Investigating the Determinants of Money Laundering Risk

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Abstract

Purpose – With the growing interconnectedness of global markets brought about by globalization and technological innovation, there is a heightened worldwide risk of money laundering, posing a considerable negative impact on economies and social equality. Therefore, the primary objective of this research is to examine factors that underpin the pervasiveness of money laundering risk.

Design/methodology/approach – By using a cross-section sample of 84 countries, the study uses ordered logit and multinomial logit regression to test and explain the role of main and varied determinants of money laundering risk covering countries' economic, social, regulatory, and corporate environment.

Findings – We conclude that, overall, the macroeconomic indicators are less relevant in influencing money laundering risk than the other factors adopted from the Basel report. Nonetheless, the volume of exports and the exchange rate were robust in both the ordered and multinomial regression analyses alongside financial secrecy, auditing standards, and corporate transparency. While more financial secrecy and a higher volume of exports were found to increase this risk, the other variables showed a negative relationship. We further conclude that it is mostly less secrecy, more transparency, and better auditing that could gradually transform a high-risk country into medium risk.

Practical implications – This study recommends the implementation of publicly accessible ownership registries to address the issues around secrecy, transparency, and auditing misconducts. Additionally, the general strengthening of laws and policies in these three domains is also necessary alongside the application of current technologies such as machine learning for the detection of money laundering.

Originality/value – We believe this study uses advanced econometric techniques rarely used in literature on money laundering. Separating the impact of economic and social/regulatory is also valuable.

Keywords Transparency, Auditing, Macroeconomic conditions, Corruption, Money laundering

Paper type Research paper

1. Introduction

Globalisation has given rise to a new global economic interdependence fuelled by the loosening of capital controls and advances in information and communication technology. These emerging opportunities were also rapidly adopted by the financial and banking sectors. As a result, a new trend of growing openness and integration among economies in terms of trade and financial flows across the globe began (Vaithilingam & Nair, 2009). However, these opportunities come with their own challenges, namely, the overall increased vulnerability to organised crime and corruption. Given the increasing integration of financial sectors, a particular focus was placed on money laundering, as it has been becoming a major concern globally (Raweh et al., 2017; Vaithilingam & Nair, 2009). Furthermore, the ongoing threats of international terrorism and the increasing level of drug-related criminal activities since the declaration of the War on Drugs in the 1980s are additional concerns that led to a heightened focus on money laundering among governments and researchers.

The money laundered globally in 2009 was estimated at 2.7% of the global GDP, around $1.6 trillion (United Nations, 2011). This figure has not been revised since, albeit the measure is only expected to have grown. Due to the clandestine nature of such illicit flows, the measurement and estimation of exact figures are rather difficult and can be taken only as an approximation. Besides its stealth, money laundering is also a global phenomenon by nature, therefore posing a problem equally for both developed (Cohen & Caldera, 2021; Reganati & Oliva, 2018) and developing (Aluko & Bagheri, 2012; Ba & Huynh, 2018; Murray-Bailey, 2019; Vaithilingam & Nair, 2007, 2009) countries worldwide.

Its widely proven damaging impact on economies emphasises the importance of examining the economic determinants and additional contributing factors at a country level. Although the severity of money laundering is undeniably on the rise, there is relatively little theoretical work, and even less empirical work, produced on the topic. In response to that, this study set out to investigate and bring new empirical insights to the existing literature regarding factors that can contribute to raising or mitigating the risk of money laundering on a country level. Researchers have tested the statistical significance of money laundering-specific (and socioeconomic) variables (e.g. Amara et al., 2020; Reganati & Oliva, 2018; Vaithilingam & Nair, 2007, 2009). However, there has not been enough attention devoted to different macroeconomic factors in this regard. The research question that this piece of work aims to answer is, “What factors and macroeconomic conditions have a significant influence in determining the level of anti-money laundering (AML) risk in a country?” To gain a deeper understanding of causalities, hypotheses were particularly tested for the relationship between some macroeconomic indicators (GDP growth, exports, exchange rate, primary net income from abroad) and AML risk. The study found that, although exports and exchange rate significantly influence AML risk, the most robust determinant factors are the level of financial secrecy and the strength of auditing standards in a given country. The findings of this research provide not only novel empirical contribution to the current money laundering literature, but also bring important implication regarding policy-making efforts aimed at reducing money laundering.

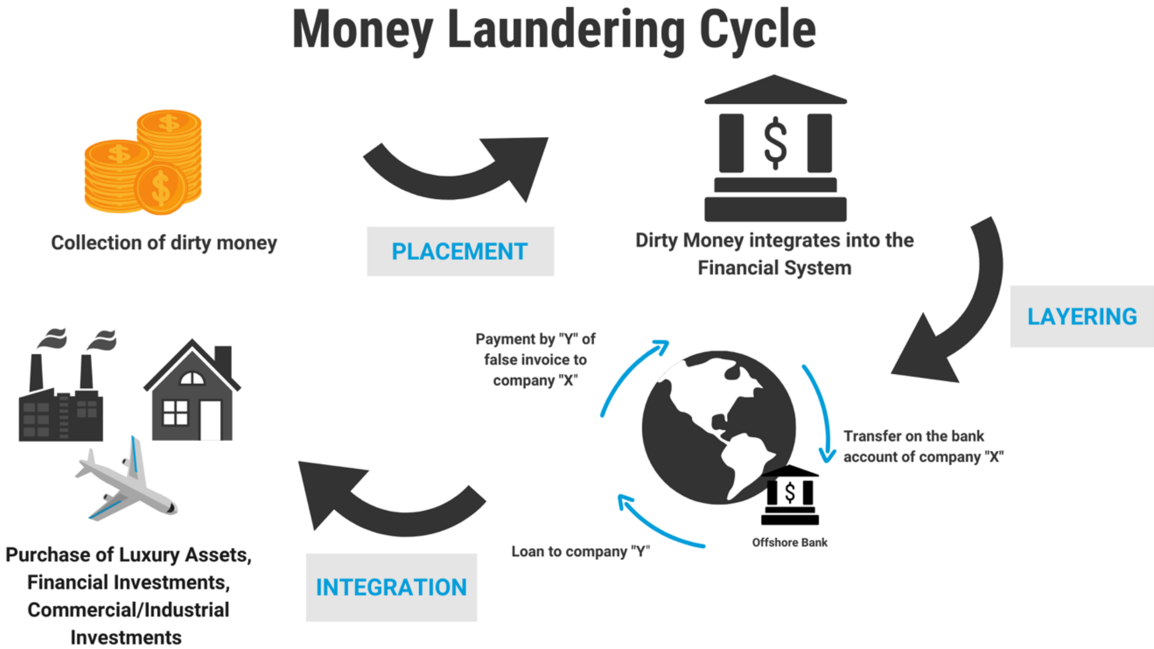
The next section comprehensively reviews money laundering literature, followed by the methodology section, where the data and econometric models used for this research are introduced. In the fourth analysis section, the results of the estimation models are critically analysed and interpreted to provide answers to the research question along with the hypotheses. The fifth and last section presents the conclusions and main implications of this research paper.

