The Global Dirty Laundry: A Heckman-adjusted gravity model of illicit financial flows

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Abstract: This study aims to identify key factors that shape the global network of Illicit Financial Flows (IFFs) related to money laundering and other financial crimes. Specifically, it examines the factors determining both i) the selection of destination countries and ii) the volume of illicit funds laundered. We developed a Heckman-adjusted gravity model of illicit financial flows, utilizing data from Suspicious Matter Reports lodged between 2007 to 2017. The first stage of the model analyses the selection of destination countries, while the second stage estimates the volume of laundered funds. Our findings indicate that larger economies attract higher levels of illicit financial flows. However, high-quality financial services deter both the selection of a country for laundering and the volume of funds laundered. IFFs are more likely to originate from countries with high corruption and conflict levels. Trade and geographic proximity significantly influence both the likelihood and magnitude of IFFs. The study highlights the deterrent effects of robust financial services and AML/CTF regulations on money laundering activities. It underscores the importance of international cooperation and stringent regulatory frameworks in mitigating illicit financial flows.

Keywords: money laundering, illicit financial flows, gravity model, suspicious matter reports

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1. Introduction

Illicit Financial Flows (IFFs) represent a pervasive challenge to the integrity of the global financial system. The UNODC estimate that between US$800 to $2 trillion of IFFs circulate in the global financial system, which represents approximately 5% of global GDP (UNODC 2017). IFFs are linked to various predicate crimes such as money laundering, weapons proliferation, terrorism financing, tax evasion. These flows pose a significant threat to the political integrity of public institutions and facilitate the proliferation of transnational organised crime. The UN's 2030 Agenda for Sustainable Development identified the reduction of IFFs as a priority area to build peaceful societies around the world. Combatting IFFs is a crucial component of global efforts to promote peace, justice and strong institutions as reflected in the SDG target 16.4. "[b]y 2030, significantly reduce illicit financial flows and arms flows, strengthen the recovery and return of stolen assets and combat all forms of organised crime" (United Nations 2022).

Studying the evolving global network of bilateral IFFs between countries provides crucial insights into the money laundering strategies of transnational crime groups and other bad actors (Ferwerda et al. 2013). Ferwerda et al. (2020) and Walker and Unger (2009) have developed models to examine the global flow of illicit funds in specific regions of the Netherlands and Australia. Building on these efforts, we employ a novel two-stage gravity model of bilateral IFFs that corrects for selection bias using a Heckmann correction term. The advantage of this model is that it enables researchers to empirically examine both the factors that influence the choice of destination countries (in the first stage) and the volume of laundered funds (in the second stage). This is a crucial adjustment as the network of observed bilateral IFFs between countries is sparse: only 10% of all possible bilateral flows possess non-zero values. A second contribution of this study is that it considers new variables that capture the geopolitical climates within countries including: armed conflicts, corruption levels, tax haven status, and Financial Action Task Force (FATF) blacklisting.

A third contribution of this study is that we use newly available data to examine the long run network structure of international illicit financial flows worth US$35 billion across 129 countries and 10 years (2007 to 2017). The data is sourced from the FinCEN Files published by the International Consortium of Investigative Journalists (ICIJ). A growing number of scholars studied the FinCEN files to analyse corruption typologies (Diviák and Lord 2024, Snider 2024) and assess the effectiveness of AntiMoney Laundering & Combating the Financing of Terrorism (AML/CFT) regimes (Lopez-de-Silanes et al. 2022, D'avino 2023).

Illicit Financial Flows are recorded in Suspicious Activity Reports (SARs) that are filed by financial institutions when they have reasonable grounds for suspecting that certain transactions are suspicious and may be involved in financial crimes, such as money laundering (Chaikin 2009). They serve as a crucial mechanism for the monitoring and reporting of IFFs (Johnson 2000). In theory, these reports enable national Financial Intelligence Units (FIUs) to identify and investigate suspicious transactions (FATF 2017; Ping 2005). As the international effort to encourage financial institutions to monitor, detect and report IFFs has grown, a key outstanding question is how effective AML/CFT regimes are effective in deterring illicit flows. Critics have noted that despite their heavy financial burden, regulatory policies appear to be somewhat ineffective (see for example, Gerbrands et al. 2022; Pol 2020). We seek new empirical evidence to help assess the effectiveness of these monitoring and surveillance regimes.

The structure of this paper is as follows: Section 2 provides a background review of the relevant literature pertinent to our study. Section 3 covers the data sources and Section 4 details the methodology of the gravity model and Section 5 presents the results. In Section 6 we discuss our findings in relation to existing literature, pointing to key areas/risks that should be observed in the development of AML/CFT policy. We then conclude with reflections on the limitations of our study and the potential avenues for future research.

2. Background

Suspicious Activity Reports (SARs)[1] are essential tools used by financial institutions to flag transactions that may be linked to various criminal activities, including money laundering, terrorism financing, tax evasion, scams and fraud, bribery and corruption. These reports are submitted to FIUs when a financial institution has reasonable grounds to suspect that a transaction is linked to criminal activities. According to the Financial Crimes Enforcement Network (2015), grounds for suspicion include transactions that are inconsistent with a customer's known legitimate business, unusual patterns of transactions, and attempts to evade reporting requirements through structuring transactions. Financial institutions are required to report these suspicious activities to help law enforcement agencies detect and prevent financial crimes (Gara et al., 2023; Somare et al., 2016).

[1] Also known as Suspicious Transaction Reports or Suspicious Matter Reports in some jurisdictions.

This paper explores factors that contribute to probability of observing bilateral IFFs that are reported via SARs. The existing literature suggests that these factors can be categorized into two broad categories::

A. The capabilities & appetite of financial institutions to report suspicious activity. In the following discuss how a country's compliance with FATF standards, it's surveillance and quality of financial institutions may influence reporting capabilities.

B. the underlying level of illicit activity that generates IFFs. This is a function of the size of the shadow economic activity in source countries, the extent to which it is openly connected with other economies, as well as the anticipated net payoff from engaging in financial crime and the perceived risk of detection and getting caught & punished by authorities (Freeman 1999). In the following, we consider how the size of the trade, people & remittance flows impact observed IFFs by lowering the risk of detection and how level of shadow economic activity generate greater demand for IFFs.

We briefly describe each of these factors below.

2.1. Trade, people and remittance flows

When examining which countries serve as destinations for IFFs, the Routine Activity Theory (RAT) provides a useful framework (Cohen and Felson 1979). RAT specifies that three components must exist to create the conditions necessary for a crime to occur: a target (e.g. foreign workers), a motivated offender (e.g. a money launderer), and an opportunity where the offender can interact with the target (e.g. poorly regulated financial environment) (Eck 1994). It is the convergence of these three factors and the absence of an effective guardian that leads to the crime opportunity (Benson et al. 2009). Based on RAT, we predict that IFFs are highly correlated with the established flow of goods, people, and capital between countries. For example, international trade flows represent an opportunity that facilitates the movement of IFFs. A good example is trade-based money laundering, where trade transactions are manipulated to obscure the origins of illicit funds, making it a significant concern for countries with strong trade relationships (FATF 2006). Similarly, remittance flows that involve the transfer of money by foreign workers to their home countries and can be used to move illicit funds across borders (World Bank 2021). Given these dynamics, we also expect geographic distance between countries to be negatively correlated with bilateral IFFs since bilateral distance reduces trade volumes. We also expect relatively more IFFs to be observed in small, open economies specialized in finance, tourism & trade, such as Switzerland, Macao and Hong Kong (e.g. Liao and Acharaya 2011),

2.2. Regulatory factors, surveillance and the quality of institutions

Effective AML/CFT regimes are designed to deter IFFs (Masciandaro 1999). Such regimes follow international standards set by the FATF and tend to feature stringent penalties for non-compliance that encourage regulated entities to report suspicious activity (FATF 2019). Many scholars have noted that since sanctions only apply to omitted SARs, regulated entities have an incentive to over-report suspicious flows (Takàts 2009, Gara and Pauselli 2020). As a result, an open question is whether reported IFFs are positively or negatively correlated with effective AML/CFT regimes. On the one hand, the deterrence effect suggests that suspicious flows are likely to decline in jurisdictions with effective surveillance regimes as money launderers may seek to avoid jurisdictions where the probability of detecting IFFs is high. On the other hand, observed levels of suspicious flows could rise in the same countries due to the over-reporting effect (Braun et al. 2016).

