Supplementary Information

Trade networks multiply the global health returns to bilateral aid

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Contents

1 Theoretical Model

This section presents the formal model connecting bilateral aid, knowledge capital accumulation, trade-network diffusion, and health outcomes. The model assembles established components from several literatures: the knowledge accumulation equation follows the international R&D spillovers framework of Coe and Helpman, 1995, where a country's stock depends on its own inputs plus a trade-weighted sum of partners' stocks; the network multiplier is a Leontief inverse applied to a spatial network, as in Acemoglu et al., 2012; the strategy of deriving a spatial autoregressive estimating equation from a structural model with network spillovers follows Ertur and Koch, 2007; the diminishing-returns mechanism draws on absorptive capacity theory (Cohen and Levinthal, 1990; Nelson and Phelps, 1966); and the direct/indirect effect decomposition follows LeSage and Pace, 2009. The contribution is combining these components to generate distinctive predictions about aid effectiveness conditional on network position.

1.1 Health production function

Country i's health outcome H_i depends on direct aid inputs A_i and the accumulated knowledge capital stock K_i:

$$H_i = \alpha_0 A_i + \beta K_i - \alpha_1 A_i K_i + \varepsilon_i \tag{1}$$

where $\alpha_0 > 0$ captures the direct effect of aid spending (e.g., antiretroviral distribution, clinic construction), $\beta > 0$ captures the productivity of knowledge capital (e.g., testing protocols, prevention strategies), and $\alpha_1 > 0$ generates diminishing returns: countries with high knowledge stocks gain less from each additional dollar of direct aid, because the knowledge that aid generates is redundant with what the country has already absorbed (Cohen and Levinthal, 1990).

1.2 Knowledge dynamics

Knowledge capital evolves according to the law of motion:

$$K_{it} = (1-\rho)K_{i,t-1} + \gamma A_{it} + \delta \sum_j w_{ij} K_{j,t-1} \tag{2}$$

where $\rho \in (0,1)$ is the depreciation rate, $\gamma > 0$ is the rate at which aid generates new knowledge, $\delta > 0$ is the diffusion rate through trade networks, and w_{ij} is the row-standardised trade weight between countries i and j.

Three processes drive knowledge accumulation: (i) domestic generation through aid-funded programmes (γA_{it}); (ii) absorption from trading partners ($\delta \sum_j w_{ij} K_{j,t-1}$), following the trade-weighted spillover structure of Coe and Helpman, 1995 and Keller, 2004; and (iii) depreciation as knowledge becomes obsolete or personnel turn over ($(1-\rho)K_{i,t-1}$).

1.3 Steady-state solution

Setting $K_{it} = K_{i,t-1} = K_i$ and $A_{it} = A_i$ in Equation 2:

$$\begin{aligned} \rho K_i &= \gamma A_i + \delta \sum_j w_{ij} K_j \\ (\rho \mathbf{I} - \delta \mathbf{W})\mathbf{K} &= \gamma \mathbf{A} \\ \mathbf{K} &= \frac{\gamma}{\rho}\left(\mathbf{I} - \frac{\delta}{\rho}\mathbf{W}\right)^{-1} \mathbf{A} \equiv \tilde{\gamma}\, M\, \mathbf{A} \end{aligned} \tag{3}$$

where we define compound parameters $\tilde{\gamma} \equiv \gamma/\rho$ (depreciation-adjusted production rate), $\tilde{\delta} \equiv \delta/\rho$ (depreciation-adjusted diffusion rate), and the **network multiplier matrix** $M \equiv (\mathbf{I} - \tilde{\delta}\mathbf{W})^{-1}$.

The matrix M has the power-series representation:

$$M = \mathbf{I} + \tilde{\delta}\mathbf{W} + \tilde{\delta}^2\mathbf{W}^2 + \tilde{\delta}^3\mathbf{W}^3 + \cdots \tag{4}$$

which converges provided $\tilde{\delta} < 1/\lambda_{\max}(\mathbf{W})$. This Leontief inverse structure appears throughout input-output economics and network models of aggregate fluctuations (Acemoglu et al., 2012). Each term captures a higher order of network propagation: $\tilde{\delta}\mathbf{W}$ is the direct diffusion from first-order trade partners; $\tilde{\delta}^2\mathbf{W}^2$ is diffusion from second-order partners (partners of partners); and so on. The entry M_{ij} gives the total steady-state knowledge that country i absorbs per unit of aid to country j, summing across all network paths. Lumenga-Neso, Olarreaga, and Schiff, 2005 show that such indirect trade-related spillovers can be quantitatively important even when direct bilateral links are weak.

1.4 Reduced-form health outcomes

Substituting Equation 3 into Equation 1:

$$\mathbf{H} = \alpha_0 \mathbf{A} + \beta\tilde{\gamma}\, M\, \mathbf{A} - \alpha_1\tilde{\gamma}\, \mathbf{A} \odot (M\, \mathbf{A}) + \boldsymbol{\varepsilon} \tag{5}$$

where $\odot$ denotes the elementwise (Hadamard) product. Country i's health outcome depends on its own aid ($\alpha_0 A_i$), the network-weighted knowledge generated by all countries' aid ($\beta\tilde{\gamma}(M\mathbf{A})_i$), and the interaction between own aid and accumulated network knowledge ($-\alpha_1\tilde{\gamma}A_i(M\mathbf{A})_i$), which generates diminishing returns.

1.5 Total marginal effects (Jacobian)

Differentiating Equation 5 with respect to the aid vector:

$$\frac{\partial \mathbf{H}}{\partial \mathbf{A}} = \alpha_0\,\mathbf{I} + \beta\tilde{\gamma}\,M - \alpha_1\tilde{\gamma}\ \mathrm{diag}(M\mathbf{A}) - \alpha_1\tilde{\gamma}\ \mathrm{diag}(\mathbf{A})\,M \tag{6}$$

The four terms have distinct economic interpretations:

1. $\alpha_0\,\mathbf{I}$: Direct aid effectiveness (diagonal only — own aid affects own health).
2. $\beta\tilde{\gamma}\,M$: Knowledge productivity channelled through the trade network (both diagonal and off-diagonal — own and partner aid generate useful knowledge).
3. $-\alpha_1\tilde{\gamma}\ \mathrm{diag}(M\mathbf{A})$: Diminishing returns from accumulated network knowledge (diagonal only — high knowledge stocks reduce the marginal return to own aid).
4. $-\alpha_1\tilde{\gamma}\ \mathrm{diag}(\mathbf{A})\,M$: Cross-modulation (both diagonal and off-diagonal — own aid level modulates how much benefit is received from partner knowledge spillovers).

1.6 Hypotheses

The Jacobian generates four testable predictions:

Hypothesis 1 (Direct effectiveness)**.** *PEPFAR aid reduces HIV incidence in recipient countries:*

$$\frac{\partial H_i}{\partial A_i} = \alpha_0 + \beta\tilde{\gamma}\,M_{ii} - \alpha_1\tilde{\gamma}(M\mathbf{A})_i - \alpha_1\tilde{\gamma}\,A_i\,M_{ii} > 0 \tag{7}$$

This holds when the direct benefit ($\alpha_0 + \beta\tilde{\gamma}M_{ii}$) exceeds the diminishing-returns drag, which is satisfied for empirically relevant parameter values.

Hypothesis 2 (Conditional effectiveness)**.** *PEPFAR's direct effect diminishes with trade integration:*

$$\frac{\partial^2 H_i}{\partial A_i\,\partial E_i} < 0 \tag{8}$$

where $E_i = (\mathbf{W}\mathbf{A})_i$ is country i's trade-weighted exposure to PEPFAR-funded partners. Higher exposure raises $(M\mathbf{A})_i$, which increases the diminishing-returns terms in the direct effect. Countries already embedded in the PEPFAR network through trade have absorbed much of the knowledge that additional aid would generate.