2. Literature review

Money laundering is essentially the act of giving dirty money a legitimate appearance (Tiwari et al., 2020). The United Nations (2022) define it as: "the conversion or transfer of property, knowing that such property is derived from any offence(s), for the purpose of concealing or disguising the illicit origin of the property or of assisting any person who is involved in such offence(s) to evade the legal consequences of his actions."

The complex process of money laundering is normally carried out in three stages (Figure 1). First, through the placement stage, the ill-gotten cash from punishable activities is physically infiltrated into a legal financial system and converted into book money in primary (small bank deposits) or secondary (other assets) deposits (Schneider & Windischbauer, 2008). Then, through the layering stage, criminals attempt to conceal the source of illegal income through many transactions creating a complex web of financing transactions between different stages and piling up several layers of dealings. The final step involves the integration of the transformed or transferred capital into formal economy through property (direct investments in companies and real estates) or financial investments (stocks, specific deposits) (Schneider & Windischbauer, 2008). It is logical from a criminal's point of view that the integration step is completed in a country with the highest chances of evasion through the process, ultimately raising the money laundering risk of such countries.

Figure 1: Money Laundering Cycle



Source: United Nations Office of Drugs and Crime, 2022

In the following, first, this literature review aims to discover ways in which money laundering can negatively impact economies, and therefore, societies globally. Then, the focus shifts over to the detection and countering efforts that are being amped up continuously to eliminate or reduce the opportunities of getting away with such criminal activities.

2.1 Impact of money laundering on the economy

As the current study is concerned with ways to reduce money laundering risk, it is essential to first explore some of its macroeconomic impacts, and through that, some factors that could play a key role in raising or mitigating this risk. Hendriyetty and Grewal (2017) categorise the macroeconomic effects of money laundering as the ones on the scope of the shadow and underground economies on illicit capital flows and those on tax revenue. While a relatively large informal economy in one country greatly facilitates money laundering, these activities also lead to the growth of shadow economies. As Unger and Hertog (2012) argue: "Laundered money seems to move like water, which always finds its way through stones and other hindrances". Different anti-money laundering (AML) systems make the formal channels to shift money too risky, thus, money launderers rely more on the informal sectors to move their money. The growth of this shadow economy brought about by extensive money laundering is concerning for several reasons outlined by Schneider and Enste (2002).

Participation rates and hours worked in the official economy may fall as more people work in the hidden sector. This tendency distorts the official economic indicators of a country, resulting in a depressed output figure and potentially self-defeating policy set based on unreliable statistics (Aluko & Bagheri, 2012). Although money laundering can affect countries of any level of development, the presence of shadow economies is estimated to be approximately 10 - 20% of the annual GDP in mature economies and can get up to 60% in emerging economies (Schneider & Enste, 2002). Aluko and Bagheri (2012) highlight how this poses a pronounced effect on legally operating businesses in developing economies specifically. Here, the front companies (that clean illegal proceeds) operating in the legitimate economy can subsidise their products and services well below market rates with their access to substantial "excess" funds. This makes it difficult, or sometimes impossible, for legitimate businesses to compete against these front companies with subsidised funding, and in most cases, also results in overcrowding of criminal organisations in the private business sectors of developing countries (Aluko & Bagheri, 2012). A real growth of the domestic economy could, however, mitigate money laundering, as the opportunity for earning a higher income is expected to increase the chances for employment in the legal sectors of the economy (Reganati & Oliva, 2018). For this reason, the first hypothesis that this research tests is:

H1: Higher GDP growth results in lower AML risk.

Moving and keeping money outside a jurisdiction can help money launderers disguise transactions from the illegal origin or to predicate crimes, bringing about substantial cross-border illicit capital flows (Hendriyetty & Grewal, 2017). A popular way of retaining funds abroad is through the misreporting of export volumes (Collin, 2019; Kellenberg & Levinson, 2019). Therefore, the analysis will test the following assumption:

H2: Higher export volume results in higher AML risk.

Such a large scale of unexpected cross-border transfers of funds can, thereafter, result in potentially disrupting volatility in both exchange rates and interest rates (Quirk, 1996). Murray-Bailey (2019) describes a phenomenon whereby the exchange rate differential in Nigeria reflected a premium that buyers of foreign exchange would pay to falsify trade documents so they could make transfers otherwise illicit, i.e. money laundering. Thus, the next hypothesis to be tested is:

H3: Higher exchange rate results in lower AML risk.

In relation to illicit cross-border capital flows, Aluko and Bagheri (2012) pointed to more aspects in which developing countries' economies could more severely feel the negative impacts of money laundering. As they offer attractive characteristics and attributes for criminals to easily disguise their wealth through these informal economies, they attract a higher proportion of illicit funds. For instance, it has also been highlighted that, in some tax haven states such as Hong Kong or Panama, companies' income from abroad is altogether exempt from tax, making these locations very attractive for conducting money laundering operations (George-Dorel, 2013). These arguments motivate the last assumption of this research:

H4: Higher primary net income from abroad results in higher AML risk.

