The Latent Factors of Money Laundering Risk: A Cross-national Study

by

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Abstract

I present a new perspective on 'money laundering,' understanding it from a risk perspective using confirmatory factor analysis (CFA). I initially discuss the models studied so far in the money laundering and anti-money laundering literature, pointing out their shortcomings. I then set up my CFA model to identify the hidden factors of money laundering risk using observed variables across 203 countries. I compare my model with a competing data configuration proposed by the Basel Institute on Governance. I present a comprehensive application of CFA to understand how to combat money laundering risk and touch on the role of structural equation modelling in anti-money laundering policy-making. Using this method, I illustrate the hidden dimensions of money laundering risk. My findings will be useful for anti-money laundering policy experts around the world.

Keywords: Anti-money Laundering; Money Laundering; Structural Equation Modelling; Confirmatory Factor Analysis; Crime; Risk.

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All praise is due to Allah, the most beneficent and the most merciful. We praise the almighty and seek his forgiveness. Peace and blessings upon the final Messenger Muhammad (Sal.), upon his family, his noble companions, and all the believers. Aameen.

I am grateful for my mother, father, family, and all the loved ones who supported me to get into Canada for my higher studies. May Allah show his mercy upon all of them. Aameen.

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Table of Contents

List of Tables

List of Figures

List of Acronyms

AML	Anti-money Laundering
CFA	Confirmatory Factor Analysis
CFI	Confirmatory Factor Index
DF	Degrees of Freedom
FATF	Financial Action Task Force
FINTRAC	Financial Transactions and Reports Analysis Centre of Canada
FIU	Financial Intelligence Unit
ML	Money Laundering
RMSEA	Root Mean Square Error of Approximation
SEM	Structural Equation Modelling
STR	Suspicious Transaction Report
SWIFT	Society for Worldwide Interbank Financial Telecommunications
TLI	Tucker Lewis Index

Chapter 1.

Introduction

The global spread of money laundering (ML) crime is an unsettled business for many countries. Financial systems worldwide are actively combatting this crime by adding new regulations to prevent the facilitation of washing the proceeds of crime. However, launderers find new avenues in the global financial system to network their crime-related transactions. Consequently, through multiple layering processes, the proceeds of crimes are cleaned from the predicate offences and are ultimately reunited with the criminals. The term 'money laundering' is defined as "the process of transforming illegal assets into legal assets," and the process of ML falls into three stages, which are placement, layering, and integration (Schneider & Windischbauer, 2008). An example of ML would be an individual opening an offshore company in a tax haven with a lawyer's help to clean his illegally obtained cash. As the ML process has three steps, anti-money laundering (AML) experts are actively researching this field to know what constitutes ML. Despite the greyness in this field, AML experts have established measures to assess the risk of ML. The most prominent measure is the Basel AML Index, initiated by the Basel Institute on Governance.

The issue of 'money laundering' has put AML experts to research its various facets. The literature review that follows hints that a compelling strategic problem about ML is about measuring ML risk in Canada and globally. In other words, who, what, why, and where are the areas that we need to know regarding ML risk. The academic literature on ML and the AML offers a partial solution to measuring ML risk in Canada or globally through the Basel Institute on Governance AML index (2017). According to this index, Canada has a score of 5.14 on a 0-10 scale, where 0 indicates the lowest risk level, and 10 indicates the highest risk level of ML. As shown in Table 1.1 below, its counterpart, New Zealand, has a score of 3.91. On the other hand, Sri Lanka, a developing country, has a score of 7.15, and Afghanistan, a least developed country, has the worst score of 8.38. Thus, we see considerable variation in ML risk even within countries of a similar per capita income level. This paper aims to understand better how to measure ML risk by examining hidden factors and observed measurable variables. A wide array of hidden factors and observed measurable variables of 'ML risk' can be categorized by comparing them to the Basel Institute's data configuration. I classify plausible variables into the most important, somewhat important, and least important factors and observed measures from this exercise. Then, I use a statistical technique to present an optimized dimension of hidden (latent) factors and the most critical observed measurable variables. AML experts then can use my model to measure ML risk and design AML policies.

Table 1.1: Basel AML Score

Country	Development Status	Basel AML Score
Canada	Developed	5.14
New Zealand	Developed	3.91
Sri Lanka	Developing	7.15
Afghanistan	Least Developed	8.38

Note: Basel AML Score - 0-10 scale, where 0 indicates the lowest risk level, and 10 indicates the highest risk level of ML

The Basel data configuration appears to be state of the art in ML risk measurement. *The Basel data configuration's weakness is that it entirely relies on expert opinion*. My study will include variables that are subjectively-driven such as Transparency International's corruption score. However, my analysis aims to improve the 'entirely subjective' ML risk measure of the Basel Institute on Governance by incorporating a statistical methodology absent in the Basel model. To make my study more meaningful, I use the same statistical technique to the Basel model to check if my data configuration has improved upon the Basel's expert opinion data configuration. It is essential to make two critical points for the readers to show them the limitations of my study. First, this paper does not explore a causal theory but selecting commonly cited and plausible variables from the extant literature and finding data to see if I can improve the existing Basel data configuration, which relies on expert opinion. Second, I use a statistical technique to derive a more reliable and data-driven model and avoid other methods such as regression analysis. I avoid regression analysis as we do not have a clear dependent variable to provide evidence of causality.

My overarching **research question** is: Are the empirically observable measures of money laundering risk identified in the money laundering and anti-money laundering literature captured in the hypothesized latent factors of money laundering risk? Thus, this paper has three primary purposes. First, it aims to review the approaches used to measure ML risk. The

Basel model is the consensus state of the art in measuring ML risk. However, it is essential to show the readers the other models and methods available in the ML literature, point out their strengths and weaknesses, and use them to survey possible input variables that provide a more reliable and objective measurement for ML. Second, to identify the hidden factors and measurable or observable variables of ML risk from the literature for my exploratory data analysis. The words 'measurable,' 'indicator,' and 'observable,' and the words 'hidden' and 'latent' will interchangeably remain used in this paper. Third, this paper's empirical model will deliver findings to help AML policy experts in Canada and globally solve the problem at hand, mainly to measure ML risk. My academic contribution will allow for further investigation of causal relations among hidden factors and observed measurable variables in an a priori specified, theory-derived model.

In this paragraph, I will provide a snapshot of each chapter written in my paper. In **Chapter 2**, I cover the literature review. Chapter 2 includes two sub-section, which are academic literature and empirical literature review. I give substantial weightage to Chapter 2 because I try to find an area missing or unclear in ML and AML studies. So, my paper can be a useful contribution to the literature. **Chapter 3** proposes the method that I aim to use to solve the problem found in Chapter 2. Chapter 3 provides a comprehensive description of how I intend to interpret the results, the assumptions used, and why I use them. I am thoughtful of the audience; therefore, I present this chapter in an uncomplicated language because of the mathematical complexity associated with this paper's statistical technique. In **Chapter 4**, I begin with the analysis goals. Based on each goal set, I deliver the finding by reporting the statistical numbers and explain what it means to AML policy experts. Chapter 3 guides Chapter 4; in other words, I interpret the results based on the guideline given in Chapter 3. Accordingly, I advise readers to refer to Chapter 3 when reading the results and analysis section for clarity. In **Chapter 5**, I discuss the problems that I came across when I performed my empirical testing. The bulk of this chapter provides engaging details to AML policy experts based on my findings. Then, I reflect on my hypotheses, explain my work's contribution, and look at future research. Most of my tables and figures remain built within the text, and I offer the R's statistical output in the Appendix section. In the end, I give all the references used, including websites.

Chapter 2.

Literature Review

This section will look at what we know about this research topic, identifying areas that have remained studied inadequately or remain unclear and contradictory. The review will be chiefly from academic literature, including empirical reviews to spot potential gaps. I will discuss the competing theoretical models used to measure ML risk. From the literature, I will identify potential hidden factors and observed measurable variables useful for my exploratory data analysis within these models. The literature review will consider contributions from the AML policy experts around the globe. These steps will help me find the hidden factors and the observed measurable ML risk variables and bridge the gap between academics and AML policy experts regarding measuring ML risk.

2.1. Academic Literature Review

Most of the academic literature on ML is purely speculative in nature, trying to estimate the monetary value using an equation, and most of the equations are without underpinning theoretical models. Some literature refers to "estimates without ever mentioning the source and methods, and one source refers to the other source, without much empirical work" (Unger, 2007). An example of this is the study done by James et al. (2019). They estimate ML in British Columbia, Canada, by calibrating the Walker's Gravity Model. In contrast, my research aims to add a theoretical and empirical insight to the literature that illustrates the relationship between the hidden factors and observed measured variables to determine a method that can measure ML risk in Canada and globally. Indeed, a comprehensive social, economic, or criminological theory regarding ML is still missing on the academic side. The different approaches to examining the hidden factors and the observed measurable variables of ML risk are based on case studies, surveys, expert interviews, measuring indirect variables related to ML, and statistical and econometric models.

2.1.1. Field and Case Studies

One way to find out about what money launderers do, how they launder, and how they achieve the three stages of ML is to study prosecutions and criminal convictions of different countries. A case study can give us a rough idea of the money launderers' circumstances, motivations, and behaviours, allowing us to identify a few hidden factors and observed measurable ML risk variables. In the Netherlands, criminologists Meloen et al. (2003) analyzed 52 ML criminal cases to measure and estimate ML. Even before looking at the results, one should question this approach to measure and estimate ML. The main problem is that it is unclear about the data representativeness. "Do the 52 money laundering cases stand for .5 percent, 5 percent, 10 percent or 40 percent of the money launderers in the Netherlands?" Meloen et al. (2003). Are the money launderers caught representing all money launderers, or are only specific offenders caught within a certain range? (Unger, 2009). If I were to select the approach used by Meloen et al. (2003) to measure ML risk, there would be other questions. For instance, is the behaviour of the 52 cases representative of other launderers throughout the Netherlands or elsewhere? Another problem is that this approach omits the range of ML practices, social network analysis (SNA), and behavioural assumptions. Therefore, assumptions about representative behaviour that must combine with theories are still missing on the academic side.

Additionally, the 52 cases of Meloen et al. (2003) probably might reflect a selection bias because the authors do not explain their randomization technique. Hence, this may not reflect the actual population parameters, leading their estimations to be vulnerable. Moreover, his case study approach does not highlight or suggest any ML risk variables that I can use as measurable variables for my exploratory data analysis. In conclusion, I cannot use Meloen et al.'s approach to identify the hidden factors and the observed measurable ML risk variables because of the deficiencies identified above. As a result, while it offers some insights, this approach remains an unsuitable method for measuring ML risk.

2.1.2. Surveys and Expert Interviews

Another way to examine the hidden factors and the observed measurable variables of ML risk is to interview business individuals and experts from law enforcement. In 1992, the

AUSTRAC (Australian Financial Intelligence Unit) unit appointed John Walker (1995) to undertake the debut survey of expert opinions on the volume of ML. Walker wanted to find out what the average proceeds for each type of crime were. As with all surveys, Walker's approach remains limited by various biases, including that the sample might not be representative. The people interviewed or questioned might have had their own opinion biases. As Unger (2007) further critiques, "an example of this would be where there might be an overestimation of ML by the authorities responsible for combatting ML." At the same time, "there might also be an underestimation of ML by the same people if they felt that they were fulfilling their tasks properly."