Hypothesis 3 (Cross-border spillovers)**.** *Aid to country j improves health outcomes in trade-connected country $i \neq j$:*

$$\frac{\partial H_i}{\partial A_j} = \tilde{\gamma}\, M_{ij}(\beta - \alpha_1 A_i) > 0 \qquad (i \neq j) \tag{9}$$

The spillover is proportional to the network multiplier entry M_{ij} (trade-network proximity) and is positive provided $\beta > \alpha_1 A_i$. For non-recipient countries ($A_i = 0$), this simplifies to $\beta\tilde{\gamma}\, M_{ij} > 0$: non-recipients receive unambiguously positive spillovers proportional to their trade connectivity to aid recipients.

Hypothesis 4 (Trade-mediated diffusion)**.** *Countries more exposed to PEPFAR-supported partners through trade exhibit greater health improvements, even absent direct aid. The off-diagonal Jacobian elements establish that $\partial H_i/\partial A_j > 0$ for trade-connected partners. Because network exposure $E_i = (\mathbf{WA})_i$ aggregates these partner-aid effects weighted by trade intensity, countries with higher E_i should experience larger indirect health gains. For non-recipients:*

$$\sum_{j \neq i} \frac{\partial H_i}{\partial A_j} = \beta\tilde{\gamma} \sum_{j \neq i} M_{ij} > 0 \tag{10}$$

which is increasing in the density and strength of trade connections to aid recipients.

1.7 Mapping theory to estimation

The theoretical model motivates the empirical specifications in the Methods section, following the strategy of Ertur and Koch, 2007, who derive a spatial autoregressive estimating equation from a structural growth model with technology spillovers through trade. The spatial autoregressive parameter ρ in the SAR/SDM specifications operationalises the prediction that trade networks generate spatial interdependence in health outcomes. However, ρ is a *reduced-form* parameter that captures all trade-correlated spatial processes, not only PEPFAR-specific knowledge diffusion. The SLX coefficient θ on $W \times$ PEPFAR provides a more direct test of Hypothesis 3: it measures whether trading partners' aid *inputs* predict own-country outcomes, isolating the spillover channel from generic spatial dependence.

The compound parameters $\tilde{\gamma}$ and $\tilde{\delta}$ are not separately identified from the data. The empirical estimates recover ρ (the spatial autoregressive parameter, which is a function of $\tilde{\delta}$ and the network structure), β_{PEPFAR} (a reduced-form combination of α_0, β, $\tilde{\gamma}$, and α_1), and θ (a reduced-form combination of β, $\tilde{\gamma}$, and M_{ij}). The theoretical model provides the structural interpretation; the empirical models provide the causal evidence.

2 Data Construction

2.1 Sample

The analysis sample comprises 175 countries observed annually from 2004 (the first year of PEPFAR disbursements) to 2018, yielding $N \times T = 2{,}634$ country-year observations after dropping units with missing covariates or no representation in the spatial weights matrices. Of these, 45 countries received PEPFAR funding in at least one year; 31 were active recipients in 2017, the year used for cross-sectional counterfactual calculations.

2.2 HIV incidence

Annual HIV incidence rates per 100,000 population are drawn from the Institute for Health Metrics and Evaluation (IHME) Global Burden of Disease (GBD) Study (Carter et al., 2024). These are modelled estimates derived from vital registration, surveillance, survey, and census data using the Cause of Death Ensemble model (CODEm). The primary dependent variable is the first difference $\Delta y_{it} = y_{it} - y_{i,t-1}$, which captures within-country trajectory changes.

Limitation. IHME estimates are modelled, not directly observed. Country-level precision varies with the quality and availability of input data. Our credible intervals reflect parameter uncertainty but not the additional measurement uncertainty in the dependent variable.

2.3 PEPFAR disbursements

Per capita PEPFAR funding is measured using the OECD Creditor Reporting System (CRS), filtering for:

- Donor: United States
- Purpose code: 130.60 (STD control including HIV/AIDS)
- Flow type: Disbursements (not commitments)
- Deflator: Constant 2020 USD

Per capita values are computed by dividing total disbursements by UN population estimates. The median allocation among recipient country-years with positive PEPFAR funding is \$2.90 per capita. The distribution is right-skewed: the 75th percentile is \$8.25 and the maximum is \$47.43 (Namibia, 2012).

2.4 Trade integration

For each country-year, we compute:

$$\text{TradePEPFAR}_{it} = \frac{\sum_{j \in \text{PEPFAR}_t} (\text{Imports}_{ijt} + \text{Exports}_{ijt})}{\sum_k (\text{Imports}_{ikt} + \text{Exports}_{ikt})} \tag{11}$$

where PEPFAR_t is the set of PEPFAR recipient countries in year t. This variable measures the share of country i's total trade conducted with PEPFAR recipients. The sample mean is 16.1% (SD = 19.4%), ranging from 0% (countries with no trade with PEPFAR recipients) to 98.9%.

2.5 Spatial weight matrices

Three $N \times N$ weight matrices are constructed for each year:

Trade weights (W_{trade}). Bilateral trade volumes (imports + exports) from UN Comtrade. Entry $w_{ij}^{\text{trade}} = (\text{Trade}_{ij})/(\sum_k \text{Trade}_{ik})$ after row standardisation. Time-varying.

Distance weights (W_{distance}). Inverse great-circle distance between country centroids from CEPII. Entry $w_{ij}^{\text{dist}} = (1/d_{ij})/(\sum_k 1/d_{ik})$ after row standardisation. Time-invariant.

Migration weights ($W_{\text{migration}}$). Bilateral migrant stocks from the UN International Migrant Stock database. Available at five-year intervals (2005, 2010, 2015); interpolated linearly to annual frequency. Row standardised.

All matrices have zero diagonals ($w_{ii} = 0$). Row standardisation ensures that $\sum_j w_{ij} = 1$ for each i, so spatial lags represent weighted averages of neighbours' values.

2.6 Control variables

3 Estimation Details

3.1 Bayesian estimation

The primary SAR models are estimated via Hamiltonian Monte Carlo in Stan. The spatial lag is approximated using a 6th-order power series:

$$W\Delta\mathbf{y} \approx \sum_{k=1}^{6} \rho^k W^k \Delta\mathbf{y} \tag{12}$$

The design matrix X is QR-reparameterised for numerical stability: $X = Q^* R^*$ where $Q^* = Q_{\text{thin}}\sqrt{n-1}$ and $R^* = R_{\text{thin}}/\sqrt{n-1}$. Coefficients θ are estimated on the Q^* scale with

Table 1: Variable definitions and sources

Variable	Definition	Source	Transform
Dependent variable			
Δy_{it}	Change in HIV incidence per 100k	IHME GBD	First diff.
Key independent variables			
PEPFAR per capita	USD disbursements per capita	OECD CRS	First diff.
TradePEPFAR%	Share of trade with PEPFAR recipients	UN Comtrade	First diff.
TradePEPFAR%^{2}	Squared trade share	Computed	First diff.
Aid controls (per capita)			
Other STI/HIV aid	Non-U.S. HIV/STI aid	OECD CRS	First diff.
Basic health aid	General health sector aid	OECD CRS	First diff.
Reproductive health aid	Family planning, reproductive health	OECD CRS	First diff.
Infectious disease aid	Non-HIV infectious disease aid	OECD CRS	First diff.
Economic and demographic controls			
Health spending ratio	Government / out-of-pocket	IHME	First diff.
Population density	Persons per km^2	UN	Log, first diff.
GDP per capita	USD	UN	Log, first diff.
Export/import ratio	Total exports / total imports	UN	First diff.
Internet access	% of population	World Bank	First diff.
Life expectancy	Years at birth	World Bank	First diff.
Infant mortality	Deaths per 1,000 live births	World Bank	Log, first diff.

prior $\theta \sim \mathcal{N}(0,1)$, then transformed back: $\beta = (R^*)^{-1}\theta$. The spatial parameter ρ is bounded by the eigenvalue range of W with prior $\rho \sim \mathcal{N}(0,1)$.