Apart from possessing AML/CFT laws, another factor that influence the level of reported IFFs is a country's active surveillance capabilities of transnational organized crime. Following Ferwerda et al (2020), we use membership of the Egmont group as a proxy for the quality of the surveillance regime. The Egmont Group is an international network of 177 Financial Intelligence Units (FIUs) that facilitates multilateral cooperation and intelligence sharing to jointly combat money laundering, terrorist financing, and related crimes (De Vido 2013). Member countries have access to more actionable intelligence gathered from other member FIUs. We hypothesize that these capabilities could result in an increase in reported IFFs as greater intelligence capabilities could be harnessed by FIUs to monitor transactions more effectively.[2]

Furthermore, monitoring and reporting of illicit flows also depends on the quality of financial institutions. We measure the quality of institutions using the proxy of GDP per capita which is

[2] We assume that Egmont membership does not impact the level of underlying IFFs (B) discussed above). It is possible that Egmont membership could trigger crime displacement in the sense that bad actors responsible for generating IFFs take actions to avoid detection (Johnson et al. 2014, Ferwerda et al. 2020). However, this scenario is unlikely as Egmont membership covers over 177 countries. This extensive coverage makes it difficult for money launders to find alternative routes for IFFs that avoid Egmont member countries.

consistent with previous studies (Ferwerda et al. 2020).[3] Scholars have noted that countries with high levels of GDP per capita tend to possess higher quality financial services, higher penalties for financial crime and greater levels of transparency (Basel Institute on Governance 2024). This may deter IFFs as advanced financial sectors may possess better detection and reporting capabilities (Braun et al. 2016, Puffer et al. 2016).

2.3. Shadow economy and the quality of institutions

In terms of the predicate crimes that generate IFFs, jurisdictions with high levels of shadow economic activity are likely to be correlated with higher volumes of reported IFFs (Vaithilingam and Nair 2007). We therefore expect a positive correlation between reported IFFs and corruption levels, armed conflict levels (Kotecha 2020) and tax haven status (Sharman 2009). These activities have the potential to generate and attract different types of IFFs flows in the form of bribes, terrorism financing or tax evasion flows.

2.4. FATF black and grey listing

The FATF publicly identifies countries with serious gaps in their AML/CFT regimes via their grey and black listing process (Sharman 2009). The listing process has serious consequences for a country by (among other things) damaging a countries reputation among investors and raising costs of capital which increases the costs of debt servicing (de Koker at al. 2023). It incentivizes countries to enhance their monitoring frameworks which may result in an increase in reported IFFs. Blacklisting also triggers financial institutions around the world to conduct enhanced due diligence on any financial transactions that are linked to listed jurisdictions (de Koker 2024). This enhanced scrutiny may in fact trigger an increase in reported IFFs. At the same time, if money launderers anticipate this enhanced due diligence, then the opposite may also be true: listing may also trigger money launders to use alternative low risk countries where the levels of scrutiny are lower (Bowen and Galeotti 2014, Pataccini 2024). Through this displacement of IFFs, listing may trigger a decline in reported IFFs in listed countries if bad actors are risk averse and there exist alternative financial channels in other jurisdictions that can be used for money laundering purposes. Therefore, whether increases in reported IFFs

[3] From another perspective, it is also possible to hypothesize that IFFs are attracted to countries with high quality financial services. Many scholars have noted that money launderers are attracted to offshore financial centres that can assist transnational organizations and other nefarious actors in hiding their wealth (Sharman 2009).

triggered by greater scrutiny outweighs the decline in IFFs triggered by crime displacement is an open question.[4]

3. The data

We investigate transaction data reported in SARs by banks from 2007 to 2017 obtained from the ICIJ. The original dataset[5] contains information on more than US$35 billion in US denominated transactions from 2,100 Suspicious Matter Reports that were submitted to Fincen. Of these, a smaller subset of 18,153 suspicious transactions spanning 129 countries were published by the ICIJ. This smaller subset covers represents only 1.75% of the original data. The ICIJ was highly selective in the data it released to the public as it undertook its own investigation process involving 85 journalists around the world. In this process reported details contained in the SARs, such as the originator, beneficiary, address were independently verified. As a result, the subset available to the public only included transactions that where sufficient details about both the originator and beneficiary of funds were available and could be independently verified. Transactions that were judged to contain insufficient details or an outcome of defensive reporting were not included in this sample. This screening process is likely to have resulted in some biases in the sense that IFFs are less likely to be reported in regions where financial service workers with poor English writing skills or low levels of training detecting and reporting suspicious activity. In addition to this, the IICIJ journalists also required access to documents that could verify these transactions, which may have been limited in some jurisdictions. In spite of these biases, it is worthwhile examining this data since it covers a decade of reported IFFs spread across 129 countries. As such it is the largest dataset on global IFFs currently available to researchers.

The dataset covers a total of 129 countries, including 22 from Africa, 26 from the Americas, 39 from Asia, 40 from Europe, and 2 from Oceania. The pattern of observed IFFs can be categorised into two groups: 1) IFFs origin & destination countries are identical (14% of IFFs totals value); 2) IFFs the origin and destination countries are different (86% of IFFs total value). The first category represents circular flows reflective of domestic money

[4] It is worth noting that due to data limitations, our study does not provide a comprehensive picture of crime displacement as it only captures data on US-denominated international banking transactions. Other channels for international money laundering, such as shadow bank, are not captured in this study.

[5] The data is publicly available and can be accessed on the ICIJ website at https://www.icij.org/investigations/fincen-files/download-fincen-files-transaction-data/
Concerns about biased origins of the data are addressed in Appendix 1.

laundering processes (Ferwerda et at. 2020). In the second category (non-circular) there are 814 unique bilateral IFF channels of which 174 are bidirectional in these sense that both countries send and receive IFFs to and from each other. For instance, between the Russia and the Unites States, reported IFFs flows are observed going from the United States to Russia as well as from Russia to the United States. Most observed bilateral channels (466) are unidirectional, where the flow is unidirectional.[6]

We observe a great deal of variation in terms of the degree to which country is connected with other countries. A key characteristic of the global IFFs network is its sparsity as many countries do not possess any observed bilateral IFFs. Among those countries for whom bilateral flows are observed, a significant proportion of countries are observed to possess only one channel. In fact, only 10% of all possible bilateral connection**s** between countries possess non-zero bilateral IFF flows. This highlights the necessity of controlling for selection bias (Heckman 1979, Heckman 1990). Without controlling for selection bias, the estimated coefficients in existing gravity studies may be overinflated. To obtain more accurate estimates, it is crucial to adopt a two-stage approach (detailed in Section 4). Another notable feature of the bilateral network of IFFs is its asymmetry. The estimated bilateral connection weights exhibit low reciprocity, with a network reciprocity index of only 45%. This is relatively low compared to other global financial networks, such as the international trade network, which has a density of 98% and a reciprocity index of 92% (Fagiolo et al. 2010).[7] This underscores the distinct structural properties of IFFs compared to normal economic flows.

A country's overall importance in the network of global IFFs can be measured by the total number of incoming IFF connections (in-degree) and outgoing IFF connections (out-degree) to other countries. This is illustrated in Figure 1a and 1b which show that the degree distribution is highly skewed**.** In the case of outgoing IFFs (out-degree connections), the country with highest number of connections is Latvia, where outgoing IFFs were reported to over 50 countries. The country with the highest number of in-degree connections is the United Arab Emirates, with IFFs inflows reported from over 40 countries. The majority of countries possess only a few connections and only a small subset of countries serve as major hubs that facilitate

[6] Bidirectional flows account for $25 billion, while unidirectional flows account for $5.3 billion.
[7] The international trade network has similar core-periphery structure, where the countries at the core have higher GDP, and those at the periphery are less developed.

many IFFs transactions.[8] This suggests a concentration of global IFFs are channelled through a small number of jurisdictions.[9] Figure 2 shows an alternative way to measure a countries importance according to the total value of incoming and outgoing IFFs.

INSERT FIGURES 1a AND 1b AND FIGURE 2 HERE

Figure 3 shows the evolution of IFF connections over time for the top countries in the IFF network. Specifically, the figure highlights the stability of the network core structure over time. Notably, the growing importance of Hong Kong (HKD), Singapore (SGP), and the United Arab Emirates (ARE) as major recipients of incoming transfers is evident from the left part of Figure 3. These countries exhibit strong growth in the volume of IFFs flows from multiple origins. This suggest that these countries play an important role in the global IFF flows network.