In theory, surveys and expert interviews could be employed to identify the hidden factors and observed measurable ML risk variables. However, one must also anticipate response biases, non-response biases, and sample biases in this approach. Therefore, this approach remains an insufficient method for measuring ML risk.

2.1.3. Suspicious Vs. Unusual Transaction Reports

Another method of examining the hidden factors and the observed measurable variables of ML risk is analyzing suspicious or unusual transactions reported to the financial intelligence units (FIUs) (Unger, 2007). The FIU is an establishment for combatting ML in most countries. The advantage of using this method is that it allows us to identify the sources and roots of ML passing through banks and other financial institutions. Analyzing and investigating suspicious and unusual transactions with data analytics may give the researcher an edge to acquire knowledge about a few hidden factors and observed measurable ML risk variables. However, we need to know the difference between two key concepts, which are *risk-based systems* and *rule-based systems* for analyzing suspicious transactions across countries.

The government sets the threshold in a rule-based system, and every transaction that exceeds a certain threshold gets reported as suspicious of ML. In contrast, under the risk-based system, private organizations have to determine what they consider suspicious behaviour and then report the transaction according to their analytical capacity. However, depending on whether the country has a risk-based or rule-based system for reporting transactions, information overload can lead to delays in follow-up investigations into suspicious transactions (Unger, 2007). Overload here means organizations send suspicious transaction reports (STR) to the FIU for all transactions greater than $ 10,000.00. Therefore, imagine the volume if all Canadian financial institutions send STRs to the FIU greater than $ 10,000.00. The volume can be overwhelming, leading to delays and compromising the quality of the investigation.

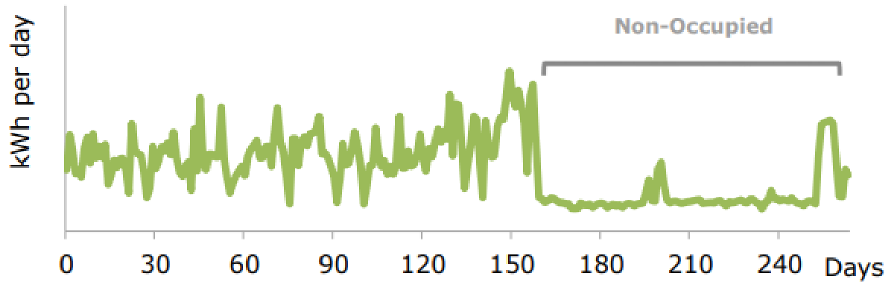
When looking at this approach, it appears that it may be more suitable for estimating ML in monetary terms. However, it has a low ability to detect the hidden factors and observed measurable variables of ML risk, and implementing this approach to measure ML risk can be time-consuming and expensive.

2.1.4. Measuring Proxy Variables

Using a proxy variable instead of using the original variable is an innovative way to identify hidden ML risk factors. A proxy variable is something you know about and intentionally include in the model to improve your results. To measure the (unobservable) total amount of illegal workers in Rotterdam, Van der Leun, Engbersen, and van der Heijden (1998) measured the amount of bread sold in districts where undocumented workers were likely to be living. "The total amount of bread sold in the districts was taken as a 'proxy' for the number of workers living there. This can be a little problematic because a particular part of the workforce may not be able to afford bread, may not like to consume bread or bake their bread, which biases the indicator. However, it happened that the sale of bread in the districts of Rotterdam, chosen for research, was significantly higher than the population recorded there could eat" (Van der Leun, Engbersen, and van der Heijden, 1998). As a result, their empirical findings concluded that the difference was the number of undocumented workers in the districts.

The use of a proxy variable technique perhaps could be useful to measure ML risk. For example, in March 2016, the City of Vancouver received a report with an analysis by Ecotagious based on BC Hydro electricity consumption data. The consultant's report found that approximately 4.8 percent of all the city houses were unoccupied for 12 months in 2014. Ninety percent of unoccupied homes were apartments and condos. As shown in Figure 2.1 below, their study estimates that approximately 10,800 homes in Vancouver were unoccupied for at least six months (City of Vancouver, 2016). In this instance, I can use electricity consumption to measure empty homes in the city. Therefore, 'empty homes' is a proxy variable by which we can infer that some of these empty homes are used for ML and speculation. I am making this assumption based on the research conducted by Gordon (2019), where he believes that money launderers typically do not declare much in income, and they often leave properties empty as they launder the money.

Figure 2.1: Empty Homes Estimation based on BC Hydro Data



Source: Ecotagious (2016)

The problem with using this as a proxy variable is that the empty homes' data are only estimates themselves based on BC Hydro data. The other problem with all proxy variables is that one does not know how close the proxy variable gets to the underlying variable that it tries to measure, in my case, which is the ML risk factor(s).

2.1.5. Observing Discrepancies in Statistics

Another method of identifying the hidden factors and the observed measurable variables of ML risk is to use statistical discrepancies or unusual statistical movements. For instance, if the exchange rate has unusual movements, it is potentially due to Hawala remittances. Hawala is money that does not go through the legitimate financial system, used as a cheap alternative to the SWIFT wire transfers. To learn the hidden ML risk factors, I believe that the following statistical discrepancies are relevant: errors and omissions in the balance of payments, differences in capital inflows and outflows, differences in money supply and money demand, and unusual price fluctuations in the real estate industry. Put practically, to understand ML in capital flight, the assumption is that errors and omissions arise primarily because of a failure to include specific private short-term capital movements. It is relevant to add them to the recorded flows of short-term capital to estimate total flows of 'hot money' (Schneider, 2006).

Tanzi (1996 and 1997) modifies four variables that determine the demand for money, such as income level, price level, payment habits, and the prevailing interest rate. Tanzi's variables appear to be promising for my study as he hypothesizes that an increase in the shadow economy will necessitate more cash, hence increasing the demand for currencies. Tanzi goes a step further to find a relationship between the amount of money printed and the money circulating in the US economy in 1984. Tanzi finds that US$5 billion had been circulating among drug dealers. Tanzi's approach to filtering ML risk variables using the currency demand approach shows us a new area. That is, to identify currency denominations offered by each country as a potential variable of ML risk to a country because criminals prefer to disguise their crime proceeds using larger denominations.

Similarly, Quirk (1997) attempts to estimate a correlation between ML and the demand for money from the IMF. In other words, he assumes that in corrupt countries, politicians loot tax revenue, other government incomes and borrow money from gatekeepers such as the IMF. Therefore, the more money demanded from the IMF by these corrupt nations, the more we can be confident that there is active ML. A major obstacle with the currency demand approach in countries in the Eurozone is that each country's money supply is not published because the European Central Bank issues the currency and does not disclose the money supply facts. Also, this means that all monetary issues related to ML are much more challenging to identify in the Eurozone (Unger, 2007).

In sum, one could argue that these approaches are more suited for measuring the monetary volume of ML in a country and not a helpful method to measure ML risk, and therefore, not feasible for my study. Additionally, these approaches can be expensive in collecting data. Therefore, the cost factor could limit the research to the country level and not allow a cross-national study.

2.1.6. Observing Abnormal Prices in the Real Estate Industry

Real estate can be a lucrative and welcoming business for launderers because it is easy to park the ill-gotten gains in this industry. However, an artificial increase in the housing market can also be due to pure speculation. An example of this is the price bubble, which caused the global financial crisis. Siegmann (2006) studies land registered prices in the City of Amsterdam. He finds that most of the city's houses changed owners several times within days and indicated unusual changes in prices. Some houses had a price eight times higher than the day before. From Siegmann's study, I observe that the primary measurable variable of ML risk in the City of Amsterdam appears to be the ease of doing business. Examples of 'ease of doing business' indicators include the time and cost required to enforce contracts, and additionally, the time and cost associated with buying and selling properties. In the City of Amsterdam, the ease of doing business related to real estate transactions are low. As a result, the real estate industry could attract launderers to clean their dirty money. Therefore, I can use the indicator variables from Siegmann's (2006) study in my exploratory data analysis. In other words, I want to check if these ease of doing business indicators capture any hidden factors of ML risk across countries. A few of the World Bank's Doing Business indicators include the time (days) taken to register a property and the cost taken to register a property.

Based on the preceding sections, one would notice that each author is attempting to contribute pieces of studies to the ML and AML literature. The nature of analysis in each section are case-specific, country-specific, or event-specific. None of these literature pieces have signalled me the right approach to measure ML risk. However, a few of them suggest some hidden factors and measurable variables that I can certainly include in my exploratory data analysis. For example, using the World Bank's Doing Business indicators as observed measurable variables appears to be a feasible way to identify the relationship between the observed measurable variables and the hidden factors. In the next section, I look at empirical studies to explore more hidden factors and measurable variables to develop an ML risk measurement model.

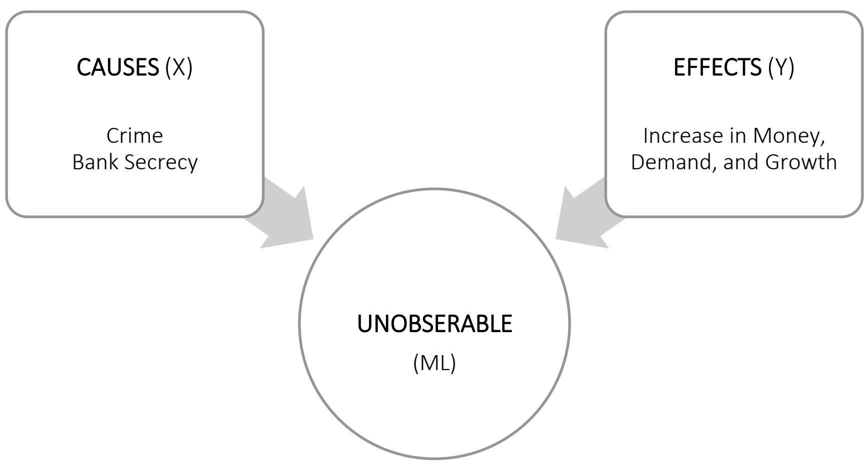
2.2. Empirical Literature Review

The empirical efforts in ML research established so far are from criminological lenses. This section will look at four popular empirical studies that exhibit and review statistical and other models used in ML research. Most of these models primarily estimate the monetary amount of ML, describe and instigate the behaviours of money launderers, and countries' behaviours to fight against transnational ML. These four models below do not have a sound theoretical underpinning. For instance, Unger (2007) criticizes Walker's Gravity model because it fails to embed a sound theory. However, the other models use some aspects from international trade theories and assumptions to justify their modelling. The next four sub-sections of the paper aim to review empirical approaches suggested by different authors to identify hidden factors and observed measurable ML risk variables.