Settings: 2 chains, 5,000 iterations (2,000 warmup), adaptive step size ($\epsilon = 0.5$, $\delta = 0.9$). Convergence is confirmed by $\hat{R} < 1.01$ and effective sample sizes $> 1{,}000$ for all parameters.

3.2 MLE estimation

MLE models are estimated using the `spatialreg` package in R (LeSage and Pace, 2009; Elhorst, 2014). The SAR and SDM use the concentrated log-likelihood with exact eigenvalue decomposition. The SLX is estimated by OLS after pre-computing the WX columns. Fourteen substantive regressors are spatially lagged; interaction terms and the lagged dependent variable are not lagged (because $W(A \times z) \neq WA \times Wz$).

3.3 Model comparison

Model fit is compared using the Watanabe-Akaike Information Criterion (WAIC) for Bayesian models:

Table 2: Model comparison (WAIC)

Model	WAIC
Non-spatial (base)	14,030.2
Non-spatial (controls)	13,978.8
SAR (W_{trade})	13,999.7
SAR ($W_{\text{trade}} + W_{\text{dist}}$)	13,999.7
SAR ($W_{\text{trade}} + W_{\text{dist}} + W_{\text{mig}}$)	14,007.9

The preferred model (SAR with trade + distance) achieves the lowest WAIC, though differences between the trade-only and trade + distance specifications are negligible.

3.4 Direct and indirect effect decomposition

The decomposition of total effects into direct and indirect components differs across the three spatial specifications. In all cases, the pre-dynamic impulse of PEPFAR aid is trade-conditioned:

$$\beta_x(z) = \beta_1 + \beta_4 z + \beta_5 z^2 + \beta_6 z^3 \tag{13}$$

evaluated at the relevant trade integration level z.

Non-spatial model. In the non-spatial specification, the LRSS is purely temporal:

$$\text{Total} = \frac{\beta_x}{1-\phi} \tag{14}$$

There is no direct/indirect decomposition because the model does not include spatial structure.

SLX model. The SLX separates direct and indirect effects through distinct coefficients (LeSage and Pace, 2009; Elhorst, 2014):

$$\text{Direct} = \frac{\beta_x}{1-\phi}, \qquad \text{Indirect} = \frac{\theta_x}{1-\phi}, \qquad \text{Total} = \frac{\beta_x + \theta_x}{1-\phi} \tag{15}$$

where θ_x is the coefficient on the spatially lagged covariate ($W \times$ PEPFAR). The direct effect captures the within-country impact of own PEPFAR aid; the indirect effect captures the impact of trading partners' PEPFAR aid. Both are scaled by the temporal multiplier $1/(1-\phi)$. No eigenvalue decomposition is needed because the SLX does not include an endogenous spatial lag. This transparency is a key advantage of the SLX specification.

SAR model. In the SAR, the spatial lag of Y ($\rho W \Delta y$) means that a change in one country's covariate affects all countries through the spatial multiplier $(I-\rho W)^{-1}$. Following LeSage and Pace, 2009, the LRSS total effect is:

$$\text{Total} = \frac{\beta_x}{1-\phi-\rho} \tag{16}$$

and the average direct effect is computed via eigenvalue decomposition:

$$\text{Direct} = \frac{1}{n}\sum_{i=1}^{n} \frac{\beta_x}{1-\phi-\rho\lambda_i} \tag{17}$$

where λ_i are the eigenvalues of W. The indirect effect is Total − Direct. For a row-standardised W, the eigenvalues sum to zero, so the direct effect is close to (but not exactly equal to) the total effect scaled by the average diagonal element of $(I-\rho W)^{-1}$.

SDM model. The SDM nests both the SAR and SLX, so the spatial multiplier $(I-\rho W)^{-1}$ operates on both the direct coefficients β and the spatially lagged coefficients θ:

$$\text{Total impact} = (I-\rho W)^{-1}(\beta_x \mathbf{I} + \theta_x W) \tag{18}$$

The average direct effect is the mean diagonal element of this matrix; the average indirect effect is the mean row sum of off-diagonal elements (LeSage and Pace, 2009). Because θ appears inside the spatial multiplier, the SDM's direct and indirect effects do not correspond simply to β and θ — both parameters contribute to both effects through the network feedback. In the first-differenced specification, $\theta > 0$ (positive) partially offsets $\beta < 0$ (negative) before the multiplier amplifies the remainder, producing the pattern shown in the SDM waterfall figure in the main manuscript's Extended Data.

Posterior credible intervals for all decompositions are computed by evaluating the relevant formula at each MCMC draw and taking quantiles.

4 Supplementary Tables and Figures

The primary spatial models are estimated via Bayesian HMC (Stan) on the first-differenced panel. Five specifications are presented: two non-spatial baselines (with and without controls) and three SAR models using trade, trade + distance, and trade + distance + migration weight matrices simultaneously. Posterior medians and 95% credible intervals are reported. The PEPFAR coefficient is stable across all specifications ($\beta \approx -0.49$). The spatial autoregressive parameter ρ is significant only for the trade network.

The SLX and SDM specifications provide a more direct test of the spillover mechanism than the SAR. The SLX includes spatially lagged covariates (WX), where the coefficient θ on $W \times$ PEPFAR measures whether trading partners' aid predicts own-country HIV outcomes. The SDM nests both the SAR and SLX, including both the spatial lag of Y (ρ) and spatially lagged covariates (θ). A lagged-aid specification (A_{t-1}) tests for reverse causality. All models are estimated via MLE with trade weights.

These Bayesian SAR models test whether spatial dependence operates through distance, migration, or combinations of networks. None of the non-trade networks produces significant spatial dependence when estimated individually or in combination, confirming that the trade channel is the operative one. The trade + migration model shows ρ_{trade} remains significant while $\rho_{\text{migration}} \approx 0$.

The long-run steady-state (LRSS) marginal effect of PEPFAR captures the cumulative impact of a sustained \$1/capita allocation, accounting for both temporal persistence (ϕ) and spatial propagation (ρ). The LRSS is computed as $\beta_x/(1 - \phi - \rho)$ for the total effect and via eigenvalue decomposition for the direct/indirect split (see Section 3). Effects are reported at two trade-integration levels: 5% (where PEPFAR is effective) and 15% (where the marginal effect approaches zero).

The cubic interaction between PEPFAR aid and trade integration ($A \times z \times z^2$) allows flex-