INSERT FIGURE 3 HERE

4. Methodology

4.1 The gravity model

We employ a gravity model to better understand the patterns and explanations behind international IFFs. The gravity model is used to measure and predict various types of flows, such as enhancing global maritime traffic network forecasting (Song et al. 2024) and international trade (see Van Bureij and Brakman 2010). Given its success, it was perhaps inevitable that the model would be adapted to study IFFs (Ferwerda et al. 2020). In the gravity model a flow from origin *o* to destination *d* is influenced by forces that either encourage or discourage this specific flow, as well as by supply conditions at the origin and demand conditions at the destination. A key hypothesis in the model that is based on Newton’s law of

[8] However, despite this skewness, the distribution does not follow a power law. Observed skewness is, in part, due to a core-periphery structure typical for financial networks, with a small number of highly interconnected countries at the core and all others in the periphery (Bech & Atalay 2010; Blasques et al. 2018; Glassermanand Young 2016). Puhr et al. (2012) find similar asymmetry between in-degree and out-degree distributions for interbank lending networks: when a bank is highly connected, it is usually because it borrows from many other banks and not because it lends to many other banks.

[9] We do observe a greater degree of variability in the distribution of in-degree connection relative to the distribution of out-degree connections. Specifically, the average country in our dataset has 6 connections to other countries. However, the distribution of out-degree connections is more skewed with a median value of 2 connections, while the median for in-degree connections is 3. The gap between the mean (6) and the median is relatively smaller for in-degree connections.

universal gravitation is that flows are larger between countries that possess large economies and are in close proximity to each other. We use the following specification:

$$y_{od} = \beta_0 + \pi \times Z_{od} + \gamma \times Z_o + \mu \times Z_d + u_{od}$$

where, y_{od} is the (log) total value (in US dollars) of the IFFs from origin country *o* to destination country *d* observed in the period 2007 to 2017. Z_{od} is a set of characteristics for bilateral origin–destination country pairs, including geographical distance, bilateral trade (both, exports and imports) or remittance flows, contiguity, common language, and shared history (such as a common colonizer or a colony relationship). Z_o is a set of characteristics for origin countries that includes (among other things) log GDP, the quality of its financial institutions as proxied by log GDP per capita, corruption index, tax haven index, FATF blacklisting, and dummer variables for the presence of armed conflict and Egmont membership. Z_d is the same set of characteristics for destination countries. u_{od} is the error term. Table 1 provides a complete list of variables and data sources used in the gravity model.

INSERT TABLE 1 HERE

4.2 Heckman selection bias adjustment

The estimation of bilateral IFFs is likely subject to sample selection bias for two key reasons: i) Absence of flows: due to the sparse nature of the network, most country pairs will not have any IFFs to report, ii) undetected flows: even when illicit flows exist, they may go unreported due to weak AML compliance in either the origin or destination country. Ignoring this selection process in the gravity model would lead to biased estimates. This is a key issue, as the data shows that most country pairs do not have any reported IFFs. To correct for this bias, we apply a two-step procedure derived by Heckman (1974, 1979), which provides unbiased estimates of the gravity model while simultaneously modelling the probability of observing IFF flows. The Heckman selection model consists of two equations:

1. Outcome equation (gravity model): This models the size of IFF flows between country pairs, regardless of whether they are observed (see equation [1a] below).
2. Selection equation: This models the probability that an IFF flow is reported (see equation [1b] below).

We estimate the gravity equation [1a], where the outcome variable, y_{1od}^*, represents the size of the flow between countries *o* and *d*, regardless of whether it is observed or unobserved:

$$y_{1od}^* = \alpha_1 \mathbb{Z}_1 + u_{1od} \quad [1a]$$

$$y_{2od}^* = \alpha_2\, \mathbb{Z}_2 + u_{2od} \quad [1b]$$

$$y_{1od} = y_{1od}^* \text{ if } y_{2od}^* > 0 \text{ and otherwise } y_{1od} = 0 \quad [1c]$$

with error terms u_{1od} and u_{2od} having the following properties:

$$u_{1od} \sim N(0, \sigma)$$

$$u_{2od} \sim N(0, 1)$$

$$\mathrm{corr}(u_{1od}, u_{2od}) = \rho$$

Equation [1b] is a probit-type selection equation that describes the probability to have an observed flow, y_{2od}^*. The variables y_{1od}^* and y_{2od}^* are unobserved, whereas y_{1od} is observed. The $\mathbb{Z}$ variables represent standard gravity model explanatory variables for bilateral flows between countries *o* and *d*, as discussed in Section 4.1. We are interested in estimating the impact of these gravity variables on the size of the flow between countries *o* and *d*. However, we cannot observe the size of the flow if it does not exist or is not reported, as expressed in equation (1c).

Heckman (1979) characterised the sample selection problem as a special case of the omitted variable problem in econometrics, where λ (the so-called inverse Mills ratio) would be the omitted variable if ordinary least squares estimation was applied to the subsample where $y_{1od} > 0$. His two-step approach involves first estimating λ using a Probit model and then estimating a modified version of equation [1a]. This second step is a combination of Heckman correction term and gravity equation of section 4.1:

$$y_{1od} = \rho \cdot \sigma\ \lambda_{od} + \beta_0 + \pi \times Z_{od} + \gamma \times Z_o + \mu \times Z_d + e_{1od} \qquad [2]$$

Heckman (1979, p. 158) tests for selectivity bias using a t-test on the coefficient of λ. To ensure the model is identified, the set of variables used in the first stage must be different from or larger than the set used in the second stage (exclusion restriction). In our case, the identifying variable for the first stage is the dummy that indicates whether two countries were historically part of the same country (shared history). It is reasonable to assume that if two countries possess a common ancestor country, then this shared history will decrease the probability of empirically observing IFFs denominated in US dollars between the two countries in question.[10] Research shows that strong historical ties between countries often lead to the use of their own national currencies for bilateral transactions, thereby lowering transaction costs

[10] We have 476 country pairs. In the set of existing IFF flows frequency "Shared history" is 0.8%, while in the set of absent flows this frequency is 2.6%.

and mitigating exchange rate risk (Boz et al., 2020; Goldberg & Tille, 2008; Gondo et al., 2020). For example, in money laundering operations involving cash transfers from Russia to Latvia, it is likely these IFFs are conducted in Roubles rather than US dollars (Pataccini 2024). Therefore IFFs denominated in non-USD currencies will not be observed in our dataset as all the transactions recorded in the ICIJ data are denominated in US dollars. Analysis of international IFFs using the World Bank residual method on Balance of Payments supports this assumption (Kar and Freitas 2012).

5. Results

Table 2 presents the results of the gravity model estimation. The first column reports the selection equation of Heckman's model in which the dependent variable is the probability of observing IFFs between the country of origin and the destination country (stage 1). The second reports the regression coefficients for the second stage of the model in which the dependent variable is the log total value of bilateral IFFs (in US dollars) between the country of origin and the destination country (stage 2). We find that the Heckman selectivity bias is statistically significant as reflected in the parameter for the identifying variable (shared history) being significant at the $p<0.01$. This underlines the importance of applying the Heckman correction to the gravity model of IFF flows.

INSERT TABLE 2 HERE

The first bilateral characteristic is the geographical distance between countries. This factor is found to be negatively correlated with both the probability that suspicious flows are observed between countries (stage 1) as well as with the observed total value of IFFs observed between countries (stage 2). In other words, the further away two countries are from each, the lower is the probability of observing IFFs between these countries. This result is consistent with global trade models that show the same relationship between distance and trade. Appendix 3 also reports that exports and imports are positively correlated to a higher probability that suspicious flows are observed between countries (stage 1) as well as with the observed value of IFF outflows observed between countries (stage 2). Concerning remittance flows, we find that these are positively and significantly correlated with a higher the probability of observing IFFs between countries (stage 1). However, they are not significantly correlated to observed value of IFFs in stage 2.

