**Foreign Aid and Knowledge Diffusion:
PEPFAR, Trade Networks, and Global Health Spillovers**

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Abstract

The same global networks that spread disease also spread knowledge. We develop a model of knowledge diffusion through international trade networks and test it using data from PEPFAR — the President's Emergency Plan for AIDS Relief — to demonstrate how bilateral health aid creates international public goods whose benefits extend well beyond recipient countries. Using spatial autoregressive panel models on a global sample of 175 countries from 2004–2020, we find that PEPFAR significantly reduces HIV incidence in recipient countries, with diminishing returns as recipients become more integrated into networks of other aid recipients. Importantly, knowledge transmitted through global trade greatly amplifies these effects: overall indirect spillovers to non-recipient countries are 20–100 times larger than direct impacts, with major economies — including the United States, China, and India — experiencing measurable HIV reductions from PEPFAR investments in Africa. Our results challenge traditional cost-benefit analyses that overlook international spillovers, reframe globalization as a process that both transmits disease risks and provides solutions, and show that the costs of dismantling programs like PEPFAR go far beyond the bilateral relationships they were designed to foster.

Keywords: Foreign aid effectiveness, Global public goods, HIV/AIDS, Knowledge diffusion, Network spillovers, PEPFAR.

1. Introduction

The Black Death traveled along the Silk Road. SARS spread through airline hubs. COVID-19 moved through the arteries of global commerce before most governments realized it was there. Each epidemic reinforces a familiar narrative: globalization serves as a transmission belt for disasters, and the more integrated the world becomes, the faster contagion spreads. However, this story only tells part of the picture. The same networks that spread disease also spread knowledge and know-how. Economic networks help connect

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seemingly disparate countries and populations, and trade relationships connect countries not just as buyers and sellers, but as learners, creating channels through which expertise developed anywhere can influence outcomes everywhere. This means that international activities targeted at one country may have significant spillovers beyond the intended target's borders.

While we know a lot about the direct effect of foreign economic assistance, we know little about spillovers. Studies evaluate whether aid improves health, governance, or economic growth within the borders of the country receiving it—and debate whether those direct effects are large, small, or conditional on institutions (Burnside & Dollar, 2000; Easterly, 2006; Sachs, 2005). This bilateral framing treats spillovers as noise to be controlled rather than as a signal worth measuring. As a result, we have no systematic account of whether and how aid generates benefits for countries that never receive it, nor of whether the aggregate value of those indirect effects might dwarf the direct impacts that dominate conventional cost-benefit calculations. In a globally interdependent economy where knowledge, not just disease, travels through trade and migration networks, this omission may substantially understate what well-designed aid programs actually accomplish.

We develop and test a model of knowledge diffusion through trade networks, using PEPFAR –the President's Emergency Plan for AIDS Relief—as the empirical setting[3]. The theoretical contribution is general: we formalize how targeted interventions generate knowledge capital that propagates through international trade, producing spillovers whose magnitude depends not on geographic proximity or formal institutional ties but on the structure of economic relationships. This framework shows how any knowledge-generating intervention—in health, governance, or elsewhere—can become a practical global public good through the diffusion infrastructure provided by trade networks. The model generates precise predictions about where spillovers flow, why aid effectiveness varies with network position, and how aggregate indirect benefits can exceed direct impacts by orders of magnitude. PEPFAR is an ideal empirical case precisely because it generates specialized, diffusible knowledge—about treatment protocols, supply chain management, and behavior change—in countries embedded in global trade, allowing us to trace the network clearly.

Using spatial autoregressive models, we find strong support for the theory's predictions. PEPFAR significantly reduces HIV incidence in recipient countries, but the aggregate indirect effects accruing to non-recipients are 20 to 100 times larger than the aggregate direct effects—a ratio that reflects both the per-capita magnitude of spillovers and the large populations of major trading partners who receive them. Major economies, including China, India, and the United States, see measurable reductions in HIV incidence from PEPFAR investments in Africa. These estimates are robust across multiple spatial

[3] PEPFAR has invested over $100 billion in HIV/AIDS programs across more than 50 countries since 2003

specifications, providing direct evidence of the theoretical prediction that partner-country aid generates spillovers through trade networks.

This paper makes three major contributions to the fields of international relations and political economy. First, we expand policy diffusion research beyond norms and institutional practices (Simmons et al., 2006; Dobbin et al., 2007; Cao et al., 2013) by demonstrating how economic networks transmit tangible health benefits. Trade relationships enable knowledge sharing through professional exchanges, technical cooperation, and demonstration effects—creating spillovers that operate independently of formal policy adoption and accumulate in systematic, predictable ways governed by network structure. Second, we challenge the bilateral-multilateral dichotomy in international cooperation theory by showing that network structure, rather than organizational form, determines whether bilateral programs generate public goods. While traditional theory emphasizes free-riding without supranational governance (Olson, 1965; Barrett, 2007), PEPFAR produces multilateral-like externalities through bilateral implementation— the "publicness" of aid arises endogenously from dense trade networks that serve as diffusion infrastructure. Third, we argue that aid effectiveness heavily depends on recipients' positions within networks—building on research on aid conditionality (Burnside & Dollar, 2000; Collier, 2007) by emphasizing network embeddedness, not just domestic institutions, as a key factor influencing program success. The marginal impact of PEPFAR decreases as countries become more connected with other aid recipients, aligning with patterns of information redundancy and limits to absorptive capacity (Cohen & Levinthal, 1990; March, 1991).

More practically, an explicit accounting of the global public-good character of bilateral aid yields substantial revisions to conventional cost-benefit calculations. Traditional analyses that consider only direct recipient impacts estimate PEPFAR's cost-effectiveness at approximately $1,800 per disability-adjusted life year (DALY) averted.[4] When network spillovers are incorporated, point estimates suggest this drops to approximately $18–$90 per DALY—a range that would place PEPFAR among the most cost-effective global health interventions, comparable to childhood vaccination programs (Ozawa et al., 2012). This range reflects genuine uncertainty stemming from variation in trade integration across recipient countries, the population-weighting procedure, and assumptions embedded in the DALY conversion; the lower bound in particular depends on spillovers to large-population trading partners. The qualitative conclusion—that accounting for spillovers dramatically improves apparent cost-effectiveness—is robust across the spatial specifications we estimate.

[4] A disability-adjusted life year (DALY) is a summary measure of disease burden that combines years of life lost to premature death with years lived with disability or illness (Murray & Lopez, 1996). One DALY represents one year of healthy life lost. Cost-effectiveness in global health is conventionally expressed as cost per DALY averted, with interventions below $100–$150 per DALY generally considered highly cost-effective by international benchmarks (Jamison et al., 2006).

These findings come at a crucial moment. Foreign aid faces unprecedented political opposition, with active proposals to dismantle PEPFAR and cut development budgets (Burki, 2025; Ratevosian et al., 2025). By showing that bilateral health aid produces significant spillovers that benefit donor countries—including the United States, which also sees HIV reductions from PEPFAR investments in Africa—our analysis challenges zero-sum views and offers strategic support for maintaining aid programs. The costs of dismantling PEPFAR go well beyond the bilateral relationships that originally motivated the program's design. This challenges the common idea that economic integration mainly promotes disease spread (Fidler, 1996; Davies, 2010). While networks do transmit pathogens, they also spread positive health knowledge through the same channels.[5]

The paper proceeds as follows. Section 2 situates our argument within existing research and identifies the theoretical mechanisms linking bilateral aid to global spillovers. Section 3 develops a formal network model of health production and knowledge diffusion, generating testable hypotheses. Section 4 describes our data and spatial econometric approach. Section 5 presents results and Section 6 concludes with theoretical and policy implications.

2. Foreign Aid, Diffusion, and Global Health Networks

We draw on three bodies of literature in building our argument. First, research on aid effectiveness shows that well-designed programs improve outcomes for recipients (Bendavid & Bhattacharya, 2009; Bendavid et al., 2012), but it primarily focuses on direct impacts while neglecting cross-border externalities. Second, policy diffusion scholarship indicates that norms and practices spread through networks via learning, emulation, and competition (Simmons et al., 2006; Gilardi, 2016), yet it seldom examines how material interventions generate spillovers or how network position influences effectiveness. Third, research on globalization and health highlights disease transmission through trade and migration (Kimball, 2008; Oster, 2012), often overlooking the ability of networks to disseminate beneficial health knowledge. We bring these literatures together by proposing that bilateral health aid creates global public goods through trade-mediated knowledge diffusion, while also identifying the conditions under which the structure of international trade networks affects both the scale and distribution of these benefits.

Our theoretical contribution focuses on several mechanisms that transform bilateral aid into a networked global public good. First, PEPFAR generates knowledge capital about effective HIV prevention and treatment. The program's investments—training health

[5] This dual role of interdependence aligns with complex interdependence theory (Keohane & Nye, 1977) and illustrates how networks shape not only vulnerability but also the propagation of solutions.

workers, strengthening supply chains, implementing treatment protocols—develop expertise that extends beyond clinical services to include organizational practices, health system management, and behavior change strategies (Bor et al., 2017). Because HIV prevention depends heavily on spreading knowledge rather than just administering clinical treatment (Kohler et al., 2007; Merson et al., 2008), these investments produce diffusible benefits that can travel through the same economic channels through which countries exchange goods and services.

Second, this knowledge spreads through international trade networks. Extensive research shows that trade promotes learning and knowledge transfer through various mechanisms (Coe & Helpman, 1995; Keller, 2004). Trade liberalization improves access to higher-quality inputs that contain advanced technologies (Amiti & Konings, 2007). Exporting firms adopt better practices by operating in foreign markets (De Loecker, 2013; Bustos, 2011). At a broader level, productivity spillovers travel through trade networks, with the network position influencing how much spillover a country receives (Lumenga-Neso et al., 2005; Chaney, 2014). Specifically in the health sector, trade creates overlapping channels for knowledge sharing: professional mobility exposes business travelers and health workers to prevention practices abroad; multinational companies share workplace health policies along supply chains; and economic interdependence creates shared incentives to invest in disease control (Zhang et al., 2011). The ways that technological and organizational knowledge spread through trade networks are structurally similar to those that spread HIV-related practices. Our empirical approach tests whether these channels produce measurable health benefits in non-recipient countries, using HIV knowledge data from surveys as direct evidence of the diffusion process.

