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Extending the Laundered Funds Destination Theory: Applying the Walker-Unger Gravity Model to Russian-Based Money Launderer Country Preference from 2000-2020

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Abstract: *Even though economists and academics have been studying money laundering for many years, there are still gaps in the research because there is a dearth of trustworthy data on the activity as well as an absence of specific sources and methods of collection in government-based reporting. The Walker-Unger gravity model was used in this study to determine the countries that Russian-based money launderers used as funding destinations between the years 2000 and 2020, as well as whether there are any variations in country rankings during economic downturns. The investigation's findings indicated that even during recessionary times, money launderers with Russian bases consistently preferred certain countries as their destination*

Keywords - *Money laundering, illicit finance, Walker-Unger model*

I. INTRODUCTION

Money laundering is the process by which the illegal source of money is concealed from regulatory and law enforcement agencies so that the money is accessible for use by criminals who acquire it through illegal means. The illegal activities that are most frequently linked to money laundering include, among others, the drug trade, trafficking in weapons, deception and corruption in government, white collar crime, tax evasion, and prostitution. A money laundering mechanism's purpose is to give law enforcement the impression that the funds were obtained through legal business activity rather than illegal activity. This illusion enables the unrestricted flow of those funds throughout the economy and allows criminals to profit financially from their illegal activities.

For many years, money laundering has been a persistent social ill in Russia; according to the most current estimates, $12 billion is laundered annually (1). In Russia, the first anti-money laundering legislation was adopted in 2001. The focus of Russia's anti-money laundering initiatives is on strengthening the legal structure and requiring the reporting of suspicious transactions. In Russia, the organization responsible for stopping money fraud is the Central Bank. However, it is still unclear how widespread illicit financial activity is and how it affects the legal economy (2)(3).

According to Fituni (1998), there are significant research gaps in the literature on money laundering regarding the drivers, destinations, frequently used techniques, and prevalence of the practice. Additionally, the dearth of theories and models in the literature on money laundering makes it difficult for analysts to interpret the issue for their respective nations. By compiling economic and country-specific data from the years 2000 through 2020 and using the Walker-Unger gravity model to calculate the proportion of laundered funds between Russia and 186 countries, this study seeks to close this gap.

The model's findings shed light on where Russian-based money launderers prefer to go, which frames one aspect of the country's money laundering actions during the period under study. The evaluation of whether Russian-based money launderers' preferences changed during the three most recent periods of global economic downturn is a secondary goal of this research. The terrorist attacks on September 11, 2001, the worldwide financial crisis of 2007–2008, and the COVID-19 pandemic were the times selected. The Laundered Funds Destination Theory of Roman and Schaefer (2022), which postulates that once a money launderer chooses a destination for their illicit funds, they are unlikely to change it unless overwhelming exogenous circumstances force change, is also applied and further validated in this investigation.

1.1 Research questions

The principal research question is:

- •Between 2000-2020, which countries were most targeted as a laundered funds destination by Russian-based money launderers?

Additional research questions include:

- •Based on the attractiveness index score, which countries were the most attractive destinations for Russian-based money launderers from 2000-2020?
- •Which countries had the highest commonalities with Russia based on the distance deterrence score?
- •Do country rankings change during the economic downturns of September 11 attacks, global financial crisis, and COVID-19?

1.2 Research questions

H1: Based on inflows of laundered funds between 2000 and 2020, the Walker-Unger model ranks countries in preference order for Russian-based money launderers.

H2: Based on the attractiveness score, the Walker-Unger model ranks countries based on attractiveness for money launderers during 2000-2020.

H3: The Walker-Unger model ranks countries commonality intensity in relation to Russia based on the distance deterrence score.

H4: Country rankings changed during the economic downturns of September 11 attacks, global financial crisis, and COVID-19.

II. LITERATURE REVIEW

Economists have significantly examined money laundering on a microeconomic degree for a number of decades with most studies having an informative methodology rather than evaluations, projections, and/or descriptive focus (6)(7). The interested individuals primarily relate to general public protection with the narrative focusing on guidelines, procedures, standards and regulations (8)(9). Educational research on money laundering has focused on deterrence techniques from a macroeconomic perspective, with arithmetic models mostly used in research methodology (10)(11).

An effective money laundering practice requires remoteness between the cash and its unlawful sources. The use of creative business techniques such as: Accounting bookkeeping, inventory methods, cost accounting, and supply chain management as well as government petitioning, facilitate this process. Examples of these activities include creatively recording profits and payments, restocking narcotics and weapons, organizing and logistics, and the persuading government and other managerial officials with payoffs, among others.

Lawful accounting, financial and business transactions have specified characteristics which make them distinguishable, while unlawful dealings lack such traits making them susceptible to auditing and forensic accounting discoverable techniques. The goal of money laundering is to transfer these acceptable attributes to illegal activities. The creation of the globalized financial system and extensive information technology have streamlined the process of connecting lawful accounting activities to unlawful trade simpler and avoiding exposure by regulatory authorities (12)(13).

Money laundering schemes consist of the following steps: (1) placement – unlawful monies enter financial system; (2) layering – monies filter through various accounting and business dealings to hide their source; and (3) integration – monies go back into economy with its source hidden and prepared for use. Preventing money laundering requires collaboration amongst policy makers, law enforcement, financial institutions and the private sector (13)(11)(10).

Money laundering in Russia can be traced back to the 15th century. Money laundering schemes have evolved and adapted from feudal fragmentation to tsarist regimes, the communist power of the USSR, and to the present socialist structure. The literature suggests that money laundering operations in Russia are influenced by cultural experiences and historical events (14). In the 1920's and 30's, Russia's involvement in illicit financial activity began by establishing a chain of overseas banks (i.e., mainly in Europe and Singapore) as financing conduits to the Communist party. These banks were controlled by the Gasbank (i.e., Russian Central Bank) who used local businessmen to bill fake invoices to the Soviet Union to provided kickbacks to party officials, which essentially served as a money laundering scheme. These illicit practices continued after the fall of the Soviet Union and have become customary banking practices in modern Russia (16).