2.2.1. Two-Sector Dynamic General Equilibrium Model

Schneider (2006) uses this approach to estimate the shadow economy of 145 countries. His approach is appealing because he uses the proxy variable technique to design his model, known as the dynamic multiple-indicators multiple causes (DYNAMIC) model. He uses two sets of observable variables and links them as a proxy to the unobservable variable. The 'cause' variable includes items such as regulations, taxation, and prosecutions.

Figure 2.2: Measuring Unobservable Variables



Source: Schneider (2006)

The other set is called the 'indicators,' which measures the 'effect,' that is, ML (unobservable). Figure 2.2 above demonstrates how the model serves. Tedds and Giles (2000) give a full description of this model under the assumption that all of the elements remain distributed normally and uncorrelated (for further explanation, see Tedds and Giles (2000)). Therefore, you can estimate ML by regressing the observables causes (proxies) on the observable effects (proxies). The model is expressed as follows with two equations:

$$y = a*ML + e \qquad (1)$$

$$ML = b*x + c \qquad (2)$$

Then you substitute (2) into (1), which is then expressed as follows:

$$y = a*bx + (a*c + e) \qquad (3)$$

This model has a simple logic behind it, that is, the use of proxy variables. However, there are a few problems that I see in Schneider's modelling. One of them is that cause and effect variables are arbitrary and not underpinned by a theoretical argument. The assumptions and statistical techniques are very sound. Therefore, they can be used as a potential approach in my study to figure out the hidden factors of ML risk based on proxy variables. In Schneider's study, he applies factor analysis to determine how well the different cause and effect variables can explain the unobservable variable. The most significant disadvantage of not using theoretical models is that statistics decide which factors form the relevant bundle for ML's causes and which are relevant to the effects of ML. In other words, statistics cannot replace theory. Nonetheless, this method allows checking for high correlations among the proxy variables to reduce the redundancies.

2.2.2. The Walker Model

Walker (1995) came up with a promising model to measure ML's monetary volume worldwide, known as the 'Walker Model.' The attractiveness index is a part of the Walker Model. It attempts to measure ML attractiveness for countries. If you look at his formula below, it suggests some interesting variables that I can use in my exploratory data analysis as observed measurable variables. For example, I can consider the corruption variable as an observed measurable variable of ML risk. He designs the attractiveness index as follows:

$$\textit{Attractiveness Index} = (\text{GNP per capita}) * (3 * BS + GA + SWIFT - 3 * CF - CR + 15)$$

Where: He assumes that a country can be more attractive to money launderers due to its higher GNP per capita, Banking Secrecy (BS), the Government's Attitude (GA) towards ML, SWIFT membership, higher levels, and high risk of conflict (CF), and a higher rate of corruption (CR). The constant 15 in the equation indicates that all attractiveness scores are favourable. He concludes that the higher the score, the more attractive the country is for launderers.

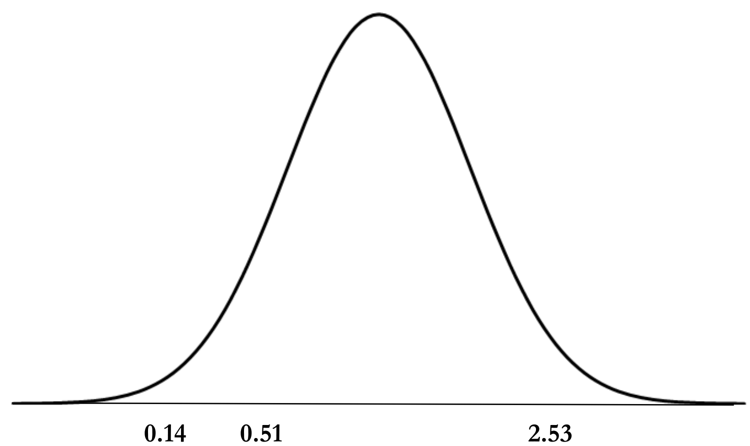
The model looks well formulated in terms of the assumptions. However, several arguments can arise if I use his model as a method to measure ML risk. Firstly, the model remains heavily criticized by Unger (2007) because it is 'ad hoc' and fails to carry a theoretical or methodological framework, overestimating the attractiveness figures. Secondly, Walker considers only the first phase of ML (i.e., the placement phase). The question then asked would be, do ML estimates, such as those generated by Walker's model, capture ML's three stages? Thirdly, it appears to me that Walker used his tacit knowledge (instincts) to calibrate his model. For example, if you look at his attractiveness index equation, the equation is multiplied by 3. He never explains why he uses 3, and I assume this is an outcome of trial and error estimation. In other words, his outcomes look predetermined, which means he might have had them in his mind before designing the model. Finally, the questions at hand are: How much can one trust the attractiveness index? Which theory supports it? After nearly a decade, Unger (2007) provides suggestions for improving the Walker attractiveness index by reconstructing the equation. Unger reconstructs Walker's attractiveness index by adding an international trade theory and by revising the variables. For instance, in the revised index, Unger adds a new variable named 'financial deposits.' The revised attractiveness equation is still controversial because it is impossible to assess the formula's quality, the fit's effectiveness, and its forecasting.

As mentioned earlier, James et al. (2019) use the Walker Model to estimate ML in British Columbia, Canada, to advise the provincial government on AML policy areas. Their AML policy recommendations were based on estimates derived from the Walker Model. Further, James et al. (2019) point out that the ML figures calculated by the RCMP and FINTRAC lacked the methodology component, explaining two crucial problems. First, the AML policy experts need a sound ML theory. Second, there is an ambiguity around how to measure ML risk in British Columbia. Often, authors use unclear theory, flawed justifications (such as the 3 and 15 added to Walker's attractive index) to derive at ML measurement. However, the policy papers seek to address problems in the absence of a sound theory, which transpires in many policy fields.

2.2.3. Abnormal Price Observation in Trade-based Money Laundering

The third empirical approach comes from Zdanowicz (2009), who linked ML with trade. His struggles to develop this method are from strong assumptions without any theoretical underpinnings. Zdanowicz's method is valid under the assumption that product prices (and product weights) remain normally distributed and that unusual prices hold a criminal intention.

Figure 2.3: Unusual Product Price for Identifying Trade-Based Money Laundering



Source: Unger (2009)

Unger (2009) explains his approach using a simple example. According to Figure 2.3 above, "it shows a product, let us say ketchup, which at an import price of .14 cents lies below the country's usual ketchup prices, which are between .51 cents and 2.53 cents. All transactions with a price below the 5th percentile (.51 cents) or above the 95th percentile (2.53 cents) remain classified as trade-based ML under the bell-curve" (Unger, 2009). Interestingly, Zdanowicz uses not only country prices but also world prices and variance measures to determine unusual transactions. His approach does not yield any contribution to my study because it has no linkage to finding hidden ML risk factors and measuring ML risk.

2.2.4. AML Policy and Crime Rates

The final empirical model developed by Ferwerda (2009) is a theory-based model following the Becker Tradition (1968). This model finds out whether AML policies reduce crime rates (see Ferwerda, 2009, for Becker's theory). In his model, he hypothesizes that "a) the probability of being caught for ML, b) the sentence for ML, c) the probability of being convicted for the predicate crime, and d) the transaction costs of ML are negatively related to the amount of crime. If all of these factors remain positively controlled by a stricter AML policy. In that case, the AML policy prevents potential criminals from illegal behaviour and therefore lowers the crime rate." He uses a unique dataset in his empirical estimation based on a Mundlak specification to prove that AML policy is unquestionably negatively correlated with crime rates. Ferwerda's estimation model is as follows:

$$\textit{Crime} = ß_0 + ß_1\text{Legal} + ß_2\text{Public} + ß_3\text{Private} + ß_4\text{International} + ß_5\text{Corruption} + ß_6\text{Common law}$$
$$+ß_7\text{Enforcement} + ß_8 \log(\text{GDP p/c}) + ß_9 \log(\text{GDP p/c}) + \text{E}$$

Where: *Crime* is the total crime rate of the country; *Legal* is the legal framework to fight ML; *Public* is the institutional framework to fight ML; *Private* is the duties of the private sector to fight ML; *International* is the international cooperation to fight ML; *Corruption* is the degree of control of corruption; *Common law* is a dummy variable for common law countries; *Enforcement* is a public enforcement index; *Log(GDP p/c)* is GDP per capita; *Log(GDP p/c)* is the average GDP per capita, and *E* is the error term for panel data. Now, if you look at his statistical model, there are a few variables that I can use as observed measurable variables of ML risk in my exploratory data analysis. For example, I may want to use per capita GDP, Legal, or Enforcement as observed measurable variables.

There are a few reasons why Ferwerda's (2009) method appears applicable and beneficial to my study. First, the main reason is that the theory reinforces the model, unlike any other empirical models that we reviewed above. Second, Ferwerda questions his model by asking whether his estimation model is relevant. Accordingly, he uses the Breusch and Pagan test to check the model's relevancy. Finally, "the estimations' results are described in terms of the association because the estimated effect is not per se a causal relationship. Thus, this opens more room for future research that can test the causality of the effect by showing Granger causality or using instrumental variables that would have a great deal of added value to the literature" (Ferwerda, 2009). Even though Ferwerda's approach looks applicable to my study, it is difficult to use it in ML risk measurement because finding a dependent variable is a challenging task to explain the causal relationships. As dependent variables can overlap with most ML risk variables (indicator or independent), an example of this would be the Basel AML Index.

Chapter 3.

Methodology

The academic and empirical reviews from above indicate that the studies on measuring ML risk are insufficient or shallow. We explored different approaches, such as: using case studies, surveys, expert interviews, and measuring indirect variables related to ML on statistical and other models. These were explored to examine the hidden factors and observed measurable ML risk variables. As discussed, there are major limitations concerning using these approaches to develop an ML risk measurement model. Thus far, in the empirical literature, the most reliable and exemplary methods are from Ferwerda (2009) and Schneider (2006). Ferwerda uses a theoretical model to support his econometric approach and employs regression analysis. On the other hand, Schneider uses proxy variables to measure unobservable variables, which are applicable to my study. I aim to use a similar and more advanced method for my study as Schneider (2006).

3.1. Method

In this section, I aim to address the following: explain what I am going to test and estimate; then discuss how I will perform the tests and estimates; and finally, explain how the results will be interpreted. Let us look at the first part of what I am going to test. As discussed in this paper's introduction, the term 'money laundering' has a broad definition, with many potential causal variables. As there remain numerous variables to consider, researchers are puzzled about which variables to choose to measure risk.. As a solution, I propose to break the concept of 'ML risk' into four clusters (factors), inspired by the factors suggested by the literature review. These factors are hidden or referred to as 'latent factors' or 'constructs,' which remain unobserved as directly affecting ML. I hypothesize observed measurable variables based on my beliefs and previous empirical works under each of these hidden factors. My primary belief is that these observed variables under each hidden factor have a common linkage. However, right now, we do not know if these hidden factors carry these variables. Meaning, do the observed variables capture the hidden factors?