Table S1: Main Results

	Non-spatial		Spatial		
	[1]	[2]	[3]	[4]	[5]
PEPFAR Aid	−0.470*	−0.490*	−0.486*	−0.492*	−0.487*
	[−0.724; −0.222]	[−0.736; −0.245]	[−0.742; −0.242]	[−0.747; −0.246]	[−0.732; −0.241]
PEPFAR Trade	0.302	−0.139	0.330	0.414	0.392
	[−3.466; 4.045]	[−3.887; 3.646]	[−3.364; 3.958]	[−3.223; 4.098]	[−3.315; 4.147]
PEPFAR Trade^2	−0.954	−0.201	−1.116	−1.138	−1.131
	[−5.624; 3.711]	[−4.865; 4.427]	[−5.697; 3.561]	[−5.636; 3.299]	[−5.756; 3.403]
PEPFAR Aid × PEPFAR Trade	3.969*	3.940*	3.969*	4.128*	4.097*
	[1.975; 5.998]	[1.942; 5.955]	[2.036; 5.966]	[2.088; 6.108]	[2.146; 6.063]
PEPFAR Aid × PEPFAR Trade^2	−8.529*	−8.340*	−8.595*	−8.956*	−8.894*
	[−12.798; −4.276]	[−12.598; −4.122]	[−12.866; −4.371]	[−13.192; −4.704]	[−13.193; −4.614]
PEPFAR Aid × PEPFAR Trade × PEPFAR Trade^2	5.557*	5.493*	5.739*	5.959*	5.925*
	[2.887; 8.194]	[2.890; 8.147]	[3.099; 8.439]	[3.337; 8.623]	[3.289; 8.639]
OECD STI aid		−0.119*	−0.116*	−0.116*	−0.116*
		[−0.156; −0.084]	[−0.152; −0.081]	[−0.154; −0.078]	[−0.152; −0.078]
OECD General health aid		−0.005	−0.006	−0.006	−0.006
		[−0.039; 0.028]	[−0.041; 0.029]	[−0.040; 0.027]	[−0.039; 0.026]
OECD Reproductive health aid		0.031	0.036	0.038	0.038
		[−0.174; 0.235]	[−0.166; 0.237]	[−0.164; 0.245]	[−0.170; 0.244]
OECD Infectious disease aid		−0.047	−0.055	−0.055	−0.056
		[−0.154; 0.061]	[−0.165; 0.055]	[−0.161; 0.055]	[−0.161; 0.051]
Public/Private health spending ratio		0.962*	0.952*	0.943*	0.942*
		[0.387; 1.537]	[0.397; 1.513]	[0.354; 1.528]	[0.366; 1.501]
Pop. density°		−5.215	−5.208	−5.253	−5.238
		[−18.909; 8.401]	[−19.237; 9.276]	[−18.984; 8.796]	[−19.164; 8.907]
GDP PC°		0.194	0.161	0.142	0.180
		[−2.671; 3.064]	[−2.795; 3.053]	[−2.724; 3.009]	[−2.709; 3.169]
Export/Import ratio		0.251	0.206	0.206	0.203
		[−0.810; 1.323]	[−0.899; 1.299]	[−0.883; 1.304]	[−0.865; 1.281]
Internet access		0.020	0.019	0.020	0.020
		[−0.024; 0.064]	[−0.028; 0.064]	[−0.024; 0.065]	[−0.025; 0.066]
Life expecectancy		−1.548*	−1.655*	−1.641*	−1.646*
		[−2.164; −0.932]	[−2.275; −1.045]	[−2.269; −1.037]	[−2.264; −1.018]
Infant mortality°		3.433	3.261	3.300	3.294
		[−1.124; 7.940]	[−1.518; 8.168]	[−1.372; 8.072]	[−1.443; 8.076]
HIV incidence rate (per 100k, lag)	0.622*	0.613*	0.612*	0.614*	0.614*
	[0.590; 0.654]	[0.579; 0.645]	[0.580; 0.645]	[0.582; 0.646]	[0.582; 0.647]
Rho - Trade			0.115*	0.122*	0.122*
			[0.051; 0.175]	[0.056; 0.184]	[0.051; 0.188]
Rho - Distance				−0.106	−0.105
				[−0.278; 0.128]	[−0.276; 0.133]
Rho - Migration					0.002
					[−0.075; 0.073]
FE - Country	Yes	Yes	Yes	Yes	Yes
FE - Year	Yes	Yes	Yes	Yes	Yes
Log lik.	−6848.149	−6808.372	−6809.657	−6806.408	−6813.418
WAIC	14030.151	13978.831	14006.214	13999.745	14212.139
N	2634	2634	2634	2634	2634

* Null hypothesis value outside the confidence interval. ∘ denotes logged variable.

Table S2: Robustness: Spatial Specification Alternatives

	Spatial alternatives			Timing robustness
	SAR (baseline)	SLX	SDM	SAR (lagged aid)
HIV incidence rate (per 100k, lag)	0.615***	0.619***	0.623***	0.570***
	(0.016)	(0.016)	(0.016)	(0.017)
PEPFAR Aid	−0.490***	−0.504***	−0.551***	
	(0.121)	(0.130)	(0.122)	
PEPFAR Trade	0.053	0.074	−0.061	−1.298
	(1.794)	(1.870)	(1.762)	(1.887)
PEPFAR Trade^2	−0.580	−0.457	0.131	1.569
	(2.216)	(2.311)	(2.179)	(2.349)
PEPFAR Aid × PEPFAR Trade	3.965***	3.762***	4.719***	
	(0.966)	(1.007)	(0.954)	
PEPFAR Aid × PEPFAR Trade^2	−8.468***	−7.994***	−10.430***	
	(2.072)	(2.161)	(2.051)	
PEPFAR Aid × PEPFAR Trade × PEPFAR Trade^2	5.608***	5.288***	6.825***	
	(1.286)	(1.345)	(1.276)	
PEPFAR Aid (lag 1)				−0.346**
				(0.129)
W × PEPFAR Aid		0.135*	0.309***	
		(0.064)	(0.062)	
W × PEPFAR Trade		9.048*	0.753	
		(3.879)	(3.735)	
W × PEPFAR Trade^2		−8.401	4.649	
		(5.027)	(4.889)	
Controls	Yes	Yes	Yes	Yes
FE - Country	Yes	Yes	Yes	Yes
FE - Year	Yes	Yes	Yes	Yes
Num. obs.	2634	2634	2634	2452
Parameters	216		230	215
Log Likelihood	−6695.178		−6640.082	−6247.908
AIC (Linear model)	13822.610		13808.708	12923.982
AIC (Spatial model)	13822.355		13740.163	12925.816
LR test: statistic	2.255		70.544	0.166
LR test: p-value	0.133		0.000	0.684
R^2		0.939		
Adj. R^2		0.934		

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$ All models use trade spatial weights. Controls included but not shown. ∘ denotes logged variable. SLX estimated by OLS; SAR and SDM by MLE.