Third, network structure influences both the extent of spillovers and the conditional effectiveness of bilateral aid. Dense trade networks facilitate diffusion, transforming bilateral programs into practical global public goods through what Kaul et al. (1999) describe as "aggregation technology"—where individual contributions create benefits that spread throughout the entire network. However, this same connectivity can lead to diminishing returns for recipients. Countries that are highly integrated with other PEPFAR-supported partners already acquire HIV knowledge indirectly through trade, leading to information redundancy and increased coordination costs that diminish the marginal value of additional bilateral assistance (Cohen & Levinthal, 1990; March, 1991). Therefore, aid effectiveness relies heavily on network position: peripheral countries benefit most from direct assistance, while highly connected recipients see smaller marginal gains but produce larger spillovers throughout the broader network.

We integrate these mechanisms by creating a networked health production model that formalizes how bilateral aid leads to both domestic outcomes and network-mediated spillovers. The formal model suggests four testable hypotheses regarding direct effects, conditional effectiveness, network spillovers, and knowledge diffusion mechanisms. Our empirical approach employs spatial autoregressive (SAR) models to measure spatial dependence in HIV outcomes as a simplified test of the theory's predictions, and we enhance these with Spatial Durbin and SLX specifications that incorporate spatial lags of

PEPFAR aid itself—offering a more direct way to operationalize the model's prediction that partner-country aid causes spillovers through the network. The data on HIV knowledge from surveys further demonstrate the diffusion process and differentiate knowledge transmission from general trade-related shocks.

3. A Network Model of Bilateral Aid, Knowledge Diffusion, and Global Spillovers

Foreign aid is often viewed as bilateral: donors provide resources directly to recipients, with interventions occurring within national borders and benefits mainly accruing to the recipient country. This perspective assumes that policy impacts are confined, with spillovers limited to nearby countries through disease transmission or migration. However, health interventions function in a globally interconnected economy, where knowledge—not just disease—spreads through economic and social networks (Coe & Helpman, 1995; Keller, 2004; Lumenga-Neso et al., 2005).

We reconceptualize PEPFAR as operating through two mechanisms that together transform bilateral health aid into a practical global public good. First, PEPFAR creates knowledge capital about effective HIV prevention and treatment that spreads through trade networks, providing health benefits for countries whether or not they receive direct aid. Second, this diffusion shapes aid effectiveness within recipient countries: as nations engage with PEPFAR-supported networks, indirect knowledge sharing generates information redundancy that reduces the marginal value of additional bilateral assistance.

3.1 Setup

Consider a world of N countries indexed by i, observed over discrete time periods t. Countries are embedded in an international trade network represented by a row-normalized matrix $\mathbf{W}$, where $w_{ij} \geq 0$ denotes the share of country i's total trade conducted with country j. Trade networks capture more than the exchange of goods: they proxy for repeated interactions among firms, governments, and professionals, creating channels through which health-related knowledge diffuses across borders (Keller, 2004; Lumenga-Neso et al., 2005).

Health improvements H_{it} are produced using both material resources and knowledge:

$$H_{it} = \alpha(K_{it})A_{it} + \beta K_{it} + \varepsilon_{it},$$

where A_{it} is bilateral aid per capita, K_{it} is the health-related knowledge stock, and $\alpha(K_{it}) = \alpha_0 - \alpha_1 K_{it}$ captures diminishing returns: as knowledge accumulates, the marginal productivity of additional aid decreases. The term βK_{it} represents the direct contribution of knowledge to health outcomes—improved prevention practices, health system management—independent of aid flows.

Knowledge accumulates through domestic production funded by aid and diffusion through the trade network:

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

where $\rho \in (0,1)$ is the rate at which knowledge depreciates (through staff turnover, institutional decay, or obsolescence), $\gamma > 0$ governs how effectively aid generates new knowledge domestically, and $\delta > 0$ scales absorption of knowledge from trading partners.

3.2 The Network Multiplier

Solving for the steady-state knowledge stock yields a compact result that is central to the paper's argument (derivation in Appendix B):

$$\mathbf{K} = \tilde{\gamma}\, M\, \mathbf{A}, \qquad M \equiv \left(\mathbf{I} - \tilde{\delta}\, \mathbf{W}\right)^{-1},$$

where $\tilde{\gamma} = \gamma/\rho$ is the long-run knowledge yield per unit of sustained aid, and $\tilde{\delta} = \delta/\rho$ is the effective diffusion-to-depreciation ratio. The matrix M is the *network multiplier*: it exists and has non-negative entries provided diffusion does not outpace depreciation ($\tilde{\delta} < 1/\lambda_{\max}(\mathbf{W})$).

The network multiplier is the key quantity in the model. Its (i,j) entry M_{ij} measures the cumulative influence of country j's aid on country i's knowledge stock, aggregating not just direct trade links but chains of transmission through partners' partners and beyond. A country's knowledge stock therefore reflects not only the aid it directly receives but the entire constellation of aid flowing through its trade network—a formalization of the intuition that economically connected countries share health-related information and practices even without formal coordination.

Substituting the steady-state knowledge stock into the health production function yields the reduced-form relationship linking aid to health outcomes:

$$H_i = \alpha_0 A_i + \beta\tilde{\gamma}(M\mathbf{A})_i - \alpha_1\tilde{\gamma}\, A_i \cdot (M\mathbf{A})_i + \varepsilon_i.$$

The three terms capture distinct mechanisms: the direct material effect of aid ($\alpha_0 A_i$); the knowledge-mediated health benefit that depends on aid flowing through the entire network, not just to country i itself ($\beta\tilde{\gamma}(M\mathbf{A})_i$); and diminishing returns, whereby the marginal productivity of aid declines as the knowledge stock grows through network exposure ($-\alpha_1\tilde{\gamma}\, A_i \cdot (M\mathbf{A})_i$).

3.3 Direct and Indirect Effects

The total marginal effect of aid on health outcomes—the Jacobian $\partial\mathbf{H}/\,\partial\mathbf{A}$—has a natural direct/indirect decomposition (full derivation in Appendix B). The diagonal entries capture each country's marginal benefit from its own aid; the off-diagonal entries capture spillovers from country j's aid to country i's outcomes. For non-recipient countries ($A_i = 0$), the spillover expression simplifies to:

$$\frac{\partial H_i}{\partial A_j}\Big|_{A_i=0} = \beta\tilde{\gamma}\, M_{ij} > 0.$$

Non-recipients receive unambiguously positive spillovers proportional to their network proximity to aid recipients, formalized through M_{ij}. Crucially, because M_{ij} captures higher-order connections—the second-order term $\tilde{\delta}^2\mathbf{W}^2$ reaches partners' partners, and so on—spillovers propagate well beyond countries with direct trade ties to recipients. In dense global trade networks, the cumulative indirect effects aggregated across all non-recipients can substantially exceed the direct effects on the recipient itself.

3.4 Conditional Effectiveness and Diminishing Returns

The model also generates a prediction about how network position shapes aid effectiveness *within* recipient countries. Define network exposure as the weighted average of partner aid:

$$E_{it} = \sum_j w_{ij} A_{jt} = (\mathbf{WA})_i.$$

As exposure increases, the recipient's knowledge stock grows through the network channel, raising the term $-\alpha_1\tilde{\gamma}(M\mathbf{A})_i$ in the direct effect and reducing the marginal productivity of additional bilateral aid:

$$\frac{\partial^2 H_i}{\partial A_i\ \partial E_i} < 0.$$

Intuitively, a recipient already embedded in a dense network of PEPFAR-supported partners possesses substantial HIV-related knowledge acquired indirectly through trade. Additional bilateral aid delivers diminishing returns because it increasingly duplicates knowledge already available through network channels. This mechanism aligns with absorptive capacity theory: Cohen and Levinthal (1990) show that organizations can only productively integrate new knowledge at a rate determined by their existing knowledge base and the degree of overlap with incoming information. March (1991) demonstrates that exploitation of familiar knowledge crowds out the capacity to absorb genuinely novel contributions. In highly connected recipients, both effects operate simultaneously.

This naturally motivates our spatial econometric framework. The SAR parameter ρ captures the empirical magnitude of spatial interdependence in HIV outcomes transmitted through trade ties—a reduced-form operationalization of the knowledge diffusion predicted by the network multiplier. We supplement the SAR with SLX and SDM specifications that include spatial lags of PEPFAR aid directly, providing a closer empirical test of the model's prediction that partner-country aid generates spillovers through the network.

3.5 Hypotheses

The model generates four testable predictions.

Hypothesis H1: Direct Effectiveness. PEPFAR aid reduces HIV incidence in recipient countries. The marginal health benefit of aid is positive on average, reflecting direct material support and knowledge production, net of diminishing-returns drag:

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

Hypothesis H2: Conditional Effectiveness and Diminishing Returns. The marginal effectiveness of bilateral aid declines as recipients become more embedded in networks of other PEPFAR-supported partners:

$$\frac{\partial^2 H_i}{\partial A_i\ \partial E_i} < 0.$$

This comparative static reflects information redundancy and absorptive capacity constraints in highly connected recipient countries.

Hypothesis H3: Network Spillovers. Health improvements generated by PEPFAR aid spill over to other countries through the trade network. For $i \neq j$:

$$\frac{\partial H_i}{\partial A_j} = \tilde{\gamma}\, M_{ij}(\beta - \alpha_1 A_i) > 0,$$

with the spillover magnitude proportional to the network multiplier entry M_{ij}, which captures the cumulative strength of trade connections including indirect paths through intermediary partners.