Shared culture and history as proxied by common colonizer relationships also appear to influence reported IFFs. In the first stage, our results indicate that a common colonizer significantly increases the likelihood of observing suspicious flows between two countries, with a coefficient of 0.714 ($p < 0.01$). In the second stage, the value of suspicious flows is also significantly higher between countries with a common colonizer, with a coefficient of 1.260 ($p < 0.01$). These findings are consistent with previous studies which show that the modern day spread of international business networks and international trade patterns still are shaped by a country's colonial heritage and whether two countries were colonized by the same colonial power (Berthou and Ehrhard 2017).

In relation to the size of country's economy proxied by its GDP, our results in Table 2a show that larger economies are significantly more likely to be both the source and destination of IFFs. We also find that countries with more developed financial services (as proxied by GDP per capita) tend to detract global IFF flows in the first stage, given a negative correlation with the probability of observing bilateral IFF flows. In the second stage, more developed financial services also appear to negatively impact the total value of observed IFFs. The findings in the second stage are consistent with the possibility that money launderers engage in structuring when targeting countries with relatively developed financial services. The practice of structuring is designed to avoid detection where large sums of illicit money are split into multiple smaller transactions that are less detectable. To explore this further, Table A3.2 in the appendix presents results where the average value of IFFs is modelled in stage 2.[11] This shows that the GDP per capita of the origin country is negatively associated with the average value of reported IFFs at the (-0.357) at the α = 10% level of significance. In addition, Appendix 2 presents a robustness check that examines changes in GDP per capita and IFFs over time within a panel regression framework. The results indicate that an increase in a country's GDP per capita over time reduces reported IFFs.

In relation to FATF black or grey listing, our results show that if the origin country is impacted by such actions, this significantly increases the likelihood of observing IFFs originating from that country, with a coefficient of 0.140 ($p < 0.05$). This likely reflected the efforts by financial institutions to conduct enhanced due diligence on funds originating from black or grey listed jurisdictions. The second stage shows that blacklisting also significantly elevates the volume of suspicious flows, with a coefficient of 0.882 ($p < 0.05$). For destination countries, no significant association is found between a country's listing status and either the likelihood of receiving suspicious flows in stage 1 or the volume of such flows in stage 2.

A similar pattern is observed for Egmont membership: while there is a significant association between a country's membership and both the likelihood of being the origin of suspicious outflows and the volume of such outflows, no such significant association is found for destination countries. Appendix 2 presents a robustness check that confirms the association

[11] The average value of IFFs is calculated as the Total value of IFFs divided by the number of recorded transactions.

by exploiting the fact that several countries join the Egmont group during the study period that allows us to observe reported IFFs volumes before and after this event. These results show that joining Eggmont leads to a pronounced increase in reported IFFs.

A country's corruption levels are positively associated with both the likelihood and volume of suspicious flows, for both origin and destination countries. The same pattern is observed for tax havens. The presence of armed conflict within a country is positively associated with both the likelihood of being the origin of suspicious outflows and the volume of such outflows. However, no such relationship is found for destination countries. Table 2c extends this analysis by examining the relationship between the scale of conflict in a country—measured as deaths per capita—and IFFs. The scale of conflict in a destination country is negatively associated with both the likelihood of being a destination for suspicious flows and the volume of received flows.

Appendix Table A3.2 replicates the gravity model for *average* value of the bilateral IFFs between two countries instead of total accumulated value of IFFs as the main outcome variable. The results in terms of discussed associations remain the **same, which means that**

6. Discussion

6.1. Discussion of findings

Our results revealed global IFF flows are strongly correlated with the global flow of goods. Of note, exports and imports are positively and significantly correlated with both the likelihood of observing suspicious flows between countries and the volume of these flows. As discussed in Section 2, this is consistent with RAT theory and suggests that distance matters: the greater the distance, the fewer the transactions. Additionally, we find that geographical gap influences both the creation and intensity of flows. In short, countries that are geographically distant are less likely to engage in transactions with each other. These results appear consistent with previous models from the Netherlands (Ferwerda et al., 2020) and Australia (Walker & Unger, 2009), both of which have not been corrected for selection bias.

We also find that countries with more developed financial services are less likely to attract IFFs in the first stage, given a negative correlation between per capita GDP of the destination country with the probability of observing bilateral IFF flows. This result provides support for crime displacement as countries with higher quality financial services and high monitoring and detection capabilities tend to deter IFF flows.[12] Further, we also find that more advanced financial services seem to influence the volume of IFF flows observed in the second stage. In addition, Egmont group membership of the sender country is positively correlated with probability of observing bilateral IFF outflows in the first stage.

When examining the impact of FATF blacklisting on suspicious transaction flows, we find that blacklisting significantly raises the likelihood of suspicious flows originating from a country. This is likely due to banks who are more disposed to report transactions involving high-risk jurisdictions. We also find that blacklisting significantly increases the volume of suspicious flows. Similar results are found for tax haven status, where the origin country significantly increases the likelihood of suspicious flows (coefficient of 0.075, $p < 0.01$). This suggests that countries seen as being tax havens are more likely to be involved in initiating suspicious transactions (Haberly & Wójcik, 2015). This is once again aligned with our expectations of factors explaining bilateral IFFs (namely Section 2.2 – regulatory factors and surveillance and the lack of international action or influence of threat of sanctions by organisations such as FATF (Section 2.4).

We then examined the effect of culture on suspicious transaction flows, where we find that a common colonizer (proxy for history and culture) significantly increases the likelihood of observing suspicious flows between two countries. This result is likely due to established networks and mutual trust. This finding aligns with the work of Ferwerda et al. (2013), who demonstrated the importance of cultural and historical connections in trade-based money laundering. We also find that the volume of suspicious flows is significantly higher between countries that share a common colonizer. This is consistent with the findings of Walker and Unger (2009), who observed similar patterns in their gravity model analysis of ML flows. These results underscore the dual impact of shared cultural and historical ties in both increasing the probability and volume of suspicious transactions, highlighting the critical need for robust regulatory measures in these jurisdictions.

6.2. Conclusion

Unpacking the determinants of global illicit financial flows is crucial in the effort to combat organised crime. Our study uncovers new evidence that factors such as effective AML/CFT

[12] We also find a similar effect for GDP per capita in sender countries: higher quality banking services in origin countries have a negative impact on the probability of observing suspicious flows between country (stage 1) and the volume of bilateral suspicious flows (stage 2).

regimes, FATF blacklisting, corruption levels, involvement in armed conflict and tax haven status, and international cooperation do shape the global flow of illicit financial flows, as well as the associated activity related to the detection and reporting of these flows. The findings underscore the importance of robust regulatory environments and the need for continuous enhancement of monitoring systems to adapt to the rapidly evolving nature of financial crimes. By analysing these determinants, our research allows policymakers and financial institutions to better target and mitigate the risks associated with illicit financial flows. A key novelty of our study is that it has produced separate estimates of 1) the probability of observing bilateral IFF flows between countries and 2) the volumes of IFFs observed between countries. We find that many variables that are significant in stage 1 are not significant in stage 2. These variables include the quality of financial services (as proxied by GDP per capita), Egmont membership of destination countries, corruption levels in destination countries and the GDP of the destination country. These findings are consistent with the phenomenon of structuring and suggest that future research should focus more on distinguishing between how transnational organized crime choose destination countries vis-à-vis what volumes of IFFs are observed between countries. One key limitation of the current study is that observed IFFs are a product of both the underlying volume illicit flows and the efforts by financial institutions to detect and report the flows. Currently data is lacking on the extent to which illicit financial flows may go undetected due to compliance failures. Future studies could take steps to collect audit data held by FIUs that may provide estimates on the volume of IFFs that go undetected.