Next, to answer the second part about how I will perform the test mentioned above, I use **confirmatory factor analysis (CFA)** from structural equation modelling to confirm the observable variables under the hidden factors. Babyak & Green (2010) state three critical attributes of the CFA method, which may be beneficial to mention at this stage, "a) to understand the structure underlying a set of observed measures; b) reducing redundancy among a set of measured variables by representing them with a fewer number of factors; and c) exploiting redundancy and, in so doing, improving the reliability and validity of measures." After I figure out the confirmed variables, I can statistically infer that a change in the hidden factor will change the observed variables. In other words, one standard deviation change in a hidden factor will change a measurable variable by X standard deviation points. Theoretically and statistically, these changes in the hidden factors should then explain ML risk for countries.

Why is my study essential, and how will it fill the missing empirical knowledge? The CFA method in this paper will reinforce my empirical testing and seek to improve upon the Basel's ML measurement model by grounding it in more concrete and measurable variables. Further, my theory will help AML policy experts to determine the following. First, to understand the relationship between and within the clusters of observable variables and their shared characteristics. Second, to help them research the few critical dimensions (latent factors) among the observed measurable variables. Third, the latent factors will potentially help the AML policy experts focus on the macro-level variables to reduce the ML risk through pro-active policies that target them.

3.2. Theoretical Approach

In CFA, "we start with an explicit hypothesis about the number of factors (in my paper which is equal to 4), observed measures, the parameters of the model such as weights and loadings, and constraints" (Babyak & Green, 2010). The four hypothesized factors in my paper are derived from substantive theories or beliefs (see Table 3.1 below). By imposing constraints, we are forcing the model to be consistent with the theory (Babyak & Green, 2010). In other words, researchers impose constraints on a factor model based on a priori hypotheses about measures (Babyak & Green, 2010). To rationalize my substantive theories or beliefs, I use a data configuration similar to that used by the Basel Institute to categorize the factors' observed measures or indicators.

Table 3.1: Hypotheses

H1: A factor called the economy and financial system (F_1); underlies the observed variables from X_1 to X_{13}.
H2: A factor called the financial transparency and standards (F_2); underlies the observed variables from X_{14} to X_{18}.
H3: A factor called the political and legal (F_3); underlies the observed variables from X_{19} to X_{21}.
H4: A factor called the public sector transparency and accountability (F_4); underlies the observed variables from X_{22} to X_{25}.

Note: See Table 3.2 below for the observed variables.

The literature review hints at potential observed measurable variables of ML risk. For example, Walker's (1995) ML attractiveness index has the following variables: GNP per capita, Banking Secrecy (BS), the Government's Attitude (GA) towards ML, SWIFT membership, risk of conflict (CF), and corruption rate (CR). Additionally, when Ferwerda (2009) finds out whether AML policies reduce crime rates, he uses independent variables that are somewhat similar to Walker's attractiveness index variables. Ferwerda (2009) includes the following independent variables in his data configuration: the legal framework to fight ML, the institutional framework to fight ML, the duties of the private sector to fight ML, the international cooperation to fight ML, the degree of control of corruption, and GDP per capita. Based on these observed variables from the literature review, I aim to translate them as measurable variables of ML risk for my exploratory data analysis. Then see if those observed measurable variables seem to capture underlying latent factors of ML risk. Table 3.2 below summarizes the measurable variables (X_1 to X_{25}) of ML risk. It incorporates a few other indeterminate measurable variables that can potentially capture the presumed factors hypothesized in Table 3.1 above.

Within the context of the hypotheses in Table 3.1 above, we postulate that four factors called (F_1, F_2, F_3, and F_4) determine the observed measures in Table 3.2. For example, we postulate that a factor called "Political and Legal" (see Table 3.2) determines the observed scores on freedom of the press, the rule of law index, and the WEF Global Competitiveness Report - Institutional pillar measures (as well as error). Statistically, the belief is that these three measures are correlated because they have a common latent factor called "Political and Legal" (Babyak & Green, 2010). As mentioned earlier, the model reflects the belief that changes in the unobserved latent variable, "Political and Legal," is presumed to result in changes in the three variables that we have measured. The same logic applies to all four factors in my model and for the factors in the Basel data configuration. I present the variables and factors of my model in Table 3.2 below.

Table 3.2: Factor and Measurable Variables of Money Laundering Risk

Factors	Measurable Variables
F_1 - The Economy and Financial System Factor	X_1- International migrant stock X_2- Automated teller machines (per 100,000 adults) X_3- Commercial bank branches (per 100,000 adults) X_4- Battle-related deaths (deaths in the past 20 years) X_5- Starting a Business - Procedures (average for men women) X_6- Starting a Business - Time (average for men and women) X_7- Starting a Business - Cost - (% of income per capita) (average- men and women) X_8- Registering Property - Time (days) X_9- Registering Property - Procedures X_{10}- Enforcing Contracts - Time (days) X_{11}- Per capita GDP US$ X_{12}- Denominations by country (equivalent and/or greater than US$100) X_{13}- Life expectancy at birth
F_2 - Financial Transparency and Standards Factor	X_{14}- Egmont group member X_{15}- Personal remittances, paid (US$) X_{16}- Personal remittances, received (US$) X_{17}- Financial secrecy index X_{18}- WEF Global Competitiveness Report - Strength of auditing and reporting standards
F_3 - Political and Legal Factor	X_{19}- Freedom House: Freedom in the World and Freedom and the Media X_{20}- World Justice Project, Rule of Law index (Central bank independence) X_{21}- WEF Global Competitiveness Report - Institutional pillar
F_4 - Public Sector Transparency and Accountability Factor	X_{22}- World Bank transparency, accountability, and corruption in the public-sector rating X_{23}- International Budget Partnership Open Budget Index - Budget transparency X_{24}- International IDEA Political Finance Database - Political disclosure X_{25}- TI corruption score

Note: All 25 variables account for the year 2017.

Here is a different way of understanding the relationship between my hypotheses and the confirmatory factor analysis method. We can ask if the measurable variables in Table 3.2, above, from X_1 to X_{13}, each uniquely pose a risk for ML? In response to the question, I will first need to evaluate whether the relationships from X_1 to X_{13} allow us to interpret these observed measures as manifestations of a general "economy and financial system" latent factor. According to Babyak & Green (2010), "such an analysis might support the general factor conjecture but also might indicate that some measures are better than others in assessing it. Alternatively, we might discover more than one dimension or even that the measures are too distinct to be jointly related to latent factors. CFA is ideally suited to address these types of questions."

Table 3.3 below demonstrates the Basel Institute's presumed factors and observed measures, which are comparable to the latent factors and observed measures in my model (see Table 3.2). However, I like to explain why I want to compare my model to the Basel model. The Basel Institute on Governances' AML experts have logically designed their model, which prompts me to compare it with my model. Additionally, one may ask how my model improves upon the Basel model. If you compare Table 3.2 and Table 3.3, you will notice that I have 11 more variables than the Basel model. Therefore, the additional variables can potentially capture hidden factors, which are not captured by the Basel model.

Table 3.3: Basel Institute Factor and Measurable Variables of Money Laundering Risk

Factors	**Measurable Variables**
F_1 - Quality of AML Framework Factor	X_1- FATF Mutual Evaluation Reports X_2- US State Department International Narcotics Control Strategy Report (INCSR) X_3- Financial secrecy index
F_2 - Bribery and Corruption Factor	X_4- TI corruption score
F_3 - Financial Transparency and Standards Factor	X_5- Doing Business Ranking (World Bank) Business extent of corporate transparency X_6- WEF Global Competitiveness Report - Strength of auditing and reporting standards X_7- WEF Global Competitiveness Report - Regulation of securities exchanges X_8- World Bank IDA Resource Allocation Index - Financial sector regulations
F_4 - Public Transparency and Accountability Factor	X_9- International IDEA Political Finance Database - Political disclosure X_{10}- International Budget Partnership Open Budget Index - Budget transparency X_{11}- World Bank transparency, accountability, and corruption in the public-sector rating
F_5 - Legal and Political Risks Factor	X_{12}- Freedom House: Freedom in the World and Freedom and the Media X_{13}- WEF Global Competitiveness Report - Institutional pillar X_{14}- World Justice Project Rule of Law Index

Note: As I decided to drop X_4; therefore, the "Bribery and Corruption" factor moves out from the model. Consequently, F_3 becomes F_2, F_4 becomes F_3, and F_5 becomes F_4 (see the introduction to 'Results and Analysis' section below for the reason as to why I am dropping X_4). **Source**: Basel Institute on Governance (2017).

3.3. Data

My study positions itself in an international playfield. I aim to use quantitative data from 203 countries (N) to derive the observed measurable variables that capture latent factors for ML risk across countries. Therefore, the dataset is cross-sectional because all of the observations are from the same point in time (i.e., 2017) and represent different individual economic entities. The majority of my dataset variables are from organizations such as the World Bank and the UN, which confirms data validity as they are from trusted sources. For example, I have six variables that come from the World Bank's Doing Business indicators. A few variables in the Basel and my dataset had missing data for some countries. Therefore, I used the 'multiple imputation' technique built in the '*Amelia*' package in R programming language software. 'Multiple imputation' is a technique used to replace missing values with substitute values.

There are two similarities between this paper's dataset and the Basel Institute's dataset. First, both datasets have the same sample size. Second, around eight indicator variables overlap between the two datasets. Additionally, I have rescaled the source's raw data to run from 1-10 using the Min-Max method. The Basel Institute uses the same rescaling approach for its dataset (Basel Institute on Governance, 2017).

3.4. Interpretation of Results - Method

In CFA, there are three components to analyze, 1) the model specification, 2) the model estimation, and 3) the assessment of the fit between the specified model and the data. Before going into the 'interpretation of results' method for model estimates and the assessment of fit, we need to cover some universal assumptions used in CFA.

3.4.1. Universal CFA Assumptions

First, the factor variance will remain constrained to one as Babyak & Green (2010) states that "the metric constraint is often a bit mysterious to CFA structural equation modelling." It stands mysterious because the "metric of the factor is arbitrary, and the latent variable has no inherent metric or scales. For example, we would not know whether a factor representing length stays measured in inches, feet, or meters" (Babyak & Green, 2010). As a result, CFA researchers recommended fixing the variance of the factor to one. Additionally, Babyak & Green (2010) mentions that "fixing the variance of a factor to one, essentially defines the units of the factor to be in Z-score (conventional standardized) units." Therefore, the factors' variance will remain constrained to one for all the models in the paper (i.e., $\sigma^2_{F1} = 1$; $\sigma^2_{F2} = 1$; $\sigma^2_{F3} = 1$; $\sigma^2_{F4} = 1$) (Babyak & Green, 2010).

Second, we look at factor covariance. We constrain factor covariance to zero if the factors are uncorrelated and leave it free when the factors remain correlated in the model specification. Third, to obtain proper estimates of the model parameters, it makes sense to constraint all covariance between errors to remain zero. (Babyak & Green, 2010). Last, suppose I obtain any negative loadings from my models' outputs. In that case, I aim to reverse code the raw data of such variables. Getting negative loadings in CFA models is a common phenomenon. Therefore, CFA researchers have strongly suggested reverse coding of the raw data (Brown, 2006).

