Pulling Back The Curtain: Evaluating Illicit Financial Flow Risk Factors and Estimation Approaches (DRAFT)

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Abstract

Debanking, the phenomenon whereby developing nations face exclusion from international financial partnerships due to perceived risks of illicit financial flows (IFFs), constitutes a formidable obstacle to both global financial stability and the developmental aspirations of nations, notably in regions such as the Caribbean. This paper critically examines the prevailing practices within financial institutions that employ country-level risk assessments to gauge the prevalence of IFFs. By probing the complexities inherent in this process, the research seeks to provide insights essential for stakeholders, policymakers, and financial institutions in refining methodologies for assessing and mitigating the risks associated with IFFs. Furthermore, the study underscores the imperative of fostering accurate measurements to enhance financial inclusion and fortify the resilience of the global financial architecture, thereby advancing broader objectives of sustainable economic development.

JEL Codes:

- F38 - International Financial Policy: Financial Transactions Tax; Capital Controls
- F65 - Finance: Informal Finance; Underground Finance
- G28 - Financial Institutions and Services: Government Policy and Regulation
- H26 - Public Economics: Tax Evasion and Avoidance
- K42 - Illegal Behavior and the Enforcement of Law

Keywords: Illicit Financial Flows (IFFs), Correspondent Banking Relationships (CBRs), Money Laundering, De-risking, Anti-Money Laundering (AML), Financing of Terrorism, Global Financial System, Developing Nations, Caribbean Region, Macroeconomic Indicators, Predictive Modeling, Vulnerability Assessment, World Bank, Open-access Data, Stakeholders, Statistical Analysis, Financial Inclusion, Collateral Damage.

World Bank Data Lab

This paper was written as part of the World Bank Data Lab University Data Fellows initiative which connects World Bank researchers with academic institutions. As part of the Data Lab, students write an original research paper and present their findings to the World Bank. Students participating in the data lab are in their final semester of the Applied Economics Masters.

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1 Introduction

On September 14, 2022, the Prime Minister (PM) of Barbados, the Hon. Mia Amor Mottley, K.C., M.P., testified before the U.S. House Committee on Financial Services on the loss of correspondent banking relationships (CBRs) in Barbados and the rest of the Caribbean region. The hearing, titled "When Banks Leave: The Impacts of De-Risking on the Caribbean and Strategies for Ensuring Financial Access," shed light on the challenges Caribbean nations face when large developed countries like the United States classify them as at risk of illicit financial activity, emphasizing the adverse effects of grey-listing and potential subsequent de-risking on its economies. De-risking (also known as de-banking) is the process where a large international bank severs its relationship (CBR) with a small national bank over concerns about systemic risk in that nation, such as evidence of money laundering. While international banks end their CBRs because of a variety of risks, such as credit, geopolitical, and economic, banks often end their CBRs because they believe their CBR is aiding money laundering and other illicit financial transactions.

Mottley expressed frustration with the designation of her country as a grey-listed nation, a Financial Action Task Force (FATF) label suggesting significant deficiencies in a nation's anti-money laundering/counter-terrorist financing (AML/CFT) safeguards. She argued against the proxy rules that categorize countries based on perceived risks rather than focusing on the substantive prosecution of money laundering and terrorism financing. Notably, Mottley challenged the U.S. Department of the Treasury's approach, urging U.S. policymakers to concentrate on identifying actual money laundering activities instead of creating rules that disproportionately affect smaller developing nations.

The accusatory tone from Mottley stemmed from the perception that Caribbean countries, like Barbados, face de-risking due to concerns about illicit financial flow risk factors. She found this stance hypocritical, citing recent revelations about British and Swiss banks laundering Russian Oligarch money. She asked policymakers to reconsider the criteria for de-risking, emphasizing that evidence of IFFs should precede any decision on severing CBRs.

AML/CFT reforms are primarily driven by risk-based approaches (RBA) run by the FATF and FATF-style regional bodies (FSRBs). IFFs are usually part of a nation's shadow economy, making them challenging to estimate. RBA attempt to rate countries on criteria associated with prevention of shadow economies, such as the strength of financial regulation in a jurisdiction. The FATF's RBA is the most well-known methodology and thus, the most well covered by the existing literature. Previous qualitative work has criticized the FATF for promoting standards that limit financial inclusion.

This paper addresses a two-fold research question, first the correlation between currently used indicators of Illicit Financial Flow (IFF) risk and second, the occurrence of IFFs. Traditional indicators, such as Financial Action Task Force (FATF) greylisting, often lead to de-risking. However, it remains uncertain if countries that lost their Correspondent Banking Relationships

(CBRs) due to greylisting exhibit high rates of IFFs. This uncertainty arises from the challenge of measuring IFFs, with no consensus on the best estimation methodologies. The paper investigates existing methodologies unrelated to current risk indicators and assesses their relationship with these indicators, delving into the complex relationship between macroeconomic indicators, historical de-risking, and the vulnerability of nations to IFFs. The goal is to create a predictive model that can assist stakeholders, particularly the World Bank, in proactively identifying nations at risk of IFFs and preventing unwarranted de-banking.

1.1 Definition of Illicit Financial Flows

Illicit financial flows (IFF) are a broad group of financial transactions that stem from cash generated through illegal or illicit activities such as drug trafficking or government corruption. Transforming that cash into other assets is typically viewed as money laundering, especially when the illicit cash is concealed within licit sources. Tax evasion and IFFs often go together, especially when money is transferred from a high-tax location to a low-tax area. However, IFFs are notably different from legal tax avoidance, which involves setting up businesses in locations with low or no taxes, such as Delaware or the Cayman Islands to reduce taxes legally. Additionally, legal activities in one country might be illegal in another, thus the use of the term "illicit" captures cross-border legal differences, reflecting the perception of the activity rather than the jurisdictional legality.

In their 2020 book, *'Estimating illicit financial flows A critical guide to the data, methodologies and findings'* Cobham and Janký, two of the foremost scholars in the IFF field, believe that a legal definition of IFFs is inappropriate given the breadth of illicit transactions. Instead, they opt for a definition of IFFs as flows that are "deliberately obscured" from financial institutions and authorities.

This paper studies the flow of money from the Caribbean region to international financial systems. There is a flow of money from large nations, such as the United States and the United Kingdom, to tax havens in the Caribbean. However, those flows are not transactions that typically threaten correspondent banking relationships. CBRs fall apart over risks of money laundering and IFFs from the respondent country (the nation relying on the CBR for international banking access). While there may be a connection between flows to and from Caribbean nations, i.e., money coming in as foreign direct investment could be leaving with laundered funds, this paper only studies one-sided flows.

1.2 Summary of Correspondent Banking Relationships and De-risking

Correspondent Banking Relationships (CBRs) act as vital conduits connecting smaller national banks, respondents, to the global financial system through larger international banks, correspondents. These relationships facilitate critical financial services, including wire transfers and foreign exchange settlements, essential for developing nations' access to foreign income sources, such as remittances from family members living abroad.