Table S3: Supplemental Results - Bayesian models

	W1 - Distance	W1 - Migration	W2 - Distance + Migration	W2 - Trade + Migration
PEPFAR Aid	-0.488^*	-0.487^*	-0.489^*	-0.487^*
	$[-0.735; -0.239]$	$[-0.732; -0.242]$	$[-0.742; -0.245]$	$[-0.732; -0.242]$
PEPFAR Trade	-0.157	-0.263	-0.191	0.345
	$[-3.827; 3.527]$	$[-3.862; 3.314]$	$[-3.841; 3.442]$	$[-3.305; 4.058]$
PEPFAR Trade^2	-0.191	-0.247	-0.329	-1.102
	$[-4.676; 4.374]$	$[-4.652; 4.144]$	$[-4.824; 4.137]$	$[-5.687; 3.422]$
PEPFAR Aid × PEPFAR Trade	3.908^*	3.859^*	3.899^*	3.970^*
	$[1.955; 5.862]$	$[1.870; 5.778]$	$[1.855; 5.949]$	$[1.988; 5.891]$
PEPFAR Aid × PEPFAR Trade^2	-8.279^*	-8.105^*	-8.176^*	-8.603^*
	$[-12.521; -4.016]$	$[-12.232; -3.846]$	$[-12.493; -3.885]$	$[-12.805; -4.271]$
PEPFAR Aid × PEPFAR Trade × PEPFAR Trade^2	5.461^*	5.346^*	5.382^*	5.745^*
	$[2.814; 8.095]$	$[2.700; 7.929]$	$[2.719; 8.050]$	$[3.051; 8.355]$
OECD STI aid	-0.120^*	-0.122^*	-0.122^*	-0.116^*
	$[-0.158; -0.083]$	$[-0.158; -0.085]$	$[-0.156; -0.087]$	$[-0.153; -0.080]$
OECD General health aid	-0.005	-0.006	-0.005	-0.006
	$[-0.040; 0.029]$	$[-0.040; 0.027]$	$[-0.038; 0.028]$	$[-0.040; 0.028]$
OECD Reproductive health aid	0.032	0.029	0.029	0.038
	$[-0.165; 0.228]$	$[-0.175; 0.241]$	$[-0.171; 0.237]$	$[-0.167; 0.236]$
OECD Infectious disease aid	-0.046	-0.049	-0.049	-0.054
	$[-0.155; 0.063]$	$[-0.158; 0.059]$	$[-0.157; 0.059]$	$[-0.161; 0.052]$
Public/Private health spending ratio	0.965^*	0.970^*	0.970^*	0.948^*
	$[0.436; 1.513]$	$[0.413; 1.516]$	$[0.410; 1.529]$	$[0.382; 1.512]$
Pop. density$^\circ$	-5.149	-5.111	-5.067	-5.354
	$[-18.763; 8.450]$	$[-18.933; 8.533]$	$[-19.441; 8.937]$	$[-19.141; 8.426]$
GDP PC$^\circ$	0.189	0.152	0.174	0.181
	$[-2.719; 3.105]$	$[-2.610; 3.007]$	$[-2.814; 3.068]$	$[-2.673; 2.996]$
Export/Import ratio	0.241	0.246	0.232	0.194
	$[-0.812; 1.323]$	$[-0.830; 1.315]$	$[-0.877; 1.364]$	$[-0.854; 1.253]$
Internet access	0.020	0.018	0.019	0.019
	$[-0.025; 0.064]$	$[-0.027; 0.063]$	$[-0.026; 0.065]$	$[-0.025; 0.065]$
Life expecectancy	-1.545^*	-1.586^*	-1.585^*	-1.649^*
	$[-2.176; -0.931]$	$[-2.192; -0.963]$	$[-2.223; -0.944]$	$[-2.274; -1.034]$
Infant mortality$^\circ$	3.415	3.357	3.333	3.283
	$[-1.420; 8.256]$	$[-1.391; 8.166]$	$[-1.251; 7.972]$	$[-1.385; 7.996]$
HIV incidence rate (per 100k, lag)	0.612^*	0.612^*	0.613^*	0.612^*
	$[0.581; 0.645]$	$[0.581; 0.644]$	$[0.580; 0.645]$	$[0.579; 0.644]$
Rho - Trade				0.117^*
				$[0.048; 0.181]$
Rho - Distance	0.014		-0.037	
	$[-0.216; 0.248]$		$[-0.250; 0.207]$	
Rho - Migration		0.043	0.046	-0.005
		$[-0.020; 0.103]$	$[-0.022; 0.109]$	$[-0.079; 0.065]$
FE - Country	Yes	Yes	Yes	Yes
FE - Year	Yes	Yes	Yes	Yes
Log lik.	-6809.512	-6810.825	-6809.803	-6810.145
WAIC	13998.224	13992.539	13990.196	14005.269
N	2634	2634	2634	2634

* Null hypothesis value outside the confidence interval. $\circ$ denotes logged variable.

Table S4: PEPFAR- LRSS Marginal Effects

	Non-Spatial (controls)	Spatial (W1 - Trade)
PEPFAR Trade - 5%	-0.805^*	-1.136^*
	$[-1.296; -0.314]$	$[-1.961; -0.444]$
PEPFAR Trade - 15%	-0.175	-0.230
	$[-0.549; 0.199]$	$[-0.808; 0.303]$

* Null hypothesis value outside the confidence interval.

ible nonlinearity but also permits implausible positive effects at extreme trade values. Four robustness checks address this: the baseline SAR, a specification dropping the cubic term, a nonparametric specification using binned trade-integration quartile dummies, and a specification excluding country-years near the zero-crossing threshold (12–18% trade integration). All models are estimated via MLE with trade weights.

The first-differenced (FD) specification measures effects on the *change* in HIV incidence; a levels specification measures effects on incidence directly. The levels specification extends the zero-crossing from approximately 19% to 28–49% trade integration, eliminating the functional-form artifact that produces implausible positive effects for high-integration recipients in the FD specification. All models include country and year fixed effects; controls are in first differences in both DV specifications.

Posterior summaries from the three-network SAR model estimated simultaneously with trade, distance, and migration weight matrices. The posterior probability that $\rho_{\text{trade}} > \rho_{\text{distance}}$ is 0.96, confirming that spatial dependence in HIV outcomes operates through commercial relationships rather than geographic proximity.

The direct LRSS effect of PEPFAR varies across recipients because it depends on each country's trade integration with other PEPFAR recipients (through the cubic interaction). Countries with low integration (Haiti, Nigeria) show large negative effects; countries above approximately 20% integration show effects indistinguishable from zero. Recipients above 70% integration (Swaziland, Botswana, Lesotho) show implausible positive effects — a functional-form artifact confirmed by the levels specification (Table S6), which assigns negative effects to all 31 recipients.

Table S5: Robustness: Functional Form Alternatives

	Functional form robustness			
	SAR (baseline)	No cubic term	Binned trade	Drop 12–18%
HIV incidence rate (per 100k, lag)	0.615***	0.614***	0.601***	0.622***
	(0.016)	(0.016)	(0.015)	(0.016)
PEPFAR Aid	−0.490***	−0.185	−0.289*	−0.499***
	(0.121)	(0.099)	(0.138)	(0.120)
PEPFAR Trade	0.053	−0.139	0.001	0.086
	(1.794)	(1.785)	(1.027)	(1.842)
PEPFAR Trade^2	−0.580	0.341		0.022
	(2.216)	(2.207)		(2.267)
PEPFAR Aid × PEPFAR Trade	3.965***	0.189		5.032***
	(0.966)	(0.393)		(0.965)
PEPFAR Aid × PEPFAR Trade^2	−8.468***	0.321		−11.257***
	(2.072)	(0.371)		(2.083)
PEPFAR Aid × PEPFAR Trade × PEPFAR Trade^2	5.608***			7.415***
	(1.286)			(1.294)
PEPFAR Trade bin: Q2 (med-low)			−0.217	
			(0.232)	
PEPFAR Trade bin: Q3 (med-high)			−0.099	
			(0.281)	
PEPFAR Trade bin: Q4 (high)			−0.120	
			(0.440)	
PEPFAR Aid × Trade bin Q2			0.404	
			(0.246)	
PEPFAR Aid × Trade bin Q3			0.017	
			(0.135)	
PEPFAR Aid × Trade bin Q4			0.457***	
			(0.136)	
Controls	Yes	Yes	Yes	Yes
FE - Country	Yes	Yes	Yes	Yes
FE - Year	Yes	Yes	Yes	Yes
Num. obs.	2634	2634	2634	2341
Parameters	216	215	218	216
Log Likelihood	−6695.178	−6692.527	−6686.767	−5917.493
AIC (Linear model)	13822.610	13838.975	13836.989	12297.797
AIC (Spatial model)	13822.355	13815.054	13809.533	12266.985
LR test: statistic	2.255	25.921	29.456	32.811
LR test: p-value	0.133	0.000	0.000	0.000

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$ All models use trade spatial weights estimated by MLE. Controls included but not shown. ◦ denotes logged variable. Col. (3) replaces continuous trade integration terms with quartile-bin dummies. Col.