Hypothesis H4: Knowledge Diffusion Mechanism. Countries more exposed to PEPFAR-supported partners through trade exhibit greater health improvements even absent direct aid. For non-recipients:

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

which is increasing in the density and strength of trade connections to aid recipients. We test this directly by examining whether trade exposure to PEPFAR recipients predicts improvements in HIV/AIDS knowledge among non-recipient countries.

Together, these four hypotheses summarize the core empirical implications of the model and guide the specification and interpretation of the estimating equations developed in Section 4.

4. Data and Research Design

Enacted in 2003 under President George W. Bush's administration, the President's Emergency Plan for AIDS Relief (PEPFAR) is the largest commitment by any nation to fight a single disease in history. Driven by the devastating HIV/AIDS epidemic sweeping through sub-Saharan Africa — where infection rates exceeded 20% of the adult population in several countries and AIDS had become the leading cause of death — PEPFAR authorized $15 billion over five years to expand antiretroviral treatment, prevention initiatives, and health system capacity. The program initially focused on fifteen countries in the first phase (Botswana, Côte d'Ivoire, Ethiopia, Guyana, Haiti, Kenya, Mozambique, Namibia, Nigeria, Rwanda, South Africa, Tanzania, Uganda, Vietnam, and Zambia), chosen based on epidemic severity and their ability to absorb aid. A 2008 reauthorization under the Lantos-Hyde Act increased funding to $48 billion and added a second group of recipients (Angola, Burundi, Cameroon, the Democratic Republic of the Congo, Lesotho, Malawi, Swaziland, and Zimbabwe), expanding the program's reach across sub-Saharan Africa. By 2023, PEPFAR had supported antiretroviral treatment for over 20 million people, funded more than 700,000 health worker positions, and operated in over 50 countries (PEPFAR, 2023; UNAIDS, 2024).

FIGURE 1: First and Second Phase PEPFAR Recipient Countries

This phased, geographically focused rollout offers the variation in bilateral aid exposure we analyze throughout our study. The two waves of recipient designation — 2003 and 2008 — create meaningful differences in the timing and amount of aid across countries that maintain trade relationships, helping us differentiate between direct effects on recipients and indirect spillovers to their trading partners. We test these hypotheses using spatial autoregressive models on panel data from 175 countries between 2004 and 2020, a sample that includes both PEPFAR recipients (45 countries receiving aid at least once) and non-recipients. Importantly, the non-recipient countries are not a traditional control group — instead, they are the main context for observing spillover effects, as knowledge spreads outward through their trade connections to recipients.

Outcome Variables

Our main outcome for hypotheses 1-3 is the yearly change in HIV incidence rate per 100,000 people ($\Delta y_{it} = y_{it} - y_{i,t-1}$), sourced from the Institute for Health Metrics and Evaluation (IHME) Global Burden of Disease Study.[6] First-differencing removes time-invariant country characteristics (such as health system capacity, cultural factors, geographic features) that could be related to PEPFAR allocation, focusing our analysis on changes in HIV trends.

To test the knowledge transmission mechanism (H4), we measure HIV/AIDS knowledge as the percentage of women aged 15–49 with comprehensive, correct understanding of HIV prevention methods, based on data from Demographic and Health Surveys (DHS).[7] This measure reflects the population-wide dissemination of HIV-related information, which measures behaviors that reduce risk (De Neve et al., 2017).

Independent Variables

[6] https://www.healthdata.org/research-analysis/gbd

[7] https://dhsprogram.com/

Our primary measure of U.S. bilateral HIV/AIDS assistance is drawn from the OECD Creditor Reporting System[8], focusing on purpose code 130.60 to capture PEPFAR-related aid. We calculate per capita allocations in constant 2020 U.S. dollars, adjusting all values using the U.S. GDP deflator from the World Development Indicators[9] and recipient population data from the UN World Population Prospects.[10] This approach ensures comparability across countries and over time, isolating the variation in PEPFAR disbursements that is most relevant for evaluating differential program impacts.

To examine the conditional effectiveness of PEPFAR aid (H2), we construct a measure of each recipient country's trade integration with contemporaneous PEPFAR partners using data from CEPII.[11] Specifically, for country i in year t, we define TradePEPFAR%$_{it}$ as the share of annual total trade (imports plus exports) conducted with other PEPFAR recipients:

$$\text{TradePEPFAR\%}_{it} = \frac{\sum_{j \in \text{PEPFAR}_t} (\text{Imports}_{ijt} + \text{Exports}_{ijt})}{\sum_j (\text{Imports}_{ijt} + \text{Exports}_{ijt})}.$$

This time-varying indicator captures a recipient's integration into the PEPFAR network and operationalizes our prediction that highly connected countries experience diminishing marginal returns to direct aid. Following the logic of organizational learning and network spillovers, we include linear, quadratic, and higher-order interaction terms between PEPFAR aid and trade integration to allow for non-linearities in the relationship between network position and aid effectiveness. The theoretical model predicts that diminishing returns should accelerate with exposure: at low levels of integration, additional network connections provide genuinely new information, but as integration deepens, the marginal contribution of each additional connection declines more rapidly due to compounding information overlap and coordination frictions. The higher-order terms capture this accelerating nonlinearity.

To assess indirect spillover effects (H3), we construct annual trade weight matrices, W_t^{trade}, in which each element $w_{ij,t}$ reflects the volume of bilateral trade (imports plus exports) between countries i and j. Diagonal elements are set to zero, and rows are normalized to sum to one, ensuring that each country's exposure is expressed as a weighted average of its trading partners' outcomes. These year-specific matrices are stacked into a block-diagonal panel structure, capturing the dynamics of the entire global trade network rather than limiting analysis to direct PEPFAR connections. This structure

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[8] https://www.oecd.org/en/publications/serials/creditor-reporting-system-on-aid-activities_g1gha57a.html

[9] https://databank.worldbank.org/source/world-development-indicators

[10] https://population.un.org/wpp/

[11] https://www.cepii.fr/CEPII/en/bdd_modele/bdd_modele_item.asp?id=8

allows us to trace how improvements in one country's HIV outcomes diffuse through interconnected economies.

Finally, we include various covariates to account for alternative determinants of HIV trends and aid allocation. These include economic and demographic indicators, GDP per capita (Penn World Table), population size (UN), and urbanization (World Bank), as well as health system characteristics, such as life expectancy, infant mortality, the ratio of government to private health spending (IHME), internet access (World Bank), and non-HIV health aid per capita (IHME). These variables were selected because prior research indicates they shape both a country's vulnerability to HIV and the allocation or effectiveness of foreign health aid.[12] Together, these controls mitigate confounding influences and help isolate both the direct and network-mediated effects of PEPFAR interventions.

4.1 Estimating Framework

To capture both direct and indirect channels simultaneously, our baseline specification takes the following form:

$$\begin{aligned}\Delta y_{it} = \rho \sum_j w_{ij,t}\, \Delta y_{jt} &+ \beta_1 \text{PEPFAR}_{it} + \beta_2 \text{TradePEPFAR\%}_{it} + \beta_3 \text{TradePEPFAR\%}_{it}^2 \\ &+ \beta_4 (\text{PEPFAR}_{it} \times \text{TradePEPFAR\%}_{it}) + \beta_5 (\text{PEPFAR}_{it} \times \text{TradePEPFAR\%}_{it}^2) \\ &+ X_{it}\zeta + \alpha_i + \delta_t + \varepsilon_{it}.\end{aligned}$$

The dependent variable, Δy_{it}, is the annual change in HIV incidence per 100,000 population. Country fixed effects, α_i, absorb all time-invariant national characteristics, including baseline disease burden, health system capacity, and institutional features, while year fixed effects, δ_t, capture global shocks and common trends in HIV treatment and prevention. All models include a vector of time-varying controls, X_{it}, described above.

The spatial lag term, $\rho \sum_j w_{ij,t}\, \Delta y_{jt}$, captures interdependence in HIV outcomes across countries linked through trade. In the theoretical model, this interdependence arises endogenously from the diffusion of aid-generated knowledge stocks through the network multiplier $(\mathbf{I} - \tilde{\delta}\mathbf{W})^{-1}$. The SAR specification provides a reduced-form operationalization of this mechanism: the parameter ρ measures the net degree of spatial interdependence in HIV outcome changes transmitted through trade ties, encompassing the knowledge diffusion channel emphasized by the theory alongside any other trade-correlated processes. Rather than estimating the structural diffusion parameter directly, we use the SAR framework to quantify the total spatial dependence in HIV outcomes and then decompose it into direct and indirect effects following LeSage & Pace (2009). This approach is conservative in that ρ captures the aggregate spatial relationship without restricting it to a single channel, while the theoretical model provides the interpretive framework for understanding why trade networks—rather than geographic or migration

[12] See Bendavid & Bhattacharya (2009) on health system capacity and aid effectiveness, and Dreher et al. (2019a) on aid allocation criteria and recipient characteristics.

networks—generate this dependence. As a more direct test of the theory's prediction that partner aid generates spillovers through trade, we also estimate Spatial Lag of X (SLX) and Spatial Durbin (SDM) specifications that include spatial lags of PEPFAR aid itself (Section 5.2, Table 4).

4.2 Direct Effects and Conditional Effectiveness (H1 and H2)

Hypothesis H1 predicts that bilateral PEPFAR assistance reduces HIV incidence in recipient countries. The coefficient β_1 captures the effect of aid when a country has no trade exposure to other PEPFAR recipients. Hypothesis H2 follows from the model's assumption of diminishing marginal returns to aid as knowledge accumulates: as countries become more integrated into networks of other PEPFAR-supported partners, additional bilateral assistance yields smaller gains.

We operationalize this mechanism by interacting PEPFAR aid with a country's share of trade conducted with other PEPFAR recipients. Because the theory predicts that diminishing returns accelerate with network exposure, the specification includes higher-order interaction terms that allow the marginal effect of aid to vary nonlinearly with trade integration. We verify in Appendix Table A4 that the qualitative threshold pattern is robust to alternative functional forms, including specifications that omit the higher-order term and replace the polynomial with binned trade-integration dummies. The marginal effect of aid at a given level of trade integration c is:

$$\frac{\partial \Delta y}{\partial \text{PEPFAR}} = \beta_1 + \beta_4 c + \beta_5 c^2.$$

Consistent with H1, this marginal effect should be negative at low levels of integration. Consistent with H2, its magnitude should attenuate as trade integration increases. We report marginal effects evaluated at substantively meaningful values of trade integration and compute both short-run effects and long-run steady-state effects that account for spatial feedback through the network.