The illegal cross-border movement of large sums of capital undermines not only the integrity of financial systems in these countries (Hendriyetty & Grewal, 2017), but it can also result in economic distortion, investment instability, or even a complete loss of control of national economic policies (Aluko & Bagheri, 2012). One notable example of this lies within the inefficiency of the allocation of these resources, as ill-gotten proceeds are being diverted from one economic venture to another without sound economic reasons. The fact that money launderers do not pursue high profit-generating investments can infringe the law of economics, as capital moves from countries with a high rate of return to those with poorer regulations and policies and low rates of return (Aluko & Bagheri, 2012).

Most important, the misreporting and under reporting of income due to money laundering led to reduced tax revenues for the government (Aluko & Bagheri, 2012). Economic difficulties in many countries are central to the government budget deficit (Hendriyetty & Grewal, 2017) since tax evasion has a major impact on macroeconomic stabilisation (Quirk, 1996). Schwarz (2011) observed the relationship between money laundering and tax havens and found that mostly poorer tax havens that lack a credible reputation are normally the ones that strive to create a conducive environment for the integration stage of money laundering, as they are reluctant to provide the necessary regulatory environment to fight such crimes. It is also highly important to note that as, wealthy individuals can move large sums of illegal proceeds under cover and avoid tax payments, global inequality will only continue to grow.

2.2 Fighting money laundering – the role of country's social, regulatory and corporate environment

It is imperative to explore the countering actions being taken to control money laundering and how these activities are being detected today. Recognising the threat posed to the banking system and to financial institutions, the Financial Action Task Force on Money Laundering (FATF) was established by the G-7 Summit in 1989 (FATF, 2022). The main objective of this inter-governmental body is to set international standards that aim to prevent illegal money laundering and the inherent harm it causes to society. The FATF has, therefore, developed a set of recommendations and standards that ensure a coordinated global response and help authorities track down the money of criminals (FATF, 2022). Additionally, the importance of the reduction of illicit financial flows as a priority area to build peaceful societies around the world is also recognised in the 2030 Agenda for Sustainable Development. The Sustainable Development Goals target 16.4 states a goal; "by 2030, significantly reduce illicit financial flows and arms flows, strengthen the recovery and return of stolen assets and combat all forms of organised crime" (United Nations, 2022).

Despite the increasing global recognition and policy-making efforts around money laundering, the ultimate responsibility of detecting suspicious and illicit activities lies with financial institutions. As banking is the most significant sector affected by money laundering (Raweh et al., 2017), its transaction monitoring ability plays an especially vital role in detecting criminals during the layering stage of the process. According to Labib et al. (2020), "The term AML points out to all procedures, laws, policies, regulations and pieces of legislation that force financial institutions to monitor their clients and doing their best in order to prohibit money laundering and corruption. This requires financial institutions to report any financial offence they find and stop it."

Financial institutions began notifying their governments regarding large suspicious transactions in 1970, which marked the start of money laundering detection (Alsuwailem & Saudagar, 2020). Anti-money laundering is essentially a software system designed for this purpose. The aim is to detect suspicious transactions and anomalies in a large withdrawal, a sudden increase in funds, or small patterned transactions, by analysing customer profile data (Labib et al., 2020). In the late 1990s, these statistical techniques used for pattern detection were mostly present in temporal sequence matching and Bayesian models (Alsuwailem & Saudagar, 2020). The use of operational models based on embedded rules was popular in the past few decades due to their simplicity and being easy to code (Chen et al., 2018). The apparent drawback, however, is that, as more exceptions arise from the existing rules, more new rules need to be added, and integrating those will impair the system performance. The formulation of new rules also requires expert human knowledge gained from working experience. Additionally, it is extraordinarily difficult to evaluate the performance of all rules, which makes the results unreliable (Chen et al., 2018).

Although machine learning techniques have been around since 2004 (Alsuwailem & Saudagar, 2020), many banks still rely on rule-based systems based on these pre-generated static rules by experts to filter out suspicious transactions (Chen et al., 2018). Instead, a more effective option is to extract possible evidence of abnormal activities from the data using mathematical algorithms through machine learning (Goecks et al., 2022). According to Chen et al. (2018), "The most perceptible function with machine learning is its ability to create generalisations on the data during the training phase." This means that, in comparison to the traditional rule-based system, the information gained from this machine learning training phase can effectively interpolate and extrapolate on new scenarios without having to be taught of a possibility (Chen et al., 2018).

Recently, researchers have explored the potential of applying artificial intelligence and machine learning methods to improve the detection of suspicious transactions and patterns in terms of efficiency and accuracy. These models generally can be classified using two main categories: supervised and unsupervised learning. While supervised learning predicts the value of an outcome measure based on several input measures, unsupervised learning has no outcome to measure; its objective is rather to identify patterns and associations among a set of input measures (Hastie et al., 2021).

3. Methodology

This section of the study first introduces the two logistic regression models used in the analysis for answering the research question. Then, the variables used in the regression models along with the data sources are presented. The design of this study is, to some extent, based on the methodology framework applied by Ba and Huynh (2018). Instead of the external factors, this research paper analyses; their study concentrates on bank specific internal indicators' significance in explaining money laundering risk such as customer characteristics. For this purpose, they have "applied the logistic regression model because of its concordance in statistics for covering all of the cases of categorical dependent variable that was homological with the categories of very high, high, medium, and low money laundering risk customer" (Ba & Huynh, 2018). Two kinds of logistic regression models appear in their study: ordinal logistic regression, where the variables are evaluated in the ordered multiple categories, and multinomial logistic regression, where the independent risk factors are analysed with more than two different outcome categories. Following Ba and Huynh (2018), the 84 sample countries of this study were divided into three categories from low to high risk of money laundering (see Appendix 1) based on the Basel AML risk index (2021) for these logistic regressions. Firstly, the ordered logistic regression is used to predict the relations of the ordered AML risk categories as the dependent variable and the independent factors described above. The proportional odds model on which the probability equation is based was developed by McCullagh and Nelder (1989):

$$p_{ij} = \Pr(y_j = i) = \Pr(\kappa_{i-1} < x_j\beta + u \leq \kappa_i) = \frac{1}{1 + \exp(-\kappa_i + x_j\beta)} - \frac{1}{1 + \exp(-\kappa_{i-1} + x_j\beta)}$$

where the κ outcome categories are $i = \{1; 2; 3\}$, and that outcome is dependent on x_j, the observed values of the independent variables (Sections 3.2.2., 3.2.3.) for the j^{th} observation.