Table S6: Parameter Comparison: First-Differenced vs. Levels DV, SAR vs. SLX vs. SDM

Spec	ϕ	β_{PEPFAR}	ρ	$W \cdot PEPFAR$
OLS (FD)	0.6150	-0.4908	—	—
SAR (FD)	0.6149	-0.4900	0.0516	—
SLX (FD)	0.6186	-0.5037	—	0.1353
SDM (FD)	0.6230	-0.5508	0.2468	0.3090
OLS (Levels)	0.9756	-0.5867	—	—
SAR (Levels)	0.9709	-0.5966	0.0085	—
SLX (Levels)	0.9807	-0.3973	—	1.8150
SDM (Levels)	0.9763	-0.4028	0.0099	1.8379

Table S7: Marginal Effect of $1/capita PEPFAR at Different Trade Integration Levels

Model	0%	5%	10%	15%	20%
OLS (FD)	-0.491	-0.314	-0.174	-0.068	0.009
SAR (FD)	-0.490	-0.312	-0.173	-0.067	0.009
SLX (FD)	-0.504	-0.335	-0.202	-0.101	-0.029
SDM (FD)	-0.551	-0.340	-0.176	-0.055	0.030
OLS (Levels)	-0.587	-0.448	-0.327	-0.221	-0.131
SAR (Levels)	-0.597	-0.455	-0.329	-0.218	-0.123
SLX (Levels)	-0.397	-0.332	-0.272	-0.216	-0.166
SDM (Levels)	-0.403	-0.335	-0.270	-0.210	-0.154

Table S8: Descriptive statistics

	Mean	SD	Min	Max
HIV incidence rate (per 100k)	-3.380	11.933	-146.7	21.790
PEPFAR Aid	1.093	4.631	0.0	47.429
PEPFAR Trade	0.161	0.194	0.0	0.989

Table S9: Descriptive statistics

	Mean	SD	Min	Max
OECD STI aid	0.093	3.408	-85.738	116.076
OECD General health aid	0.066	3.684	-65.145	82.286
OECD Reproductive health aid	0.018	0.614	-6.932	7.764
OECD Infectious disease aid	0.029	1.155	-23.615	23.615
Public/Private health spending ratio	0.046	0.266	-1.898	3.405
Pop. density°	0.015	0.016	-0.069	0.194
GDP PC°	0.023	0.050	-0.650	0.676
Export/Import ratio	-0.011	0.121	-1.120	0.948
Internet access	2.722	3.034	-8.742	24.881
Life expecectancy	0.337	0.327	-1.459	2.256
Infant mortality°	-0.033	0.034	-0.577	0.536

Note:

∘ denotes logged variable.

Table S10: Spatial Dependence Parameters: Trade vs. Distance vs. Migration

Network	Median	95% CI	SD	$\Pr(\rho > 0)$	$\Pr(\rho > 0.01)$
Trade (single-W)	0.1154	[0.0512, 0.1755]	0.0318	1.000	1.000
Trade	0.1228	[0.0484, 0.1884]	0.0349	0.999	0.999
Distance	-0.1155	[-0.2786, 0.1266]	0.1084	0.176	0.155
Migration	0.0020	[-0.0772, 0.0738]	0.0386	0.519	0.414

Table S11: Actual PEPFAR Recipients: Direct LRSS Effects Ranked by Magnitude

Country	PEPFAR $/cap	Trade (%)	HIV/100k	LRSS/100k	Cases Averted	% Reduction
Haiti	9.80	12.0	127	-3.10 [-6.94, 0.66]	-336	-3.9%
Dominican Republic	1.28	2.8	38	-1.27 [-1.99, -0.56]	-136	-4.3%
Nigeria	2.55	9.5	90	-1.20 [-2.24, -0.18]	-2,313	-1.6%
South Africa	8.79	17.0	952	-0.68 [-4.04, 2.61]	-386	-0.1%
Vietnam, Democratic Republic of	0.70	6.4	19	-0.48 [-0.80, -0.16]	-450	-3.0%
Ethiopia	2.28	14.0	52	-0.47 [-1.36, 0.37]	-513	-1.7%
Papua New Guinea	0.75	7.8	77	-0.44 [-0.76, -0.12]	-40	-0.6%
Angola	0.52	13.6	130	-0.12 [-0.32, 0.07]	-36	-0.1%
Myanmar (Burma)	0.19	13.0	20	-0.05 [-0.13, 0.02]	-26	-0.3%
Indonesia	0.03	7.1	5	-0.02 [-0.04, -0.01]	-59	-0.4%
India	0.02	12.2	7	-0.01 [-0.01, 0.00]	-85	-0.1%
Cambodia (Kampuchea)	0.99	19.2	13	0.00 [-0.38, 0.37]	0	0.0%
Ukraine	0.32	19.5	34	0.00 [-0.12, 0.12]	1	0.0%
Ghana	0.42	19.9	84	0.01 [-0.15, 0.17]	3	0.0%
Cameroon	1.53	20.7	167	0.07 [-0.53, 0.66]	18	0.1%
Congo, Democratic Republic of (Zaire)	0.41	39.8	37	0.10 [-0.05, 0.24]	82	0.5%
South Sudan	1.95	64.1	85	0.19 [-0.28, 0.64]	20	0.2%
Burundi	1.56	43.5	26	0.34 [-0.19, 0.87]	38	1.8%
Malawi	3.66	62.9	359	0.35 [-0.54, 1.21]	63	0.2%
Zimbabwe (Rhodesia)	3.87	72.9	477	0.62 [-0.16, 1.39]	91	0.2%
Cote D'Ivoire	5.33	31.3	151	1.25 [-0.87, 3.27]	309	1.7%
Tanzania (Tanganyika)	6.76	31.1	214	1.57 [-1.12, 4.13]	884	1.4%
Zambia	18.88	63.5	462	1.81 [-2.76, 6.24]	313	0.6%
Mozambique	9.37	45.8	779	1.92 [-1.19, 4.91]	550	0.3%
Kenya	10.70	26.7	228	1.96 [-2.29, 6.07]	958	1.3%
Rwanda	8.32	40.2	83	1.99 [-1.05, 4.86]	243	4.2%
Uganda	8.25	35.1	307	2.07 [-1.17, 5.08]	830	1.2%
Namibia	31.79	74.7	529	6.07 [-0.07, 12.14]	143	1.8%
Botswana	28.67	80.3	672	9.62 [4.48, 14.82]	231	2.2%
Lesotho	11.79	92.6	1221	11.50 [7.96, 15.19]	250	1.2%
Swaziland (Eswatini)	25.07	92.4	1132	23.96 [16.59, 31.63]	276	3.6%

The indirect effects from a hypothetical PEPFAR allocation are decomposed by the recipient status of the beneficiary country. Approximately 80% of indirect cases averted flow to countries that later became PEPFAR recipients in Wave 2 (driven by China and India, which received small PEPFAR allocations from 2008). Approximately 16% flow to true never-recipients. This decomposition uses the SLX direct/indirect LRSS estimates applied to 2017 population data weighted by bilateral trade shares.

Table S12: Decomposition of Spillover Effects by PEPFAR Recipient Status

Ideal Country	Beneficiary Type	N Countries	Cases Averted	95% CI	% of To
GuineaBissau	Direct (own country)	1	-55	[-85, -24]	2.5%
GuineaBissau	Indirect: Non-recipient	142	-367	[-874, -101]	16.9%
GuineaBissau	Indirect: PEPFAR recipient	35	-1,748	[-4,163, -481]	80.6%
Gabon	Direct (own country)	1	-36	[-62, -9]	1.7%
Gabon	Indirect: Non-recipient	142	-293	[-781, -62]	14.0%
Gabon	Indirect: PEPFAR recipient	35	-1,765	[-4,697, -375]	84.3%
EquatorialGuinea	Direct (own country)	1	-18	[-35, -1]	1.0%
EquatorialGuinea	Indirect: Non-recipient	142	-346	[-1,004, -19]	18.9%
EquatorialGuinea	Indirect: PEPFAR recipient	35	-1,463	[-4,250, -81]	80.1%
Djibouti	Direct (own country)	1	-11	[-23, 1]	0.9%
Djibouti	Indirect: Non-recipient	142	-176	[-541, 16]	15.5%
Djibouti	Indirect: PEPFAR recipient	35	-952	[-2,928, 87]	83.6%

4.1 PEPFAR and HIV/AIDS knowledge — baseline and spillovers

Dependent variable: comprehensive correct knowledge of HIV/AIDS prevention, women aged 15–49 (DHS), measured on a 0–100 scale. PEPFAR was initiated in 2003, providing HIV/AIDS funding to 15 Wave 1 recipient countries in Sub-Saharan Africa. A second wave of 16 additional countries entered the programme in 2008.