Money laundering operations in Russia in the current global economic climate emerged after the financial meltdown at the end of the 20th century. The most famous example of this meltdown was the default of approximately $40 billion by the Russian government in 1999, which led to a serious devaluation of Russian currency. The default resulted in capital flight and approximately $4.2 billion in transfers from Moscow to New York (45). This capital flight urged the Russian government to focus efforts in developing an anti-money laundering (AML) regime, over the past few decades. Russia's AML regime, whose main accomplishments are reporting requirements of transactions exceeding 600,000 rubes and updated the legal framework, garnered acceptance by the international financial community to the point where the country was taken off money-laundering blacklist of countries by the Financial Action Task Force (FATF) (17)(18)(19).

The Central Bank of the Russian Federation has made strengthening banking infrastructure to combat money laundering a priority with the recent creation of an interbank system that safeguards client identity data (20). Yet, there is a growing concern of the role cryptocurrency can play in facilitating money laundering operations (21). The Russian invasion of Ukraine has also alarmed the international financial community and resulted in increased scrutiny of international Russian business transactions with an aim of identifying money laundering operations (22).

Research gaps on the roots of money laundering, estimates, its proliferation, preferred destinations, techniques, and effectiveness of AML legislation exist, and must focus research efforts to understand money laundering in Russia (4). Very few publications study the problem in detail. Particularly scarce are those which reveal the roots of the phenomenon, its real spread and relevance, as well as techniques and laundering schemes. One case study that looked at the link between foreign direct investment and roundtripping between Russian and Cyprus found that lax enforcement of existing banking law by Cypriot regulators led to Russian-based money launderers exploiting the system as a transit point of illicit funds (1). Knowledge is also very limited about how Russian authorities and law enforcement agencies are combating the legalization of illicit funds (23).

Bastrykin (2021) assessed the methods used by the Investigative Committee of Russia to identify and investigate money laundering and terrorism finance. The author focused on evaluating the effectiveness of prevention and suppression methods, Internet fund raising, and the legal framework. The author concluded Russian prevention and suppression methods appear to be the most effective in anti-money laundering regime.

Defossez (2017) evaluated the most recent Russian anti-money laundering law, which looked to update the initial 2002 measure. An exhaustive literature review is used as the study design. The author concluded the updated law fails to effectively address terrorism, yet it does improve anti-organized crime regulations. Weaknesses in Russian banking infrastructure, the lack of international consensus on defining terrorism finance, and the political motivations of the Russian government in pursuing anti-money laundering regime are the main drivers of money laundering activity. Defossez (2017) highlighted the law's stated purpose of combating terrorism and organized crime falls well short of international standards.

Zabyelina (2015) looked at the prevalence of reverse money laundering techniques in Russia. The author examines several case studies of fraudulent encashment schemes to illustrate reverse money laundering schemes. Findings suggest reverse money laundering schemes in Russia are facilitated by banking institutions alluding to structural weaknesses in addressing money laundering. Favarel-Garrigues (2005) highlighted these structural weaknesses as tacit evidence of the Russian government's fragile commitment to anti-money laundering (AML) regimes. The author noted that pursuing AML measured may clash with Russian domestic political objectives.

Stack (2015) looked at Latvian-based shell companies and their role in facilitating Russian money laundering operations. The author used a qualitative methodology drawing research data from various public sources to include databases, financial intelligence unit reports, journalist interviews, non-governmental organizations investigations, and whistleblower reports. The author concluded the Latvian banking infrastructure aids in the creation of shell companies inadvertently supporting Russian money laundering.

Swamy (2011) conducted a case study on the ethical financial management practices of India, Nigeria, and Russia and any efforts undertaken to implement reform. The author stated the level of corruption in Russia during the advent of globalization caused capital flight from international investors, which may have exacerbated money laundering activity. Most notable was the Russian Central Banks scandal involving money laundering activity in 1998. Efforts to curb corruption were undertaken to stop the capital flight. For instance, the Russian Association of Industrialist and Entrepreneurs in their 2001 Congress introduced a framework of rules regarding ethical behavior and corporate governance.

The author also highlighted several techniques commonly used by Russian-based money launderers, which include exceedingly low pricing, unreturned currency earnings, fictitious purchase orders, overuse of advanced payments, off-shore zone company and insurance registrations, revenue splitting, and business existence of less than three months. Swamy (2011) noted several instances of Russian-based money launderers using the banking infrastructure of Canada, Caribbean, Cyprus, Hungary, Hong Kong, Israel, Latvia, Poland, Ukraine, and the United Arab Emirates as transit points of their laundered funds. However, no mention is made of the laundered funds destination, which is a gap this research will attempt to address.

Subbotina (2008) analyzed the anti-money laundering (AML) regime in Russia to assess its compliance with international standards. The author used a comparative design to examine Russian regulations in the context of the internationally accepted AML prevention pillars of customer due diligence, reporting, regulation, and sanctions. Findings suggest the regulations mostly adhere to international standards although more time is needed to assess their effectiveness. Orlova (2008) also examined Russian AML regime with a design focused on using primary and secondary data to develop results. The author concludes the Russian AML regime has been ineffective. The main drivers appear to be structural weaknesses in the Russian banking system, lack of regulatory business culture, and the use of AML regime by Russian authorities to increase political control (32).

A review of the literature reveals the cause of research gaps on anti-money laundering efforts are based on a dismal reliable data of money laundering operations. The lack of data extends to weak or nonexistent laundering estimates, inconsistent preferred destinations, unreliable detection methods, disparate regulations, and uneven schemes, among others (33)(2)(34). In the case of Russia, a myriad documented of cases exist involving Russian-based money launderers leveraging the banking system of Euro-Russian countries to transfer illicit funds from Russia to the West. For instance, a $470 billion money laundering scheme involving Russia's largest private bank in which the bank transferred the funds of the country's elite to Western countries was uncovered by international regulators (35).

