699	0.000	3,042
2019	1.000	0.689	0.000	3,056
2020	1.000	0.660	0.000	2,808
2021	1.000	0.661	0.000	3,070

Note(s): Binary reciprocity = 1.000 reflects the log (trade +1) retention of all dyads. Weighted reciprocity (Squartini *et al.*, 2013) measures the share of bilateral trade volume matched by a counter-flow and reveals persistent structural asymmetry (0.64–0.73). Transitivity = 0.000 every year reflects the bipartite donor–recipient structure of the network. Computed using igraph Csardi and Nepusz (2006)

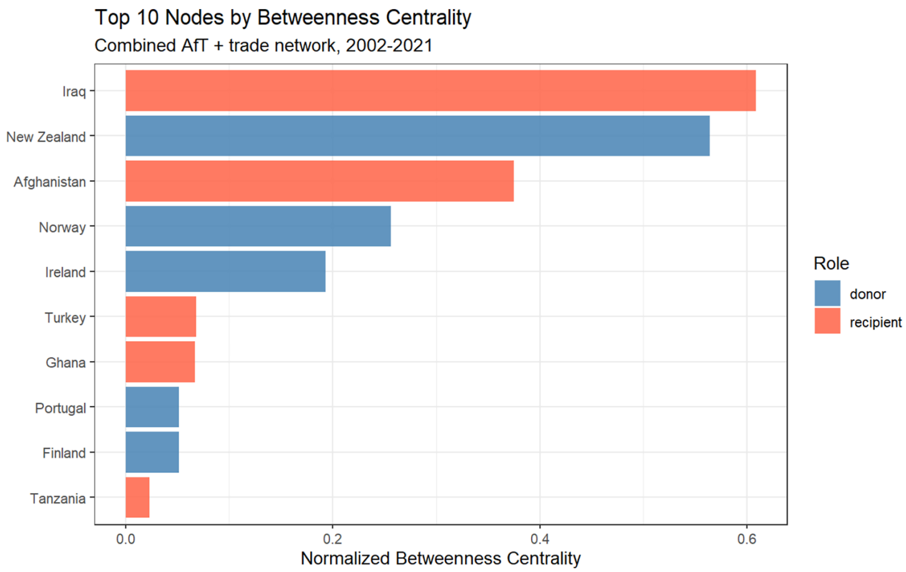

Figure 5. Top 10 nodes by normalized betweenness centrality in the combined AfT and bilateral trade network (pooled, 2002–2021). Blue = donor countries; orange = recipient countries. Iraq and Afghanistan dominate among recipients, and New Zealand and Norway dominate among donors

betweenness centrality: it rewards structural uniqueness, not volume. The United States and Japan each disburse AfT to over 130 recipient countries, creating dense but highly redundant connections. By contrast, New Zealand concentrates its AfT program on Pacific Island nations (Fiji, Samoa, Tonga, the Solomon Islands and Papua New Guinea), which receive aid from very few other donors. New Zealand is therefore the primary or sole pathway connecting these island states to the broader AfT and trade network, generating high betweenness despite modest total disbursements. Norway similarly focuses on a targeted group of fragile African states whose limited integration into the donor network makes Norway a uniquely important structural link.

This pattern has direct policy implications. The high betweenness of small, geographically focused donors suggests that concentrated programs serving underrepresented recipient groups generate greater structural integration value than broad programs that duplicate connections already provided by large donors.

4.5 Robustness check: first-difference model

To assess whether the positive level results reflect genuine AfT effects or spurious co-trending between AfT disbursements and trade volumes over time, we re-estimated the AME model using first differences of both the dependent and independent variables (ΔTrade as the dependent variable (DV); lagged ΔAfT as regressor). The robustness estimates use reduced MCMC draws (nscan = 10,000) given computational constraints. Figure 6 presents the delta-model coefficients for AfT sent and AfT received across all estimation years, in a layout mirroring Figure 3 to facilitate direct comparison.