To answer the research question, this model is first implemented for variables identified from the Basel AML risk report (2021), forming the base model to check their statistical significance in determining the money laundering risk level for each country in this study. For testing the hypotheses, the ordered logit model is, then, extended to include the previously robust base model variables along with the macroeconomic indicators as the first extension of the model. Additionally, as brought forward by Amara et al. (2020), an alternative regression for the extended ordered logit regression model is conducted, which is based on the interaction of two variables: one Basel risk indicator and one macroeconomic. The aim of this is to investigate any potential change in results when two factors' impacts on money laundering risk are combined and measured together.

Then, the multinomial logistic regression is implemented to deepen the findings and understanding regarding the hypotheses by analysing the conditional probabilities of countries falling into a risk category compared to a base outcome. The multinomial logit approach is a form of logistic regression when the nominal value of the dependent indicator is identified with more than two levels, and therefore, the probability distribution is multinomial based on each category of the observation instead of binomial or less (Ba & Huynh, 2018). According to Findley et al. (2015), multinomial models serve to capture all possible outcomes without loss of information from collapsing the data. Therefore, from this regression, it is possible to determine specifically which independent variables (x_j) play a significant role in the probability of a country falling into a risk category compared to another (base) category. This probability function model for the base outcome $i = 1$ was developed in Greene (2012):

$$p_{ij} = \Pr\left(y_j = i\right) = \begin{cases} \dfrac{1}{1 + \sum_{m=2}^{k} \exp(x_j \beta_m)}, \text{if } i = 1 \\ \dfrac{\exp(x_j \beta_i)}{1 + \sum_{m=2}^{k} \exp(x_j \beta_m)}, \text{if } i > 1 \end{cases}$$

where β_m is the coefficient vector for outcome m.

4. Data

By its very nature, the real volume of illicit financial flows is rather difficult to measure and even harder to aggregate. For this reason, the Basel Institute's Anti-Money Laundering Index report (2021) is adopted as a baseline for this macro analysis as seen in previous AML studies (e.g. Amara et al., 2020; Amara & Khlif, 2018; Collin, 2019; Moore, 2014). Instead of the unmeasurable magnitude of money laundering, this report estimates the risk level of each country. Thus, it serves as a highly useful indicator for empirical research on this topic in lack of any other exact figures. Further secondary quantitative data for the study are collected from a wide range of publicly accessible sources. The sample for this cross-county research comprises 84 observations as per data availability.

Dependent variable: money laundering risk

The Basel AML report (2021) uses a weighted method for determining the overall score of jurisdictions in terms of their AML risk exposures based on 17 indicators in five domains of importance to money laundering and terrorist financing. The data for those indicators are drawn from both quantitative and qualitative independent third-party sources. Out of the 110 observations, on a 0-10 scale, Haiti scores highest risk (8.49) and Finland the second lowest with 3.06. Andorra is the lowest risk country with a score of 2.73 but was excluded from the study due to data unavailability. For the ordered and multinomial logistic regressions, the sample countries are categorised as either low, medium, or high risk based on this measure (see Appendix 1).

Independent variables – country's social, regulatory and corporate environment

For building the model, seven of the quantitative indicators representing a country's environment in terms of social, regulatory, and corporate conditions were adopted from the Basel AML risk report's (2021) methodology as independent variables (see Appendix 2). Firstly, the financial secrecy score provides information on relevant environmental and jurisdictional factors conducive to money laundering by measuring the scale of a country's offshore banking activity, the level of bank secrecy, and the size of its financial centre. The logic employed by the index is that larger financial sectors provide more opportunities for illicit flows to be hidden. The indicator is scored from 0, meaning no secrecy, to 100 full secrecy and, as more financial secrecy leaves more room for laundered money to be successfully concealed, the expected relationship is positive. Corruption is a common predicate offence to money laundering, so countries with high exposure or vulnerability to corruption have a higher risk of money laundering. The Corruption Perception Index (CPI) score is the most widely used and recognised source for assessing the level of corruption on a scale of 0-100. The score 0 is assigned for highly corrupt, while 100 is for clean countries, thus, a negative coefficient is expected for this variable. Additionally, bribery is another important form of corruption and generates significant proceeds of crime that need to be laundered to enter the financial system. The bribery deterrence score considers both formal enforcement mechanisms (governmental) and the less formal ways bribery is discouraged (societal disapproval). On a 1-100 scale, 1 means the lowest bribery risk and 100 the highest. As the ability to bribe officials (e.g. accountants, auditors, law enforcement) encourages money laundering in one country, a positive relationship is expected.

The transparency of corporate information in the business sector is highly desirable, as secrecy in these areas allows the true ownership of assets to be hidden - an essential aspect of money laundering. Counties are scored 0-100 by the extent of the Corporate Transparency Index, where 0 (100) represents the worst (best) regulatory performance. Therefore, a negative relationship is expected with AML risk. Robust auditing and reporting standards need to be in place to protect companies and the financial industry from being misused for financial crime. Audits can detect irregularities and prevent money laundering activities within the private sector including the financial sector. Countries are scored 0-100, i.e., weak to strong in the Global Competitiveness Report (World Economic Forum, 2019). The expected coefficient is negative, as countries with a low level of auditing and reporting standards might be more vulnerable to money laundering.