A well-known case is Danske Bank officials, which is Denmark's biggest commercial bank, being aware of questionable but highly profitable accounts from Russian-based actors with ties to illicit activities (36)(37). Another case is the theft and laundering via shell companies of $1.9 million from the Russian Treasury by Russian investors for real estate deals in New York City (38). Another high-profile case took place in Moldova were government officials accused Russia's security apparatus of laundering more than $22 billion through their financial system. The money was moved from 2011 through 2014 and used Latvian banks as an intermediary for its final destination in the West (39).

Concern has also emerged that Russian government officials have used AML regimes as a political targeting tool (40). For instance, Russian government investigators initiated a probe against the Russian President's opposition leader Aleksei Navalny's foundation. The foundation's aim was to investigate the origins of Russian oligarch's wealth (41). Another example of using Russia's AML regime for potential political targeting, is the launching of a fraud case against former Bank of Moscow executives that had criticized the Russian government (42).

U.S. Federal Prosecutors indicted the former President of the Bank of New York for involvement in laundering billions of dollars for Benex, a Russian-based company suspected of criminal activity (43). Swiss law enforcement officials charged executives of Mabatex, a Russian-owned Swiss-based company, of sending kickbacks to Kremlin officials. Mabatex executes used Italian banks to funnel the millions of dollars of funds to Russian government officials from 1994 to 1999 (44). The use of non-cash assets to hide income was also a major scandal in the early 1990's. Several regional branches of Russia's Central Banks engaged in the money laundering schemes, which was a throwback of Communist Russia banking (45).

Some crucial academic undertakings to investigate social phenomena need to be improved due to the reports produced by Russian agencies that do not accurately describe the methods and sources of collection. One of the challenges many academics face is the need for more detail in various contexts of the to study money laundering.

Money laundering recognition models began as ad-hoc techniques centered on criminal knowledge of unlawful dealings. The most accepted model for recognition of money laundering is the use of auditing procedures to identify abnormalities in lawful transactions. Globalization and the e-commercialization of monetary markets have made traditional quantification and discovery representations obsolete. Today many of these money laundering systems have progressed and support in the discovery of unlawful schemes. To keep up with the people and entities committing fraud, anti-money laundering research, techniques and detection models must also advance with the inclusion of a more holistic approach (46). While some advancement has been made, the role of several entities in money laundering events, the magnitude of money laundering in the legitimate economy, and detection methods, substantial gaps still exist, to include research that emphasizes the effects that money laundering continues to have on our societies today (3).

There are numerous approaches researchers can use to model money laundering activity (15). The Walker-Unger gravity model has become one of the greatest methods used to examine illicit financial movements. This method has been garnering backing in the academic community due to its foundation on international economic model and dependence on criminology due to the inclusion of economic viewpoints (47). Nonetheless, the model has been criticized for creating inaccurate outcomes (48)(49).

The Walker-Unger model has been used in several studies in a variety of circumstances, building its credibility as a dependable simulation for money laundering financial cash flows. For instance, Roman and Schaefer (2022) used the model to determine the ideal target of laundered funds for U.S.-based money launderers amongst the years 2000 to 2020. The conclusion of the study showed U.S.-based money launderer destination preference continued the same even throughout recessionary inflationary stages. The conclusion of the investigation served as the basis for the laundered funds destination model.

In a destination study conducted during 2021 by Roman et al., the model was applied to money laundering flows in Mexico for the years 2000-2015. Some of the conclusions of the study suggested that Mexican-based money launderers favor destinations with adjacent geographical and economic financial proximity, along with countries that have developed monetary markets and cultural sympathy. The results of the study noted that the results were statistically significant at a .05 confidence level.

In their study Ferwerda et al. (2013) observed several attempts to measure money laundering activity including the difficulty to assess the effectiveness of the models. Ferwerda et al. proposed that by using trade-based money laundering models – TBML – (e.g., Walker-Unger model), which originated on established international trade principles, the results tend to be more accurate. Ferwerda et al. (2020) applied the gravity-based simulation to demonstrate global financial money laundering streams and observed that illicit funds commonly represent a few percentage points of GDP for each country. An interesting discovery in their study is that most money laundering takes place in the United States and the United Kingdom, with Belgium and Luxembourg having the greatest portion of money laundering as a ratio of GDP while Japan and South Korea were revealed as having the smallest portion of money laundering flows.

In their research Balani et al. (2017) followed Ferwerda et al.'s (2013) suggestion and used TBML models to estimate money laundering activity in emerging Asian economies from the years 2001-2015. It was found that Asian countries gravitate towards each other for illicit financial activity. Another example of the use of the Walker-Unger model in the literature as a technique to forecast the flow of laundered funds is applied by Wahaj et al. (2018) to Pakistan and concluded that money launders favored countries with large financial sectors, monetary strength and political strength. The first application of the model by Unger et al. (2006), centered on money laundering financial cash flows for the Dutch economy and concluded that Dutch-based money launderers favored destinations with close economic, monetary and geographical connections.

Researchers have applied or created other monetary models to quantify illicit economic activity. Roy (2017) in his research, applied the IS-LM model to calculate the global underground economy, and learned that an expansionary economy coupled with low unemployment levels affected declines in the shadow economy. Gasparėnienė et al. (2018) used the MIMIC model to observe the shadow economy, and discovered that access to the following: Internet, information technology, presence on innovative financial and economic instruments, strong eCommerce presence, and financial flow of crypto currencies, did not offer adequate data to estimate the underground financial economy. The study further noted that the results were impacted by the short duration of various financial instruments. Remeikienė et al. (2018) discovered that employment level, gender pay disparity and income differences are casual factors of the informal economy, by utilizing the MIMIC technique for the 2005-2016 period in the Eurozone.

Chan et al. (2020) created a method to recognize casual factors that influence an individual's intention to report questionable financial transactions. The study observed that regulatory focus and administrative culture are the most significant factors on reporting illicit financial activity while the strongest detractors were stress and character straits. Moreover, Loayza et al. (2019) created a long-run growth model that analyzed criminal financial activities alongside those of legitimate enterprises in Colombia. The model generated valuations of the size of illegitimate income in conjunction with the quantity of laundered assets. While the model produced some tangible estimates, some of the theories used like various financial and economic environments, asset assessments, and capital supply, to name a few, may not be applicable in all situations.