The log-difference specification yields coefficients that oscillate closely around zero throughout, with most 95% credible intervals spanning zero. This volatility reflects a fundamental characteristic of AfT disbursements: they are lumpy and concentrated in large multiyear infrastructure projects rather than smooth annual flows, making year-to-year differencing an inappropriate transformation for capturing their trade effects. AfT operates

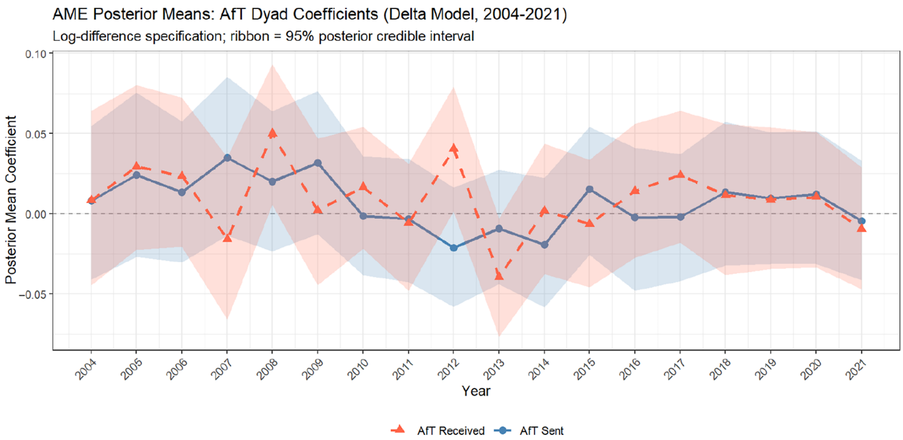

Figure 6. AME posterior means for AfT dyad coefficients under the log-difference (delta) specification, 2004–2021. Blue solid line and ribbon = AfT sent (mean and 95% CI); red dashed line and ribbon = AfT received (mean and 95% CI). Coefficients oscillate around zero, consistent with AfT operating through long-run structural channels rather than year-to-year variation

through long-run structural changes in trade capacity, precisely the variation that first-differencing removes. We therefore treat the first-difference result as inconclusive rather than as confirmation of the levels estimates. To test the long-run channel directly, we estimate specifications using three- and five-year cumulative AfT in place of the two-year lag; these recover positive AfT-sent associations of the same sign as the levels model (posterior means 0.196 and 0.194, respectively), which is the evidence on which we rest the long-run interpretation (Table 5).

We also assess sensitivity to the treatment of zero-trade dyads under the log (trade +1) outcome. Re-estimating the model with an inverse hyperbolic sine transform, which is defined at zero without an additive constant and separately on the subsample of strictly positive flows, leaves the AfT-sent and AfT-received coefficients essentially unchanged in sign, significance and magnitude (Table 6). We therefore retain the Gaussian AME on the log (trade+1) outcome as a transparent and robust choice.

Table 5. Cumulative (stock) AfT: mean AfT coefficients using three- and five-year cumulative disbursements in place of the two-year lag

Specification	Mean AfT sent	Mean AfT recv
3-year cumulative AfT	0.196	0.150
5-year cumulative AfT	0.194	0.154

Table 6. Zero-handling sensitivity: mean AfT coefficients under alternative zero-trade dyad treatments

Outcome transform	Mean AfT sent	Mean AfT recv
log(trade +1), all dyads	0.210	0.163
Inverse hyperbolic sine	0.216	0.173

Finally, we run a placebo specification in which current bilateral trade is regressed on a two-year *lead* of AfT rather than a lag. Future aid cannot cause current trade, so a coefficient near zero would support a causal reading. Instead, the placebo AfT-sent coefficient is 0.200, close to the contemporaneous lagged estimate (0.213). This indicates that much of the measured association is carried by persistent, time-invariant features of donor–recipient pairs rather than by aid generating subsequent trade, and it reinforces our interpretation of the estimates as conditional associations rather than causal effects. A design capable of isolating the causal component, such as an instrument for AfT supply, remains an important direction for future work (Table 7).