De-risking (or debanking) is the process through which international banks end their CBRs with a respondent nation over concerns about risk in that nation's financial system. There are a variety of reasons why an international bank might initiate a de-risking process, from reputational concerns to fears of involvement in illegal activity. De-banking can occur on the individual level, ie a bank can close the account of one person, or it can sever the entire relationship with a group of people, a country, or an entire region.

Banks must adhere to Anti-Money Laundering/Countering the Financing of Terrorism (AML/CFT) guidelines, conducting due diligence on account holders to ensure that deposited funds are obtained through licit means. Banks that violate AML/CFT requirements can face large penalties and reputational risk. Thus, banks face inherent risk exposure from opening a CBR because they do not have the information or ability to conduct the same level of due diligence on depositors that they might conduct on their own clients. Conducting AML/CFT diligence has a cost that also drives banks away from opening a CBR.

The Biden Administration is generally opposed to the current de-risking regimes present in the international banking community. In April of 2023, the Treasury Department issued a revamped de-risking strategy, writing in the accompanying statement that indiscriminate de-risking is "driving financial activity out of the regulated financial system, hampering remittances, preventing low- and middle-income segments of the population from efficiently accessing the financial system, and preventing the unencumbered transfer of humanitarian aid and disaster relief".[1]

2 Literature Review

A substantial body of literature has explored how economists can measure illicit financial flows. While academic economists contribute reports suggesting broad data sources and methodologies, organizations like the IMF and the United Nations, with a stake in understanding and curtailing IFFs, often propose more specific ideas. This literature falls into two main categories: top-down and bottom-up approaches.

Top-down approaches involve examining macroeconomic trends and indicators to identify patterns indicating illicit financial transactions. One common approach is Balance of Payments (BoP) analysis, which considers the mismatch between recorded capital inflows and their utilization. However, BoP analysis faces challenges, including the assumption that mismatches solely result from illicit capital flight and the inclusion of legitimate transfers, such as foreign security purchases, in capital outflows.

The World Bank Residual Method (WBRM) is a popular BoP formula that estimates that difference between inflows and use of those inflows. Below (Equation 1) is a version of the WBR from Cobham and Janký's 2017 paper written as part of their expert consultation on the United Nation's sustainable development goal (SDG) Indicator on IFFs.

$$A + B + C + D + E + F + G + H = 0 \tag{1}$$

where:

A : current account balance
B : net equity flows (including net FDI and FPI)
C : other short-term capital of other sectors
D : FPI involving other bonds
E : change in deposit-moneybanks' foreign assets
F : change in reserves of the central bank
G : net errors and omissions (NEO)
H : change in external debt

Kar, Cartwright-Smith, & Hollingshead (2010) used the WBRM to estimate financial flows from developing countries for Global Financial Integrity (GFI). They consider their estimate

[1] U.S. Department of the Treasury. (2023, April 25). Treasury Department Announces 2023 De-Risking Strategy [Press release]. Retrieved from https://home.treasury.gov/news/press-releases/jy1438

conservative given that they exclude illicit flows generated through smuggling and trade misinvoicing. In 2017, GFI (Salomon and Spanjers 2017) produced new estimates using a variation of the WBRM called the Hot Money "Narrow" Method (HMN) which is simply put the difference between credit and debt, assuming "those unreported leakages (here representing potential inflows as well as outflows) represent unrecorded and presumably illicit transactions". While they assume some HMN estimates are also capturing legitimate reporting errors, Salomon and Spanjers argue that their methodology is already an undercount so the small fraction of their total estimate that may result from errors would not make their estimate an overcount of total IFFs.

Salomon 2019, also from GFI, used Direction of Trade (DOT) statistics in addition to BoP data to estimate IFFs, using data from the IMF, World Bank, and United Nations Comtrade database. They find that this methodology is more robust than previous analyses which exclude what they believe is a significant driver of IFFs, trade misinvoicing.

Trade misinvoincing is a form of value gap analysis which looks at the difference between the declared value of goods and the estimated actual value. Salomon and Spanjers (2021) also uses bi-lateral trade data and estimates trade-based IFFs through analysis of the gap between reported value of traded goods between two countries. The United Nations Conference on Trade and Development (UNCTAD) published official estimates of IFFs in 2021 as part of their agenda on sustainable development. UNCTAD relies on trade misinvoicing to measure IFFs, specifying six categories that countries can use to capture illicit flows from national indicator data. Thus, country-by-country implementation and data collection can vary but all center around these methodologies. First, the Partner Country Method Plus (PCM+) looks at asymmetric customs reporting between countries to determine potential value inflation. In a similar vein, the Price Filter Method Plus (PFM+) searches for abnormalities in transaction prices, also using customs data. Countries could also exploit data on multinational enterprises (MNEs) to construct data in line with either the Global distribution of MNEs' profits and corporate taxes or MNE vs comparable non-MNE profit shifting methods. Lastly, the UNTAD data comprises of estimates from flows of undeclared offshore assets and flows of offshore financial wealth by country.

Cobham et al (2021) illustrate a top-down approach by estimating IFFs based on a jurisdiction's relative financial secrecy. Using information from the Bank for International Settlements (BIS) to construct financial flow estimates as well as additional data on foreign direct investment, the authors generate exposure estimates based on the volume of transactions and financial secrecy. While this paper's work on financial flow estimates is relevant to this research, the secrecy index is highly correlated with current FATF risk indicators, meaning we cannot use this exact work to correlate vulnerability and IFF estimates.

On the other hand, bottom-up approaches concentrate on micro-level flows, utilizing transactions known to originate from illicit cash to generate estimates reflecting the broader financial system. Walker (1995) is a seminal paper on money laundering in Australia that introduced the Walker Model, starting with crime statistics to estimate illicit cash entering the financial system. Ferwerda et al. (2020) expanded on Walker's work, considering flow-through transactions and distinguishing between money moving through a country and remaining within it. Despite potential robustness in original crime data, the Walker Model requires substantial guesswork and assumptions at each step of the estimation process.

3 Data

Data for this project is split into three categories, IFF estimates, IFF risk indicators, and country-level control variables. This paper uses three IFF estimates based on guidance from Cobham and Janksý (2020), a meta-analysis on current IFF research practices. Within the literature, there are two main methodologies for studying IFFs (excluding methodologies for tax avoidance estimates from developed nations to developing nations): trade statistics and wealth estimates. Within trade statistics, economists often use abnormal pricing or mirror trade statistics, both of which look at the prices of various goods as compared to trends. For wealth estimates, researchers study abnormalities in capital accounts or capital flight. This analysis selects 3 data sources deriving from different methodologies for measuring IFFs, trade data (Salomon and Spanjers 2021), wealth data (World Bank data based on a formula from Ndikumana & Boyce (1998), and a hybrid approach (Salomon and Spanjers (2017)).