4.3 Network Spillovers and Indirect Effects (H3)

Hypothesis H3 predicts that health improvements generated by PEPFAR diffuse to other countries through trade networks. To test this prediction and distinguish trade-based diffusion from alternative sources of spatial dependence, we estimate models with multiple spatial weight matrices:

$$\Delta y = \sum_{k=1}^{K} \rho_k W_k \Delta y + X\beta + \varepsilon,$$

where each W_k represents a different network structure ($k \in \{\text{trade, geographic distance, migration}\}$), with all matrices row-standardized. The theory predicts a positive and robust coefficient on the trade network, reflecting the diffusion of HIV-related knowledge embedded in trade relationships.

To interpret the magnitude of spillovers, we follow LeSage & Pace (2009) and decompose estimated impacts into Average Direct Effects (ADE), Average Indirect Effects (AIE), and Average Total Effects (ATE) using the spatial multiplier matrix. This decomposition mirrors the theoretical distinction between within-country effects of aid and indirect effects transmitted through higher-order network connections.

4.4 Knowledge Diffusion Mechanism (H4)

The theoretical framework attributes spillovers to the diffusion of HIV-related knowledge rather than to material transfers. We test this mechanism by examining changes in HIV/AIDS knowledge among countries that never received PEPFAR assistance. Restricting the sample to non-recipient countries, we estimate:

$$\text{Knowledge}_{it} = \alpha_i + \delta_t + \beta_1 \text{TradePEPFAR\%}_{it} + X_{it}\zeta + \varepsilon_{it}.$$

Country and year fixed effects absorb all stable national characteristics and global trends. Hypothesis H4 predicts $\beta_1 > 0$: greater trade exposure to PEPFAR recipients should increase HIV-related knowledge even in the absence of direct aid. Parallel specifications using migration-based exposure allow us to assess alternative transmission channels.

4.5 Identification and Inference

Our identification strategy addresses three potential threats: endogeneity of aid allocation, the reflection problem in contemporaneous spatial lags, and the possibility that spatial dependence reflects correlated shocks rather than knowledge diffusion.

Aid allocation and reverse causality. PEPFAR disbursements are determined through Country Operational Plans (COPs) negotiated bilaterally between the U.S. government and recipient countries, with planning cycles of 12–18 months preceding actual disbursement. This institutional lag means that contemporaneous aid flows cannot respond to same-year changes in HIV incidence. Moreover, PEPFAR allocation criteria emphasize disease burden levels, governance capacity, and strategic priorities rather than short-run incidence trends or the recipient's trade relationships with third countries. First-differencing the dependent variable further removes time-invariant confounders correlated with both aid allocation and baseline disease burden. To the extent that any residual endogeneity exists—for instance, if anticipated incidence trends influence planning—the bias runs against our findings: countries experiencing worsening epidemics would receive more aid, biasing the direct effect toward zero. Our estimates are therefore conservative.

Disentangling diffusion from correlated shocks. The contemporaneous spatial lag $\rho \sum_j w_{ij}\, \Delta y_{jt}$ may capture correlated shocks structured along trade networks—such as synchronized economic downturns, pharmaceutical supply disruptions, or common exposure to global health campaigns—rather than knowledge diffusion per se. Year fixed effects absorb global shocks but not shocks that load specifically onto the trade network. We address this concern through four complementary strategies. First, we estimate models with multiple network matrices (trade, geographic distance, and migration) simultaneously. If spatial dependence reflected generic correlated shocks among economically linked countries, we would expect similar patterns across network types — but knowledge diffusion operating through professional exchange, corporate practices, and institutional cooperation should load specifically onto trade networks rather than geographic proximity or migration. Second, SLX and SDM specifications that include spatial lags of PEPFAR aid itself — $\mathbf{W} \times$ PEPFAR Aid— provide a more direct test of the diffusion mechanism by asking whether aid to a country's trading partners independently predicts reductions in its own HIV incidence. Third, we examine HIV knowledge transmission directly among non-recipient countries, providing evidence of the diffusion mechanism independent of its health consequences. Fourth, the conditional effectiveness pattern (H2) — whereby the marginal impact of direct aid diminishes with trade exposure to other PEPFAR recipients — is a distinctive prediction of knowledge-based diffusion models that would not arise from generic spatial correlation. Results from all four strategies are reported in Section 5.

Estimation and inference. All spatial autoregressive models are estimated by maximum likelihood with heteroskedasticity-robust standard errors clustered at the country level. SLX models are estimated by OLS. Because cross-sectional dependence is modeled explicitly through the spatial lag in SAR and SDM specifications, clustering addresses serial correlation and heteroskedasticity within countries rather than spatial correlation itself. Substantive interpretation focuses on simulated direct and indirect effects derived from the spatial multiplier rather than on individual coefficients, following LeSage & Pace (2009).

5. Results

5.1 Descriptive Patterns

Across the full sample, the annual change in HIV incidence averages −3.38 cases per 100,000 population (SD = 11.93), reflecting the widespread decline in HIV transmission during the study period alongside substantial cross-national heterogeneity. First-differenced incidence ranges from −146.7 to 21.8, underscoring that countries experienced markedly different trajectories even amid global improvements.

Among PEPFAR recipient countries, per capita HIV/AIDS assistance averages $1.09 (SD = 4.63), with allocations ranging from zero to $47.43. Trade integration with other PEPFAR recipients also varies widely: on average, countries conduct 16.1% of their total trade with PEPFAR-supported partners (SD = 19.4%), with values spanning nearly the entire unit interval. This dispersion is central to our theoretical argument, which predicts that both the direct effectiveness of aid and the magnitude of spillovers depend on a country's position within the global trade network.

Table 1 presents mean changes in HIV incidence stratified by PEPFAR recipient status and trade integration with other PEPFAR countries. Among non-PEPFAR recipients, countries with high trade exposure to PEPFAR partners experienced substantially larger average HIV incidence reductions (−1.524 per 100,000) than those with low exposure (−0.412), a difference of −1.103 [95% CI: −1.58, −0.63] that is statistically significant (Welch t-test: $t = -4.5, p < .001$). This pattern is broadly consistent with the theoretical framework, though these comparisons are unconditional.

Table 1: HIV Incidence by PEPFAR Status and Trade Integration

5.2 Direct Effects, Conditional Effectiveness, and Network Spillovers

Direct Effects of PEPFAR Aid

Table 2 presents results from the spatial autoregressive models. PEPFAR aid per capita is negatively and significantly associated with changes in HIV incidence across all specifications (H1). The coefficient on PEPFAR aid ranges from approximately −0.47 to −0.49 across spatial and non-spatial models, indicating that a one-dollar increase in per capita aid reduces HIV incidence by roughly 0.5 cases per 100,000 population. Importantly, the magnitude and significance of this effect are largely unchanged when spatial dependence is introduced, indicating that PEPFAR's direct effectiveness is not an artifact of unmodeled network correlations.

Conditional Effectiveness and Diminishing Returns

Consistent with our model, the effectiveness of bilateral PEPFAR aid depends systematically on recipients' exposure to other PEPFAR-supported countries through trade. The interaction between PEPFAR aid and trade integration is positive and statistically significant, while the interaction with the squared trade term is negative and significant across all models. Together with the higher-order interaction term (PEPFAR Aid × PEPFAR Trade × PEPFAR Trade^2), these coefficients imply that the marginal impact of PEPFAR aid declines nonlinearly as recipients become more embedded in PEPFAR trade networks, consistent with H2. The higher-order term captures the theoretical prediction that diminishing returns accelerate with network exposure, as information redundancy compounds beyond a threshold level of integration. The qualitative pattern—large negative marginal effects at low integration, rapid attenuation, and statistical insignificance beyond roughly 15%—is robust to alternative functional forms, including specifications that omit the higher-order term or replace the polynomial with binned trade-integration dummies interacted with aid (Appendix Table A4).

Figure 2 (Panel A) illustrates these conditional effects. When trade exposure to PEPFAR recipients is zero, the marginal effect of aid is largest, reducing HIV incidence by approximately 1.8 cases per 100,000 (95% CI: [−2.87, −0.73]). As trade integration increases, this effect attenuates sharply: at 5% exposure, the marginal effect declines by more than one-third; at 10%, it falls by over two-thirds; and beyond roughly 15% integration, the marginal effect is no longer statistically distinguishable from zero.

Figure 2: Conditional Long Run Steady State Effects

This pattern aligns closely with the theory of knowledge-driven health production. Countries with limited exposure to PEPFAR networks receive novel information and practices through bilateral aid, yielding large marginal gains. As exposure increases, however, recipients increasingly access HIV-related knowledge indirectly through trade-linked partners, generating information redundancy and coordination constraints that reduce the incremental value of additional bilateral assistance.

Table 2: Main Results

Long-Run Effects and Network Feedback

Accounting for spatial feedback further reinforces these conclusions. Long-run steady-state marginal effects, reported in Table 3, show that at low levels of trade integration (e.g., 5%), PEPFAR continues to produce meaningful reductions in HIV incidence even after accounting for network effects. At higher levels of integration (15% and above), long-run effects become small and statistically non-significant, confirming the presence of threshold effects implied by the model.

Table 3: Long-Run Steady-State (LRSS) Marginal Effects of PEPFAR Aid

Network Spillovers and Trade-Specific Diffusion

The spatial autoregressive models also provide strong evidence of network spillovers transmitted through international trade. The trade-based spatial parameter is positive and statistically significant across all specifications ($\rho \approx 0.12$), indicating that declines in HIV incidence in one country are associated with contemporaneous declines in its trading partners. This coefficient implies a spatial multiplier of approximately 1.13, amplifying equilibrium effects by 13% through network feedback and directly supporting Hypothesis H3.