Table 1. Average values and data sources for explanatory variables used in the analysis

Explanatory variables	Average value in Full sample	Average value in Non-zero IFFs sample	Data source and Notes
bilateral characteristics			
Shared history	0.03	0.01	CEPII (GeoDist) (Mayer & Zignago, 2011)
log (Geographical distance between countries)	8.41	8.24	CEPII (GeoDist)
Shared border	0.05	0.06	CEPII (GeoDist)
Shared language	0.19	0.20	CEPII (GeoDist)
Common coloniser	0.08	0.12	CEPII (GeoDist)
Colony-coloniser relation	0.02	0.04	CEPII (GeoDist)
Bilateral Imports (in \$ mln.)	1,130	5,333	IMF
Bilateral Exports (in \$ mln.)	1,087	6,180	IMF
Bilateral Remittances (in \$ mln.)	84	423	WorldBank WorldBank[13]
Origin country			
GDP per capita (in \$)	5,633	11,720	CEPII (GeoDist), data refers to 2010
GDP (in \$ mln.)	54,053	149,824	CEPII (GeoDist), data refers to 2010
FATF Black or Gray listed	0.20	0.21	FATF
Corruption index	50.3	60.2	Transparency International Corruption index (2024)
Tax haven index	1.53	3.06	Tax haven index (Haberly, D., & Wójcik, D. (2015))
Egmont membership (as of 2007)	0.59	0.82	Egmont Group14
Armed conflict indicator	0.15	0.20	Centre for Systemic Peace, War conflict indicator and the size of a conflict measured as deaths from a conflict per capita[15]
Destination country			
GDP per capita (in \$)	5,608	11,975	Same sources as listed above
GDP (in \$ mln.)	54,379	160,817	
FATF Black or Gray listed	0.20	0.21	
Corruption index	50.2	61.4	
Tax haven index	1.52	3.24	
Egmont membership (as of 2007)	0.59	0.82	
Armed conflict indicator	0.15	0.17	

13 https://blogs.worldbank.org/peoplemove/bilateral-remittance-matrix-new

14 https://egmontgroup.org/members-by-region/eg-member-fiu-information/)

15 https://www.systemicpeace.org/warlist/warlist.htm

Table 2. Gravity model estimation with Heckman correction

Explanatory variables	Stage 1 - probability of bilateral IFF existence		Stage 2 - (log) total value of bilateral IFFs	
	(1)		(2)	
Heckman selectivity effect λ= ρ· σ			(+)	
the inverse hyperbolic tangent of ρ			0.532***	(0.137)
(log) the standard error of the residual σ			1.101***	(0.058)
bilateral characteristics (origin-destination pairs)				
Shared history	-0.885***	(0.263)		
log (Geographical distance between countries)	-0.187***	(0.035)	-0.884***	(0.142)
Shared border	0.152*	(0.092)	-0.691	(0.478)
Shared language	-0.204**	(0.085)	-1.345***	(0.308)
Common coloniser	0.714***	(0.128)	1.260***	(0.431)
Colony-coloniser relation	0.300**	(0.117)	3.419***	(0.574)
Origin Country				
log GDP per capita	-0.084***	(0.031)	-0.418**	(0.213)
log GDP	0.132***	(0.016)	0.252***	(0.087)
FATF Black or Gray listed	0.140***	(0.047)	0.882**	(0.370)
Corruption index	0.011***	(0.002)	0.045***	(0.015)
Tax haven index	0.075***	(0.007)	0.245***	(0.046)
Egmont membership (as of 2007)	0.286***	(0.056)	0.739	(0.458)
Armed conflict indicator	0.331***	(0.058)	0.945***	(0.359)
Destination country				
log GDP per capita	-0.148**	(0.075)	-0.200	(0.325)
log GDP	0.158***	(0.043)	0.180	(0.160)
FATF Black or Gray listed	0.184	(0.123)	0.087	(0.675)
Corruption index	0.015***	(0.005)	0.023	(0.024)
Tax haven index	0.093***	(0.025)	0.330***	(0.069)
Egmont membership (as of 2007)	0.247	(0.189)	0.837	(0.544)
Armed conflict indicator	0.190	(0.136)	0.697	(0.656)
Constant	-6.191***	(1.317)	10.224*	(5.826)

Note: the table presents estimates from the baseline gravity regression model specified in the methodology section. Column (1) presents first-stage estimates (probability of flow), and Column (2) presents second-stage estimates (value of flow). The number of observations on the first stage is 16.699, on the second stage (selected) - 675.
*** p<0.01, ** p<0.05, * p<0.1, Standard errors clustered on a country level are given in parentheses.

Table 2c. Impact of war conflicts – alternative measures

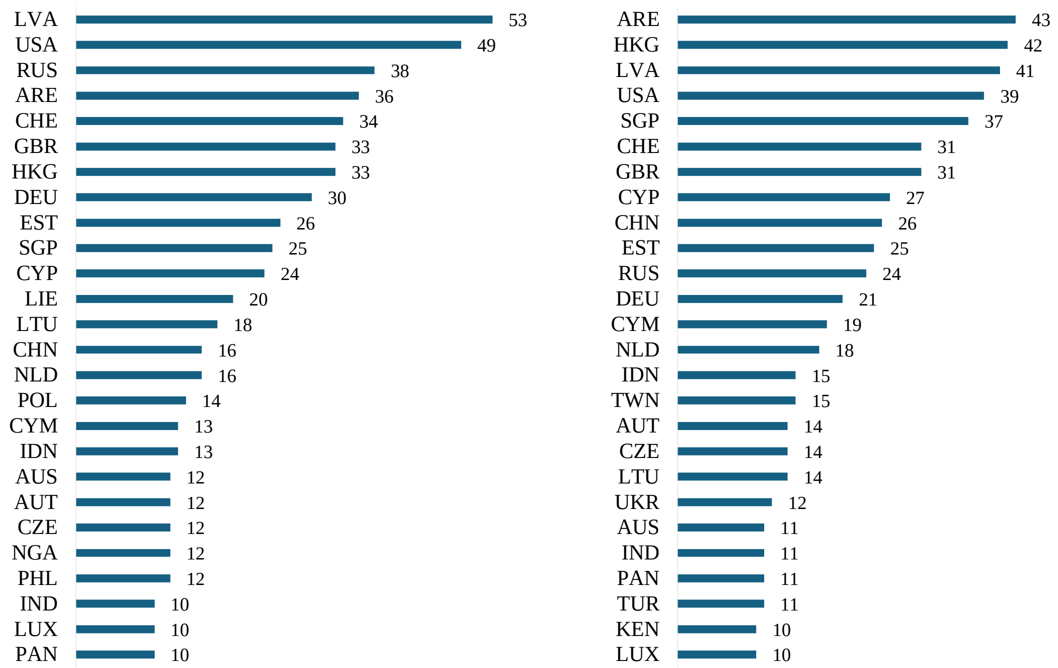
	First stage selection equation - probability of bilateral IFF existence		Second stage - (log) value of bilateral IFF	
	(1)		(2)	
Origin country				
Conflict scale (death per capita)	0.029	(0.019)	0.129*	(0.069)
Destination country				
Conflict scale (death per capita)	-0.320***	(0.115)	-1.409***	(0.473)

Note: the table presents estimates from gravity regression models, analogous to the baseline model in Table 2a, where *Armed conflict indicators* in the country of origin and destination are replaced by the measure of size of these conflicts (death per capita). Column (1) presents first-stage estimates (probability of flow), and Column (2) presents second-stage estimates (value of flow). *** p<0.01, ** p<0.05, * p<0.1, Standard errors clustered on a country level are given in parentheses.

Figure 1a. The most connected countries in the global IFF network

Top IFF donor countries as measured by out-degree connections

Top IFF recipient countries as measured by the number of in-degree connections



Note: A countries' connectedness can be measured either in terms of the number countries that receive IFFs (in-degree, right hand side Figure) and the number of recipient countries that a country exports IFFs to (out-degree, left hand side Figure). Only countries with more than 10 different connecting countries are displayed.