3.1 Trade Data - Misinvoicing

We use data from Salomon and Spanjers (2021) on trade-based IFFs for the trade-misinvoicing estimate. Salomon and Spanjers (2021) estimates derive from the United Nation's bilateral trade data (Comtrade database), looking at 134 developing nations and their trade with 36 developed nations and global trading partners. Comtrade measures each nation's annual exports and imports. Value gaps, another term for misinvoicing, occur when two countries report different values for the same transaction.

Salomon and Spanjers (2021) trade data only focuses on goods transactions, not services, which is a severe limitation of their methodology and an indication that their estimation is likely an IFF undercount.

3.2 Capital Flight

Capital flight measures the capital outflow from a country. Capital flight can occur for a variety of licit reasons including currency depreciation or tax avoidance. However, capital flight measurements would also capture illicit financial flows from a country. Thus, an estimate of capital flight from a nation would be an overestimate of IFFs as it counts both licit and illicit financial flows. Ndikumana & Boyce (1998) estimate capital flight using information on a nation's capital inflows and outflows. Formula (2) estimates the gap between capital inflows and outflows (KF_t), some of the gap which can be attributed to IFFs.

Ndikumana & Boyce (1998) measure capital flight as the sum of a series of observable capital figures, as shown in equation 2:

$$KF_t = CDEBT_t + DFI_t - (CA_t + TRES_t) \tag{2}$$

1. $CDEBT_t$ is the change in total external debt outstanding
   (a) An increase in external debt is caused by a myriad of conditions, such as foreign investors divesting from that nation over rising geopolitical risk
2. DFI_t is net foreign direct investment (FDI)
   (a) A decrease in FDI is caused by factors that reduce a creditors desire to invest in a developing nations, potentially indicating that the nation receiving aid is no longer credit-worthy or investment contains substantial risk
3. CA_t is the current account balance
   (a) An increase in the current account balance means that a country is importing more than it exports

4. $TRES_t$ is the additions to reserves and related items

   (a) A decrease in reverses is caused by capital leaving a country, often denominated in foreign currencies as foreign investors pull money out of a country's banks

We calculate capital flight for each country using formula 2, which shows that capital flight is a function of the change in external debt, net foreign direct investment, the current account balance, and reserves. These country-level estimates use 2018 World Bank data (the last full year prior to COVID), slightly changing the formula based on data availability. $CDBET_t$ is the change in service on external debt. An increase in the service on external debt indicates that a country is paying more to borrow money, ie higher interest rates or that loans are being called in.

Table 1 shows the composite summary statistics that generate IFF estimates using the Ndikumana & Boyce (1998) formula with 2018 World Bank data.

Table 1: Capital Flight Estimate Summary Statistics (in millions of USD)

	Mean	SD	Min	Max
Capital Flight (2018)	2648.30	8540.53	-19703.81	44022.50
Δ Service on External Debt	348.66	2253.19	-6819.82	14161.76
Δ Net Foreign Direct Investment	155.31	1548.20	-4404.11	9277.23
Δ Current Account Balance	-1027.53	4982.41	-29456.53	19804.00
Δ Reserves and Related Items	-1116.81	3811.22	-18718.15	5913.38

Data from 2018 World Bank Open Data (Change in Debt Service on External Debt, Change in Net Foreign Direct Investment, Change in Current Account Balance, Change in Reserves and Related Items), formula from Ndikumana & Boyce (1998). There are 90 observations of each variable. China and Russia are excluded due to data validity issues and outlier status

3.3 Hybrid IFF Model

Salomon and Spanjers (2017) from Global Financial Integrity estimated IFFs using IMF data on merchandise misinvoicing and leakages in the balance of payments, a hybrid estimation approach taking into account trade imbalances and wealth abnormalities and shows that the majority of IFFs come from misinvocing, a mis-match in the value shown on accounts between the two countries. Their methodology is based on the World Bank residual and is adjusted to account for trade-misinvociing. Salomon and Spanjers also break out their values into high and low estimates. The high estimate is the scaled version of the low estimate that accounts for misinvoicing between the country of interest and other developing nations. However, the high estimate may double-count trade misinvoicing while the low estimate excludes trade misinvoicing between developing countries and thus is an undercount. This paper uses the middle estimate, which is an arithmetic mean of the high and low.

3.4 Risk Factor Data

The second component of this research is IFF risk factor indicator data. Mutual evaluation reports (MER) are the primary source we use to determine which countries are *perceived* as at high risk of IFFs. The FATF, along with other regulatory bodies such as other monitoring bodies in their global alliance such as the Committee of Experts on the Evaluation of Anti-Money Laundering Measures and the Financing of Terrorism (MONEYVAL), evaluates each country based on their vulnerability to IFFs, breaking up the rankings into "compliance" and "effectiveness" categories. Compliance scores measure whether a country has policies and reforms in place to combat illicit financial flows and money laundering. Effectiveness scores measure how well those IFF and anti-money laundering (AML) policies achieve the desired outcomes.

MERs are conducted by peer countries and can take up to 18 months to finalize. The process of rating each country involves many highly involved steps and each country is re-rated every few years. There have been 4 complete rounds of MERs since the 1990s and the fifth round is underway. This research uses ratings from the fourth round.

Below are the MER scoring criteria and the numerical value I assigned to each categorical level of effectiveness and compliance. Assigning numerical values allows us to conduct statistical inference with the categorical assessments.

1. Effectiveness (11 categories)
   (a) High level of effectiveness - The Immediate Outcome is achieved to a very large extent. Minor improvements needed. (4 points)
   (b) Substantial level of effectiveness - The Immediate Outcome is achieved to a large extent. Moderate improvements needed. (3 points)
   (c) Moderate level of effectiveness - The Immediate Outcome is achieved to some extent. Major improvements needed. (2 points)
   (d) Low level of effectiveness - The Immediate Outcome is not achieved or achieved to a negligible extent. Fundamental improvements needed. (1 points)
2. Technical Compliance (40 categories)
   (a) Compliant (4 points)
   (b) Largely compliant - There are only minor shortcomings. (3 points)
   (c) Partially compliant - There are moderate shortcomings. (2 points)
   (d) Non-compliant - There are major shortcomings. (1 points)

I sum each country's performance on the "compliance" and "effectiveness" ratings to make an index for each rating which can be used to rank countries in terms of FATF-determined risk level. Figure 1 displays each country's total MER rating, with higher numbers representing less systemic risk of IFFs based on FATF assessment criteria. Moreover, I use the Committee on Payments and Market Infrastructure (CPMI) quantitative review of correspondent banking data. This dataset summarizes the change in CBRs by country over a 10 year period. Measuring changes in CBRs is akin to using a variable for country-level risk as de-risking occurs when a certain nation or region appears vulnerable to IFFs. For this analysis, I use the change in the cumulative CBR transactions over the 10 year period.