3.4.2. Interpretation of Estimates

The equation below shows a measurable variable, which remains randomly selected from Table 3.2 above. The lambdas (λ) in the equation below is the factor weights or loadings, which can be interpreted essentially like regression coefficients (Babyak & Green, 2010). In my study, if you take factor one, for example, for every 1-unit increase in the "Economy and Financial System" factor, F_1, the expected change in 'Registering Property - Time (days),' X_8, will be λ_8.

$$X_8 = \lambda_8 F_1 + 0\ F_2 + 0\ F_3 + 0\ F_4 + E_1$$

However, as I noted in my discussion earlier, the factors have no defined units. In other words, one standard deviation change in a latent variable without an inherent metric or scales is still substantively meaningless. Therefore, *the true meaning comes when the factor loadings are compared to each other*; this allows the researcher to determine which variables load most on which factors and which load least. The results of my study come to light at this stage when I try to find the observed measurable variables that load more on the latent factor, which, in turn, will capture the latent factors of ML risk. Additionally, we will be using the standardized factor loading for evaluation in our analysis as it is one of CFA's universal norms. The advantage of selecting the standardized factor loadings is because the loadings remain standardized by the standard deviation of both the predictor (the factor, F) and the outcome (measurable variable, X). Last, as for any p-value interpretation, we would consider a loading statistically significant and confirmed under the factor if the p-value remains less than .05.

3.4.3. Measures of Fit Interpretation

Before looking into the interpretation of the fit measures, it would be logical to introduce the measures of fit used in CFA. There are several statistical measures available to test the fit of the model in CFA. However, as far as most of the structural equation modelling research using CFA is concerned, researchers have frequently used four popular statistical measures, which are as follows: a) Model Chi-Square χ^2, b) Confirmatory Factor Index (CFI), c) Tucker Lewis Index (TLI), and d) Root Mean Square Error of Approximation (RMSEA). We consider CFI and TLI as an incremental or relative fit index and RMSEA as an absolute fit index from the four measures above. The difference between the two will remain explained below.

Table 3.4: Measures of Fit Commonly Reported in CFA

Measure	Name	Description	Cut-off for good fit
χ^2	Model Chi-Square	Assess the overall fit and the discrepancy between the sample and fitted covariance matrices. Sensitive to sample size. H_0: The model fits perfectly.	p-value> .05
CFI	Confirmatory Factor Index	A revised form of TLI. Not very sensitive to sample size. Compares the fit of a target model to the fit of an independent or null model.	CFI ≥.90
TLI	Tucker Lewis Index	A TLI of .95 indicates the model of interest improves the fit by 95% relative to the null model.	TLI ≥ 95
RMSEA	Root Mean Square Error of Approximation	A parsimony-adjusted index. Values closer to 0 represent a good fit.	RMSEA < .05

Source: Parry (2020).

Table 3.4 above summarizes the four measures of fit and showing the cut-off for a good fit in the last column. In the next few paragraphs, we will explore more on these measures. Naturally, the cut-off for good fit criteria explains how to interpret the results of the fit measures.

However, at this stage, it is necessary to mention a few measurement properties that will remain applicable to the 'measures of fit' calculation below. Among them, the first one, the computation of known values. The known values derive from the population variance-covariance matrix Σ, given by the formula p $(p+1)/2$, where p is the number of indicators or measurable variables.

Next, the computation of the degrees of freedom (df), which is as follows:

$$df = \text{number of known values - number of free parameters}$$

To calculate the number of free parameters, we need to sum the lambdas (λ) (the factor loadings or coefficients) with the residual (error) variance.

The final measurement property is model identification. For model identification, we use the variance standardization method (fixes each factor's variance to 1 but freely estimates all loadings) instead of the marker method (fixes each factor's first loading to 1). In exceptional situations, we use the marker method to avoid high standard errors in the factor loadings. If we obtain positive df, then the model stands identified. The goal is to maximize the df so that the model becomes identified. If the df is zero; then, we call it a saturated model, and if it is negative, then we call it an under-identified or flawed model (UCLA Statistical Consulting, 2020).

We require a minimum of three measurable variables per factor for an uncorrelated CFA model to result in a saturated model where the number of free parameters equals the number of elements in the variance-covariance matrix (i.e., the degrees of freedom is zero) (Lee, 2019). However, in some cases, the model fails to compute factor loadings and standard errors when saturated; in such instances, we equate the three loadings under such factor that prevents model identification. For example, we would equate ($\lambda x_9 = \lambda x_{10} = \lambda x_{11}$) from the uncorrelated Basel model to avoid potential 'computation denials' as three factors have three observed measurable variables each. "The limitation of doing this is that there is no way to assess the fit of this model. For example, suppose we have the following hypothetical model where the true λ_9=.8 and the true λ_{10}=.2. If we fix $\lambda_9=\lambda_{10}$, we will obtain a solution, not knowing that the model is a completely false representation of the truth since we cannot assess its fit. It is always better to fit a CFA with more than three items and assess the fit of the model unless cost or theoretical limitations prevent you from doing otherwise" (UCLA Statistical Consulting, 2020). Now, we will look at how we aim to interpret the four measures of fit.

Model Chi-Square - We can assess the hypothesis that the researcher's model is correct in the population. "More specifically, we can ask whether the reproduced covariance matrix based on the model $\sum_{\text{Model}}$ (estimated model) is equal to the population covariance matrix among the measures $\sum$" (Babyak & Green, 2010). As shown in the equation below, the null hypothesis, H_0, states the model-implied (reproduced covariance matrix) and population covariance matrices are equal. In contrast, the alternative view, H_A, indicates that these two matrices are different (Babyak & Green, 2010).

$$H_0: \sum - \sum_{\text{Model}} = 0$$

$$H_A: \sum - \sum_{\text{Model}} \neq 0$$

In general, rejecting a null hypothesis is good; however, it is the opposite in CFA models because if we reject the null, we are rejecting our model. "Failing to reject the model is good for our model because we have failed to disprove that our model is bad. Based on the logic of hypothesis testing, failing to reject the null hypothesis does not prove that our model is the true model, nor can we say it is the best model because there may exist many other competing models that can also fail to reject the null hypothesis. However, we can certainly say it is not a bad model, and it is the best model we can find at the moment" (UCLA Statistical Consulting, 2020). Additionally, if you look at CFA model research papers, the goal of equalizing the model-implied covariance matrix with the population covariance matrix is nearly impossible.

Further, if the p-value is less than .05, we reject the null, which means the researcher's model fails to fit the data well. The phrase 'fit the data' here means the model should be consistent with our substantive theory or beliefs (Babyak & Green, 2010). In other words, if we hypothesize a factor to capture variables from X_1 to X_{13} and then run the model, the results (i.e., factor loadings) should be high (usually >.4), which will then prove that the model is consistent with our substantive theory. A point to note here is that according to Kline (2016), model chi-square is sensitive to large sample sizes. However, the question is, what is the recommended sample size? Kline (2016) responds to it by stating that a model that has a sample of fewer than 100 cases is untenable and suggests 20 observations for one measurable variable.

CFI and TLI - When we consider these two measures of fit, we must understand the meaning of incremental or relative fit index. Historically, in the structural equation modelling literature, model chi-square was the only measure of fit, "but in practice, the null hypothesis stays often rejected due to the chi-square's heightened sensitivity under large samples. Approximate fit indexes that stay not based on accepting or rejecting the null hypothesis remained developed to resolve this problem. Approximate fit indexes can remain further classified into a) absolute and b) incremental or relative fit indexes. An incremental fit index (or relative fit index) assesses the ratio of the user model's deviation from the worst fitting model (or baseline model) against the saturated model's deviation from the baseline model. Conceptually, if the deviation of the user model is the same as the deviation of the saturated model (or best-fitting model), then the ratio should be 1, which is the goal. In other words, the more discrepant the two deviations, the closer the ratio is to 0" (UCLA Statistical Consulting, 2020).

RMSEA - The RMSEA measure of fit compares the user model against the observed data, in contrast to CFI and TLI, which compares against the baseline model.

$$\text{RMSEA} = \sqrt{(\delta/df(n-1))}$$

Where: $\delta = \chi^2 - df$

The cut-off for good fit according to Kline (2016) is RMSEA ≤ .05. RMSEA between .05 and .08 (reasonable approximate fit, fails close-fit but also fails poor-fit), and >= .10 (poor-fit).

Chapter 4.

Results and Analysis

This section's goals are: 1) specify the model, 2) perform model estimates, and 3) assess the fit between the specified model and the data using the four priori hypotheses specified in Table 3.1. Then, repeat the same exercise to the data configuration proposed by the Basel Institute in Table 3.3. In terms of the tests, I will first analyze the results of an uncorrelated (orthogonal) four-factor model specification with 25 measurable variables, which I will call 'Researcher Model 1.' Then, compare it with the correlated (oblique) version of the same four-factor, 25 measurable variables model specification, which will be called 'Researcher Model 2.' Next, perform a similar exercise for the Basel Institute's four-factor, 14 measurable variables model specification. The uncorrelated Basel model will be called 'Basel Model 1' and the correlated Basel model will be called 'Basel Model 2.' After we have the two competing models' results, we will look if the model proposed in this paper fits better with the data than the Basel Institute's model. Additionally, after each model's results, I aim to provide the model's implications to the AML policymaking. You will notice that Table 3.3 above shows five factors, and my previous sentence mentions a four-factor model for the Basel Institute. The Basel Institute's model will remain forced to be four-factor because if you look at factor number two, which is "Bribery and Corruption," there is only one measurable variable under this factor. It would be illogical to work with a factor that has only one variable.

This paragraph will explain the logical progression of how researcher model 1 becomes 2, and how Basel model 1 becomes 2. First, the common features in the researcher model and Basel model are uncorrelated and correlated factors. Second, both models have four factors each. In both models, the transition occurs from being uncorrelated to then becoming a correlated model. Therefore, one may ask what an uncorrelated versus a correlated model says about measuring ML risk. In response to this question, an uncorrelated factor model means that the four hidden ML factors are independent, and they do not have any interconnections within the model. In other words, the measurable variables under each of the ML hidden factors will only capture its respective hidden factor. E.g., X_1, the 'International migrant stock' observable variable (see Table 3.2) will only capture F_1 "The Economy and Financial Systems" factor. X_1 will not capture F_2, F_3, or F_4. The same logic applies to the uncorrelated Basel model. Then, I transition from uncorrelated to a correlated model (i.e., from researcher model 1 to 2 and Basel model 1 to 2. Correlated models have the exact opposite meaning. Now, X_1, the 'International migrant stock' variable, has the tendency to capture the other three hidden ML factors (F_2, F_3, and F_4) in the model due to potential cross-loading between the hidden factors and the observable variables. Again, the same logic applies to Basel's correlated model. Finally, I look at how we can improve the researcher models (1 or 2) for AML policy experts. When determining a revised model, which I call 'Researcher Model 3,' my decision to correlate or uncorrelated the hidden ML factors depends on the model fit performance of researcher models 1 and 2. Importantly, I will consider only the factor loadings that remain >.4 and statistically significant at the .05 significance level from the researcher model(s) (Brown, 2006).