Columns 1–3 restrict the sample to the 15 original PEPFAR recipient countries. The treatment variable PEPFAR equals 1 for recipient country-years after 2003. Column 1 is bivariate; column 2 adds controls (income, urbanisation, female school enrolment); column 3 adds country fixed effects. The coefficients (6–13 percentage points, all significant) confirm that PEPFAR directly increases HIV knowledge within treated countries.

Columns 4–6 test for knowledge spillovers to non-recipient countries after PEPFAR's launch. Column 4 includes all African countries that never received PEPFAR (Wave 1 excluded). Column 5 additionally excludes Wave 2 recipients. Both show a significant post-2003 knowledge increase of approximately 8 percentage points ($p < 0.01$), consistent with knowledge spillovers from PEPFAR recipients to neighbouring non-recipients. Column 6 restricts to Asian non-recipients as a placebo: the coefficient is negative, small, and insignificant, confirming that the African spillover is not a global time trend.

All standard errors clustered by country.

Table S13: PEPFAR and HIV Knowledge — Baseline and Reduced-Form Spillovers. Dependent variable: comprehensive correct knowledge of HIV/AIDS prevention, women 15–49 (DHS, 0–100 scale). Columns 1–3: Wave 1 PEPFAR recipients; PEPFAR = 1 post-2003. Columns 4–5: non-recipient African countries. Column 6: Asian non-recipients (placebo). Clustered SEs by country.

	PEPFAR Recipients			Non-Recipients		
	(1)	(2)	(3)	(4)	(5)	(6)
PEPFAR	12.991***	6.253*	8.740*			
	(3.284)	(3.440)	(4.218)			
Log(GNI)		10.411***	3.884	2.020	−4.053	4.690
		(2.202)	(2.799)	(3.961)	(4.046)	(3.324)
Urban Pop (%)		−0.586**	1.086	−0.289	0.034	−0.119
		(0.206)	(0.616)	(0.220)	(0.228)	(0.172)
Female Schooling		0.269**	0.062	0.144**	0.132**	0.209*
		(0.094)	(0.138)	(0.069)	(0.061)	(0.116)
Post-2003				7.477***	7.846***	−2.159
				(2.689)	(2.422)	(6.650)
Observations	59	50	50	102	85	53
Adjusted R^2	0.118	0.547	0.756	0.204	0.139	0.157

4.2 PEPFAR trade and migration exposure — HIV knowledge spillovers

Dependent variable: comprehensive correct knowledge of HIV/AIDS prevention, women aged 15–49 (DHS), measured on a 0–100 scale. Sample excludes all 31 PEPFAR recipients (Waves 1 and 2) for all years, isolating non-recipient countries only.

Three candidate channels for knowledge diffusion are tested: (i) trade exposure, measured as the sum of bilateral trade shares (trade flow from origin / destination GDP) with Wave 1 PEPFAR recipients; (ii) geographic distance, measured as the log of the average population-weighted distance to Wave 1 recipients; and (iii) migration exposure, measured as the sum of bilateral migrant stocks (origin-born population in destination / combined population) from Wave 1 recipients.

Column 1 includes trade exposure and distance with country fixed effects only. Column 2 adds controls (income, urbanisation, female school enrolment). Column 3 adds migration alongside trade and distance. Column 4 drops trade and retains migration and distance only.

Trade exposure is significant at $p < 0.01$ across all specifications that include it (columns 1–3), with coefficients of 1.9–2.6 per unit of GDP-scaled trade exposure. Distance loses significance once controls are added (columns 2–4). Migration is insignificant in all specifications (columns 3–4), with an implausibly large negative coefficient that likely reflects multicollinearity with trade.

The finding that trade exposure — but not distance or migration — predicts HIV knowledge in non-recipient countries, using within-country variation and country fixed effects, provides independent confirmation of the main spatial econometric result: knowledge generated by PEPFAR diffuses through commercial relationships, not through geographic proximity or population movement.

All models include country fixed effects. Standard errors clustered by country.

Table S14: PEPFAR Trade and Migration Exposure — HIV Knowledge Spillovers. Dependent variable: comprehensive correct knowledge of HIV/AIDS prevention, women 15–49 (DHS, 0–100 scale). Sample: non-PEPFAR recipients only (Waves 1 and 2 excluded, all years). All models include country FE. Clustered SEs by country.

	Non-PEPFAR Recipients (Country FE)			
	(1)	(2)	(3)	(4)
Trade Share w/PEPFAR	1.898***	2.629***	2.607***	
	(0.658)	(0.856)	(0.849)	
Ln(Dist to PEPFAR)	1.097***	0.403	0.387	0.385
	(0.201)	(0.465)	(0.480)	(0.478)
Log(GNI)		4.071	4.126	4.145
		(3.182)	(3.247)	(3.235)
Urban Pop (%)		0.133	0.164	0.162
		(0.467)	(0.485)	(0.484)
Female Schooling		0.114	0.108	0.105
		(0.097)	(0.090)	(0.091)
Migration Share w/PEPFAR			−2340.100	−2367.844
			(4873.256)	(4885.899)
Observations	213	176	176	176
Adjusted R^2	0.820	0.833	0.832	0.833

5 Spillover Effect Calculations

5.1 Two approaches

We quantify indirect health effects using two complementary approaches that differ in their assumptions about how spillovers propagate:

1. **First-order (SLX).** Counts only direct spillovers from PEPFAR recipients to their immediate trading partners. Uses the SLX coefficient $\theta_{\text{PEPFAR}} = 0.135$.
2. **Full network (SDM).** Allows spillovers to cascade through second- and higher-order trade connections via the network multiplier $(I - \rho W)^{-1}$ with $\rho = 0.247$.

5.2 First-order calculation (SLX)

For each country j, the first-order indirect effect is:

$$\text{Indirect per 100k}_j = \theta_{\text{PEPFAR}} \times (W \cdot A)_j \tag{19}$$

where $(W \cdot A)_j = \sum_k w_{jk} A_k$ is the trade-weighted average PEPFAR spending of country j's partners. Converting to cases:

$$\text{Indirect cases}_j = \frac{\theta_{\text{PEPFAR}} \times (W \cdot A)_j}{100{,}000} \times \text{pop}_j \tag{20}$$

Summing across all countries in the 2017 cross-section:

Component	Cases	Share
Direct (in PEPFAR recipients)	1,311	29%
First-order indirect (all countries)	3,203	71%
Total	**4,514**	100%
Indirect-to-direct ratio	**2.4:1**	
Total multiplier	**3.4**×	

5.3 Full-network calculation (SDM)

The SDM equilibrium is computed directly from the SDM coefficients ($\beta_{\text{PEPFAR}} = -0.551$, $\theta_{\text{PEPFAR}} = 0.309$, $\rho = 0.247$) applied to the 2017 cross-section of PEPFAR allocations, populations, and trade weights. The pre-multiplier impulse vector combines the within-country direct effect ($\beta \times A_i$) and the first-order partner-aid spillover ($\theta \times (WA)_i$). The full equilibrium is then $(I - \rho W)^{-1} \times$ impulse.

Decomposition of the SDM net total:

Component	Cases	Note
Direct within-country ($\beta \times A$)	−22,397	Large negative (HIV-reducing)
First-order partner-aid ($\theta \times WA$)	+7,312	Positive in FD (see main text)
Network feedback ($\rho W + \rho^2 W^2 + \ldots$)	−2,536	Reinforces overall reduction
Net total	**−17,620**	Approx. 13× the SAR direct-only estimate

The positive θ in the first-differenced specification partially offsets the direct effect before network feedback amplifies the remainder. This offsetting structure is why the SDM decomposition is less transparent than the SAR-based approach used for the primary aggregate estimates (Section 5.2 above). The main text treats the SAR-based decomposition (3.4× multiplier) as primary and the SDM (∼13×) as an upper bound. See the SDM waterfall figure in the main manuscript's Extended Data for a visual representation.