MER assessments are one piece of the information that a bank considers when they de-risk a country. Banks often sever CBRs over profitability or rising operating costs. Thus, FATF risk evaluation scores and CPMI's data on changes in CBRs do not line up perfectly. However, low scores from a mutual evaluation report usually indicate that a country will receive the designation "Jurisdiction under Increased Monitoring", known informally as the "greylist". Current countries "greylisted" are Bulgaria, Burkina Faso, Cameroon, Democratic Republic of the Congo, Croatia, Haiti, Jamaica, Kenya, Mali, Mozambique, Namibia, Nigeria, the Philippines, Senegal, South Africa, South Sudan, Syria, Tanzania, Turkey, Vietnam, and Yemen. As of 2024, the FATF ended their period of increased monitoring on Barbados, Gibraltar, Uganda, and the United Arab Emirates. In this paper, we set a dummy variable for greylisted jurisdictions found to have strategic AML/CFT deficiencies at the conclusion of the fourth round MERs: Albania, Barbados, Burkina Faso, Cambodia, Cayman Islands, Democratic Republic of the Congo, Gibraltar, Haiti, Jamaica, Jordan, Mali, Morocco, Mozambique, Nicaragua, Pakistan, Panama, Philippines, Senegal, South Sudan, Syria, Tanzania, Türkiye, Uganda, United Arab Emirates, and Yemen. Morevoer, Russia and China are omitted from the analysis since their IFF estimates are outliers.

3.5 Summary Statistics

Lastly, I use country-level fixed effect data to generate control variables for my model specifications. Namely, I pull World Bank data on national characteristics such as GDP-per-capita and regional dummy indicators.

Table 2 summarizes the remaining data, excluding the capital flight data from Table 1.

Table 2: Main Variable Summary Table

	Mean	SD	Min	Max	N
FATF MER Effectiveness	20.11	6.26	11.00	34.00	165
FATF MER Compliance	109.82	17.57	57.00	152.00	165
GDP-PC (World Bank)	19601.06	29789.42	364.69	228667.94	136
Δ CBR Transactions[1]	61.49	67.20	-74.60	421.00	184
Salomon and Spanjers (2021)	262997.86	536634.78	13.80	1380914.51	113
Salomon and Spanjers (2017)	3299.16	8328.11	0.00	68468.88	122

[1] *CPMI quantitative review of correspondent banking data measures net change in CBRs over 11 year period. Data on GDP Per Capita comes from the World Bank. The Effectiveness and Compliance scores are the sums of the FATF's mutual evaluation report of each country, broken up into scores under the compliance and effectiveness scores and then summed respectively. The Saloman and Spanjers (2021) and Saloman and Spanjers (2017) estimates are both in millions. China and Russia are excluded due to data validity issues and outlier status*

4 Methodology

4.1 IFF estimate and FATF risk factor regressions

To test whether higher values of IFF estimates cause increases in a nation's IFF risk assessment, we run three linear regressions, one for each source of IFF estimate data. In each regression, we keep the same control variables, which are dummy indicators for region and GDP-per-capita. Below are the three specifications:

4.2 Risk Factors on IFFs Regression Models

$$y = \beta_0 + \beta_1 * X_{\text{comply}} + \beta_2 * X_{\text{effect}} + \beta_3 * X_{\text{GDP-per-capita}} + \beta_4 * X_{\text{regions}} + \epsilon$$

where:

- y represents the IFF estimate of which this paper has three specifications (listed below).

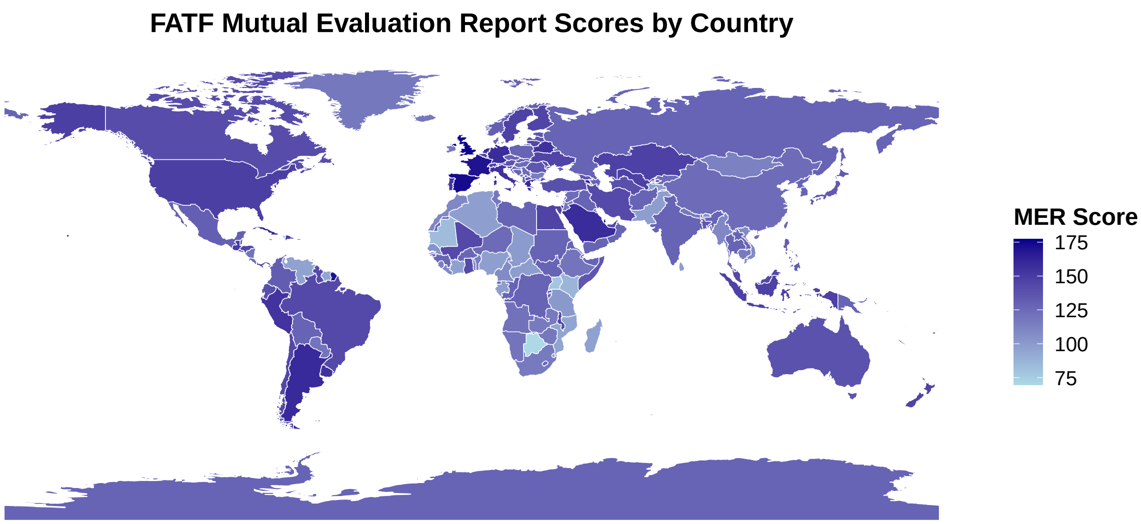

Figure 1: Total Risk Score by Country: *Higher scores indicate better compliance with FATF guidelines compared to countries with lower scores.*

- β_0 is the intercept.
- β_1 and β_{effect} are the coefficients for FATF compliance and effectiveness scores, respectively.
- β_2 is the coefficient for GDP per capita.
- β_3 includes coefficients for various regions.
- β_4 is a dummy variable for whether the country was greylisted at the conclusion of the 4th round MER.
- ϵ denotes the error term.

4.2.1 Regression Models Using Different IFF Estimates (y)

1. Salomon and Spanjers (2021) Trade-Misinvoicing Data
2. Ndikumana & Boyce (1998) Data from World Bank
3. Salomon & Spanjers (2017) Data Regression

4.3 IFFs on Change in CBRs Regression Models

Additionally, I run three regressions using the IFF estimate data and the change in CBRs variable from the (CPMI) quantitative review of correspondent banking data. These regressions investigate whether high instances of IFFs actually correlate to a higher rate of de-risking.

4.4 CBR and IFF estimate Regression Models

$$y_{\text{change in CBR}} = \beta_0 + \beta_1 * X_{\text{IFF}} + \beta_2 * X_{\text{GDP-per-capita}} + \beta_3 * X_{\text{regions}} + \beta_4 * X_{\text{greylist}} + \epsilon$$

where:

- $y_{\text{change in CBR}}$ represents the change in CBR transactions over the 2011-2022 period.
- β_0 is the intercept.
- β_1 denotes the coefficients for the specific IFF data source (Salomon and Spanjers (2021), Ndikumana and Boyce (1998), and Salomon and Spanjers (2017)).
- β_2 is the coefficient for GDP per capita.
- β_3 includes coefficients for various regions.
- $\beta_4$is the coefficient on a dummy variable for whether the country was greylisted at the conclusion of the 4th round MER.
- ϵ denotes the error term.