Crucially, these spillovers are specific to trade networks. When geographic distance and migration networks are included alongside trade, their spatial parameters are small and statistically non-significant ($\rho_{\text{distance}} = -0.108$, 95% CI: [−0.279, 0.133]; $\rho_{\text{migration}} = 0.001$, 95% CI: [−0.074, 0.071]; Table 2, columns 4–5), while the trade coefficient remains stable. Additional models using only distance or migration weights likewise fail to detect spatial dependence (Appendix Table A2). This trade-specificity is difficult to reconcile with a correlated-shocks interpretation and is consistent with knowledge diffusion operating through channels embedded specifically in trade relationships.

Taken together, the results in Tables 2 and 3 strongly support the theoretical framework. PEPFAR aid produces significant direct health improvements, but its marginal effectiveness decreases as recipients become part of networks that already spread HIV-related knowledge. At the same time, these networks also spread health benefits internationally, turning bilateral aid into a global public good.

Alternative Spatial Specifications and Robustness

The baseline SAR model captures spatial interdependence through a contemporaneous lag of the outcome, which is a reduced-form measure that encompasses multiple channels of trade-correlated spatial dependence. To test more directly whether PEPFAR aid to trading partners generates spillovers—as the theoretical model specifically predicts—we estimate two alternative specifications that include spatial lags of PEPFAR aid itself, as well as a specification with lagged aid to address timing concerns. Table 4 reports these results alongside the baseline SAR for comparison.

The Spatial Lag of X (SLX) specification adds $\mathbf{W} \times$ PEPFAR Aid as a regressor, testing whether aid allocated to country i's trading partners independently predicts reductions in country i's HIV incidence. The coefficient is positive and statistically significant (0.135, $p < .05$; Table 4, column 2), providing direct evidence that partner aid generates health spillovers through trade networks. The Spatial Durbin Model (SDM) combines the spatial lag of the outcome with spatial lags of the regressors, offering a more flexible specification that nests both the SAR and SLX as special cases. In the SDM, the $\mathbf{W} \times$ PEPFAR Aid coefficient strengthens to 0.309 ($p < .001$; Table 4, column 3), and the model achieves substantially better fit than the baseline SAR (AIC: 13,740 vs. 13,822). Critically, the core PEPFAR coefficients—the direct effect, the interaction terms capturing conditional effectiveness, and the higher-order interaction—remain statistically significant and are broadly consistent with the baseline estimates across all three spatial specifications. The LR test for the SDM against the SAR is highly significant ($p < .001$), indicating that the spatial lags of PEPFAR aid carry independent explanatory power beyond what the spatial lag of the outcome captures.

To address concerns about the timing of disbursements and potential reverse causality, column 4 of Table 4 replaces contemporaneous aid with one-year lagged PEPFAR disbursements (PEPFAR$_{i,t-1}$). Because lagged aid was determined 12–18 months before the outcome is measured, this specification rules out same-year feedback from incidence changes to aid allocation. The lagged aid coefficient is negative and statistically significant (-0.346, $p < .01$), somewhat attenuated relative to the contemporaneous estimate (-0.490) but qualitatively consistent. This attenuation is expected: some fraction of PEPFAR's impact operates through rapid-response mechanisms (e.g., antiretroviral provision) that affect incidence within the year of disbursement, and the one-year lag mechanically misses these contemporaneous channels. The persistence of a significant effect at the one-year lag confirms that PEPFAR's impact is not an artifact of endogenous aid allocation.

Table 4: Spatial Specification Alternatives and Timing Robustness

5.3 Estimating the Magnitude of Spatial Spillovers

To quantify the scale of PEPFAR's spillover effects through global trade networks, we utilize the spatial multiplier matrix, formally expressed as:

$$M(\rho) = \left[\mathbf{I} - \sum_{k=1}^{K} \rho_k W_k\right]^{-1}.$$

This matrix captures the cumulative feedback effects across interconnected countries mediated by multiple spatial relationships. Building on our regression models that incorporate the interaction between PEPFAR aid and trade integration, we decompose the total marginal effect into three distinct components: the average direct effect (ADE), which measures the impact of aid within the recipient country itself; the average indirect effect (AIE), representing spillover impacts on trading partners; and the average total effect (ATE), the sum of these direct and indirect contributions.

Applying the framework of LeSage & Pace (2009), this decomposition is critical for isolating the relative contributions of within-country improvements and cross-border diffusion of health benefits via trade. Figure 2 visualizes this decomposition across different levels of PEPFAR trade integration. At approximately 5% trade integration, the direct effect (Panel A) of PEPFAR aid reduces HIV incidence by about 0.8 cases per 100,000 population, while indirect spillovers (Panel B) contribute a reduction of roughly 0.5 cases per 100,000. This corresponds to an indirect-to-direct ratio of approximately 0.6, underscoring the substantial role of network-mediated diffusion.

A note on the interpretation of indirect-to-direct ratios is warranted. Throughout this analysis, the ratios we report (ranging from approximately 20:1 to 100:1) compare aggregate quantities: the total number of HIV cases averted across all non-recipient trading partners through indirect spillovers versus the number of cases averted within the recipient country through direct effects. These aggregate indirect effects reflect the multiplication of modest per-capita effects across large populations. The prominence of China in Table 6—accounting for 70–80% of indirect cases averted across all simulated scenarios—reflects precisely this mechanism: China's extensive trade linkages with African PEPFAR recipients and its population of 1.4 billion amplify small per-capita spillovers into substantial aggregate case reductions. This population-scaling dynamic is not an artifact of methodological choices but rather the central mechanism our theory predicts: trade networks transmit knowledge benefits across population scales, and the global reach of trade ensures that even modest per-capita spillovers accumulate into significant aggregate health gains. Nevertheless, readers should interpret the headline ratios as comparing aggregate case counts (direct recipient totals versus global indirect totals) rather than per-capita magnitudes.

Notably, this per capita comparison understates the broader policy impact of spillovers. Indirect effects accumulate simultaneously across all trading partners, whereas direct effects are confined to the recipient country alone. Given that PEPFAR recipients typically trade with dozens of countries, the aggregate population benefiting from spillovers significantly exceeds the direct beneficiary population. Furthermore, disparities in population sizes amplify this effect: smaller African economies receiving aid often trade extensively with much larger economies, including China, India, the United States, and various European countries. When accounting for these population differences, indirect effects yield far greater total reductions in HIV incidence than direct effects, as demonstrated through the counterfactual simulations below.

To further assess the magnitude and distribution of spillovers, we simulate hypothetical PEPFAR allocations to four non-recipient countries with substantial HIV burdens and varying levels of trade integration. The four countries and their characteristics are shown below, followed by Table 5, which reports estimated cumulative reductions in HIV cases.

Counterfactual Simulation Countries

Table 5: Hypothetical PEPFAR Intervention — Cumulative HIV Case Reductions

These simulations reveal a striking disparity between direct and indirect effects. For Guinea-Bissau, direct PEPFAR aid is estimated to prevent 54.8 HIV cases, whereas indirect spillovers yield approximately 2,117.5 cases averted globally, an indirect-to-direct ratio of nearly 39:1, with over 97% of total benefits accruing to non-recipient countries. This pattern intensifies with increasing trade integration: Gabon exhibits a ratio of 58:1, Equatorial Guinea 101:1, and Djibouti 105:1, despite direct and indirect effects diminishing in absolute terms. As PEPFAR trade integration rises from 2.68% to 11.36%, direct effects decline by roughly 80% and indirect effects by 47%, consistent with the hypothesized diminishing returns driven by information redundancy and coordination costs. Crucially, however, the persistently high ratios indicate that 90 to 99% of PEPFAR's total health impact is realized through spillovers to non-recipient countries within the trade network. These findings suggest that conventional program evaluations focusing solely on direct effects substantially underestimate PEPFAR's global health contribution, by factors ranging from 20 to 100.

Examining the geographic distribution of spillovers (Table 6) reveals that China consistently emerges as the principal indirect beneficiary, accounting for 70 to 80% of the prevented HIV cases across all hypothetical scenarios. This prominence reflects China's extensive trade linkages with Africa and its large population base. Other notable beneficiaries include India, the United States, France, Pakistan, and Brazil, highlighting the global diffusion of health benefits spanning Asia, Europe, North America, and Africa.

Table 6: Hypothetical PEPFAR Intervention — Top Indirect Beneficiaries

5.4 Knowledge Diffusion Mechanism

Trade-Mediated Knowledge Spillovers

The baseline specification in Table 7 (Column 1) reveals a robust positive association between trade exposure and HIV knowledge: each percentage-point (pp) increase in trade share with PEPFAR recipients corresponds to an increase of approximately 27.83pp in comprehensive HIV knowledge ($p < .05$). This effect remains consistent under various robustness checks. Excluding countries that received PEPFAR aid in 2008 yields a similar estimate of 25.15pp (Column 2, $p < .05$), while controlling for regional fixed effects further strengthens the relationship to 30.39 and 28.13pp in Columns 3 and 4, respectively (both $p < .05$). These regional effects are notable, with respondents in the Americas, Europe, and North America exhibiting baseline HIV knowledge levels 10–14 percentage points higher than those in Africa, consistent with documented differences in policy diffusion rates across regions (Simmons et al., 2006).

Table 7: Trade and HIV/AIDS Knowledge Diffusion

Specifications incorporating country and year fixed effects (Table 7, columns 5 and 6) yield attenuated coefficients (6.15 and 7.31 pp) that fall below conventional significance thresholds. This attenuation is expected given the data structure: within-country temporal variation in trade shares is limited (median within-country standard deviation = 2.1 pp, compared to between-country standard deviation = 6.7 pp), leaving insufficient variation for the fixed-effects estimator to detect effects of the magnitude observed cross-sectionally. A rough calculation illustrates the power constraint: detecting even half the cross-sectional effect size (approximately 14 pp) with 95% confidence would require within-country variation roughly three times larger than what the data provide. The absorption of variation by time-invariant country characteristics—health infrastructure, literacy rates, media penetration—further compounds this limitation. Crucially, the point estimates in Table 7 columns 5–6 remain positive (approximately 25% of the cross-sectional estimates), consistent with attenuation from reduced variation rather than a reversal of the relationship. No specification produces a negative coefficient, which would be expected if the cross-sectional results were driven entirely by omitted variable bias.