Schneider (2019) studied white-collar crime in Paraguay from the perspective of prevention hypothesis and determined that the prevalence of fraudulent activity provides the ideal setting for misallocation of financial assets and human capital, resulting in inefficient goods and services. The study observed that soft fraud-deterrence laws and policies (e.g., the lack of prosecuting white-collar crime) may encourage more financial crimes, since they escape punishment. Barone et al. (2017) applied MIMIC model to examine the relationship between illegal market, money laundering, and the business cycle. The study theorized that business cycles are able to influence underground monetary activity, concluding that the size of illicit funds may be affected by interest rates during the course of economic business cycle.

In this research the Walker-Unger gravity model as employed in several studies like, Roman and Schaefer (2022), Roman et al. (2021), Ferwerda et al. (2020), Wahaj et al. (2018), Balani et al. (2017), and Ferwerda et al.'s (2013) is utilized to generate the results. Below is the formula applied:

$P(X, y_i) = 1 / n \sum i = 1$ [attractiveness (y_i) / distance (X, y_i)] * attractiveness (y_i) / distance $(X, y_i)^2$

where;

P(X, y_i): Is the proportion of money flowing from country X to country yi. For example, X... a particular country (Russia), yi... another country i i=1.....n all countries of the world. For instance, when the distance between Russia and China is weighted, the relative quantity of money flowing from country X (Russia) to country Y (China) equals Russia's desirability. To make sure that the totals add up to 1, this weighted attractiveness index for money laundering is adjusted for the overall weighted attractiveness results across all countries.

Attractiveness (y_i): The extent of interest that country$_y$ creates for country$_x$-based money launderers to participate in money laundering events in country$_y$.

Distance (X, y_i)^2: The ease, or complexity, with which country$_x$-based money launderers are able to participate in money laundering activities in country$_y$.

This research will add to Unger et al.'s (2006) original gravity model. Below is clarification of the variables and sources of data used in this study.

- For the period 2000–2020, GDP per head (GDP) is calculated in US dollars ($) and adjusted for Russia. The research makes use of data from the World Factbook published by the Central Intelligence Agency (CIA).
- Bank Secrecy (BS) is a measure from 1 (no secrecy laws) to 4 (bank secrecy laws enforced). The data sources are the newest obtainable reports of the following entities: (a) Organization for Economic Co-Operation and Development (OECD) report towards global tax co-operation: Progress in identifying and eliminating harmful tax practices; (b) OECD report on improving access to bank data for tax purposes. A country received a score of 1 if it has no additional privacy laws and a legal structure based solely on civil law. Countries that have no other particular bank secrecy laws but a legal system derived from common law were given a 2 rating. A 3 was given to countries with additional secrecy clauses, and a 4 was given to countries on the FATF, FSF, or OECD "blacklists".
- Government Attitude (GA) is a scale ranging from 0 (government anti-laundering) to 4 (tolerant of laundering). Countries that are part of the FATF are given a value of 0, while countries that are currently on the FATF "Non-Cooperative list" are classified with a 4. Countries that were formerly on this list receive a value of 3. Countries that are part of an anti-money laundering class, other than the FATF are allocated a value of 1 and countries that are not a part of any group or used to be on the non-cooperative register but are currently part of a group receive a 2.
- Society for Worldwide Interbank Financial Telecommunication (SWIFT) member is 0 for non-member countries and 1 for members.
- Financial Deposits (FD) are monetary system deposits to GDP. This variable includes demand, time and saving deposits in banks and additional financial institutions as a share of GDP, calculated by Unger et al. (2006) using the following deflation method:

  {(0.5)*[Ft/P_et + Ft-1/P_et-1]}/[GDPt/P_at]

  where;

  Ft: Demand and time and saving deposits,
  P_et: End-of period CPI,
  P_at: Average annual CPI.
  GDPt: End of period gross domestic product

Raw data was acquired from the most recent available electronic version of the IMF's International Financial Statistics. GDP data in local currency, end-of period consumer price index (CPI), and annual CPI was obtained from the electronic version of the IMF. Computations were from the most recent available Beck.T, Demitguc-Kunt, A. and R. Levine's "A New Database on Financial Development and Structure."

- Conflict (CF) is a scale from 0 (no conflict) to 4 (conflict situation exists). 0 is used if there has been no conflict since 1989. A value of 1 is assigned if there was conflict at a minor level and is now terminated. A value of 2 represents the prior existence of a dispute at a higher level and is now terminated. A value of 3 is used if there is a disagreement situation at present, and a 4 represents an ongoing war situation. The sources of data for the CF variable were from the most recent available online version of the Uppsala Conflict Data Project report.
- Corruption (CR) is the adjusted Transparency International index (1=low, 5=high) Data for corruption was taken from the most recent available Transparency International Corruption Perception index and transferred into a 1 to 5 scale. The constant 10 was incorporated to ensure that all scores are above 0.

- Egmont Group (EG) is a 0 (not member) or 1(member). The Egmont group is a group of FIUs set up for the encouragement of international co-operation.

The Walker-Unger model's distance deterrence and proportions section also takes into account the remaining five variables, which are language, culture, colonial history, commerce, and physical distance. Adding attractiveness scores and a distance deterrence number to the model is a crucial move. The space between two countries is known as distance deterrence. The closer two countries are together, the more likely money laundering is. According to the original Walker model (1995), distance deterrence measures the real distance between countries. However, given the globalization of the financial markets, it seems unlikely that physical distance poses a major obstacle to the flow of money. Physical distance might be a factor, but it is more likely that other variables also have an impact. Physical distance and other factors can be combined to create a distance deterrence score for each country in relation to the other countries. Unger et al.'s (2006) distance formula is as follows:

$Distance_{ij}^2$ = Language + Trade + Colonial background + Physical distance
where;
Language: Indicates whether the native language between $country_x$ and $country_y$ is the same.
Trade: Indicates the degree of legitimate economic activity between $country_x$ and $country_y$.
Colonial background: Indicates whether $country_x$ and $country_y$ have ever been colonies of a foreign entity.
Physical distance: Indicates whether the geographic space between $country_x$ and $country_y$ is ample, defined as the length of the space in geographical miles between $country_x$ and $country_y$.