4.5 MER risk factors and de-risking

Lastly, I run a regression of FATF effectiveness and compliance scores on the CMPI change in CBR data. This regression explores the relationship between the FATF rating systems and the instances of de-risking.

$$y_{changeinCBR} = \beta_0 + \beta_1 * X_{comply} + \beta_2 * X_{effect} + \beta_3 * X_{GDP-per-capita} + \beta_4 * X_{region} + \beta_{\text{greylist}} + \epsilon$$

Since high scores on MER indicate that a country has put in place adequate AML/CFT safeguards, we expect an inverse relationship between MER scores and the estimated IFF values. We also expect an inverse relationship between IFF estimates and the change in CBRs where high incidence of IFFs should decrease the number of CBRs in a country. Additionally, we hypothesize that MER risk factors should also have a positive relationship with the change in CBRs as higher compliance with FATF guidelines should indicate that a country has fewer IFFs and thus, more CBRs.

5 Regression Results

5.1 Main Regression Tables

Table 3 displays the results of the regressions of MER risk factor data on IFF estimates. The table has three columns, one for each of the IFF estimate specifications: Saloman & Spanjers (2021), Ndikumana & Boyce (1998), and Salomon & Spanjers (2017). All three regressions show the expected inverse relationship between compliance scores and illicit financial flows but a positive relationship between effectiveness and IFFs. According to the coefficient on MER effectiveness scores, countries with higher performance on the FATF's criteria for effective AML/CFT reforms are those with higher rates of illicit financial flows as compared to countries with worse performance. This means that as a country makes its AML/CFT reforms more "effective" according to the FATF guidelines, it experiences higher rates of IFFs. This relationship is especially interesting given the fact that the FATF rated most of these countries a few years after the data used by the three IFF estimation methodologies. This indicates that the positive relationship between effectiveness and IFF estimates is likely not due to high IFF estimates preceding a country's reforms. The coefficients on the MER effectiveness scores are statistically significant at the 1% level.

The coefficient on the greylist dummy is inconsistent across the three IFF estimate models. While the greylist dummy is correlated with an increase in IFFs as compared to non-greylisted countries for the Saloman and Spanjers trade estimate and the Ndikumana and Boyce Capital Flight estimate, the dummy shows a negative relationship with the Saloman and Spanjers Hybrid Estimate. The lack of statistical significance for the greylist dummy variable indicates that perceived risk as determined by the FATF does not mean a country has high rates of illicit financial flows.

Moreover, the coefficients on the regional dummies convey the average difference in IFFs between the specified region and the control region, which in this regression model is the dummy for East Asia and the Pacific. For example, in regression (1), countries in Latin America and the Caribbean have on average $-13 billion less in IFFs than countries in East Asia and the Pacific.

The overall fit of these models does not indicate that there is a particularly strong relationship between risk factors and IFF estimates. The Ndikumana & Boyce and Salomon & Spanjers regressions have little explanatory power, signifying that explaining illicit financial flows through risk factor data is a poor mechanism to understand which nations have higher IFFs.

Table 4 displays how changes in CBRs are affected by IFF estimates and MER scores. Across the three IFF estimate models, we see negative, but statistically insignificant, relationships between IFF valuations and the change in CBR transactions which is the expected direction of the result as higher rates of IFFs should lead financial institutions to sever CBRs. Additionally, there is an insignificant positive relationship between MER scores and the change in CBR transactions, meaning that better compliance with FATF guidelines causes more CBRs, which is the expected relationship. Overall, modeling CBRs as a function of IFF estimates provides no significant evidence that the countries losing their CBRs due to high instances of IFFs. We also do not see strong evidence that FATF evaluation scores can predict derisking.

While this research analyzed MER scores on three IFF estimates, the Saloman and Spanjers (2017) estimate should be given more weight than the others. By nature of construction, the hybrid estimation approach is more accurate than just trade and capital flight based approaches since it includes more information.

Table 3: Illicit Financial Flows Estimates Regression Results

	Dependent variable:		
	Salomon and Spanjers Trade Estimate (millions USD)	Ndikumana & Boyce Capital Flight Estimate (millions USD)	Salomon & Spanjers Hybrid Estimate (millions USD)
	(1)	(2)	(3)
MER Compliance Score	−69.652	−50.487	−61.371
	(109.454)	(69.374)	(65.850)
MER Effectiveness Score	1,554.328***	1,225.122***	929.818***
	(440.103)	(301.408)	(269.116)
GDP Per Capita	0.139	0.114	0.182*
	(0.166)	(0.313)	(0.103)
Europe and Central Asia	−11,711.940**	−15,301.380***	−6,686.550**
	(4,816.312)	(3,169.546)	(2,860.237)
Latin America and Caribbean	−13,894.020***	−8,949.437***	−2,222.170
	(4,349.299)	(3,061.473)	(2,645.226)
Middle East and North Africa	−11,906.990**	−10,724.430***	−3,464.781
	(5,565.864)	(3,779.276)	(3,475.197)
South Asia	−7,881.415	−2,277.064	−1,218.027
	(6,574.853)	(3,953.226)	(4,117.085)
Sub-Saharan Africa	−7,315.739*	−1,850.079	412.060
	(4,331.262)	(2,672.819)	(2,673.075)
Greylist	3,006.275	−703.140	−1,350.257
	(3,368.496)	(2,071.599)	(2,032.297)
Constant	−5,247.794	−7,781.790	−5,341.275
	(9,328.973)	(5,883.718)	(5,586.189)
Observations	104	90	114
R^2	0.281	0.306	0.221
Adjusted R^2	0.212	0.228	0.154
Residual Std. Error	12,622.570 (df = 94)	7,506.119 (df = 80)	7,911.839 (df = 104)
F Statistic	4.087*** (df = 9; 94)	3.913*** (df = 9; 80)	3.278*** (df = 9; 104)

Note: Russia and China removed — *p<0.1; **p<0.05; ***p<0.01

6 Discussion

The purpose of this analysis was to investigate whether the FATF's MER guidelines are adequate stand-in measures for the risk of IFFs from a country, given the inherent difficulty in measuring illicit flows. While there is no one measure of IFFs accepted by the field, there are two general methodologies that economists use to estimate IFFs, trade misinvoicing and capital flight.