Migration-Mediated Knowledge Spillovers

Table 8 examines migration networks as an alternative and complementary pathway for knowledge transmission. The baseline estimate of 27.15pp (Column 1, $p < .05$) closely mirrors the trade channel effect and remains positive and statistically significant across robustness checks (ranging from 21.11 to 22.79pp in Columns 2 to 4, all $p < .05$). Similar to the trade models, inclusion of country and year fixed effects (Columns 5 and 6) attenuates the coefficients to 3.79 and 3.78pp, respectively, rendering them statistically insignificant. The parallel attenuation patterns suggest that migration and trade channels share analogous dynamics in how knowledge transmission manifests over time and across contexts.

The congruent results for trade and migration networks underscore their complementary roles as conduits for the diffusion of HIV/AIDS knowledge. The sizable cross-sectional effects (ranging from 25 to 30pp) alongside attenuation in fixed effects models are consistent with theoretical expectations of diminishing marginal returns to knowledge accumulation. Initial exposure through these networks provides substantial informational gains, but additional increments yield smaller benefits as countries approach informational saturation.

Table 8: Migration and HIV/AIDS Knowledge Diffusion

Taken together, the evidence for H4 is multifaceted. Cross-sectional variation provides robust support for a positive association between network exposure to PEPFAR recipients and HIV-related knowledge (Tables 7–8, columns 1–4), with effect sizes that are large, stable across specifications, and consistent across both trade and migration channels. Within-country estimates are attenuated by limited temporal variation in trade shares, yielding positive but statistically insignificant coefficients (Tables 7–8, columns 5–6)—a pattern consistent with a statistical power limitation rather than absence of the mechanism.

Importantly, the knowledge evidence does not stand alone: it complements the trade-specificity of spatial dependence in the main models (Table 2, columns 3–5, showing that trade networks generate significant ρ while distance and migration do not), the direct evidence from spatial lags of PEPFAR aid in the SLX and SDM specifications (Table 4, columns 2–3, where $\mathbf{W} \times$ PEPFAR Aid is significant at $p < .05$ and $p < .001$ respectively), and the conditional effectiveness pattern predicted by knowledge diffusion theory (H2). The weight of this combined evidence supports knowledge transmission as a key mechanism underlying PEPFAR's observed spillovers, while acknowledging that definitive within-country identification of the knowledge channel remains a direction for future research with richer temporal variation in trade exposure.

6. Conclusion

Bilateral foreign aid can produce global public goods by distributing knowledge through economic networks. Our analysis indicates that PEPFAR generates spillover effects that extend far beyond recipient countries, with total indirect benefits exceeding direct impacts by 20 to 100 times — and traditional bilateral evaluations that ignore these spillovers significantly underestimate the program's value.

Our findings contribute to various debates in international relations and political economy. The policy diffusion literature shows that trade networks spread norms and policy models (Simmons et al., 2006); we also demonstrate that they transmit tangible material benefits from successful interventions. Countries gain from PEPFAR spillovers through trade connections without needing to implement similar programs at home — a distinct diffusion mechanism that operates through the economic infrastructure of globalization rather than deliberate political processes. The dual nature of trade networks — transmitting both disease risk and health knowledge — expands complex interdependence theory (Keohane & Nye, 1977) to illustrate how the same channels that create vulnerability can also spread solutions, creating positive-sum dynamics often overlooked in conventional globalization narratives.

The rise of China and India as key spillover beneficiaries — despite not providing direct funding — shows how emerging powers benefit from existing institutional arrangements (Ikenberry, 2008; Lake et al., 2021). If programs like PEPFAR deliver measurable health benefits to both established and rising powers, they promote shared interests in keeping effective global health governance, even amidst geopolitical competition — serving as a strategic reason for institutional cooperation that goes beyond the humanitarian purpose of aid. From a policy standpoint, development agencies should incorporate network effects into their evaluation frameworks and decision-making: central nodes in trade networks create larger overall spillovers, while peripheral countries gain the most from direct assistance. The best strategies would balance both approaches rather than focusing solely on bilateral cost-effectiveness.

The costs of dismantling PEPFAR extend well beyond recipient countries; they are spread across the global trade network, reaching nations with no formal stake in the program's continuation. In an era of increasing skepticism about international cooperation, our findings show that bilateral programs can accomplish much more than traditional evaluations suggest. The same economic networks that spread disease also transmit solutions, creating positive-sum dynamics where both donor and recipient countries gain measurable benefits — and providing pathways to sustain global public goods that align with the realities of twenty-first-century interdependence.

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Appendices

Table A1: Descriptive Statistics — Main Variables

	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

Summary statistics for main analysis variables. Annual change in HIV incidence rate per 100,000 population. PEPFAR Aid is per capita USD. PEPFAR Trade is share of total trade with PEPFAR recipient countries.

Table A2: Descriptive Statistics — Control Variables

	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 expectancy	0.337	0.327	−1.459	2.256
Infant mortality°	−0.033	0.034	−0.577	0.536

° denotes logged variable. All variables are first-differenced.

Table A3: Supplemental Results — Bayesian Models with Alternative Spatial Weights

	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 Trade²	−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 Trade²	−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 Trade²	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°	−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°	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 expectancy	−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°	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	2,634	2,634	2,634	2,634

* Null hypothesis value outside the 95% credible interval. ° denotes logged variable. Coefficients are posterior means; 95% credible intervals in brackets.

Table A4: Robustness — Functional Form Alternatives

	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 Trade²	−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 Trade²	−8.468***	0.321		−11.257***
	(2.072)	(0.371)		(2.083)
PEPFAR Aid × PEPFAR Trade × PEPFAR Trade²	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.	2,634	2,634	2,634	2,341
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. Col. (3) replaces continuous trade integration terms with quartile-bin dummies. Col. (4) excludes country-years with 12–18% trade integration.*

Table A5: Supplemental Results — MLE Models with Alternative Spatial Weights

	Trade	Migration	Distance
PEPFAR Aid	−0.490***	−0.491***	−0.503***
	(0.121)	*(0.121)*	*(0.120)*
PEPFAR Trade	0.053	−0.139	−0.069
	(1.794)	*(1.789)*	*(1.782)*
PEPFAR Trade²	−0.580	−0.135	0.029
	(2.216)	*(2.210)*	*(2.199)*
PEPFAR Aid × PEPFAR Trade	3.965***	3.981***	4.556***
	(0.966)	*(0.964)*	*(0.964)*
PEPFAR Aid × PEPFAR Trade²	−8.468***	−8.464***	−9.732***
	(2.072)	*(2.076)*	*(2.073)*
PEPFAR Aid × PEPFAR Trade × PEPFAR Trade²	5.608***	5.579***	6.333***
	(1.286)	*(1.290)*	*(1.287)*
OECD STI aid	−0.119***	−0.119***	−0.117***
	(0.018)	*(0.018)*	*(0.018)*
OECD General health aid	−0.005	−0.005	−0.006
	(0.016)	*(0.016)*	*(0.016)*
OECD Reproductive health aid	0.034	0.033	0.039
	(0.100)	*(0.100)*	*(0.099)*
OECD Infectious disease aid	−0.050	−0.046	−0.044
	(0.053)	*(0.053)*	*(0.053)*
Public/Private health spending ratio	0.963***	0.964***	0.943***
	(0.275)	*(0.275)*	*(0.274)*
Pop. density°	−5.256	−5.239	−4.912
	(6.864)	*(6.864)*	*(6.835)*
GDP PC°	0.172	0.185	0.202
	(1.410)	*(1.410)*	*(1.404)*
Export/Import ratio	0.227	0.243	0.269
	(0.531)	*(0.531)*	*(0.529)*
Internet access	0.020	0.020	0.025
	(0.022)	*(0.022)*	*(0.022)*
Life expectancy	−1.598***	−1.539***	−1.476***
	(0.304)	*(0.304)*	*(0.303)*
Infant mortality°	3.362	3.427	3.544

	(2.300)	*(2.301)*	*(2.291)*
HIV incidence rate (per 100k, lag)	0.615***	0.615***	0.623***
	(0.016)	*(0.016)*	*(0.016)*
FE – Country	Yes	Yes	Yes
FE – Year	Yes	Yes	Yes
Num. obs.	2,634	2,634	2,634
Parameters	216	216	216
Log Likelihood	−6695.178	−6696.123	−6688.028
AIC (Linear model)	13822.610	13822.610	13822.610
AIC (Spatial model)	13822.355	13824.246	13808.057
LR test: statistic	2.255	0.365	16.554
LR test: p-value	0.133	0.546	0.000

****p<0.001; **p<0.01; *p<0.05. ° denotes logged variable. Standard errors in parentheses. All models estimated by MLE with country and year fixed effects.*

Appendix B: Formal Derivations

This appendix provides full derivations for the results stated in Section 3. Sections B.1 through B.3 derive the steady-state knowledge stock, the reduced-form health equation, and the full Jacobian decomposition. Section B.4 formally establishes the conditional effectiveness result.