Measured within the same report, the independence of the judiciary is another one of the key prerequisites in the successful fight against financial crimes. The score 0 is assigned for not independent, and 100 for independent. This coefficient is also expected to be negative, as a politically dependent judiciary may lead to politically motivated prosecutions, besides mislead about the number of convictions in money laundering. Finally, strong political rights serve as powerful mechanisms for monitoring money laundering offences and ensuring the integrity of AML systems. Political and social activists can hold politicians accountable for the quality of AML systems and the country's resilience to money laundering threats. In contrast, where political rights are routinely violated, criminals and corrupt politicians are more easily able to launder their money with impunity. Countries are rated 1-7 from "free" to "not free", thus, a positive relationship is expected.

Independent variables extensions – role of country's economic conditions

The extensions of the model primarily test the hypotheses and reveal answers to the research question. Each macroeconomic independent variable corresponds to the hypotheses set up and were introduced under Section 2.1. Data for the following selected macro variables – GDP growth per capita, export volume index, exchange rate index, net primary income from abroad – were collected from the World Bank's World Development Indicators database. Furthermore, the additional interaction variable of one Basel and one macro indicator, asev, was selected based on Kellenberg and Levinson's (2019) cross-country empirical research. They found that the strength of auditing and accounting standards is a significant negative determinant of the level of exports underreporting in a jurisdiction. If that finding holds, the overall export volume is expected to lose significance for a well-reported country, as the number of suspicious misreported exports should be proportionately considerably less in that country in theory. For that reason, the coefficient of the auditing standards is expected to prevail for the new interaction variable. The results of the extension model with the interaction variable can, therefore, demonstrate whether the strength of accounting standards taken with the volume of exports from the same country show a different effect on money laundering risk than measured separately.

5. Analysis

The logistic regression results are presented in this section. Analysing these results regarding the regression coefficient and the statistical significance of the chosen variables helps in answering the research question. This was done in four steps as described under Section 3.1. The base model results are interpreted first based on which the robust variables were selected to augment macroeconomic variables, which is then extended to include an interaction variable. Finally, the results of the multinomial regression are analysed, bringing a deeper insight into the significant determining factors of AML risk.

Base model estimates

The ordered logistic regression base model regression results can be seen in Table 1 under columns (1 - 2). This estimation measures how the seven selected Basel index factors contribute to jurisdictions' money laundering risk. Although only four indicators are statistically robust, however, the signs of the regression coefficients are almost entirely as expected. The results show that the strongest determinant factor of AML risk is financial secrecy with a p-value of 0. This confirms Collin (2019), who also found a significant positive relationship between money laundering scores and the financial secrecy indicator. Based on that study's argumentation, another conclusion that can be drawn is that tax evasion is also a strong motive for money laundering, as most countries characterised by a high level of financial secrecy on the index are considered tax havens. Moreover, in line with Amara et al.'s (2020) findings, the level of auditing and reporting standards in a country is also a significant indicator of AML risk with $p=0.025$ and a negative coefficient. Indeed, it has been proven that good reporting and auditing infrastructure plays an important role in reducing financial crimes, as it creates a favourable environment for auditors to combat money laundering by detecting and revealing financial crimes to judicial authorities (Amara et al., 2020). Nonetheless, Kellenberg and Levinson (2019) presented evidence for the auditing standards' significant mitigating effect on exports underreporting, which is another contributor to increasing money laundering risk in a country explained under Section 4.2.

Somewhat surprisingly, the level of citizens' political rights within a jurisdiction also turned out to be a significant (p=0.044) positive contributing factor to money laundering risk based on the regression results. Bartilow and Eom (2009) have previously stressed the significance of political rights, stating that "the level of individual political freedom, defined in terms of the level of political and civil liberties of citizens, is an important aspect of the incentive structure that shapes the level of drug trafficking." Although money laundering and drug trafficking are two highly interrelated activities, these authors have found a reverse (negative and statistically significant) relationship in connection to the latter. Their argument for the negative relationship is based on the fact that, while political rights protect the civil liberties of citizens, they also constrain officers' ability to combat the drug trade. According to these authors, high levels of political freedom could shield drug traffickers from arbitrary state power and reduce the chances for interdiction (Bartilow & Eom, 2009). This contradicts the assumption of this model based on the Basel report (2021) according to which political activists can hold politicians accountable for the country's resilience to money laundering threats and the quality of AML systems, that way granting integrity to AML systems in countries with powerful political rights. Nonetheless, Bartilow and Eom (2009) concluded that drugs are more likely to be smuggled through countries where political rights are relatively high as compared to countries where individual political freedoms are low and the state is not constrained by the civil liberties of its citizens.

[Insert table 1 about here]

The final robust factor found to contribute to money laundering risk is corporate transparency with a p-value of 0.045 and a negative coefficient. In this context, Cohen and Caldera (2021) explained the emergence of Canada's 'snow-washing' reputation with its weak corporate transparency regime described by exceptionally little AML enforcement and beneficial ownership reporting. They argue that, "While not a silver bullet to fixing all of Canada's money laundering problems […], a publicly accessible registry can act as a strong deterrent against criminals who seek to abuse shell companies to finance the proceeds of crime." Evidence found in the United Kingdom proves the importance of transparent, publicly accessible corporate ownership registries in deterring criminal activity. After Scottish limited partnerships that were used to launder £80 billion from Russia, firms were required to disclose beneficial owners, the number of registrations reduced by 80% in the next year (Cohen & Caldera, 2021). This level of improvement evidently confirms the significant negative relationship between corporate transparency and the level of money laundering risk found in the ordered logit regression base case model.