Results of the three primary regressions modeling the relationship between illicit financial flows and FATF risk assessments display no significant relationship between IFF estimates and perceived risk aside from the coefficient on the effectiveness scores for both the Saloman and Spanjers trade estimation regression and the Saloman and Spanjers hybrid IFF estimate regression. These empirical results agree with the anecdotal evidence, such as that presented by

Table 4: Change in Correspondent Banking Regression Results

	Dependent variable:			
	Change in Volume of CBR Transactions (2011-2022)			
	(1)	(2)	(3)	(4)
Salomon & Spanjers Trade Estimate	−0.001			
	(0.001)			
Ndikumana & Boyce Capital Flight Estimate		−0.001		
		(0.002)		
Salomon & Spanjers Hybrid Estimate			−0.001	
			(0.001)	
MER Compliance Score				−0.183
				(0.492)
MER Effectiveness Score				0.645
				(1.768)
GDP Per Capita	−0.002	−0.015***	−0.002	−0.0004
	(0.001)	(0.005)	(0.001)	(0.0003)
Europe and Central Asia	−29.862	−24.885	−46.179	0.846
	(41.118)	(45.704)	(38.457)	(18.238)
Latin America and Caribbean	−73.697*	−26.286	−67.128*	14.320
	(40.475)	(47.260)	(37.966)	(20.057)
Middle East and North Africa	−75.307	−139.090**	−73.014	−6.965
	(50.622)	(58.350)	(49.427)	(24.903)
North America				20.183
				(44.953)
South Asia	−0.096	−22.807	5.987	12.397
	(60.294)	(61.163)	(58.788)	(34.835)
Sub-Saharan Africa	−35.083	−52.696	−19.534	40.099*
	(37.515)	(39.231)	(34.686)	(21.467)
Greylist	−3.396	−12.191	2.600	19.496
	(30.334)	(31.485)	(28.786)	(17.076)
Constant	169.572***	222.551***	159.803***	60.870
	(33.319)	(37.828)	(30.711)	(43.357)
Observations	103	89	113	157
R^2	0.115	0.201	0.117	0.112
Adjusted R^2	0.040	0.121	0.049	0.052
Residual Std. Error	115.490 (df = 94)	116.210 (df = 80)	113.971 (df = 104)	68.573 (df = 146)
F Statistic	1.529 (df = 8; 94)	2.510** (df = 8; 80)	1.724 (df = 8; 104)	1.849* (df = 10; 146)

Note: Russia and China removed *p<0.1; **p<0.05; ***p<0.01

Barbados PM Mottley, suggesting that FATF's risk assessments do not target the countries with the highest rates of IFFs.

This paper presents robust findings that countries with poor MER results should not be debanked solely on that premise. However, it also pushes back on the relevance of MERs to derisking regimes generally. This analysis finds no information that low MER scores can identify countries with high IFF incidence or that low MER scores prempt derisking.

We found no significant relationship between IFF estimates and the change in CBRs. This indicates that financial institutions are ending CBRs either over reasons not related to the incidence of IFFs or that the proxy variables that banks are using to evaluate IFF risk in a nation are inadequate.

Risk-based assesments run by the FATF and FSRBs have costly side effects for the global economy. Low scores on mutual evaluation reports can breed financial exclusion and stigma, an especially challenging situation for developing nations that receive high proportions of income from foreign remittances and foreign direct investment. The results of this research provide further evidence that FATF risk assessments are poor proxy variables for AML/CFT compliance and IFF prevention.

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8 Appendix

8.1 Regression Results using Information Criteria

The main regression results provide an overall picture MER results lack of usefulness in determining IFF risk. However, MERs are comprised of a variety of graded criteria: 11 effectiveness and 40 technical compliance categories. Generally, we see a positive relationship between effectiveness ratings and estimated IFF values and an inverse one between compliance and those same values, albeit the later relationship is not statistically significant.

However, not all MER categories are created equal. Some of the categories likely have large implications for a country's AML/CFT regime while others less, such as effectiveness category 4 "Financial institutions, DNFBPs (Designated Non-Financial Business and Professions) and VASPs (Virtual Asset Service Providers) adequately apply AML/CFT preventive measures commensurate with their risks, and report suspicious transactions" and technical compliance category 11 - preventive measures in record keeping, respectively. The former speaks greater volumes to a country's AML/CFT policies than the later.

In order to isolate the MER criteria that have the largest impact on the overall fit of our models, we use a stepwise procedure. A stepwise algorithm adds and removes covariates until it finds the model with the lower value of Akaike information criterion (AIC) based on all the possible combinations. AIC is an information criterion that uses maximum likelihood estimation to determine how well each additional covariate contributes to the model while also penalizing each additional variable.

$$\text{AIC} = -2(LL) + 2(K+1) \tag{3}$$

where $2(K+1)$ is the penalty term that increases linearly with the number of parameters

The following tables (5,6,7) displays regression results using the stepwise algorithm. Table 5 through 7 look at specific MER categories on the three IFF estimates. Table 8 shows the relationship between the chosen MER categories and the change in CBRs using the CPMI data. Overall, the four regressions in Table **??** show many statistically significant coefficients and better model fit than the non-stepwise regressions.

Stepwise analysis of the MER guidelines underscores the lack of consistency across the evaluation criteria when regressed with IFF estimates. Our stepwise procedure is akin to assuming the IFF estimates are accurate valuations of illicit flows and fitting the best model to those flows. When we do that, we see that high MER scores cannot predict which countries have higher instances of IFFs. It is especially concerning that higher scores on effectiveness category - "Supervisors appropriately supervise, monitor and regulate financial institutions, Designated Non-Financial Business and Professions (DNFBPs) and Virtual Asset Service Providers (VASPs) for compliance with AML/CFT requirements commensurate with their risks" is correlated with a higher value of IFF across all three estimates.

Additionally, our stepwise selected model for change in CBRs shows large directional discrepancies between MER criteria. Fitting the FATF guidelines to the 11 year change in CBRs conveys that MERs cannot accurately determine which countries are at risk of losing CBRs.

Table 5: Regression Results with AIC Selection Criteria - Salomon and Spanjers 2021