5. Discussion

The consistently positive AfT coefficients across the full 2002–2021 period substantially strengthen prior evidence from shorter estimation windows. The descriptive scaling of 11–22 dollars of bilateral trade per dollar of AfT is sizable, but we read it as a conditional association rather than a causal multiplier. The placebo-lead specification (Table 7) returns an AfT-sent coefficient close to the contemporaneous estimate, indicating that much of the measured relationship is carried out by persistent, time-invariant features of donor–recipient pairs rather than by aid generating subsequent trade. The figure should therefore be read as a descriptive return ratio and not as the trade created by an additional dollar of AfT.

Two mechanisms can generate a positive AfT-sent coefficient. The first is capacity-building: AfT improves recipient infrastructure, logistics and trade facilitation, raising trade in both directions. The second is procurement-induced: where AfT finances equipment, construction or consulting services supplied by donor-country firms, part of the measured donor-to-recipient trade is the direct counterpart of the aid disbursement rather than an improvement in recipient capacity. To probe these channels, we disaggregate AfT into its major OECD-CRS purpose categories and re-estimate. The AfT-sent association is of similar magnitude across categories rather than concentrated in any one: the posterior mean is 0.207 for productive-capacity AfT, 0.201 for trade policy and regulation and 0.173 for trade-related infrastructure, all positive with credible intervals excluding zero. Notably, the effect is *not* larger for infrastructure, the category most exposed to donor-side procurement; if procurement-induced exports were the dominant driver, we would expect infrastructure to stand out and it does not. The broadly uniform association across purpose codes is more consistent with a general capacity-building and trade-facilitation channel than with procurement-driven exports concentrated in donor-financed infrastructure, though we retain procurement as a partial contributor and caution against reading the aggregate effect as a pure measure of recipient capacity gains (Table 8).

Several structural features of the network point to a donor-side political economy rather than a commercial-integration logic behind AfT allocation. The betweenness results (Section 4.4) show that high-centrality recipients are dominated by post-conflict and fragile states such as Iraq and Afghanistan and that small, geographically concentrated donors such as New Zealand and Norway outrank far larger ones – patterns more consistent with diplomatic and

Table 7. Placebo-lead test: regressing current trade on a two-year lead of AfT. A near-zero coefficient would support a causal reading; the placebo is close to the baseline lagged estimate

Specification	Mean AfT sent	Mean AfT recv
Placebo (2-year AfT lead)	0.200	0.161
Baseline (2-year AfT lag)	0.213	0.160

Table 8. Purpose-code disaggregation: mean AfT coefficients with AfT split into major OECD-CRS categories

AfT category	Mean AfT sent	Mean AfT recv
Productive capacity	0.207	0.191
Trade policy and regulation	0.201	0.241
Trade-related infrastructure	0.173	0.131

strategic allocation than with commercial-integration objectives. This structural result is consistent with a long-standing literature characterizing major donors' motivations as strategic and diplomatic rather than integrationist. Japan, the dominant donor in our sample with cumulative disbursements of USD 107.5 billion, has been documented as using official development assistance to establish regional hegemony and international credibility rather than to build reciprocal commercial interdependence with recipients (Lancaster, 2007). Alesina and Dollar (2000) generalize this pattern across DAC donors: aid allocation reflects diplomatic and political-economy considerations at least as strongly as recipient development need. Miyashita (1999) further documents the reactive-proactive dynamic in Japanese aid, showing that domestic political pressure rather than recipient integration drives allocation patterns. If AfT is deployed primarily for geopolitical positioning rather than for embedding recipients in donor-anchored trade networks, the persistent reciprocity asymmetry we document, with roughly a quarter to a third of bilateral trade volume unmatched by a counter-flow, is a predictable consequence of donor-side political economy rather than a failure of AfT execution.

This donor-side logic is compounded by constraints on the recipient side. Because AfT flows disproportionately toward the world's poorest and most structurally peripheral countries, nations with weak institutional capacity, limited productive diversification and thin domestic financial markets, recipients lack the complementary capabilities needed to parlay bilateral donor relationships into broader multilateral trade integration. They may increase bilateral exports to specific donors without becoming more deeply embedded in the multilateral trading networks that underpin long-run export diversification. Whether AfT as currently designed mitigates or inadvertently reinforces the core–periphery divide it seeks to overcome is a question our bipartite donor–recipient data cannot resolve: the recipient-to-recipient (South–South) and donor-to-donor ties that would reveal such integration are absent from the network by construction, and triadic closure is therefore not observable in this design. Testing this directly would require an expanded network incorporating South–South trade, which we leave to future work. The conjecture is at least consistent with the world-system perspective (Wallerstein, 1974) and with De Benedictis and Tajoli's (2011) documentation of the persistent core–periphery architecture of global trade. Addressing the underlying limitation may require complementary policies that build intraregional trade linkages among recipient countries themselves, rather than relying solely on bilateral donor–recipient channels.