What are the statistical measures that one would look to interpret CFA results? As mention earlier in Chapter 3, there are four popular statistical measures reported in CFA research, which are: Model Chi-Square; Confirmatory Factor Index (CFI); Tucker Lewis Index (TLI); and Root Mean Square Error of Approximation (RMSEA). These statistical measures will tell the reader how good a model is. See Chapter 3 for the detailed explanation of each of these statistical measures. I report these results in Table 4.2 below. Additionally, we need to interpret factor loadings (coefficient estimates) for CFA models, which are interpreted based on the statistical significance at the .05 significance level. Table 4.1 below shows the factor loadings, where statistically significant loadings are marked with an asterisk. Chapter 3 is a guideline for Chapter 4; therefore, it is important to seek knowledge about CFA terminologies from the preceding chapter when reading the next sections. Finally, readers will need to refer to the Appendix section that presents a comprehensive output of the results shown in Table 4.1 and 4.2.

4.1. Researcher Model 1 - Uncorrelated

4.1.1. Known Values, Parameters, Degrees of Freedom, and Estimates

First, we will look at the known values for this model from the observed population variance-covariance matrix Σ, given by the formula $p\,(p+1)/2$. Therefore, with 25 measurable variables, the number of known values is $25(25+1)/2 = 325$. Second, we look at the parameters for this uncorrelated model. As the factors are orthogonal, the factor covariances remain zero. Third, to calculate the number of free parameters, we need to sum the 25 (λ) lambdas (the factor loadings or coefficients) with the 25 residual (error) variance, which adds up to 50. Using the df formula above, we can tell that the df equals 275 (325 - 50). Fourth, we need to assess if the model remains identified. For model identification, we use the variance standardization method (fixes the variance of each factor to 1 but freely estimates all loadings) instead of the marker method (fixes the first loading of each factor to 1). Since the df is positive for researcher model 1, we can claim that this model stands identified.

Before moving on to the model fit statistics, we need to comment on the lambdas (λ). As shown below in Table 4.1, column 3 below, the 'ATMs' measurable variable has a factor loading (coefficient estimate) of .717, which is statistically significant at the .05 significance level. Further, it is important to evaluate the coefficient estimate's standard error to determine if their magnitude is appropriate. We can calculate the 95% confidence interval of the standardized parameter estimate by adding and subtracting the estimate by the product of 1.96 times the standard error (see Appendix A). For example, the 95% confidence interval of the 'ATMs' factor loading is .552 to .882; that is, $.717 \pm 1.96(.084)$. Essentially, we interpret this as indicating that we are 95% probable that the true population value of this parameter is between .552 and .882. Again, if you look at Table 4.1, column 3, you will notice that out of the 25 measurable variables, 23 of them remain statistically significant at the .05 significance level. Also, to make the factor loadings meaningful, we have to compare each loading with the other loadings and determine if they stay confirmed under a factor. To evaluate this, we consider factor loading >.4, and in this case, we have 17 loadings that are >.4; therefore, they stay confirmed under their respective latent factors.

4.1.2. Model Fit Statistics of Researcher Model 1

Model Chi-Square - Looking at Table 4.2 below, we can see the p-value is less than .05, and therefore, we have to reject the null, which means researcher model 1 fails to fit with the data well. Also, the researcher model 1 has a higher Test-statistic (2453) than the other three models, indicating the data do not fit well with the model. We noted that the model chi-square stays sensitive to large sample sizes. In researcher model 1, we have approximately eight observations (203(N)/25) per measurable variable, which about half of what has been recommended by Kline (2016) for sample size.

Table 4.1: Standardized Lambda Coefficient Estimates (Factor Loadings)

Indicator Variables	Latent Factor	Researcher Model 1	Researcher Model 2	Basel Model 1	Basel Model 2	Researcher Model 3
1. International	RF1	0.379*	0.352*	-	-	-
2. Life	RF1	0.760*	0.730*	-	-	0.726*
3. Egmont	RF2	0.742*	0.379*	-	-	0.453*
4. Freedom	RF3, BF4	0.486*	0.596*	0.486*	0.618*	0.601*
5. TI	RF4	0.865*	0.976*	-	-	0.976*
6. ATMs	RF1	0.717*	0.662*	-	-	0.689*
7. Battle	RF1	0.428*	0.460*	-	-	-
8. Commercial	RF1	0.506*	0.430*	-	-	0.478*
9. AProcedures	RF1	0.431*	0.465*	-	-	-
10. ATime	RF1	0.301*	0.327*	-	-	-
11. ACost	RF1	0.437*	0.501*	-	-	-
12. NProcedures	RF1	0.261*	0.266*	-	-	-
13. Register	RF1	0.242*	0.288*	-	-	-
14. Enforce	RF1	0.232*	0.240*	-	-	-
15. GDP	RF1	0.799*	0.841*	-	-	0.883*
16. RemittencesP	RF2	0.226*	0.277*	-	-	-
17. RemittancesR	RF2	0.149	0.088	-	-	-
18. Transparency	RF4, BF3	0.843*	0.743*	0.097*	0.783*	0.739*
19. Rule	RF3, BF4	1.302*	0.944*	1.302*	0.972*	0.934*
20. Secrecy	RF2, BF1	0.514*	0.443*	1.005*	0.674*	-
21. Denominations	RF1	0.570*	0.515*	-	-	0.545*
22. Disclosure	RF4, BF3	0.057	0.019	0.361*	0.012	-
23. Budget	RF4, BF3	0.562*	0.518*	0.193*	0.599*	0.523*
24. Auditing	RF2, BF2	0.467*	0.681*	0.936*	1.003*	0.784*
25. Quality	RF3, BF4	0.592*	0.821*	0.592*	0.788*	0.825*
26. FATF	BF1	-	-	0.452*	0.480*	-
27. Narcotics	BF1	-	-	0.147*	0.200*	-
28. CorT	BF2	-	-	0.138	0.094	-
29. SecEX	BF2	-	-	0.892*	0.832*	-
30. FinSec	BF2	-	-	0.546*	0.505*	-

Note: RF - Researcher model factors, and BF - Basel model factors. *$p<0.05$
See Appendix F the full representation of each indicator variable.

CFI and TLI - For researcher model 1, the CLI and TLI are way below the cut-off for a good fit, as shown in Table 4.2 below. The ratios .268 (CLI) and .198 (TLI) explains to us that there is a significant discrepancy between the two deviations. **RMSEA** - In the case of researcher model 1, N = 203, df = 275, χ^2 = 2452.88. Therefore, if we fit the values to the formula (√((2452.88-275)/275(203-1))), we would get an RMSEA of .198. Looking at the RMSEA of researcher model 1, we can see that it falls into the poor fit category, according to Kline (2016).

Table 4.2: Model Fit Statistics

Measures	Cut-off for Good Fit	Researcher Model 1	Researcher Model 2	Basel Model 1	Basel Model 2	Researcher Model 3
1. Model Chi-Square χ^2	p-value > .05	.000 *(2453)	.000 *(1541)	.000 *(1025)	.000 *(631)	.000 *(449)
2. Confirmatory Factor Index (CFI)	CFI ≥.90	.329	.608	.413	.650	.813
3. Tucker Lewis Index (TLI)	TLI ≥ 95	.268	.563	.326	.545	.753
4. Root Mean Square Error of Approximation (RMSEA)	RMSEA < .05	.198	.153	.263	.217	.180

Note: *Test-statistic

4.1.3. Implications of Researcher Model 1 to AML Policy

Although we reject researcher model 1 statistically, we can draw some conclusions, which may be useful for AML policy experts. If you look back at the 'method' section under methodology, I highlighted three key benefits of this study to AML policy experts. First, to understand the relationship between and within the clusters of observable variables and their shared characteristics. In researcher model 1, we can only examine the relationship and shared characteristics within the clusters or factors as the model remains uncorrelated. For example, if we consider factor 4, the "Public Sector Transparency and Accountability Factor," it has four measurable variables. However, only three out of the four have a certain degree of commonality within them because only three measurable variables load commonly and significantly to factor 4. Second, 17 out of the 23 statistically significant loadings confirm the four critical dimensions or the latent factors, forcing AML experts to research and study more on the 17 confirmed observable variables and the four latent factors. Finally, this may mean that the AML policy experts can use the confirmed observable variables as independent variables to perform a regression analysis to measure ML risk by factors with appropriate dependent variable(s).

It may be interesting to see the descriptive statistics of the highest loaded observed measures of researcher model 1 based on the raw data. From Table 4.1, we can see that the top five loadings are 'Rule' (1.30), 'Transparency' (.84), 'GDP' (.79), 'TI' (.86) and 'Life' (.76). We can now make a meaningful connection between these highest loaded measures and their raw data by countries. For instance, if you select the GDP measure from Table 4.3 below, you notice that the mean is \$14,054.73 (average GPD), and the standard deviation is \$18,518.72. The standard deviation explains to us that most of the countries are far away from the average GDP. You can verify it by looking at the difference between Canada's GDP versus Sri Lanka's GDP. Likewise, I have calculated the descriptive statistics for the other four highest loaded measures for researcher model 1. For consistency, I have used the same four countries in Table 1.1, Chapter 1. The descriptive statistics help us see if the CFA results are intuitively plausible and illustrate data distribution. Canada's ML risk position within developed countries' cluster looks satisfactory in terms of the top five loadings' raw data. For instance, if you compare the five indicator variables in Table 4.3 below, you would notice that Canada and New Zealand are close in each score with small differences. However, the differences increase when compared with developing countries like Sri Lanka.

Table 4.3: Descriptive Statistics of Observed Measures

	Rule	Transparency	GDP	TI	Life
Mean	.55	3	14,054.73	44.42	72.37
SD	.15	.95	18,518.72	19.09	8.54
Canada	.81	4.73	45,032.12	82	82
New Zealand	.83	5.23	42,940.57	89	81
Sri Lanka	.52	2.73	4,073.73	38	77
Afghanistan	.34	2	550.07	15	52

Note: N=203

Further, we can see from Table 4.1 above that some loadings surprisingly have a lower loading from researcher model 1, such as 'International.' This indicator 'International' explains to us the level of international migrant stock in each country. From the literature, we can deduce that there is a Hawala remittance (illegal cross-border money transfer) risk when international migrant stock is high in a particular country. Hawala remittance falls into the definition of ML; therefore, the higher Hawala activities, it should pose ML risk for those countries. However, we notice from this model that most of the loadings go with the hypothesis presented in Table 3.1 and the previous literature. In contrast, some loadings are surprisingly high; for instance, the 'Rule' (the rule of law) indicator has a loading of 1.302. Although previous authors have used this as an indicator of ML risk, from researcher model 1's indicators, 'Rule' appears to be an outlier, which indicates to AML policy experts there is something significant between this indicator and ML risk.

In summary, researcher model 1 does not meet any of the cut-offs for a good fit, as shown in Table 4.2 above. Therefore, in the next section, let's see the same model if we correlate the factors. When we correlate the factors, we believe that there is potential cross-loading between factors and observed measures, giving us a different picture of the relationship between the hidden factors and the observed variables. That is why it forces me to look at the next model.