Figure 1b. Distribution of IFFs out- and in-degree across all countries

Number of IFF recipient countries (in-degree)

Number of IFF donor countries (out-degree)

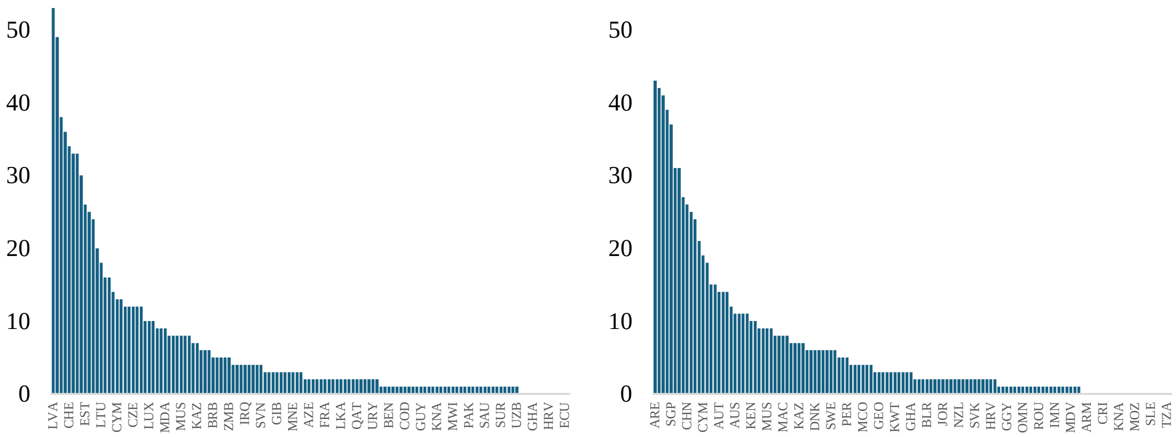
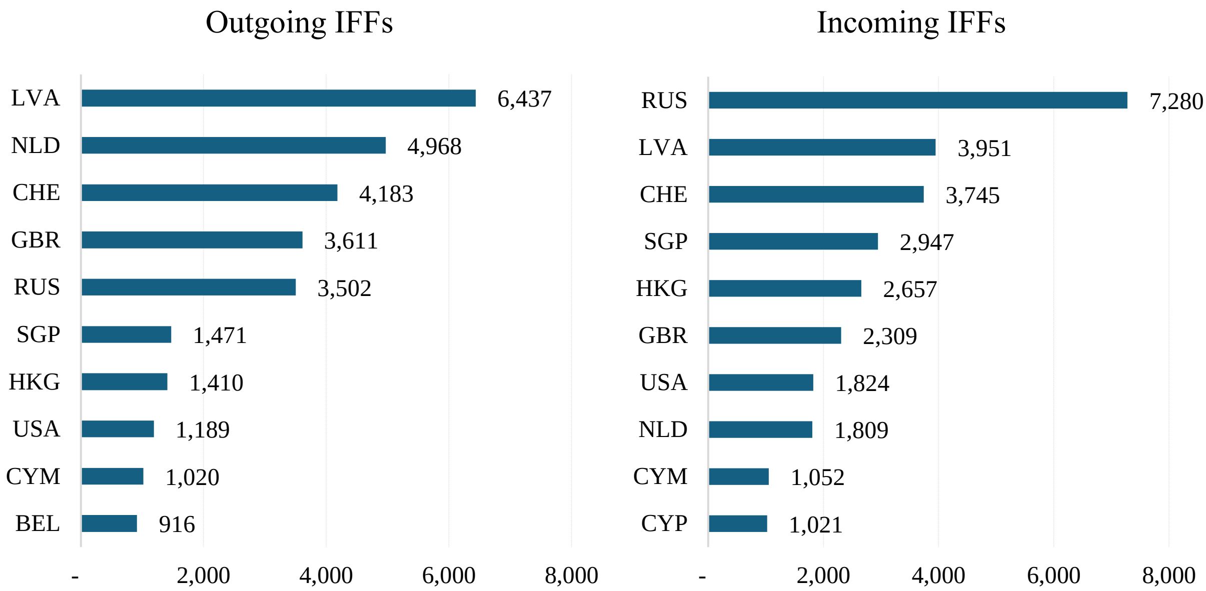
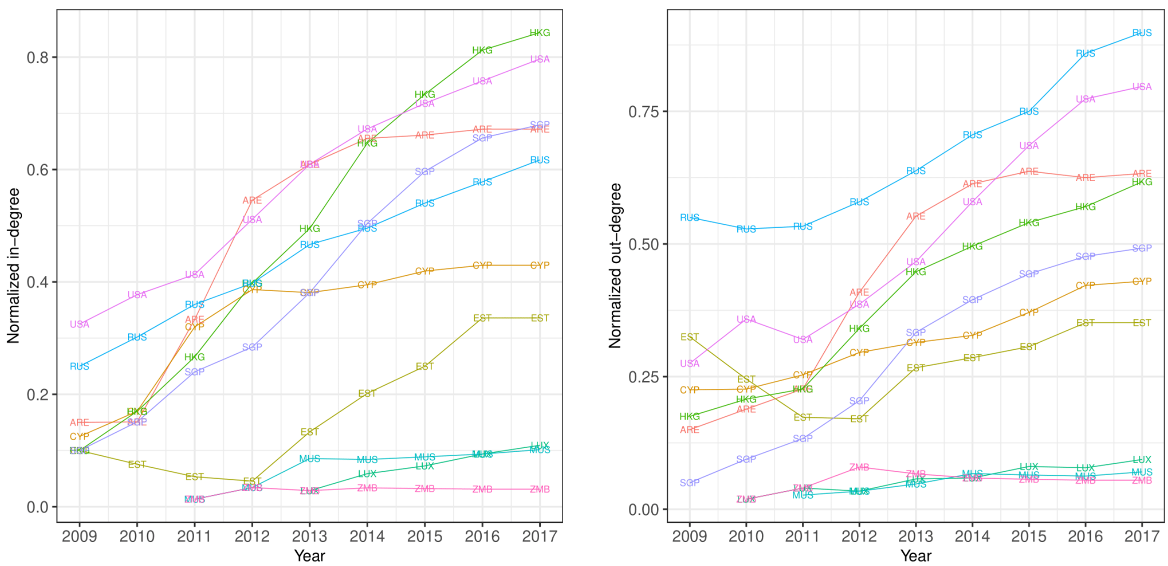


Figure 2. Top countries by total value) of reported IFFs (in US$ million).



Note: The left side refers to top IFF donor countries, while the right figure lists top IFF recipient countries.

Figure 3. Evolution of in/[out] degree overtime for top countries on the network



Note: In-degree is the number of different countries - origins of incoming transfers. Out-degree is the number of different countries – destinations of outgoing transfers. The degrees are rescaled to the [0,1] interval to enable meaningful comparisons over time. As the network expands and new connections between countries are added, the relative importance of having 5 connections in 2007 differs from having 5 connections later, making rescaling necessary for consistent analysis.

Additional Information

Appendix 1. Discussion of biases in the data

According to the estimates of Somare et al. (2016), more than 50% of IFF reports worldwide are filed by US based regulated entities. Not surprisingly, the majority (80%) of filers in our dataset are US based correspondent banks. Given that more than 50% of international trade transactions worldwide are invoiced in US dollars – even when US firms are not involved in the transaction – correspondent banking in US is a critical tool for the functioning of the global trading system. Intermediary banks in such transactions obtain information about the counterparts even if two transacting counterparts are not necessarily US institutions.

Correspondent banking is vital for many smaller and regional banks that may lack a vast network of direct partner banks around the globe. But this represents the limitation of the dataset, which doesn't have transfers reported if intermediary bank was not involved – *id est* transfers executed using direct partner banks. Another limitation is that transactions in national currencies are not covered. For example, if US dollar transfer has as a destination HKD it doesn't necessarily mean that HKD is a real final destination. In HKD, money can be further converted into Yuan and transferred to CNH.

Nevertheless, given the findings of previous studies on the subject and the compelling patterns observed in our analysis, this dataset can be considered broadly representative of global suspicious transaction flows, particularly given the central role of U.S.-based correspondent banks in international trade and finance.

Appendix 2 Additional analysis strengthening gravity model results

(a) negative association between GDP per capita and IFFs

To confirm the relation between increasing quality of financial services proxied by the GDP per capita acting as deterrent for IFFs, we setup a panel regression in which (log) value of IFFs of country i in year t, y_{it}, is regressed on (log) GDP per capita of a country in year t, $lnGpc_{it}$, and (log) GDP of a country in year t, lnG_{it}, with time and countries fixed effects. Countries' fixed effects effectively level out possible biased focus of the FinCEN dataset towards certain countries (as we suspect that it might have been the case that certain countries were investigated by ICIJ more than others). Year fixed effects level out the fact that the overall number of reported flows grows over time.

The setup of a panel regression adds to the evidence observed in the gravity model exploiting the time dimension of the dataset. Results suggest that richer countries generate and attract global illicit flows, but that the quality of financial services tend to lower the volumes of money being laundered (see Table A1 below).