5.4 Cost-effectiveness

Total PEPFAR spending in 2017 was approximately $4.07 billion.

Metric	Direct only	SAR (with spillovers)
Cases averted	1,311	4,514
Cost per case	$3,104	$901
DALYs averted[a]	32,775	112,850
Cost per DALY	$124	$36

[a] Assumes 25 DALYs per averted HIV case.

Under the SDM upper bound (∼17,600 total cases), the cost per DALY falls to approximately $19. Conservative adjustment for heterogeneous disability weights (lower DALYs per case in high-income indirect beneficiaries) raises the range to $40–60 per DALY. The main text reports the full range as $19–60.

DALY heterogeneity caveat. The uniform 25 DALYs/case assumption overstates the DALY gain for high-income indirect beneficiaries (where ART access reduces disability weights) relative to Sub-Saharan African direct beneficiaries (where ART access is more limited and populations at risk are younger). A conservative adjustment for this heterogeneity raises the lower bound from $19 to approximately $40–60 per DALY. Even under conservative assumptions, PEPFAR with spillovers falls in the range of the most cost-effective global health interventions.

5.5 Sensitivity

The headline multiplier is most sensitive to three parameters:

$\theta_{\mathbf{PEPFAR}}$ **(SLX coefficient).** A one-standard-error perturbation (SE = 0.052, clustered) shifts the first-order ratio from 2.4:1 to 1.5:1 (lower) or 3.4:1 (upper).

ρ **(SDM spatial lag).** If ρ were halved to 0.12, the network amplification would drop from ∼15% to ∼7%, reducing the SDM multiplier from 6.5× to approximately 5.5×.

Population weighting. The indirect effect is mechanically larger when PEPFAR recipients trade with large-population countries. China alone captures ∼77% of indirect effects from a Guinea-Bissau allocation, driven entirely by population size and bilateral trade weights. The headline numbers depend on the population distribution of trade partners, not just the coefficient estimates.

6 Additional Sensitivity Analyses

6.1 Malaria placebo test

Table S15: Programme specificity: PEPFAR reduces HIV but not malaria. The table compares the PEPFAR coefficient across two disease outcomes estimated with the identical specification (first-differenced DV, lagged DV, full controls, country and year fixed effects, SAR with trade weight matrix). The PEPFAR coefficient is significant only for HIV — the disease the programme targets. Trade-network spatial dependence (ρ_{trade}) is present for both diseases, consistent with generic spatial correlation in health outcomes among trade-connected countries. The PEPFAR-specific spillover channel operates exclusively for HIV. Malaria incidence is per 1,000 population at risk (World Bank).

	HIV incidence (per 100,000)	Malaria incidence (per 1,000 at risk)
β_{PEPFAR}	−0.490***	−0.570
	(0.126)	(0.811)
ρ_{trade}	0.052**	0.129***
PEPFAR significant?	Yes ($p < 0.001$)	No ($p = 0.47$)
ρ significant?	Yes ($p < 0.05$)	Yes ($p < 0.01$)
N	2,634	1,521

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. SAR with trade weights, MLE.

Table S16: Robustness of the PEPFAR coefficient to replacing contemporaneous trade weights with pre-PEPFAR (2000–2003) average bilateral trade. The neighbour structure (which countries trade with which) is held fixed; only the weight values (how much they trade) are replaced with pre-period averages. The PEPFAR coefficient and all interaction terms change by less than 2.5%, confirming that endogeneity of the time-varying trade weight matrix does not drive the results.

Parameter	Contemporaneous W	Pre-PEPFAR W (2000–03)
ρ_{trade}	0.052	−0.070
β_{PEPFAR}	−0.490	−0.487
PEPFAR × Trade	3.965	3.912
PEPFAR × Trade^2	−8.468	−8.305
PEPFAR × Trade × Trade^2	5.608	5.486
β change		0.7%
Max interaction change		2.2%

SAR with MLE. Pre-PEPFAR W uses 2000–2003 average bilateral trade.

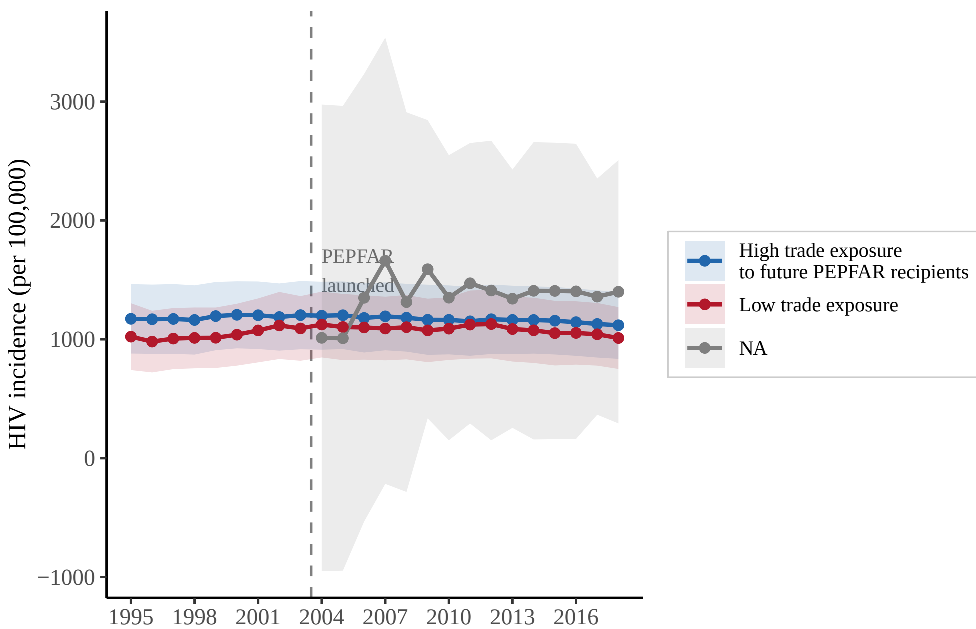

Figure 1: Pre-trend analysis: HIV incidence trajectories in non-recipient countries by trade exposure to future PEPFAR recipients, 1995–2018. Countries are split into high and low exposure groups based on their 1995–2003 average trade share with the 15 countries that would become Wave 1 PEPFAR recipients in 2003. The vertical dashed line marks PEPFAR's launch. Before 2004, both groups follow parallel trajectories (pre-trend interaction: $\beta = -2.4$, $p = 0.93$; year-by-year joint F-test: $p = 1.00$). The absence of differential pre-trends confirms that the post-PEPFAR spatial dependence in HIV outcomes through trade networks is attributable to the programme rather than pre-existing differential trajectories. $N = 153$ non-recipient countries; all PEPFAR recipients (Waves 1 and 2) excluded. Shaded regions show 95% confidence intervals around group means.

6.2 Robustness to pre-PEPFAR weight matrix

6.3 Pre-trend analysis

6.4 Oster (2019) bounds for omitted variable bias

The PEPFAR coefficient is exceptionally stable to the inclusion of controls. Moving from a restricted specification (lagged DV and fixed effects only) to the full specification with 11 time-varying controls changes β_{PEPFAR} from -0.471 to -0.491 (a 4% increase in magnitude) while R^2 increases from 0.931 to 0.934. The Oster, 2019 δ is -716: selection on unobservables would need to be 716 times stronger than selection on the full set of observable controls to explain the coefficient. The Cinelli and Hazlett, 2020 robustness value is $RV_{q=1} = 0.076$ (7.6% of residual variance in both treatment and outcome). These values place the PEPFAR coefficient among the most robust estimates in the applied economics literature. For context, Oster, 2019 recommends a threshold of $\delta > 1$; our estimate exceeds this by nearly three orders of magnitude.

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