4.2. Researcher Model 2 - Correlated

4.2.1. Known Values, Parameters, Degrees of Freedom, and Estimates

We arrive at a known value of 325 (25(25+1)/2). Note that the known value has not changed because we have not changed anything from the model, except now we are forcing the model factors (F_1 to F_4) to stay correlated. Next, looking at the researcher model 2's parameters, we should expect a few changes because of the model factor correlation. Therefore, the factor covariances will now remain freely estimated and not constrained to zero. However, the factor variance will remain constrained to one as for any CFA model.

Next, we have to determine the df, where the known values (325) minus the number of freely estimated parameters (50 + 6), which equals 269. You will note a six added to the previous model's 50 freely estimated parameters. The new additions are the freely estimated factor covariance as the four factors correlated with each other, resulting in six additional parameters. Finally, we need to assess the model identification using the variance standardization method. Since the df is positive for researcher model 2, we can claim that this model stands identified. However, the df has diminished by six. The reduction in df looks insignificant; however, even this minor reduction can significantly impact the measures of fit such as RMSEA, even CFI, and TLI.

If you see Table 4.1, column 4, you will notice that out of the 25 measurable variables, 23 of them remain statistically significant at the .05 significance level. To make the factor loadings meaningful as we did earlier, we have to compare each loading with the other loadings and determine if they stay confirmed under a factor. To evaluate this, we consider factor loading >.4, and in this case, we have 16 loadings that are >.4 confirmed under their respective latent factors.

4.2.2. Model Fit Statistics of Researcher Model 2

Model Chi-Square - Concerning researcher model 2, again with the same sample size of 203 observations, we have to reject the null as the p-value is less than 0.05. However, if you look at Table 4.2 above, it shows a significant reduction in the test-statistics (from 2453 to 1541) when we merely correlate the same model factors. However, let's look into the other measure of fit to see if they have improved from researcher model 1.

CFI and TLI - The relative fit indexes have almost doubled in researcher model 2 due to the factor correlation effect. However, they have not passed the cut-off for a good fit, as presented in Table 4.2 above. CFI has improved from 0.329 to 0.608, and on the other hand, TLI has improved from 0.268 to 0.563. **RMSEA** - Again, like the last three measures, RMSEA; has improved from 0.198 to 0.153; however, it has not qualified the cut-off for a good fit.

4.2.3. Implications of Researcher Model 2 to AML Policy

Even though researcher model 2 remains statistically weak, we can draw some conclusions which may be useful for AML policy experts, as we discussed for researcher model 1. First, in researcher model 2, AML policy experts can examine the relationship and shared characteristics between and within the factors as the model remains correlated. As the model is correlated, a commonality exists within factors, while there remains potential cross-loading between measures and factors. In other words, for example, a measurable variable originally hypothesized under the factor "Financial Transparency and Standards" can potentially capture a different latent factor of ML risk within the model. Second, 16 out of the 23 statistically significant loadings confirm the four critical dimensions or the latent factors, forcing AML experts to research and study more on the 16 confirmed observable variables and the four latent factors. Finally, as mentioned previously, this may mean that the AML policy experts can use the confirmed observable variables as independent variables to perform a regression analysis to measure ML risk with an appropriate dependent variable. However, this time, not by factors but overall due to potential cross-loading.

In summary, researcher model 2 has not met any cut-off criteria for a good fit, similar to what we observed in researcher model 1. However, we can see that the correlated model has somewhat improved the good fit; and has brought them close to the cut-off for a good fit. Further, if we had a higher df for researcher model 2, we would have seen significant improvements to the measures of fit, such as RMSEA. Next, we will examine an uncorrelated and correlated version for a different data configuration proposed by the Basel Institute's AML research experts.

4.3. Basel Model 1 - Uncorrelated

4.3.1. Known Values, Parameters, Degrees of Freedom, and Estimates

The Basel data configuration stands different from the researcher data configuration, where there are four factors with 13 indicator variables. Therefore, the known value for Basel model 1 equals 91 (13(13+1)/2). For Basel model 1, the parameter freeing or constraining logic will remain similar to researcher model 1 (orthogonal). Typically, we force the factor variance to 1 as a metric constraint. The factor covariance will remain forced to be equal to zero as the model factors are uncorrelated. However, we will make two changes to this model that we did not do in the researcher model 1. First, for factor 1, the "Quality of AML Framework" of the Basel Model, we get high standard errors for the three-factor loadings. Therefore, to reduce high standard errors, I have used the marker method by fixing the first loading of that factor to 1. Second, as mentioned earlier, we have three factors in the Basel model with three measurable variables in each factor. As a result, the model saturates and fails to compute the factor loadings. Therefore, I have equated the three loadings ($\lambda x_9 = \lambda x_{10} = \lambda x_{11}$), under the factor "Public Transparency and Accountability."

Next, looking at the df, with 91 known values, when (13 loadings + 13 residual variances - 1 maker constrained loading - 2 equality constraints) remain subtracted, we derive at 68, which is comparatively lower in contrast with researcher models 1 and 2. Lastly, looking at the model identification, we can claim the model to be identified as it has a positive df. However, similar to researcher model 2, the df has diminished significantly, leaving the measures of fit at potential risk. The diminishing effect in df transpired due to the reduction in the number of measurable variables to 13 compared to 25 in researcher models 1 and 2.

In Table 4.1, column 5, you will notice that out of the 13 measurable variables, 12 of them remain statistically significant at the .05 significance level. Again, to make the factor loadings meaningful as we exercised earlier, we have to compare each loading with the other loadings and determine if they stay confirmed under a factor. As a result, we have eight loadings that are >.4. Therefore, we can comment that they stay confirmed under their respective latent factors.

4.3.2. Model Fit Statistics of Basel Model 1

Model Chi-Square - From Table 4.2 above, compared to the researcher models 1 and 2, the test-statistic of Basel model 1 (1025) has improved, which is the goal of model chi-square. However, with the sample size sensitivity, we are unfortunate to have a p-value less than .05 forcing us to reject the null hypothesis that the data does not fit the model well. In other words, the model-implied covariance matrix is not equal to the population covariance matrix.

CFI and TLI - The relative fit indexes are far away from the cut-off for a good fit. Also, note that Basel model 1's CFI (.413) and TLI (.326) are somewhat similar to the researcher model 1's relative fit indexes, as presented in Table 4.2 above. **RMSEA** - As the df significantly diminished to 68 with 23 free parameters, the RMSEA has worsened its position for Basel model 1, at 0.263.

4.3.3. Implications of Basel Model 1 to AML Policy

The model implications to AML policymaking in this model are similar to researcher model 1. First, we can examine the measurable variables' shared characteristics loaded commonly and significantly to each factor. Second, in Basel model 1, we have 8 out of the 12 statistically significant loadings confirming four critical dimensions or the latent factors, forcing AML experts to research and study more on the 8 confirmed observable variables and the four latent factors. Again, this may mean that the AML policy experts can use the confirmed observable variables as independent variables to perform a regression analysis to measure ML risk by factors with appropriate dependent variable(s).

In summary, we can see a similarity between the measures of fit between researcher model 1 and Basel model 1 because the model factor stays uncorrelated. Next, using the same data configuration, let's assess the fit measures by correlating the factors.

4.4. Basel Model 2 - Correlated

4.4.1. Known Values, Parameters, Degrees of Freedom, and Estimates

The known value will remain similar to Basel model 1 at 91 with the factor covariances freely estimated and constraining the factor variance to one as a metric constraint. The freely estimated parameters equal 31 (13 loadings + 13 residual variances + 6 freely estimate factor covariance - 1 maker constrained loading due to high standard error), and therefore, we should see the df falling in Basel model 2 to 60 (91 - 31) from 68 in the earlier model. Then, using the variance standardization method, let's examine the model identification. As the df stands positive, we confirm that the model continues identified.

The standardized factor loadings reported in Table 4.1, column 6, shows 13 measurable variables, 11 of them remain statistically significant at the .05 significance level. Again, to make the factor loadings meaningful, as we commented earlier, we have to compare each loading with the other loadings and determine if they stay confirmed under a factor. As a result, we have ten loadings that are >.4, and therefore, we can comment that they stay confirmed under their respective latent factors.

4.4.2. Model Fit Statistics of Basel Model 2

Model Chi-Square - From Table 4.2, Basel model 2 has the best test-statistic among the four models studied so far at the lowest of 631. However, the lower test-statistic has not changed the p-value. It is still below .05, which explains to us that there is a difference between the model-implied covariance matrix and the population covariance matrix. In other words, we have to reject the null, which is disturbing in confirmatory factor analysis.

CFI and TLI - As shown in Table 4.2, the incremental or relative fit indexes have doubled; similarly, how it doubled when I translated researcher model 1 (uncorrelated) to researcher model 2 (correlated). CFI in Basel model 2 has increased to .650 from .413, and on the other hand, TLI has risen to .545 from .326. **RMSEA** - In contrast to the previous model, RMSEA has slightly improved from .263 to .217. However, the figure is still away from the cut-off for a good fit.

4.4.3. Implications of Basel Model 2 to AML Policy

First, AML policy experts can examine the shared characteristics between and within the factors as the model remains correlated. Second, 10 out of the 11 statistically significant loadings confirm the four critical dimensions or the latent factors, forcing AML experts to research and study more on the ten confirmed observable variables and the four latent factors. AML experts have an opportunity to study the hidden dimensions presented in my models because statistics support my model results. Therefore, it is a question of how accurate experts' subjective estimates are. Finally, as mentioned previously, this may mean that the AML policy experts can use the confirmed observable variables as independent variables to perform a regression analysis to measure ML risk with an appropriate dependent variable. However, this time, not by factors but overall due to potential cross-loading similar to researcher model 2.

In summary, we observed a pattern between the researcher models and the Basel models. To describe more, the results of the uncorrelated (orthogonal) researcher model somewhat matches with the uncorrelated Basel model. Likewise, the correlated (oblique) researcher model results, to some extent, match with the correlated Basel model. However, the measures of fit from the four models failed to meet the cut-off for a good fit, which inspires us to consider a revised researcher model that will satisfy the cut-off for a good-fit or at least be close to the cut-off for a good fit. The next section will examine a revised model based on two criteria, explained in the next section.

4.5. Researcher Model 3 - Correlated

In researcher model 3, the number of indicators or measurable variables in the latent constructs remains reduced based on two criteria with the ultimate goal of achieving a good fit model. That is to consider factor loadings >.4 and statistically significant at the .05 significance level from researcher models 1 and 2. Based on the previous models' results, I decided to keep the model correlated as the preceding correlated models resulted in a somewhat good fit than the uncorrelated models. The substantive theory or beliefs change, to some extent, significantly different from the hypothesized relationship in Table 3.2. See Table 4.4 below for researcher model 3's configuration. Remember that the latent factors remain the same; only the observed measurable variables change in the researcher model 3. Additionally, there is a reason as to why researcher model 3 is better than the models tested above for measuring ML risk. It is because of the selectiveness of the 13 measurable variables that stand out from the 25 measurable variables from Table 3.2. In other words, these 13 measurable variables capture the hidden ML factors more than the other 12 measurable variables.