Table A1. Panel data regression results

	(log) value of IFF **Out**flow		(log) value of IFF **In**flow	
	(1)		(2)	
log GDP per capita	-7.096***	(2.363)	-1.307	(2.235)
log GDP	8.746***	(0.901)	6.209***	(0.852)
Observations	1,313		1,313	
R-squared	0.111		0.092	
Number of countries	110		110	
Number of years min/max	06/12		06/12	

Note: *** p<0.01, ** p<0.05, * p<0.1, Standard errors in parentheses. Regression includes fixed effects of countries and years

(b) positive association between Egmont membership and IFFs

We exploit the event of joining the Egmont Group to see whether it impacts country's IFFs. During our study period, 37 countries from our dataset joint Egmont and 13 countries joint after 2017 (Table A2).

Table A2 Egmont Group Membership timing

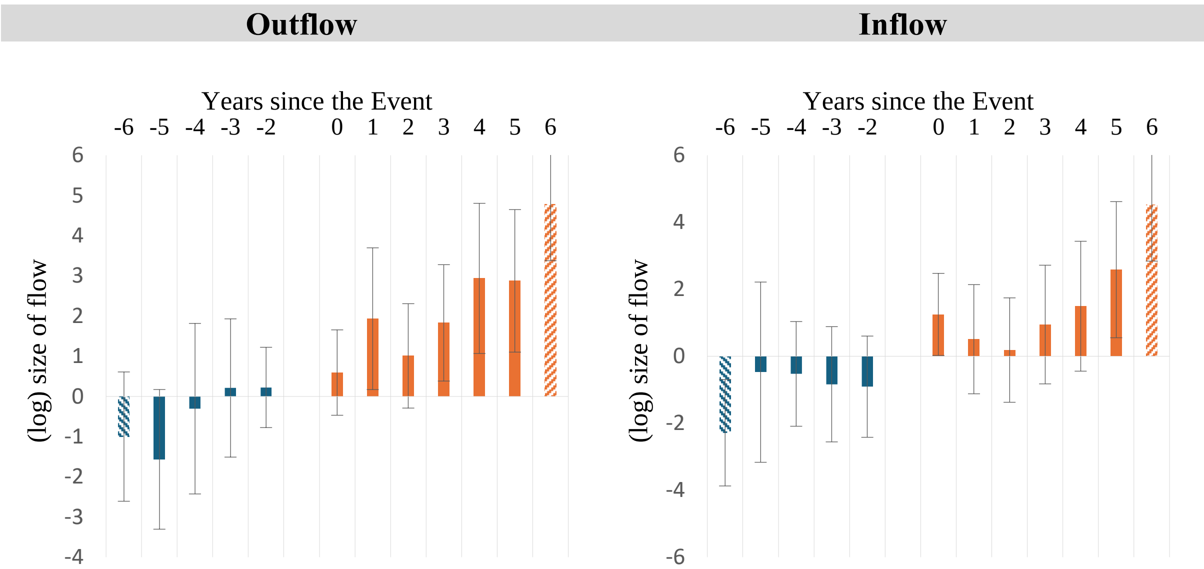
before 2006						2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018-2024
NOR	ESP	CZE	CUW	EST	LBN	NGA	MDA	CYP	CIV	KAZ	JOR	SYC	AGO	KHM	ECU	KWT	ZMB
GBR	FRA	MCO	GRC	FIN	MYS	IND	CRI	IRL	URY	UZB		BGD	TZA	NER			COG
USA	GGY	ITA	HRV	ROU	DEU	ARM	HUN	POL	LCA			TGO	JAM				AZE
AUS	AUT	PRY	LVA	IMN	MUS	JPN		LKA					GHA				BEN
NLD	HKG	SVK	BGR	COL	SRB	KNA		MAC					NAM				TKM
LUX	PAN	TWN	LTU	LIE	BHR	BLR		BMU									MNE
SVN	NZL	CHE	PRT	CYM	ATG			AND									IRQ
SWE	DNK	TUR	VGB	BHS	MLT			SAU									LAO
BEL	PHL	MEX	UKR	THA	ZAF			MWI									OMN
CAN	QAT	SGP	IDN	SLV	GIB			BLZ									KEN
BRB	PER	RUS	EGY		GEO												GUY
KOR	ISR	ARE															SUR
																	MDV

We apply the event study design framework as a way to study causal inference (Clarke & Tapia-Schythe, 2021). We observe an increase in IFFs after a country joins the Egmont group. Figure

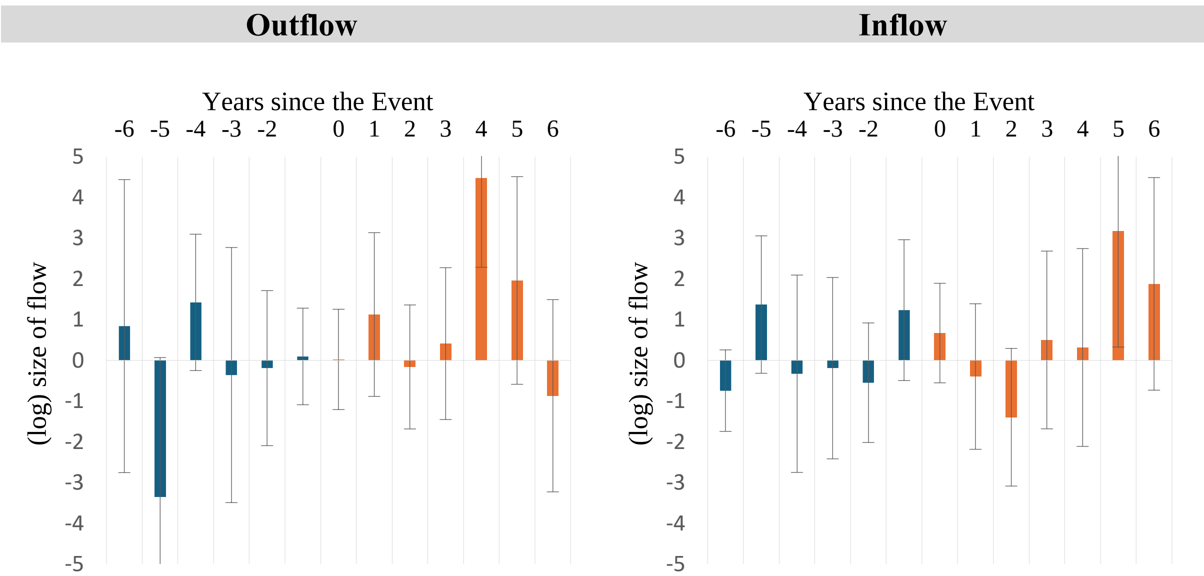
A1 reports on the results using Clarke & Tapia-Schythe (2021) estimation (a) and Callaway & Sant'Anna (2021) estimation (b). We observe the increasing trend over the years after joining, and we observe that the impact is more pronounced for outflows from an Egmont country (left panel) than for the inflows into such country (right panel).

Figure A1. Event of joining Egmont Group, impact on country's IFFs

(a) Estimation Clarke, Daniel, and Katja Tapia-Schythe. 2021



(b) Estimation Callaway, Brantly, and Pedro H. C. Sant'Anna. 2021



Note: bars with 90% confidence bands reflect the size of the difference between treated, i.e. subject to the event, and control groups of countries. Orange color stands for years after the event. Control group are not-yet-treated countries.