Although several empirical investigations previously proved the significance of corruption on money laundering risk (Amara et al., 2020; Amara & Khlif, 2018; Jayasekara, 2020; Reganati & Oliva, 2018), in our analysis, it turned out to be highly insignificant (p=0.948). The coefficient sign is in line with the literature, which argues these two crimes are intrinsically linked, as corruption generates huge proceeds that need to be laundered to be given an appearance of legality (Reganati & Oliva, 2018). The bribery deterrence indicator is another highly insignificant one with a p-value of 0.701 and a negative coefficient, although the relationship was expected to be positive. A recent study measured the reverse impact of the AML legal framework and its effective implementation on bribery, among other factors (Jayasekara, 2020). Bribery risk was found to have a significant negative relationship with the effectiveness of AML measures, implying that ineffective AML regimes could encourage criminals to get involved in bribes (Jayasekara, 2020). Finally, in line with the literature, the ordered logit base model results indicate that a jurisdiction's judicial independence is a negative but not significant factor of AML risk (Amara et al., 2020). Vaithilingam and Nair (2007), however, have previously found a significant relationship between money laundering and the efficiency of a country's legal framework. They argue that, when a legal framework is efficient, meaning a legal and regulatory framework which is effective and independent, money laundering activities are generally less pervasive (Vaithilingam & Nair, 2007).

Inclusion of macroeconomic conditions – first extension of base model

Having determined the robust Basel variables within the base model, the analysis moves on to include selected macroeconomic variables in the regression to test the hypotheses. The aim is to bring fresh empirical findings to the literature lacking evidence on which macroeconomic indicators could significantly contribute to determining the level of AML risk in a jurisdiction. The second-ordered logistic regression results are shown in Table 1 under columns (3 - 4). Only two of the four newly added macroeconomic indicators' results confirm the acceptance of the corresponding hypotheses. The exchange rate index was the most significant (p=0.011) macroeconomic determinant factor. Besides, the volume of exports is significant, but with a p-value of only 0.05 and a positive coefficient. These p values allow for accepting Hypotheses 2 and 3, according to which the higher exchange rate of currency results in lower money laundering risk in that country, and that a higher level of export transactions results in heightened AML risk.

Conversely, the GDP growth rate and income from abroad turned out statistically insignificant from the regression results with p-values of 0.205 and 0.157 respectively; therefore, Hypotheses 1 and 4 are rejected. It can be concluded these two indicators do not influence the level of money laundering risk significantly, albeit the signs of the regression coefficients are as expected.

According to that, the GDP growth rate assumes a negative relationship with AML risk, and more income from abroad is expected to raise this risk. It is also of importance to note that none of the initially significant Basel factors lost their robustness in the macroeconomic model; in fact, they all increased significance. While several research papers are concerned with the effect of money laundering on a country's different macroeconomic indicators and its overall social and economic state (Aluko & Bagheri, 2012; Hendriyetty & Grewal, 2017; Murray-Bailey, 2019; Quirk, 1996; Schwarz, 2011; Schneider & Enste, 2002), there is a lack of empirical investigations on the significance of these selected macroeconomic variables on money laundering risk identified within the existing literature, which this study aims to fill. One study draws a connection between exports and exchange rates - the two new robust indicators of the model - regarding money laundering (Murray-Bailey, 2019). It is argued that trade mis-invoicing, being a popular method for illicit capital flight (Collin, 2019; Kellenberg & Levinson, 2019), causes considerable distortions to a country's export and import indicators, which is further associated with volatility in the exchange rates due to the level of unanticipated cross-border fund transfers (Murray-Bailey, 2019). Finally, regarding the most essential macroeconomic indicator, GDP growth, Reganati and Oliva (2018) also found it an insignificant, however positive, factor in their empirical research on the determinants of money laundering in Italy. The positive sign contradicts the study's assumption according to which higher income should translate into more opportunities for the population to earn better wages in the legal sectors of the economy.

According to the first extension of the base model, financial secrecy, corporate transparency, auditing standards, political rights, export volume, and exchange rate are the factors that turned out to have a significant influence in determining the level of AML risk in a country. These empirical results are investigated further in the following sections of the analysis.

Interaction country's exports volume and auditing standards – second extension

The second extension to the ordered logistic regression base model includes the interaction of two previously statistically significant variables, following Amara el al.'s (2020) methodology, each selected from the Basel indicators and macroeconomic variables. The aim is to test whether the interaction of two robust and related variables would produce a different outcome compared to when measured separately. It has been argued that the underreporting of exports is a popular method for money laundering among criminals (Collin, 2019). An empirical investigation conducted by Kellenberg and Levinson (2019) also revealed that good auditing and accounting standards in a country significantly decreases such misreporting of trade invoices. Based on that finding, the interaction of these two previously statistically significant/robust variables is expected to show an even more robust negative effect on money laundering risk. Due to the mitigating effect of accounting standards on misreporting, the overall volume of exports would be less significant.

The results of the third ordered logit regression are shown in Table 1 under columns (5 - 6). The interaction variable of accounting standards and export volume is insignificant (p=0.329) with a negative coefficient. It can also be observed that both previously robust original variables turned insignificant when adding the interaction, but their coefficients are unchanged. A higher p-value was expected in export volume since, based on Kellenberg and Levinson's (2019) conclusion, strong auditing compliance would have eliminated the proportion of underreported exports out of the overall, making the overall figure less important. Although insignificant, the interaction variable took the auditing standards' negative coefficient as expected, and its implication is the following. A country where good auditing standards are in place is likely to have a lower risk of money laundering, as adherence to these standards not only counters the overall AML risk but is also an underlying factor in terms of export misreporting. Having interpreted the ordered regressions, the analysis now moves on to the results of the multinomial model to gain a deeper insight regarding the final conclusion of the study.

Multinomial logit model estimates

Additional interesting conclusions and answers to the research question and policy recommendations can be drawn from the multinomial logistic regression results. By interpreting these, one can discover essentially which factors play the most significant role in a country falling into a given (compared to a base) risk category. The study points to a couple of important policy implications in terms of, for instance, what laws and policies a high-risk jurisdiction should put more focus and resources into enforcing to support the global efforts in fighting money laundering and become medium then low risk and which factors can distinguish a low-risk country from the ones classified as medium-risk, for example. The results of the multinomial logistic regression can be seen in Table 2.