Distance deterrence assigns a value to countries in relation to their relative distance to other countries depending on language, culture, colonial background, trade and physical distance. Countries have more distance if they speak different languages, have no cultural affinity or trade relations, and/or have a large geographical distance.

- Language = 0 or 1(same language 0, different language 1)
- Colonial Background = 0 or 1(same=0, different =1)
- Trade = 0 or 1 (0 same, 1 different), taken from countries import/export partners. Data was taken from the World Trade Organization (WTO) and the CIA World Factbook
- Culture = 0 or 1(same ethnicity 0, different ethnicity 1)
- Physical distance = number for zones (1 to 7) 1 if countries are in the same region, 7 if countries have large geographical distance. Regional zones are used to simplify calculations.

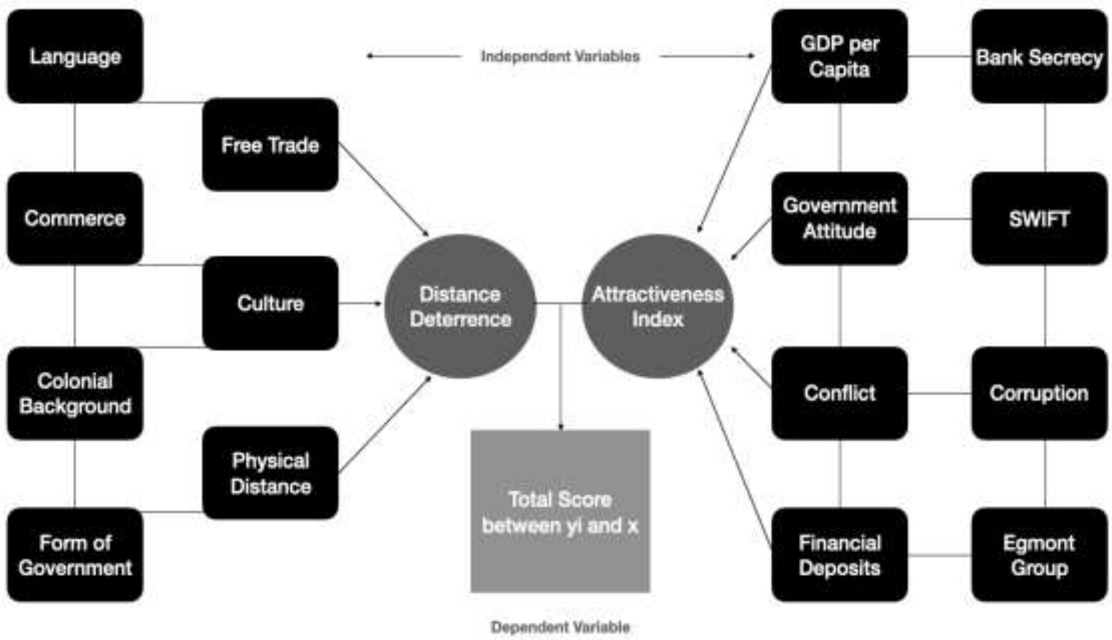
A score of 0 indicates that there is less distance between two countries if their official languages are the same or if they share a common tongue. The term "colonial background" refers to whether a countries was a colony in the past, is one now, or is connected to another countries in a comparable way. The countries are given a 0, which indicates that there is less distance between them, if they are associated. The CIA World Factbook provided information on language and imperial history.

The modified Walker-Unger gravity model is expanded with the Form of Government and Free Trade variables in the Distance Deterrence index. The literature highlights the use of the centralized government apparatus and international trade ties by Russian-based money launderers to facilitate money laundering operations (FINTRAC, 2022; Fojcik, 2019; Repousis et al., 2019; Sher, 2003; Fituni, 1998). As such, a variable which measures the impact of the form of government along with free trade agreements (FTA) on money launderer preference was needed to increase the reliability of the model. A score of 0 though 3 was developed for the form of government. Countries were rated depending on their current government structure. Free trade was assigned a score of 0, 1, or 2 depending on if an FTA exists, doesn't exist, or if there is a memorandum of understanding (MoU) or an FTA is being negotiated. Below are the details of the new variables.

- Form of Government: Full Democracy = 0; Flawed Democracy = 1; Hybrid Regime = 2; Authoritarian Regime = 3;
- Free Trade = FTA exists = 0; MoU exists, or FTA is being negotiated = 1; No FTA or MoU exists = 2

Figure 1 presents the conceptual map of the model, which includes the variables that make up the model, their relationship, and the estimate that the model generates.

Figure 1. Walker-Unger Gravity Model



Note: Conceptual map of the Modified Walker-Unger Model.

III. METHOD

The intention of this study was to rank the degree of attractiveness each country represents to Russian-based money launderers during 2000–2020-time frame. A secondary objective was to investigate if variations in country rankings occur during economic declines (i.e., September 11 attacks, global financial crisis, and COVID-19). The Walker-Unger gravity model as applied by Roman et al. (2021) is applied to perform the examination. This study adheres faithfully to the method as employed by Roman et al. (2021) in order to offer consistency in the application of the Walker-Unger model and validating the attractiveness simulation.

The simulation tests the analytical capability of the independent variables to establish the degree of desirability each country represents for the funds of Russian-based money launderers. A result is produced by the model to examine, evaluate and interpret its importance in relation to all tested countries. Sources of data have been provided in Appendix A. All historical records used to generate the model were obtained in August 2022 (Appendix B).

3.1 Research instrument

Publications, statistics, journals, and databases from worldwide and academic organizations were part of the research method of this study. Data was collected and aggregated with MS Excel® 2010, SPSS Graduate Pack 18.0 for Windows® software, and the Walker-Unger model (i.e., modified to reflect the observed time intervals) at the .05 level of significance. The regression analysis was conducted using data involving streams of money laundering along with the indicators, independent, and dependent variables as utilized and illustrated by Roman et al. (2021), Ferwerda et al. (2020), Wahaj et al. (2018), Balani et al. (2017), Ferwerda et al.'s (2013), and Unger et al. (2006). The use of international organizations as the data source may have exposed said data to fundamental participant preferences or publication inaccuracies, which may have had a marginal influence on the findings. Regardless, this investigation assumes objectivity in the processing, encrypting, evaluation, and accumulating of published data.