Appendix 3 Table A3.1 Gravity model estimation with Heckman correction

	First stage selection equation - probability of bilateral IFF existence									
Explanatory variables	(1)		(2)		(3)		(4)		(5)	
bilateral characteristics										
Shared History	-0.885***	(0.263)	-0.907***	(0.261)	-0.697***	(0.246)	-0.773***	(0.231)	-0.413*	(0.229)
log (Geographical distance between countries)	-0.187***	(0.035)	-0.186***	(0.035)						
log (Exports between countries)					0.101***	(0.014)				
log (Imports between countries)							0.134***	(0.015)		
log (Remitances between countries)									0.065***	(0.016)
Shared border	0.152*	(0.092)	0.140	(0.096)						
Shared language	-0.204**	(0.085)	-0.177**	(0.088)						
Common coloniser	0.714***	(0.128)	0.758***	(0.128)						
Colony-coloniser relation	0.300**	(0.117)	0.274**	(0.122)						
Origin Country										
log GDP per capita	-0.084***	(0.031)	-0.136***	(0.030)	-0.062*	(0.032)	-0.070**	(0.033)	-0.046	(0.038)
log GDP	0.132***	(0.016)	0.163***	(0.015)	0.001	(0.022)	-0.030	(0.022)	0.035	(0.026)
FATF Black or Gray listed	0.140***	(0.047)	0.174***	(0.045)	0.107**	(0.046)	0.108**	(0.046)	0.095*	(0.055)
Corruption index	0.011***	(0.002)	0.011***	(0.002)	0.010***	(0.002)	0.011***	(0.002)	0.010***	(0.002)
Tax heaven index	0.075***	(0.007)	0.081***	(0.007)	0.077***	(0.007)	0.071***	(0.007)	0.060***	(0.009)
Egmont membership (as of 2007)	0.286***	(0.056)	0.312***	(0.056)	0.294***	(0.055)	0.275***	(0.055)	0.351***	(0.077)
Armed conflict indicator	0.331***	(0.058)			0.374***	(0.058)	0.375***	(0.059)	0.543***	(0.064)
Conflict scale (death per capita)			0.029	(0.019)						
Destination country										
log GDP per capita	-0.148**	(0.075)	-0.174**	(0.073)	-0.117	(0.079)	-0.131	(0.080)	-0.005	(0.079)
log GDP	0.158***	(0.043)	0.176***	(0.045)	0.025	(0.049)	-0.006	(0.048)	0.084	(0.053)
FATF Black or Gray listed	0.184	(0.123)	0.239**	(0.122)	0.173	(0.124)	0.184	(0.123)	0.188	(0.130)
Corruption index	0.015***	(0.005)	0.014***	(0.005)	0.014***	(0.005)	0.014***	(0.005)	0.010*	(0.005)
Tax heaven index	0.093***	(0.025)	0.094***	(0.024)	0.091***	(0.026)	0.089***	(0.025)	0.067***	(0.024)
Egmont membership (as of 2007)	0.247	(0.189)	0.234	(0.193)	0.228	(0.199)	0.225	(0.197)	0.116	(0.189)
Armed conflict indicator	0.190	(0.136)			0.246*	(0.129)	0.246*	(0.130)	0.240*	(0.133)
Conflict scale (death per capita)			-0.320***	(0.115)						
Constant	-6.191***	(1.317)	-6.075***	(1.383)	-2.837*	(1.465)	-1.348	(1.527)	-5.994***	(1.589)

	Second stage - (log) total value of bilateral IFFs									
Explanatory variables	(1)		(2)		(3)		(4)		(5)	
Heckman selectivity effect λ= ρ· σ										
the inverse hyperbolic tangent of ρ	0.532***	(0.137)	0.494***	(0.149)	0.518***	(0.165)	0.527***	(0.167)	0.708***	(0.219)
(log) the standard error of the residual σ	1.101***	(0.058)	1.088***	(0.059)	1.122***	(0.065)	1.134***	(0.065)	1.270***	(0.092)
bilateral characteristics										
log (Geographical distance between countries)	-0.884***	(0.142)	-0.845***	(0.147)						
log (Exports between countries)					0.388***	(0.057)				
log (Imports between countries)							0.377***	(0.073)		
log (Remitances between countries)									0.093	(0.080)
Shared border	-0.691	(0.478)	-0.655	(0.491)						
Shared language	-1.345***	(0.308)	-1.295***	(0.302)						
Common coloniser	1.260***	(0.431)	1.375***	(0.463)						
Colony-coloniser relation	3.419***	(0.574)	3.374***	(0.593)						
Origin Country										
log GDP per capita	-0.418**	(0.213)	-0.524**	(0.230)	-0.357**	(0.182)	-0.329*	(0.199)	-0.852***	(0.300)
log GDP	0.252***	(0.087)	0.346***	(0.086)	-0.237**	(0.093)	-0.197**	(0.096)	0.091	(0.112)
FATF Black or Gray listed	0.882**	(0.370)	0.922**	(0.392)	0.888**	(0.402)	0.857**	(0.384)	1.666***	(0.458)
Corruption index	0.045***	(0.015)	0.039***	(0.014)	0.040***	(0.014)	0.041***	(0.014)	0.074***	(0.017)
Tax heaven index	0.245***	(0.046)	0.256***	(0.050)	0.234***	(0.044)	0.203***	(0.048)	0.280***	(0.058)
Egmont membership (as of 2007)	0.739	(0.458)	0.859*	(0.472)	0.885**	(0.436)	0.905**	(0.447)	1.461**	(0.617)
Armed conflict indicator	0.945***	(0.359)			0.849**	(0.383)	0.761**	(0.381)	1.201**	(0.605)
Conflict scale (death per capita)			0.129*	(0.069)						
Destination country										
log GDP per capita	-0.200	(0.325)	-0.294	(0.329)	0.115	(0.379)	0.036	(0.390)	0.213	(0.495)
log GDP	0.180	(0.160)	0.245	(0.160)	-0.345**	(0.168)	-0.332**	(0.160)	-0.075	(0.208)
FATF Black or Gray listed	0.087	(0.675)	0.222	(0.675)	-0.011	(0.726)	0.141	(0.739)	0.035	(0.828)
Corruption index	0.023	(0.024)	0.018	(0.025)	0.011	(0.028)	0.015	(0.028)	0.005	(0.037)
Tax heaven index	0.330***	(0.069)	0.329***	(0.070)	0.266***	(0.069)	0.271***	(0.068)	0.295***	(0.087)
Egmont membership (as of 2007)	0.837	(0.544)	0.825	(0.519)	0.764	(0.587)	0.785	(0.584)	1.061	(0.733)
Armed conflict indicator	0.697	(0.656)			0.796	(0.714)	0.792	(0.732)	0.820	(0.877)
Conflict scale (death per capita)			-1.409***	(0.473)						
Constant	10.224*	(5.826)	9.934*	(5.984)	19.399***	(6.253)	18.557***	(6.198)	10.727	(8.824)
Observations	16,699		16,699		15,052		15,195		12,382	

Table A3.2 Gravity model estimation with Heckman correction for average value of IFF transaction

	First stage selection equation - probability of IFF Outflows existence		Second stage - (log) **average value** of IFF transaction	
	(1)		(2)	
Heckman selectivity effect λ= ρ· σ			(+)	
the inverse hyperbolic tangent of ρ			0.500*	(0.294)
(log) the standard error of the residual σ			0.840***	(0.111)
Bilateral characteristics				
Shared History	-0.885***	(0.263)		
log (Distance between countries)	-0.187***	(0.035)	-0.598***	(0.148)
Shared border	0.152*	(0.092)	-0.358	(0.368)
Shared language	-0.204**	(0.085)	-1.084***	(0.254)
Common coloniser	0.714***	(0.128)	0.659	(0.459)
Colony-coloniser relation	0.300**	(0.117)	1.968***	(0.384)
Origin Country				
log GDP per capita	-0.084***	(0.031)	-0.357*	(0.195)
log GDP	0.132***	(0.016)	0.124	(0.081)
FATF Black or Grey listing	0.140***	(0.047)	0.549**	(0.252)
Corruption index	0.011***	(0.002)	0.035**	(0.015)
Tax heaven index	0.075***	(0.007)	0.192***	(0.051)
Egmont membership (as of 2007)	0.286***	(0.056)	0.515	(0.351)
Armed conflict indicator	0.331***	(0.058)	0.584	(0.397)
Destination country				
log GDP per capita	-0.148**	(0.075)	-0.045	(0.236)
log GDP	0.158***	(0.043)	0.068	(0.123)
FATF Black or Gray listed	0.184	(0.123)	0.052	(0.479)
Corruption index	0.015***	(0.005)	0.011	(0.019)
Tax heaven index	0.093***	(0.025)	0.250***	(0.059)
Egmont membership (as of 2007)	0.247	(0.189)	0.697*	(0.373)
Armed conflict indicator	0.190	(0.136)	0.328	(0.522)
Constant	-6.191***	(1.317)	11.636**	(4.927)

Note: the table presents estimates from the baseline gravity regression model specified in the methodology section. Column (1) presents first-stage estimates (probability of flow), and Column (2) presents second-stage estimates (value of flow). The number of observations on the first stage is 16.699, on the second stage (selected) - 675.
*** p<0.01, ** p<0.05, * p<0.1, Standard errors clustered on a country level are given in parentheses.

Data Availability Statement

The data that support the findings of this study are openly available in International Consortium of Investigative Journalists at https://www.icij.org/investigations/fincen-files/download-fincen-files-transaction-data/ (see footnote 3 at Section 3. The data).

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