It is evident from the results that financial secrecy is the main and most important factor in determining whether a country has low, medium, or high money laundering risk prevailing, given the nearly 0 probability values for all three scenario outcomes. To address the prime issue of financial secrecy within a country, the policy recommendation for a global asset register has recently gained rapid traction (Balmer, 2022; Basel, 2021; Partridge, 2022). According to the Tax Justice Network (2022), this comprehensive international registry of all high-value wealth and assets, along with their real beneficial owners, can link up national and regional asset registries around the world. By providing a centralised global record of true ownership, implementing this policy would not only significantly mitigate money laundering risk globally, but would also bring the rule of law to the unmeasurable wealth hidden abroad, facilitating to understand and address global inequality as well.

[Insert table 2 about here]

Columns (3 - 6) in Table 2 reveal interesting results in relation to the "dangers" that contribute to a country's classification as high-risk compared to medium-risk and the aspects that need to be improved for a high-risk country to fall into medium-risk. Columns (3) and (5) show highly significant coefficients for both corporate transparency (p=0.016) and auditing standards (p=0.008) besides financial secrecy. The negative coefficients under column (3) imply that a country characterised by low corporate transparency or weak auditing standards is more likely to fall into the high AML risk category compared to the medium risk than countries that generally have high corporate transparency and strong auditing standards. Put differently, from the positive signs under column (5), it can be read that, for a country to be described as having only a medium/low level of money laundering risk compared to high, corporate transparency needs to be high and auditing standards need to be strong. These two robust indicators point to the importance of implementing a public asset registry globally to improve these factors, and with it, the risk of money laundering. It has already been pointed out previously in this analysis that Canada's existing money laundering issue is due to its weak corporate transparency regime, and the adaptation of public beneficial ownership registries was proposed as the best deterrent solution against this corrupt and illegal activity (Cohen & Caldera, 2021). A review by Tiwari et al. (2020) lists further supporting evidence of the importance of transparency for countering money laundering in public ownership registers.

Although there is evidence of its implementation having a positive AML effect on countries such as the United Kingdom (Basel, 2021; Cohen & Caldera, 2021), the Basel report (2021) argues that, on average, the data reveals no strong correlation between the compliance and effectiveness of this policy, and policy measures of different nature are still needed. It is crucial to stress the urgency for undertaking further legislation to strengthen transparency and consolidate the role of auditors in combating money laundering in countries with weak auditing standards. By implementing a strong auditing infrastructure for a country, auditors will have more incentives to report and combat financial crimes (Amara et al., 2020). Finally, export volume is also significant with a p-value of 0.039 in determining whether a country has a medium or high-risk level of money laundering. Compared to the previous three indicators, however, it is generally not in a country's interest to lower the volume of its exports and risk create a trade deficit, as it is a highly important source of income and a productivity booster in any economy. Instead, strengthening accounting standards in a jurisdiction will not only contribute directly to lowering the overall AML risk, but will also improve the level of export mis-reporting committed for money laundering purposes as well (Kellenberg & Levinson, 2019).

This multinomial analysis solidified some findings made by the ordered logit model. The high significance of secrecy, transparency, and auditing has been reiterated. However, from the results in Table 2, it can be concluded that macroeconomic indicators do not seem to play an explicitly important role in determining the AML risk of a country. To confirm or contend this finding, future research should be conducted with testing different macro variables from the ones selected for this study.

6. Conclusion

This study's main focus is on money laundering based on the Basel AML risk index report (2021) and factors that can contribute/mitigate this risk. Besides the lack of existing empirical investigations around this topic, the growing importance and attention around detecting and countering money laundering motivated this research. Its negative impact on the economy in, e.g., reduced tax revenue, and on society as it deepens inequality, is pronounced in both developed and developing economies. The research question of this study set out to investigate what social, regulatory, and political/judicial factors and macroeconomic indicators contribute significantly to a country's money laundering risk to then draw important implications for policymakers. The empirical estimation was done using the ordered and multinomial logistic regression methods.

Because of those analyses carried out, the data seems to suggest that, besides financial secrecy, corporate transparency, auditing standards, and political rights, there are significant contributing factors to AML risk. Then, the four hypotheses were tested by including the macroeconomic indicators in the first extension of the model. While exchange rate showed a negative relationship, and export volume was positive, the statistical significance of both indicators brings new empirical findings to the current knowledge. Hypotheses 1 and 4 were rejected regarding the significance of net primary income from abroad and GDP growth rate. The interaction variable of two previously robust variables (auditing standards and export volume) was found insignificant. For a deeper insight into the research question, the multinomial logit model results further highlight the importance of financial secrecy and good corporate governance and strong auditing standards – and to some extent the volume of exports – in determining the level of money laundering risk in a country. Based on the aggregate findings, perhaps macroeconomic indicators influence AML risk to a lesser extent than expected and when compared to other money laundering specific factors. Although opinions regarding its effectiveness are not unanimous, this study recommends the implementation of publicly accessible ownership registries to address the issues around secrecy, transparency, and auditing misconducts. Additionally, the general strengthening of laws and policies in these three domains is also necessary alongside the application of current technologies such as machine learning for the detection of money laundering. One notable limitation of the paper is the lack of time-series analysis due to the scarcity of the data. As the literature on the significance of macroeconomic factors' impact on AML risk is still lacking evidence, future research could focus on testing other important macro indicators.