The high reciprocity finding requires careful interpretation. The perfect (1.000) reciprocity under the log (trade+1) specification does not indicate balanced bilateral trade: D2R flows (donor exports to recipients) generally exceed R2D flows (recipient exports to donors), as shown in Figure 2. The weighted reciprocity measure of Squartini *et al.* (2013) which accounts for flow magnitude rather than edge presence, confirms persistent structural asymmetry: across 2002–2021, only 64–73% of bilateral trade volume is matched by a counter flow, with no trend toward convergence and a pronounced dip during the 2008–2009 global financial crisis. Binary reciprocity therefore reflects structural network density rather than AfT-induced commercial interdependence. The AME model's decomposition of outcomes into sender and receiver random effects reinforces this interpretation: sender variance components (1.15–3.37) confirm that unobserved donor-side heterogeneity is a meaningful structural determinant of bilateral trade volumes alongside the AfT relationship itself.

From a policy perspective, AfT effectiveness evaluation should move beyond aggregate recipient export growth to assess structural network embeddedness: whether recipients are building reciprocal and diversified relationships with a broad range of partners, including other developing countries. South–South and regional trade channels, which are absent from the donor–recipient dyadic data set, may be more important pathways for developing country trade integration than the bilateral AfT channel.

Limitations. First, the AME model is estimated on independent annual cross sections rather than a dynamic panel, precluding direct causal inference about network evolution. Second, potential endogeneity in AfT allocation is not addressed; instrumental variable approaches exploiting exogenous variation in donor budgets would strengthen causal identification. Third, the purpose-code analysis (Table 8) estimates broad OECD-CRS categories in separate models; a fully joint AME with category-specific dyad covariates remains for future work. Fourth, recipient-to-recipient (South–South) trade flows are absent from the data set, limiting the assessment of AfT's indirect integration effects. Fifth, the MCMC goodness-of-fit statistics for transitivity and cycle dyad were not computed by the amen package for networks of this size; empirical igraph statistics were used instead (Csardi and Nepusz, 2006). Sixth, the first-difference robustness specification suggests that AfT effects are long-run in nature; future work employing error-correction models may better capture both short- and long-run dynamics simultaneously.

6. Conclusion

This paper applied the AME network model to the complete 2002–2021 AfT era, analyzing a directed network of 29 donors and 150 recipients with bilateral trade captured in both directions. Three principal findings emerge. First, AfT dyad coefficients are consistently positive (0.159–0.291 for AfT sent; 0.109–0.249 for AfT received) with posterior probabilities of 1.00 across all 18 estimation years, providing strong evidence that AfT is positively associated with bilateral trade in both directions; the corresponding descriptive scaling is roughly 11–22 dollars of bilateral trade per dollar of AfT, which we interpret as a conditional association rather than a causal multiplier. Second, global transitivity is zero throughout the sample by construction: the bipartite donor–recipient network admits no triangles, so the design cannot test whether AfT fosters triadic closure or broader structural integration, and we do not interpret the zero substantively. Third, weighted reciprocity ranges from 0.64 to 0.73, revealing that over a quarter of bilateral trade volume is not matched by a counter-flow and reflecting the persistent structural asymmetry of donor–recipient commercial relationships rather than AfT-induced commercial interdependence.

The AME framework proved essential for revealing these structural features, which are invisible to standard gravity model analysis. Future research should apply the dynamic AME model (Ward *et al.*, 2013) to examine network evolution, disaggregate AfT by purpose code within the AME framework and incorporate South–South trade flows to assess whether regional channels provide the structural integration this bipartite donor–recipient design cannot observe.

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