	Dependent variable
	Saloman and Spanjers 2021
Money laundering and terrorist financing risks are understood and, where appropriate, actions co-ordinated domestically to combat money laundering and the financing of terrorism and proliferation.	$7,968.414^{***}$
	(2,189.142)
International co-operation delivers appropriate information, financial intelligence, and evidence, and facilitates action against criminals and their assets.	$-6,808.078^{***}$
	(1,953.711)
Supervisors appropriately supervise, monitor and regulate financial institutions, DNFBPs and VASPs for compliance with AML/CFT requirements commensurate with their risks.	$11,794.470^{***}$
	(2,678.643)
Financial institutions, DNFBPs and VASPs adequately apply AML/CFT preventive measures commensurate with their risks, and report suspicious transactions.	$8,429.234^{***}$
	(1,933.589)
Legal persons and arrangements are prevented from misuse for money laundering or terrorist financing, and information on their beneficial ownership is available to competent authorities without impediments.	$2,954.634^{*}$
	(1,539.935)
Financial intelligence and all other relevant information are appropriately used by competent authorities for money laundering and terrorist financing investigations.	$-7,258.484^{***}$
	(2,304.232)
Money laundering offences and activities are investigated and offenders are prosecuted and subject to effective, proportionate and dissuasive sanctions.	$-9,690.271^{***}$
	(2,162.374)
Proceeds and instrumentalities of crime are confiscated.	$-6,166.201^{***}$
	(1,640.073)
Terrorist financing offences and activities are investigated and persons who finance terrorism are prosecuted and subject to effective, proportionate and dissuasive sanctions.	$17,108.540^{***}$
	(2,178.292)
Terrorists, terrorist organisations and terrorist financiers are prevented from raising, moving and using funds, and from abusing the NPO sector.	$4,900.536^{***}$
	(1,518.378)
Persons and entities involved in the proliferation of weapons of mass destruction are prevented from raising, moving and using funds, consistent with the relevant UNSCRs.	$-2,295.420$
	(1,572.757)
Assessing Risks and Applying a Risk-Based Approach	$11,283.530^{***}$
	(2,090.162)
National cooperation and coordination	$5,089.824^{***}$
	(1,573.428)
Money laundering offence	$-3,491.373^{***}$
	(969.835)
Confiscation and provisional measures	$-4,357.502^{***}$
	(1,280.387)
Terrorist financing offence	$4,577.084^{***}$
	(1,592.017)
Targeted financial sanctions related to terrorism and terrorist financing	$-4,698.063^{***}$
	(1,402.527)
Targeted financial sanctions related to proliferation	$-4,356.342^{***}$
	(1,387.437)
Non-profit organisations	$-12,195.560^{***}$
	(2,227.072)
Financial institution secrecy laws	$6,106.816^{***}$
	(2,097.490)
Customer due diligence	$3,003.094^{*}$
	(1,595.777)
Record keeping	$-7,171.232^{***}$
	(1,349.068)
Politically exposed persons	$-7,954.179^{***}$
	(1,601.528)
Correspondent banking	$3,057.012^{**}$
	(1,483.474)
Money or value transfer services	$-7,011.750^{***}$
	(1,444.489)
New technologies	$3,954.363^{**}$
	(1,834.539)
Wire transfers	$-5,261.937^{***}$
	(1,920.325)
Reliance on third parties	$4,281.677^{***}$
	(1,562.679)
Internal controls and foreign branches and subsidiaries	$-5,891.007$
	(3,809.627)
Higher-risk countries	$-8,421.093^{***}$
	(3,095.014)
Reporting of suspicious transactions	$-22,693.620^{***}$
	(3,770.848)
Tipping-off and confidentiality	$-23,103.130^{***}$
	(4,089.461)
DNFBPs: Customer due diligence	$-2,716.682$
	(3,536.103)
Constant	No
Observations	164
R^2	0.713
Note:	*p<0.1; **p<0.05; ***p<0.01
	Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Table 6: Regression Results with AIC Selection Criteria - Ndikumana & Boyce Capital Flight Estimate

	Dependent variable
	Ndikumana & Boyce Capital Flight Estimate
Money laundering and terrorist financing risks are understood and, where appropriate, actions co-ordinated domestically to combat money laundering and the financing of terrorism and proliferation.	4.098^{***} (0.594)
International co-operation delivers appropriate information, financial intelligence, and evidence, and facilitates action against criminals and their assets.	5.650^{***} (0.832)
Supervisors appropriately supervise, monitor and regulate financial institutions, DNFBPs and VASPs for compliance with AML/CFT requirements commensurate with their risks.	1.555^{*} (0.833)
Financial institutions, DNFBPs and VASPs adequately apply AML/CFT preventive measures commensurate with their risks, and report suspicious transactions.	2.591^{***} (0.678)
Legal persons and arrangements are prevented from misuse for money laundering or terrorist financing, and information on their beneficial ownership is available to competent authorities without impediments.	3.635^{***} (0.566)
Financial intelligence and all other relevant information are appropriately used by competent authorities for money laundering and terrorist financing investigations.	9.150^{***} (0.449)
Money laundering offences and activities are investigated and offenders are prosecuted and subject to effective, proportionate and dissuasive sanctions.	1.458^{**} (0.567)
Proceeds and instrumentalities of crime are confiscated.	-8.338^{***} (0.545)
Terrorist financing offences and activities are investigated and persons who finance terrorism are prosecuted and subject to effective, proportionate and dissuasive sanctions.	-1.340^{***} (0.378)
Terrorists, terrorist organisations and terrorist financiers are prevented from raising, moving and using funds, and from abusing the NPO sector.	-3.504^{***} (0.500)
Persons and entities involved in the proliferation of weapons of mass destruction are prevented from raising, moving and using funds, consistent with the relevant UNSCRs.	5.219^{***} (0.444)
Assessing Risks and Applying a Risk-Based Approach	-3.469^{***} (0.472)
National cooperation and coordination	3.957^{***} (0.501)
Money laundering offence	1.785^{***} (0.393)
Confiscation and provisional measures	-1.424^{***} (0.424)
Terrorist financing offence	7.005^{***} (0.626)
Targeted financial sanctions related to terrorism and terrorist financing	1.777^{***} (0.456)
Targeted financial sanctions related to proliferation	-0.841^{**} (0.368)
Non-profit organisations	2.419^{***} (0.375)
Financial institution secrecy laws	2.858^{***} (0.349)
Customer due diligence	-2.090^{***} (0.357)
Record keeping	-1.255^{***} (0.354)
Politically exposed persons	1.256^{***} (0.349)
Correspondent banking	-8.966^{***} (0.587)
Money or value transfer services	7.629^{***} (0.598)
New technologies	4.691^{***} (0.494)
Wire transfers	-6.246^{***} (0.528)
Reliance on third parties	-1.823^{***} (0.488)
Internal controls and foreign branches and subsidiaries	1.674^{***} (0.358)
Higher-risk countries	-1.546^{***} (0.527)
Reporting of suspicious transactions	-1.634^{***} (0.499)
Tipping-off and confidentiality	0.949^{*} (0.548)
DNFBPs: Customer due diligence	-6.562^{***} (0.386)
DNFBPs: Other measures	-2.250^{***} (0.343)
Transparency and beneficial ownership of legal persons	6.620^{***} (0.500)
Transparency and beneficial ownership of legal arrangements	-0.809 (0.561)
Regulation and supervision of financial institutions	-3.926^{***} (0.456)
Powers of supervisors	-2.795^{***} (0.597)
Regulation and supervision of DNFBPs	-18.392^{***} (0.979)
Financial intelligence units	-6.020^{***} (0.908)
Responsibilities of law enforcement and investigative authorities	-28.647^{***} (1.383)
Powers of law enforcement and investigative authorities	-3.490^{***} (1.001)
Cash couriers	6.657^{***} (1.000)
Statistics	0.001^{***} (0.0001)
Guidance and feedback	-7.506^{***} (0.690)
Constant	No
Observations	288
R^2	0.925
Note:	*p<0.1; **p<0.05; ***p<0.01
	Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Table 7: Regression Results with AIC Selection Criteria - Salomon & Spanjers Hybrid Estimate