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Table 1: Ordered logistic regression results

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	Model 1		Model 2		Model 3	
	coef	se	coef	se	coef	se
financial_secrecy	0.1651***	(0.0407)	0.1814***	(0.0442)	0.1882***	(0.0451)
corporate_transparency	-0.0206**	(0.0103)	-0.0257**	(0.0105)	-0.0268**	(0.0108)
auditing_standard	-0.0777**	(0.0347)	-0.1071***	(0.0316)	-0.0669	(0.0511)
political_rights	0.5166**	(0.2562)	0.4347**	(0.1907)	0.4220**	(0.1910)
corruption_perception	-0.0031	(0.0465)				
bribery_deterrence	-0.0167	(0.0436)				
judicial_independence	-0.0364	(0.0299)				
asev					-0.0002	(0.0002)
GDP_pc			-0.2252	(0.1776)	-0.2521	(0.1805)
primary_income			0.0000	(0.0000)	0.0000	(0.0000)
export_volume			0.0040**	(0.0020)	0.0163	(0.0131)
exchangerate			-0.0682**	(0.0267)	-0.0687***	(0.0264)
/cut1	-0.0307	(3.6724)	-5.0273	(3.1869)	-2.2595	(4.2538)
/cut2	3.8279	(3.6978)	-0.7337	(3.0552)	2.1321	(4.2488)
Observations	84		84		84	

*** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses.

Table 2: Multinomial logistic regression results

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	Cat 1	se	Cat 3	se	Cate 1	se
	Base Cat 2		Base Cat 2		Base Cat 3	
financial_secrecy	-0.2298***	(0.0843)	0.1909***	(0.0702)	-0.4208***	(0.1081)
corporate_transparency	0.0183	(0.0175)	-0.0394**	(0.0164)	0.0577**	(0.0231)
auditing_standard	0.0507	(0.0429)	-0.1554***	(0.0586)	0.2061***	(0.0713)
political_rights	-0.4822	(0.3790)	0.3613	(0.2459)	-0.8435*	(0.4368)
GDP_pc	-0.4012	(0.3631)	-0.5343*	(0.2861)	0.1331	(0.4469)
primary_income	-0.0000	(0.0000)	0.0000	(0.0000)	-0.0000	(0.0000)
export_volume	0.0010	(0.0039)	0.0072**	(0.0035)	-0.0062	(0.0051)
exchangerate	0.0642	(0.0406)	-0.0638*	(0.0365)	0.1280**	(0.0529)
Constant	2.8526	(5.2971)	3.5289	(4.1036)	-0.6763	(6.2561)
Observations	84		84		84	

Notes. *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. Cat stands for a jurisdiction falling into a particular money laundering risk category (lower Cat 1, medium Cat 2, high Cat 3).

Appendix 1: Risk Classifications

Category	Countries included
1 - low risk (score: 0-4.5) n=22	Australia, Austria, Bahrain, Belgium, Czech Republic, Denmark, Finland, Greece, Iceland, Ireland, Israel, Lithuania, New Zealand, Norway, Peru, Portugal, Slovakia, Slovenia, Spain, Sweden, United Kingdom, Uruguay
2 - medium risk (score: 4.5-5.5) n=32	Botswana, Canada, Colombia, Costa Rica, Cyprus, Dominican Republic, Egypt, Georgia, Ghana, Guatemala, Hong Kong, Hungary, Indonesia, Italy, Japan, Latvia, Malaysia, Malta, Mauritius, Mexico, Moldova, Morocco, Russia, Saudi Arabia, Serbia, Singapore, South Korea, Switzerland, Trinidad and Tobago, Tunisia, Ukraine, United States
3 - high risk (score: 5.5-10) n=30	Albania, Bangladesh, Barbados, Burkina Faso, Cambodia, China, Ethiopia, Haiti, Honduras, Jamaica, Jordan, Kyrgyzstan, Madagascar, Malawi, Mali, Mongolia, Mozambique, Nicaragua, Pakistan, Panama, Philippines, Senegal, Sri Lanka, Tanzania, Thailand, Turkey, Uganda, United Arab Emirates, Zambia, Zimbabwe

Appendix 2: Variables and Data Sources

Series	Description	Source
AML risk	A jurisdiction's vulnerability to money laundering and terrorist financing and its capacities to counter it	Basel AML Index Report 2021
Financial Secrecy	How much scope for financial secrecy the jurisdiction's laws allow	Tax Justice Network: Financial Secrecy Index 2021 https://fsi.taxjustice.net
Corruption Perception	The perceived level of public sector corruption in a jurisdiction	Transparency International: Corruption Perceptions Index 2021 https://www.transparency.org/en/cpi/2021
Bribery Deterrence	Measures both formal and less formal ways in which bribery is enforced and discouraged in a jurisdiction	TRACE Bribery Risk Matrix 2021 https://www.traceinternational.org/trace-matrix
Corporate Transparency	Benchmarking of economies with respect to the regulatory best practice on the indicator	World Bank: Doing Business report 2020 https://www.worldbank.org/en/programs/business-enabling-environment/doing-business-legacy
Auditing Standard	Response to survey question: "In your country, how strong are financial auditing and reporting standards?"	World Economic Forum: Global Competitiveness Report 2019 https://www3.weforum.org/docs/WEF_TheGlobalCompetitivenessReport2019.pdf
Judicial Independence	Response to survey question: "In your country, how independent is the judicial system from influences of the government, individuals, or companies?"	World Economic Forum: Global Competitiveness Report 2019 https://www3.weforum.org/docs/WEF_TheGlobalCompetitivenessReport2019.pdf

Political Rights	Based on the electoral process, political pluralism and participation, and the functioning of government in each jurisdiction	Freedom House: Freedom in the World report 2021 https://freedomhouse.org/report/freedom-world
GDP per capita growth	Annual % growth rate of GDP per capita based on constant local currency	World Bank: World Development Indicators database 2020 https://databank.worldbank.org/source/world-development-indicators
Net Income from abroad	Includes net labor income (paid to nonresident workers) and net property and entrepreneurial income (investments income from ownership of foreign financial claims and nonfinancial property income)	World Bank: World Development Indicators database 2020 https://databank.worldbank.org/source/world-development-indicators
Export Volume	Ratio of the export value indexes to the corresponding unit value indexes (2000=100)	World Bank: World Development Indicators database 2020 https://databank.worldbank.org/source/world-development-indicators
Exchange Rate	Nominal effective exchange rate divided by a price deflator or index of costs (2010=100)	World Bank: World Development Indicators database 2020 https://databank.worldbank.org/source/world-development-indicators