IV. DATA

4.1 Regression Results for the Investigation's Hypotheses

Table 1. Regression Results

		Coefficients	t Stat	P-value	F-value	R Square	H1	H2	H3	H4
2020	Attractiveness Index	0.0001	54.90	1.083E-127	1794.01	0.94		Null Hypothesis is rejected.		
	Distance Deterrence	-0.1946	-9.99	1.587E-19						
2019	Attractiveness Index	0.0001	57.31	2.029E-131	1837.90	0.95		Null Hypothesis is rejected.		
	Distance Deterrence	-0.1942	-10.71	1.0775E-21						
2018	Attractiveness Index	0.0001	67.44	1.112E-145	2518.62	0.96		Null Hypothesis is rejected.		N/A
	Distance Deterrence	-0.1697	-10.39	1.0129E-20						
2017	Attractiveness Index	0.0001	72.68	2.562E-152	2955.69	0.97		Null Hypothesis is rejected.		N/A
	Distance Deterrence	-0.1633	-10.44	7.402E-21						
2016	Attractiveness Index	0.0001	81.11	4.06E-162	3691.85	0.97		Null Hypothesis is rejected.		N/A
	Distance Deterrence	-0.1506	-9.57	2.8191E-18						
2015	Attractiveness Index	0.0001	86.61	5.176E-168	4214.85	0.98		Null Hypothesis is rejected.		N/A
	Distance Deterrence	-0.1311	-8.71	8.625E-16						
2014	Attractiveness Index	0.0001	107.82	8.093E-188	6402.08	0.98		Null Hypothesis is rejected.		N/A
	Distance Deterrence	-0.1157	-8.10	4.298E-14						
2013	Attractiveness Index	0.0001	95.36	1.104E-176	4989.65	0.98		Null Hypothesis is rejected.		N/A
	Distance Deterrence	-0.1193	-7.59	9.5855E-13						
2012	Attractiveness Index	0.0001	90.00	1.804E-171	4473.63	0.98		Null Hypothesis is rejected.		N/A
	Distance Deterrence	-0.1243	-7.36	4.0566E-12						
2011	Attractiveness Index	0.0001	92.20	1.204E-173	4719.66	0.98		Null Hypothesis is rejected.		N/A
	Distance Deterrence	-0.1225	-7.35	4.286E-12						
2010	Attractiveness Index	0.0001	84.33	1.305E-165	4034.43	0.97		Null Hypothesis is rejected.		N/A
	Distance Deterrence	-0.1320	-7.77	3.1926E-13						
2009	Attractiveness Index	0.1770	18.40	6.6044E-46	243.92	0.70		Null Hypothesis is rejected.		
	Distance Deterrence	-500.6082	-7.08	2.0899E-11						
2008	Attractiveness Index	0.0001	91.53	5.547E-173	4716.89	0.98		Null Hypothesis is rejected.		
	Distance Deterrence	-0.1264	-7.32	5.0452E-12						
2007	Attractiveness Index	0.0002	91.14	1.351E-172	4661.76	0.98		Null Hypothesis is rejected.		
	Distance Deterrence	-0.1285	-7.41	2.8801E-12						
2006	Attractiveness Index	0.0002	78.02	1.22E-158	3465.11	0.97		Null Hypothesis is rejected.		N/A
	Distance Deterrence	-0.1456	-7.80	2.7769E-13						
2005	Attractiveness Index	0.0002	74.95	4.736E-155	3249.65	0.97		Null Hypothesis is rejected.		N/A
	Distance Deterrence	-0.1486	-8.08	4.7061E-14						
2004	Attractiveness Index	0.0002	77.30	8.31E-158	3464.54	0.97		Null Hypothesis is rejected.		N/A
	Distance Deterrence	-0.1448	-8.16	2.8696E-14						
2003	Attractiveness Index	0.1496	78.23	6.942E-159	3524.37	0.97		Null Hypothesis is rejected.		N/A
	Distance Deterrence	-88.5371	-7.82	2.4333E-13						
2002	Attractiveness Index	0.0002	67.78	3.952E-146	2750.13	0.96		Null Hypothesis is rejected.		
	Distance Deterrence	-0.1599	-8.70	9.3438E-16						
2001	Attractiveness Index	0.0003	71.29	1.319E-150	2979.59	0.97		Null Hypothesis is rejected.		
	Distance Deterrence	-0.1515	-8.40	6.4587E-15						
2000	Attractiveness Index	0.0003	68.04	1.795E-146	2715.02	0.96		Null Hypothesis is rejected.		N/A
	Distance Deterrence	-0.1605	-8.85	3.4396E-16						

Note: Results of the regression model.

The regression findings used to evaluate the hypotheses are included in Table 1. H_1 tested the Walker-Unger model's capability to rank country preferences for Russian-based money launderers in the 2000–2020-time frame along with the regression values that prove/disprove the hypothesis. Results suggest the Walker-Unger model does rank Russian-based money launderer country preference based on the proportion of money flows [P(X, yi)] in the examined time frame. H_2 evaluated whether the model ranked Russian-based money launderers country preference in desirability order. Model results provided country preference based on attractiveness scores for Russian-based money launderers during 2000-2020. H_3 examined the degree of country commonality with Russia based on the distance deterrence score. Walker-Unger model findings indicate that the score does rank the power between the assessed countries. H_4 looks at whether country rankings changed during the economic decline of the 9/11 attacks, the international financial crisis, and COVID-19. Model results showed changes in ranking order, but not in overall country preference. The p-value of the regression results for all research hypothesis is less than .05 indicating that the findings are statistically significant. Consequently, we accept the null hypothesis for H_1, H_2, H_3, and H_4.