B.1 Steady-State Knowledge Stock

The knowledge accumulation equation is:

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

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

$$K_i = (1-\rho)K_i + \gamma A_i + \delta \sum_j w_{ij} K_j.$$

Rearranging:

$$\rho K_i = \gamma A_i + \delta \sum_j w_{ij} K_j.$$

In matrix form, $\rho\mathbf{K} = \gamma\mathbf{A} + \delta\mathbf{W}\mathbf{K}$, which gives:

$$(\rho\mathbf{I} - \delta\mathbf{W})\mathbf{K} = \gamma\mathbf{A}.$$

Provided $\tilde{\delta} = \delta/\rho < 1/\lambda_{\max}(\mathbf{W})$, the matrix $\left(\mathbf{I} - \tilde{\delta}\mathbf{W}\right)$ is invertible, and the unique steady-state knowledge vector is:

$$\mathbf{K} = \frac{\gamma}{\rho}\left(\mathbf{I} - \frac{\delta}{\rho}\mathbf{W}\right)^{-1} \mathbf{A} \equiv \tilde{\gamma}\, M\, \mathbf{A},$$

where $\tilde{\gamma} \equiv \gamma/\rho$, $\tilde{\delta} \equiv \delta/\rho$, and $M \equiv \left(\mathbf{I} - \tilde{\delta}\mathbf{W}\right)^{-1}$ is the network multiplier. The compound parameter $\tilde{\gamma} = \gamma/\rho$ captures the steady-state knowledge yield per unit of sustained aid: aid generates knowledge at rate γ, but that knowledge depreciates at rate ρ, so the long-run stock per unit of sustained aid is γ/ρ. Similarly, $\tilde{\delta} = \delta/\rho$ is the effective diffusion-to-depreciation ratio governing the strength of network transmission relative to knowledge decay.

Existence and non-negativity of M. Expanding the inverse as a power series:

$$M = \left(\mathbf{I} - \tilde{\delta}\mathbf{W}\right)^{-1} = \mathbf{I} + \tilde{\delta}\mathbf{W} + \tilde{\delta}^2\mathbf{W}^2 + \cdots$$

The series converges whenever $\tilde{\delta} < 1/\lambda_{\max}(\mathbf{W})$, which ensures that knowledge diffusion does not outpace depreciation to the point of instability. Since $\mathbf{W}$ has non-negative entries and $\tilde{\delta} > 0$, every term in the series is non-negative, so $M_{ij} \geq 0$ for all i, j. Moreover, $M_{ii} \geq 1$ for all i (from the identity term), so the knowledge channel strictly amplifies direct effects.

The power-series representation has a natural interpretation: $\tilde{\delta}\mathbf{W}$ captures first-order spillovers from immediate trading partners; $\tilde{\delta}^2\mathbf{W}^2$ captures second-order effects through partners' partners; and so on. The (i, j) entry of M thus aggregates the cumulative influence of country j's aid on country i's knowledge stock across all path lengths in the trade network.

B.2 Reduced-Form Health Outcomes

Substituting $K_i = \tilde{\gamma}(M\mathbf{A})_i$ into the health production function $H_i = (\alpha_0 - \alpha_1 K_i)A_i + \beta K_i + \varepsilon_i$:

$$H_i = \alpha_0 A_i - \alpha_1 \tilde{\gamma}(M\mathbf{A})_i \cdot A_i + \beta\tilde{\gamma}(M\mathbf{A})_i + \varepsilon_i.$$

Rearranging:

$$H_i = \alpha_0 A_i + \beta\tilde{\gamma}(M\mathbf{A})_i - \alpha_1 \tilde{\gamma}\, A_i \cdot (M\mathbf{A})_i + \varepsilon_i.$$

In matrix form, using the Hadamard (elementwise) product $\odot$:

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

The three terms capture: (i) the direct material effect of aid; (ii) the health benefit of the knowledge stock, which depends through M on all aid in the network; and (iii) diminishing returns, whereby the interaction $A_i \cdot (M\mathbf{A})_i$ reduces the marginal productivity of aid as the knowledge stock grows.

B.3 Full Jacobian and the Direct/Indirect Decomposition

The total marginal effect of aid on health outcomes is the Jacobian $\partial\mathbf{H}/\,\partial\mathbf{A}$. Differentiating component-by-component:

$$\frac{\partial H_i}{\partial A_j} = \alpha_0\, \delta_{ij} + \beta\tilde{\gamma}\, M_{ij} - \alpha_1 \tilde{\gamma}\left[\delta_{ij} \cdot (M\mathbf{A})_i + A_i \cdot M_{ij}\right],$$

where δ_{ij} is the Kronecker delta. The third term arises from the product rule applied to $A_i \cdot (M\mathbf{A})_i$: differentiating with respect to A_j yields $\delta_{ij}(M\mathbf{A})_i$ (from $\partial A_i/\,\partial A_j$) and $A_i M_{ij}$ (from $\partial(M\mathbf{A})_i/\,\partial A_j$). In matrix form:

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

The four terms capture: (i) the direct material effect ($\alpha_0\mathbf{I}$); (ii) the knowledge-mediated benefit transmitted through the network ($\beta\tilde{\gamma}M$); (iii) diminishing returns from the recipient's accumulated knowledge stock, which loads only on the diagonal ($-\alpha_1\tilde{\gamma}\mathrm{diag}(M\mathbf{A})$); and (iv) diminishing returns modulated by the recipient's own aid level ($-\alpha_1\tilde{\gamma}\mathrm{diag}(\mathbf{A})M$), which has both diagonal and off-diagonal entries. The fourth term implies that countries already receiving substantial direct aid experience smaller marginal gains from partner spillovers, reinforcing the diminishing-returns logic.

Direct effects. The diagonal elements of the Jacobian give each country's marginal benefit from its own aid:

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

The average direct effect (ADE) across all countries is:

$$\text{ADE} = \frac{1}{N}\sum_i \left[\alpha_0 + \beta\tilde{\gamma}\, M_{ii} - \alpha_1\tilde{\gamma}(M\mathbf{A})_i - \alpha_1\tilde{\gamma}\, A_i\, M_{ii}\right].$$

Since $M_{ii} \geq 1$, the knowledge channel strictly amplifies the direct effect beyond α_0.

Indirect effects. The off-diagonal elements capture spillovers from country j's aid to country i ($i \neq j$):

$$\frac{\partial H_i}{\partial A_j} = \beta\tilde{\gamma}\, M_{ij} - \alpha_1\tilde{\gamma}\, A_i\, M_{ij} = \tilde{\gamma}\, M_{ij}(\beta - \alpha_1 A_i).$$

This expression is positive provided $\beta > \alpha_1 A_i$—i.e., provided the knowledge-productivity effect exceeds the diminishing-returns drag for country i. For non-recipients ($A_i = 0$) the condition holds trivially:

$$\frac{\partial H_i}{\partial A_j}\Big|_{A_i=0} = \beta\tilde{\gamma}\, M_{ij} > 0.$$

The average indirect effect (AIE) is:

$$\text{AIE} = \frac{1}{N}\sum_i \sum_{j\neq i} \tilde{\gamma}\; M_{ij}(\beta - \alpha_1 A_i).$$

Role of network structure. Changes in the strength or configuration of trade relationships shape the magnitude of these effects:

$$\frac{\partial H_i}{\partial w_{ij}} = \tilde{\gamma}(\beta - \alpha_1 A_i)\sum_l \frac{\partial M_{il}}{\partial w_{ij}} A_l,$$

where $\partial M/\,\partial w_{ij} = \tilde{\delta}\, M\, \mathbf{e}_i\mathbf{e}_j^\top M$ (standard matrix derivative of an inverse). Strengthening trade links to PEPFAR recipients amplifies spillovers (H3) while reinforcing diminishing returns to bilateral aid in highly connected recipients (H2).

B.4 Conditional Effectiveness: Formal Derivation

We establish formally that $\partial^2 H_i/\,\partial A_i\ \partial E_i < 0$, where $E_i = (\mathbf{WA})_i$.

From Section B.3, the direct marginal effect is:

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

The term $(M\mathbf{A})_i = \sum_j M_{ij}\, A_j$ is increasing in $\mathbf{A}$. Since $M_{ij} \geq 0$ for all i, j, an increase in $E_i = \sum_j w_{ij}\, A_j$ raises A_j for trade partners, which raises $(M\mathbf{A})_i$. Differentiating the direct effect with respect to E_i:

$$\frac{\partial^2 H_i}{\partial A_i\ \partial E_i} = -\alpha_1\tilde{\gamma}\frac{\partial (M\mathbf{A})_i}{\partial E_i}.$$

Since $\alpha_1 > 0, \tilde{\gamma} > 0$, and $\partial(M\mathbf{A})_i /\, \partial E_i > 0$, the cross-partial derivative is strictly negative:

$$\frac{\partial^2 H_i}{\partial A_i\ \partial E_i} < 0. \qquad \blacksquare$$

Intuitively, greater exposure to partner aid raises the knowledge stock $(M\mathbf{A})_i$ through the network, which in turn strengthens the diminishing-returns drag $-\alpha_1\tilde{\gamma}(M\mathbf{A})_i$ on the marginal effectiveness of own aid. Countries embedded in dense PEPFAR networks already possess substantial HIV-related knowledge; the marginal value of additional bilateral assistance therefore declines as network exposure deepens.

Table 1: HIV Incidence by PEPFAR Status and Trade Integration

PEPFAR Recipient	Trade with PEPFAR Recipients: Low	Trade with PEPFAR Recipients: High
No	−0.412	−1.524
	[−0.644, −0.179]	[−1.955, −1.093]
	Observations: 1,254	Observations: 980
Yes	−6.010	−19.329
	[−10.509, −1.511]	[−21.851, −16.806]
	Observations: 63	Observations: 337

Mean annual change in HIV incidence (per 100,000) by PEPFAR recipient status and trade integration. 95% confidence intervals in brackets.