	Dependent variable
	Salomon & Spanjers Hybrid Estimate
Money laundering and terrorist financing risks are understood and, where appropriate, actions co-ordinated domestically to combat money laundering and the financing of terrorism and proliferation.	$6,103.015^{***}$ (1,157.395)
International co-operation delivers appropriate information, financial intelligence, and evidence, and facilitates action against criminals and their assets.	$-3,402.530^{***}$ (1,161.808)
Supervisors appropriately supervise, monitor and regulate financial institutions, DNFBPs and VASPs for compliance with AML/CFT requirements commensurate with their risks.	$7,109.451^{***}$ (1,513.113)
Financial institutions, DNFBPs and VASPs adequately apply AML/CFT preventive measures commensurate with their risks, and report suspicious transactions.	$-5,154.280^{***}$ (1,402.413)
Legal persons and arrangements are prevented from misuse for money laundering or terrorist financing, and information on their beneficial ownership is available to competent authorities without impediments.	$5,106.575^{***}$ (1,292.501)
Financial intelligence and all other relevant information are appropriately used by competent authorities for money laundering and terrorist financing investigations.	$2,272.894^{**}$ (1,006.923)
Money laundering offences and activities are investigated and offenders are prosecuted and subject to effective, proportionate and dissuasive sanctions.	$-2,228.823^{**}$ (1,008.949)
Proceeds and instrumentalities of crime are confiscated.	$-3,734.211^{***}$ (974.109)
Terrorist financing offences and activities are investigated and persons who finance terrorism are prosecuted and subject to effective, proportionate and dissuasive sanctions.	$3,470.602^{***}$ (1,214.230)
Terrorists, terrorist organisations and terrorist financiers are prevented from raising, moving and using funds, and from abusing the NPO sector.	$4,636.027^{***}$ (1,293.726)
Persons and entities involved in the proliferation of weapons of mass destruction are prevented from raising, moving and using funds, consistent with the relevant UNSCRs.	$2,948.380^{**}$ (1,162.817)
Assessing Risks and Applying a Risk-Based Approach	$-4,354.945^{***}$ (936.857)
National cooperation and coordination	$1,603.685^{**}$ (778.415)
Money laundering offence	$1,866.729^{**}$ (799.558)
Confiscation and provisional measures	$2,370.840^{**}$ (1,137.627)
Terrorist financing offence	1,513.631 (1,057.063)
Targeted financial sanctions related to terrorism and terrorist financing	$-3,181.944^{***}$ (807.934)
Targeted financial sanctions related to proliferation	$2,884.621^{***}$ (759.000)
Non-profit organisations	$1,405.569^{*}$ (726.035)
Financial institution secrecy laws	$1,256.633^{*}$ (706.656)
Customer due diligence	$-8,176.352^{***}$ (1,003.199)
Record keeping	$-4,386.253^{***}$ (1,118.047)
Politically exposed persons	$4,360.370^{***}$ (1,028.882)
Correspondent banking	$-2,249.943^{**}$ (951.361)
Money or value transfer services	$-2,559.767^{***}$ (780.513)
New technologies	$1,557.624^{*}$ (850.205)
Wire transfers	$-2,445.971^{***}$ (753.589)
Reliance on third parties	$-2,889.758^{***}$ (1,041.151)
Internal controls and foreign branches and subsidiaries	$2,754.659^{***}$ (896.202)
Higher-risk countries	$-2,753.560^{***}$ (973.686)
Reporting of suspicious transactions	$-2,957.404^{***}$ (749.368)
Tipping-off and confidentiality	$1,842.083^{**}$ (881.731)
DNFBPs: Customer due diligence	1,525.714 (1,196.811)
DNFBPs: Other measures	$-9,132.451^{***}$ (2,000.123)
Transparency and beneficial ownership of legal persons	$-6,584.765^{***}$ (1,899.161)
Transparency and beneficial ownership of legal arrangements	$-6,039.218^{**}$ (2,379.970)
Regulation and supervision of financial institutions	$-4,888.425^{**}$ (2,366.841)
Powers of supervisors	−583.463 (1,750.394)
Regulation and supervision of DNFBPs	0.369^{***} (0.072)
Financial intelligence units	$2,058.687^{*}$ (1,239.621)
Constant	No
Observations	180
R^2	0.793
Note:	*p<0.1; **p<0.05; ***p<0.01

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Table 8: Regression Results with AIC Selection Criteria - Change in CBRs (2011-2022)

	Dependent variable
	Change in CBRs (2011-2022)
Money laundering and terrorist financing risks are understood and, where appropriate, actions co-ordinated domestically to combat money laundering and the financing of terrorism and proliferation.	39.012^{***} (9.126)
International co-operation delivers appropriate information, financial intelligence, and evidence, and facilitates action against criminals and their assets.	12.602 (8.367)
Supervisors appropriately supervise, monitor and regulate financial institutions, DNFBPs and VASPs for compliance with AML/CFT requirements commensurate with their risks.	-18.260 (11.764)
Financial institutions, DNFBPs and VASPs adequately apply AML/CFT preventive measures commensurate with their risks, and report suspicious transactions.	-22.106^{*} (12.119)
Legal persons and arrangements are prevented from misuse for money laundering or terrorist financing, and information on their beneficial ownership is available to competent authorities without impediments.	15.550 (10.112)
Financial intelligence and all other relevant information are appropriately used by competent authorities for money laundering and terrorist financing investigations.	-19.584^{**} (8.162)
Money laundering offences and activities are investigated and offenders are prosecuted and subject to effective, proportionate and dissuasive sanctions.	-14.307^{**} (7.042)
Proceeds and instrumentalities of crime are confiscated.	23.197^{**} (10.442)
Terrorist financing offences and activities are investigated and persons who finance terrorism are prosecuted and subject to effective, proportionate and dissuasive sanctions.	16.749^{*} (8.509)
Terrorists, terrorist organisations and terrorist financiers are prevented from raising, moving and using funds, and from abusing the NPO sector.	-22.944^{***} (8.472)
Persons and entities involved in the proliferation of weapons of mass destruction are prevented from raising, moving and using funds, consistent with the relevant UNSCRs.	-22.327^{***} (6.559)
Assessing Risks and Applying a Risk-Based Approach	-22.671^{***} (7.161)
National cooperation and coordination	-32.210^{***} (6.875)
Money laundering offence	9.658 (6.872)
Confiscation and provisional measures	-11.975 (8.002)
Terrorist financing offence	-41.783^{***} (6.629)
Targeted financial sanctions related to terrorism and terrorist financing	36.745^{***} (5.756)
Targeted financial sanctions related to proliferation	-28.693^{***} (6.593)
Non-profit organisations	7.889^{*} (4.568)
Financial institution secrecy laws	14.228^{*} (7.531)
Customer due diligence	17.920^{**} (8.641)
Record keeping	-13.600^{*} (7.480)
Politically exposed persons	40.422^{***} (6.822)
Correspondent banking	19.831^{***} (7.479)
Money or value transfer services	18.803^{***} (6.421)
New technologies	9.786 (6.449)
Wire transfers	-27.299^{***} (7.555)
Reliance on third parties	19.580^{***} (7.367)
Internal controls and foreign branches and subsidiaries	-0.0003^{*} (0.0002)
Constant	No
Observations	254
R^2	0.486
Note:	*p<0.1; **p<0.05; ***p<0.01 Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$