V. RESULTS AND CONCLUSIONS

This study represents the first empirical attempt at measuring money laundering or unlawful financial activity in Russia for the 2000-2020 period. Russia is likely a haven for white collar crime and criminal activity due to strong power sector revenues (Ferwerda et al., 2020). According to Roman et al. (2021), more empirical research is needed on country-specific illicit financial activity. The findings of this investigation add to the body of knowledge on worldwide laundering flows. In addition, the modified Walker-Unger model is one of the few tools available to quantify money laundering activity although the model is limited because it does not show the effect of money laundering on legitimate economic activity.

Model results reveal the countries with the highest attractiveness for Russian-based money launderers during 2000-2020 were Australia, Bermuda, Cayman Islands, Channel Islands, Denmark, Iceland, Liechtenstein, Luxembourg, Monaco, Norway, Qatar, Switzerland, and the United Kingdom. Model results show that over the two decades the proportion of money flow scores changed but not to a degree that would alter the country preference of Russian-based money launderers. Russian-based money launderers tended to use the same countries for their illicit financial activities, regardless of the state of the legitimate economy.

For instance, Bermuda, Monaco, and Liechtenstein were in the top 10 destination preferences of Russian-based money launderers in all but three years of the examined period. In addition, Australia, Denmark, Luxembourg, Norway, Switzerland, the United Kingdom were among the top 10 destination preferences at least 10 years of the 2000-2020 period. No major changes in destination preferences were noted for the 2001-2002, 2007-2008, and 2019–2020-time frames, which suggests the 9/11 attacks, global financial crisis, and COVID-19 global economic downturns may not have affected Russian-based money launderers assessment of the safety of their funds. Countries did move spots within the top 10 preferences but 80% of the preferred destination stayed within the top 10 pre- and post-recessionary periods.

These results are consistent with Roman and Schaefer's (2022) model results for U.S.-based money launderers. In which, U.S.-based money launderer preference did not significantly change over the same time span and the same economic markers. Findings support the Laundered Funds Destination theory, that once a money launderer selects a destination for their illicit funds, the preference towards that destination is not likely to change regardless of the standing of the legitimate economy.

Table 2. Proportion of Laundered Funds Score for the United States

Country	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
Andorra	3.249	3.503	3.670	3.134	3.818	2.521	2.396	7.254	3.258	2.147
Australia	3.687	3.978	3.216	3.920	4.288	4.203	4.580	4.614	5.609	5.663
Austria	3.645	3.819	2.587	4.138	4.253	4.270	4.417	4.765	5.693	5.327
Belgium	1.831	1.692	1.842	1.328	1.724	2.296	2.199	2.241	2.678	2.529
Bermuda	7.434	7.488	7.040	9.081	6.827	8.389	7.241	5.895	6.322	7.182
Canada	3.025	5.219	2.853	8.452	5.848	6.339	6.621	4.491	4.781	8.129
Cayman Islands	5.918	4.823	5.729	4.522	4.234	4.301	3.732	4.298	4.755	4.464
Channel Islands	6.341	5.596	5.940	6.187	6.211	5.345	4.781	5.404	4.732	3.857
Denmark	3.558	4.868	3.621	3.857	4.618	6.935	6.086	5.963	6.863	7.320
Faroe Islands	6.338	5.863	6.769	2.585	1.828	1.267	2.504	1.692	2.368	2.422
Finland	3.759	3.818	3.939	4.397	4.407	4.657	4.778	4.873	5.349	3.724
France	5.875	4.990	6.135	3.178	3.623	4.325	4.391	4.514	4.564	3.231
French Polynesia	0.358	0.493	8.427	1.176	1.262	3.662	2.383	5.116	3.548	4.269
Germany	3.965	4.371	3.987	4.406	4.362	4.241	4.295	4.351	4.415	4.567
Greenland	2.707	2.243	2.791	2.787	1.328	2.704	2.740	2.613	3.905	2.671
Iceland	8.852	9.277	8.430	9.487	6.889	7.347	6.736	4.559	5.433	5.738
Isle of Man*	3.698	3.357	4.175	3.186	3.335	3.233	3.441	5.308	3.323	3.481
Italy	3.685	3.657	3.864	3.960	3.824	3.433	3.539	5.813	3.906	4.328
Korea, Rep.	1.298	1.848	3.303	1.131	1.253	3.682	3.592	1.495	3.449	3.583
Liechtenstein	7.787	7.458	7.825	8.111	7.845	7.572	7.589	6.588	6.448	8.244
Luxembourg	7.388	7.798	7.426	7.260	7.385	6.866	7.091	7.067	5.618	5.680
Monaco	**13.502**	**16.664**	**13.808**	**18.689**	**20.292**	**20.514**	**23.326**	**18.138**	**27.858**	**21.874**
Northern Mariana Islands	3.644	3.829	5.386	4.269	4.415	4.181	4.094	5.757	3.462	3.822
Norway	5.958	6.988	6.369	5.598	5.867	4.749	4.693	5.759	6.383	6.732
Qatar	4.331	4.932	4.183	4.841	5.303	6.001	7.285	4.994	4.458	4.139
San Marino	3.995	3.919	4.140	3.651	3.275	3.368	3.145	2.873	2.721	4.241
Singapore	2.888	2.428	2.495	1.950	2.568	2.909	3.163	5.237	3.388	4.347
Sint Maarten (Dutch part)	1.757	2.501	2.558	1.571	2.508	2.031	1.859	1.842	3.825	2.218
Switzerland	4.908	5.280	5.140	6.484	6.678	6.868	6.059	5.766	5.705	6.564
United Arab Emirates	1.436	5.619	5.094	3.581	4.996	4.419	3.993	3.793	2.548	2.592
United Kingdom	4.935	4.616	5.043	3.581	4.802	4.955	5.251	5.588	6.236	6.556
United States	3.937	3.867	3.979	3.274	1.488	3.742	3.748	3.758	3.758	4.040