Table 2: 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 Trade²	−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 Trade²	−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 Trade²	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 (log)		−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 (log)		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 expectancy		−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 (log)		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	2,634	2,634	2,634	2,634	2,634

** Null hypothesis value outside the 95% credible interval. ° denotes logged variable. Bayesian spatial autoregressive panel models. Coefficients are posterior means; 95% credible intervals in brackets.*

Table 3: Long-Run Steady-State Marginal Effects of PEPFAR Aid

	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 95% credible interval. Marginal effects evaluated at the indicated level of trade integration with PEPFAR recipients.*

Table 4: Spatial Specification Alternatives and Timing Robustness

	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 Trade²	−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 Trade²	−8.468***	−7.994***	−10.430***	
	(2.072)	(2.161)	(2.051)	
PEPFAR Aid × PEPFAR Trade × PEPFAR Trade²	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 Trade²		−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

Table 5: Hypothetical PEPFAR Intervention — Cumulative HIV Case Reductions

	Direct	**Indirect**
Guinea-Bissau	−54.8*	−2,117.5*
	[−85.2; −24.4]	*[−5,045.3; −581.7]*
Gabon	−35.7*	−2,059.8*
	[−61.7; −8.9]	*[−5,485.9; −437.7]*
Equatorial Guinea	−17.9*	−1,810.9*
	[−34.7; −1.2]	*[−5,261.1; −100.6]*
Djibouti	−10.8	−1,129.6
	[−22.5; 1.0]	*[−3,475.4; 103.5]*

** Null hypothesis value outside the 95% credible interval. Values are estimated cumulative HIV cases averted over the study period. 95% credible intervals in brackets.*

Table 6: Hypothetical PEPFAR Intervention — Top Indirect Beneficiaries

Guinea-Bissau	**Gabon**
Guinea-Bissau: −55 [−85, −24]	Gabon: −36 [−62, −9]
China: −1,672 [−3,984, −459]	China: −1,454 [−3,873, −309]
Pakistan: −222 [−528, −61]	India: −278 [−740, −59]
Portugal: −56 [−134, −15]	France: −103 [−274, −22]
Indonesia: −46 [−110, −13]	United States: −89 [−238, −19]
Senegal: −21 [−51, −6]	Brazil: −19 [−49, −4]
Netherlands: −16 [−38, −4]	Belgium: −15 [−40, −3]
Thailand: −14 [−33, −4]	United Kingdom: −11 [−29, −2]
Turkey: −14 [−32, −4]	Thailand: −10 [−27, −2]
India: −13 [−32, −4]	Italy: −10 [−26, −2]
Morocco: −7 [−17, −2]	Japan: −8 [−22, −2]

Equatorial Guinea	**Djibouti**
Equatorial Guinea: −18 [−35, −1]	Djibouti: −11 [−23, 1]
China: −1,357 [−3,942, −75]	China: −812 [−2,498, 74]
United States: −213 [−620, −12]	India: −115 [−353, 11]
India: −86 [−251, −5]	France: −59 [−180, 5]
Spain: −47 [−138, −3]	Pakistan: −27 [−85, 3]
Brazil: −14 [−41, −1]	United States: −26 [−80, 2]
United Kingdom: −12 [−36, −1]	Ethiopia: −19 [−57, 2]
France: −12 [−36, −1]	Egypt: −11 [−35, 1]
Italy: −11 [−32, −1]	Japan: −9 [−28, 1]
Turkey: −10 [−30, −1]	Saudi Arabia: −7 [−23, 1]
Germany: −8 [−23, 0]	United Arab Emirates: −6 [−18, 1]

Values reflect predicted HIV case reductions. 95% credible intervals in brackets. Recipient country shown in bold at top of each panel.

Table 7: Trade and HIV/AIDS Knowledge Diffusion

	(1)	(2)	(3)	(4)	(5)	(6)
Log GNP PC	1.039 (3.495)	-3.611 (4.014)	4.222** (1.869)	3.443* (2.063)	-5.617** (2.783)	-5.217 (3.458)
% Urban Population	-0.028 (0.208)	0.181 (0.229)	-0.072 (0.107)	-0.039 (0.117)	-0.101 (0.447)	-0.208 (0.550)
Female School Enroll %	0.137** (0.044)	0.155** (0.041)	0.094** (0.043)	0.094** (0.042)	0.039 (0.061)	0.028 (0.065)
Trade % w/PEPFAR Countries	**27.83** (6.252)	**25.15** (4.640)	**30.39** (5.525)	**28.13** (5.575)	6.151 (4.425)	7.315 (5.402)
Constant	-1.746 (15.28)	18.79 (17.16)	-17.86* (9.698)	-13.99 (10.35)	54.53* (28.83)	56.18 (39.37)
N	96	81	203	184	228	206
Restricted to Africa	X	X				
Exclude 2nd Wave PEPFAR		X		X		X
Region FE			X	X		
Country FE					X	X
Year FE			X	X	X	X
Adjusted R^2	0.418	0.321	0.407	0.340	0.853	0.819

Notes: Dependent variable: comprehensive correct knowledge of HIV/AIDS prevention, ages 15–49, female. Robust standard errors clustered by country in parentheses. Significance levels: * $p < .10$, ** $p < .05$.

Table 8: Migration and HIV/AIDS Knowledge Diffusion

	(1)	(2)	(3)	(4)	(5)	(6)
Log GNP PC	-1.010 (3.328)	-5.152 (3.238)	3.380* (1.731)	2.500 (1.920)	-6.661** (3.092)	-6.363* (3.822)
% Urban Population	0.134 (0.218)	0.317 (0.207)	-0.049 (0.102)	0.033 (0.112)	-0.110 (0.403)	-0.263 (0.531)
Female School Enroll %	0.178** (0.055)	0.178** (0.050)	0.132** (0.047)	0.120** (0.046)	0.030 (0.066)	0.017 (0.074)
Migration % w/PEPFAR Countries	**27.15** (7.943)	**22.79** (7.104)	**21.11** (4.462)	**18.39** (4.633)	3.788 (5.650)	3.781 (6.401)
Constant	2.853 (15.57)	22.99 (14.88)	-13.77 (9.969)	-9.115 (10.18)	61.10** (29.98)	65.88 (41.86)
N	102	85	216	195	243	219
Restricted to Africa	X	X				
Exclude 2nd Wave PEPFAR		X		X		X
Region FE			X	X		
Country FE					X	X
Year FE			X	X	X	X
Adjusted R^2	0.354	0.250	0.363	0.300	0.850	0.815

Notes: Dependent variable: comprehensive correct knowledge of HIV/AIDS prevention, ages 15–49, female. Robust standard errors clustered by country in parentheses. Significance levels: * $p < .10$, ** $p < .05$.

Figure 1: First and Second Wave PEPFAR Recipient Countries.

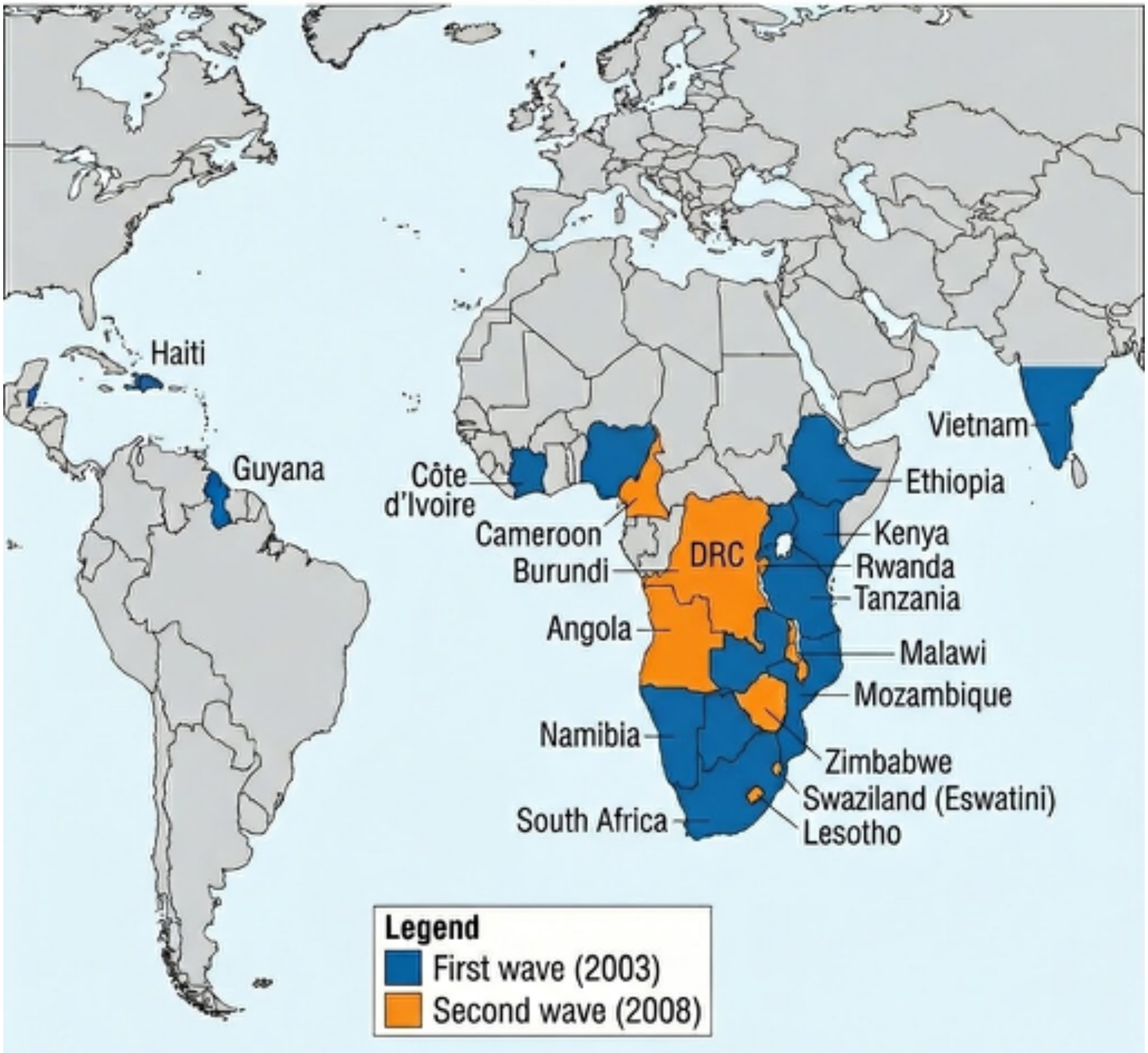

Figure 2: Conditional Long Run Steady State Effects: PEPFAR, PEPFAR Aid, PEPFAR Trade, and Trade Diffusion