Country	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Andorra	2.673	1.922	1.859	3.051	2.168	2.616	3.575	5.929	0.738	1.853	3.293
Australia	5.528	5.658	5.941	7.820	9.181	9.724	11.304	**11.889**	1.124	1.508	3.659
Austria	4.829	5.377	4.575	5.883	5.333	6.052	6.052	0.061	6.317	6.789	6.888
Belgium	2.139	1.658	1.501	1.928	1.198	1.346	3.612	4.578	4.406	5.318	5.430
Bermuda	6.760	6.801	6.447	6.690	5.988	5.955	5.078	4.884	5.354	6.131	6.328
Canada	0.134	0.098	0.388	0.097	0.098	0.123	0.131	0.142	0.157	0.385	0.188
Cayman Islands	4.348	4.264	4.431	6.075	5.295	6.218	6.276	7.383	8.598	3.212	3.223
Channel Islands	3.781	3.638	3.757	4.036	3.747	3.871	3.603	4.043	4.415	5.124	5.730
Denmark	6.739	5.351	5.409	2.986	2.692	3.539	4.472	5.248	6.055	7.583	8.489
Faroe Islands	2.495	1.813	2.118	2.366	1.194	1.794	2.735	2.985	1.263	3.491	3.862
Finland	4.331	4.239	3.584	3.687	3.674	4.619	4.566	4.903	5.357	6.297	6.980
France	3.459	3.418	2.969	2.877	2.883	1.304	4.454	4.826	5.875	8.412	8.736
French Polynesia	7.217	8.223	10.538	6.215	5.887	7.475	8.730	0.831	1.621	1.273	5.556
Germany	4.348	4.237	1.967	3.395	3.331	3.982	6.119	7.590	0.888	3.213	3.839
Greenland	5.224	4.348	6.049	3.088	2.584	3.265	2.329	2.559	2.568	1.258	3.480
Iceland	4.766	4.828	4.514	4.079	3.417	3.794	3.035	3.256	3.713	5.135	6.249
Isle of Man*	1.577	1.445	1.394	1.376	0.871	1.814	4.321	5.071	5.362	6.406	6.665
Italy	4.330	4.177	4.339	3.461	3.336	4.662	6.160	6.887	0.735	6.919	3.143
Korea, Rep.	1.581	1.642	1.547	1.548	13.032	1.533	3.049	1.180	1.198	3.448	3.529
Liechtenstein	5.870	5.511	4.240	4.497	4.294	4.871	5.562	6.239	0.821	**7.815**	8.395
Luxembourg	5.250	5.309	4.892	4.589	4.981	5.607	4.106	6.475	4.441	5.313	5.599
Monaco	**22.985**	**26.174**	**25.331**	**24.865**	**18.035**	**37.318**	4.617	5.755	5.838	7.283	**8.481**
Northern Mariana Islands	4.638	5.171	4.819	5.793	4.670	4.738	8.293	0.253	0.341	8.399	8.445
Norway	6.654	7.892	6.778	8.065	7.533	9.375	**17.568**	2.425	3.228	3.439	3.935
Qatar	3.751	3.753	3.399	3.306	2.958	3.348	4.746	5.180	5.096	6.208	8.740
San Marino	3.346	3.193	3.139	4.160	4.389	3.952	6.371	6.974	7.809	6.856	3.070
Singapore	8.084	4.687	5.171	5.197	4.634	5.393	3.258	3.573	3.698	4.453	5.171
Sint Maarten (Dutch part)	2.074	3.873	2.812	1.837	17.336	2.468	0.612	0.783	0.901	1.858	3.185
Switzerland	6.565	7.128	6.897	6.081	4.962	4.952	8.837	0.991	**11.388**	1.427	3.656
United Arab Emirates	2.387	1.968	3.217	2.053	1.683	1.785	1.607	1.835	1.629	2.493	3.080
United Kingdom	6.329	5.356	5.119	3.971	3.762	5.338	6.687	0.853	1.808	1.359	3.781
United States	3.642	3.302	1.486	4.029	3.783	4.236	4.166	4.846	5.532	6.873	8.839

Note. Countries with the top proportion of laundered funds score in Russia.

The Walker-Unger model seems to correctly identify countries involved in money laundering activities with Russia. The current literature on money laundering activities by Russian-based illicit financiers supports the countries in the Top 50 score of laundered with Russia. While model findings support existing literature, the lack of consensus on key theory is a limitation for real world applicability and comparisons with similar studies with varying approaches. The laundered financial funds destination hypothesis remains the only theory that explains money laundering flows and destination.

Money laundering literature exposes the key role of the legitimate economy on illegal financial activities. Illegitimate funds are accepted, and encouraged, due to the impact cash has on the money supply and overall economic activity. Some of the standards and measures used by U.S.-based money launderers when choosing the destination and transfer of their illegitimate funds include Monetary and economic foundation, relaxed financial transactions laws, and business relations of the countries with the top 10 rankings score of laundered with Russia.

The strength of the rankings of the countries with the highest percentage of laundered funds for Russia during the observed period is consistent with the findings by Roman (2022), Roman et al. (2021), and established international trade theory. The authors concluded that the preferred countries by Russian-based money launderers tended to remain unchanged. Additionally, trade theory beliefs indicate a robust association between legitimate and criminal economic activity.

Table 2 ranks countries by preference of Russian-based money launderers. Countries in the highest positions included: Bermuda, Monaco, and Liechtenstein. For the period of 2000-2020 Monaco has continually held the top position. The percentage of laundered funds score further indicates that country predilection is irrelevant based on legitimate economic downturns. After several major economic changes like the 9/11 attacks, the global financial crisis, or COVID-19 the scores did not change significantly.

The findings of this study in conjunction with those of Roman (2022), Roman et al. (2021), Ferwerda et al. (2020), Wahaj et al. (2018), Balani et al. (2017), Ferwerda et al.'s (2013), and Unger et al. (2006) maintain foundational tendencies supporting the laundered funds destination theory. Present literature on economic financial activity following a severe decline reveals that marketplace and consumer behavior tend to change. While simulation results suggest that preferred destination of illicit funds of Russian-based money launderers are not as volatile. As such, we can hypothesize with a certain degree of certainty that once a money launderer selects a destination for their illicit funds, the preference towards that destination is unlikely, which is the foundation of the laundered funds destination theory. Although the findings of this examination are statistically sound and contribute to the illegitimate finance and money laundering literature, further studies are needed to extend the Walker-Unger model and laundered funds destination theory.

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