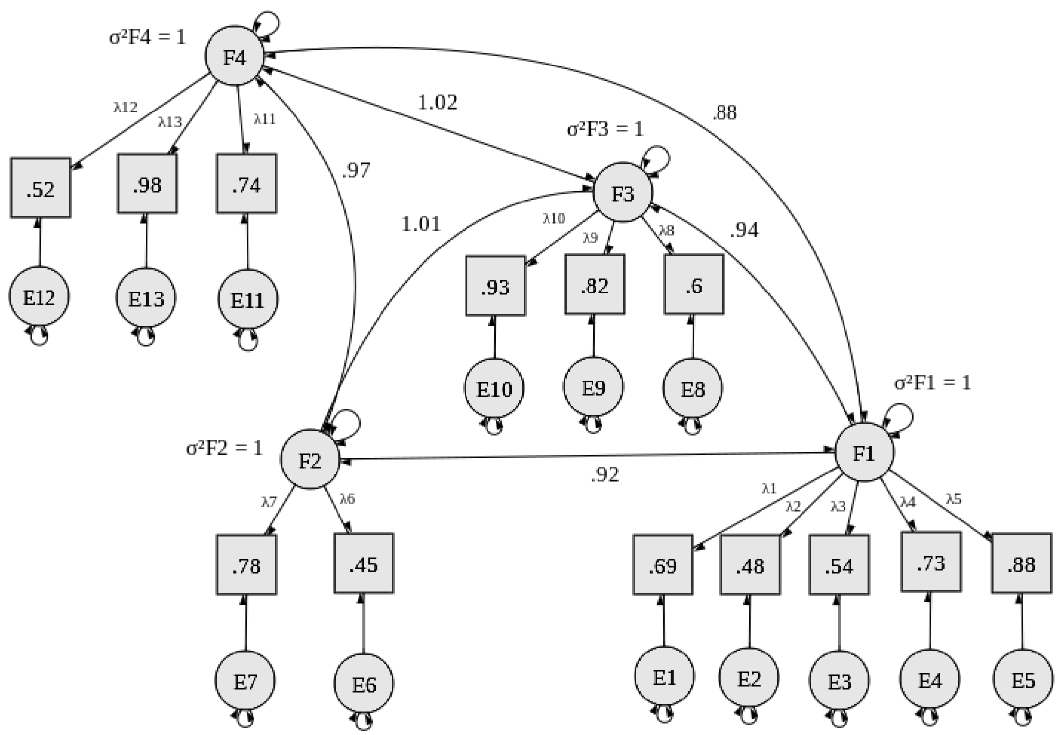
Table 4.4: Factor and Measurable Variables of Money Laundering Risk - Researcher Model 3

Factors	Measurable Variables
F_1 - The Economy and Financial System Factor	X_1- Automated teller machines (per 100,000 adults) X_2- Commercial bank branches (per 100,000 adults) X_3- Denominations by country (equivalent and/or greater than US$100) X_4- Life expectancy at birth X_5- Per capita GDP US$
F_2 - Financial Transparency and Standards Factor	X_6- Egmont group member X_7- WEF Global Competitiveness Report - Strength of auditing and reporting standards
F_3 - Political and Legal Factor	X_8- Freedom of the press X_9- World Justice Project, Rule of Law index (Central bank independence) X_{10}- WEF Global Competitiveness Report - Institutional pillar
F_4 - Public Sector Transparency and Accountability Factor	X_{11}- World Bank transparency, accountability, and corruption in the public-sector rating X_{12}- Open Budget Index - Budget transparency score X_{13}- TI corruption score

4.5.1. Known Values, Parameters, Degrees of Freedom, and Estimates

Generally, we start with the known values; with 13 measurable variables, we have 91 known values (13(13+1) /2). The factor variances will remain constrained to one as a metric constraint, as shown in Figure 4.1 below (e.g., $\sigma^2_{F1} = 1$). The factor covariances will continue to be freely estimated as our model is correlated. The df equals 59 (91 - (13+13+6)), with 32 freely estimated parameters. Note that, out of the five models, the researcher model 3 has the lowest df, which can potentially be detrimental to the measures of fit. Finally, we use the variance standardization method to determine model identification. We can tell that with positive df, the model looks identified.

Figure 4.1: Researcher Model 3 Path Diagram



Note: Generated in WebSem.

The good news is that the standardized factor loadings reported in Table 4.1, column 7, reveal all factor loadings >.4 and statistically significant at the .05 significance level. Therefore, we can say that the theory or beliefs (hypotheses) remain consistent with the results shown in Table 4.1 above, column 7, as the loadings remain confirmed within their respective latent factors. Figure 4.1 above shows the researcher model 3 path diagram. The single-headed arrows indicate the standardized factor loading, while the double-headed arrows indicate factor covariance. In a CFA path diagram, by convention, the circle shape represents the latent variable; this includes errors because errors are not directly observed. Therefore, they are classified as latent variables. The squares shapes represent the observed measurable variable. An arrow that begins and returns to the same variable represents the variance of that variable.

4.5.2. Model Fit Statistics of Researcher Model 3

Model Chi-Square - As shown in Table 4.2, the p-value continues to be less than .05, forcing us to reject the null hypothesis. If you revisit Table 4.2, you will notice that researcher model 3 has the best test-statistic value (449) out of the five models. Even though we cannot witness a p-value greater than .05 for researcher model 3, we should acknowledge the significant reduction in the test-statistic value. Remember, as stated earlier, it is unlikely to have CFA models with a model-implied covariance matrix, which perfectly matches its population covariance matrix. **CFI and TLI** - The relative fit indexes have a sensitive connection to df and sample size. According to Table 4.2, as far as researcher model 3 is concerned, CFI stands at .813 and TLI at .753. Again, the model did not meet the cut-off for a good fit. However, the good news is that it is close to the cut-off mark of CFI .90 and TLI .95. Moreover, researcher model 3's CFI and TLI values are the best among the five models, as presented in Table 4.2 above. **RMSEA** - Likewise, the RMSEA has a strong relationship with the df and sample size, which has resulted in .180. RMSEA was the only measure of fit in researcher model 3 that continued to stand away from the cut-off mark, damaging the good-fit goal.

4.5.3. Implications of Researcher Model 3 to AML Policy

First, all 13 measurable variables load significantly, confirming the four critical dimensions or the latent factors, impelling AML experts to research and study more on the 13 confirmed observable variables and the four latent factors. Additionally, researcher model 3 remains somewhat optimized so that AML policy experts can keep their study policy-focused without any redundant variables. Second, AML experts can examine the shared characteristics between and within the factors as the model remains correlated.

Finally, AML policy experts can use researcher model 3's measurable variables as a next step to perform a regression analysis to measure ML risk with an appropriate dependent variable. Like the other correlated models, AML experts can potentially work on a macro-level study due to potential cross-loading between measures and the four factors. More discussion on policy implications will proceed in the conclusion section below, as we have discovered 13 observed measurable variables that capture four latent factors of ML risk.

See next page for Chapter 5

Chapter 5.

Discussion and Conclusion

In this section, I will first discuss the statistical limitations of the models tested in this paper. Then, I will summarize the comparison between the researcher model(s) and the Basel model(s). Finally, in the conclusion section, I will discuss the models' implications for AML policy experts and my contributions to the ML and AML literature.

5.1. Discussion

5.1.1. Limitations of the Models Tested

We observed that the researcher model 3 had three fit measures except for RMSEA, which were the best among the five models. Although the measures of fit couldn't qualify the cut-off for a good fit, they came close to the cut-off mark. However, we need to discuss why our models failed to achieve the universal cut-offs for a good-fit.

First, the sample size. In the earlier sections, we discussed the recommended sample size. The four measures of fit tested in this paper are sensitive to sample size. Unfortunately, for all five models, the sample size was unsatisfactory. However, there is a natural limitation to the sample size in this paper because we are looking at countries as observations, and we have a sample (N) of 203 countries. There is nothing significant that we can do to increase the sample size for our study. Second, the model specification or configuration. The specification depends on the researcher's theories and beliefs. The theory or belief can depend on person-to-person. CFA researchers don't have a thumb rule to derive the right model specification; it continues as a trial-and-error study; while aligning to a logical hypothesis. Therefore, depending on the model specification, fit measures can change with the same sample. Third, the df. The issue of df remained mentioned continuously in the above sections. What have we learned from df in the CFA model? Ideally, we know that a lower df impairs the results of the measures of fit. A clear example would be the RMSEA. If you look at the RMSEA equation above, the df lies at the denominator of the equations. Mathematically, a lower denominator produces a higher number when divided. We have faced this obstacle throughout the five models, where the df remained small, creating higher RMSEA. The same logic applies to the other measures of fit equations, which ended up with unsatisfactory results (i.e., not meeting the statistical thresholds presented in Table 4.2).

On the other hand, one may question how we know if which model is a good fit, while ML itself is hidden. Table 4.2 explains the good fit from a CFA lens. The second way to test this would be with regression analysis because regression analysis can provide causality evidence. In other words, I would take the confirmed observed variables from the researcher and Basel models and separately perform a regression analysis, given that we have a clear dependent variable to regress against the confirmed observed variables in each model tested above. Then, the regression study would tell us which model performed better in substance, meaning ML risk. However, my research limits the analysis to CFA. In the conclusion section, I provide a comprehensive recommendation on how we can move from CFA to regression, which could be future research.

Furthermore, one may also question if the models of risk tested above are accurate. This question will lead us back to the data because each observable measure's data generating process is critical in determining the ML risk measurement model's accuracy using CFA. For example, in the introduction section, I pointed out 'expert opinion' as the Basel model's main weakness. Likewise, if you look at Table 3.2, you will notice that even data used for the researcher model(s) include index form data, which are subjective. However, this paper attempts to use a mix of subjective (E.g. X_{23} - International Budget Partnership Open Budget Index) and discrete data (E.g. X_2 - Automated teller machines). Then, apply CFA to improve Basel's expert opinion model. Therefore, it means that the model's accuracy depends on both subjective and discrete data, and we learn that it is challenging to measure ML risk solely based on discrete data. In essence, I can claim that the models tested in this paper are the least subjective compared to Basel's expert opinion model.

5.1.2. Researcher Model vs. Basel Model

In the introduction to the 'Results and Analysis' section above, I stated that I aim to check if the researcher model(s) proposed in this paper fits better with the data than the Basel Institute's model(s). Unfortunately, we never came across a single model that fitted better with the data to claim that the researcher model(s) or the Basel model(s) was better than one another. However, to make a meaningful comparison between the two competing models, I decided to check the statistically significant (at .05 significance level) and the confirmed variables (loadings >.4) as a percentage of the original data configuration. Table 5.1 below shows the percentages in the fifth row indicated by 4*.

Table 5.1: Model Comparison

	Uncorrelated Models		**Correlated Models**		
	Researcher 1	**Basel 1**	**Researcher 2**	**Basel 2**	**Researcher 3**
1*	25	13	25	13	13
2*	23	12	23	11	13
3*	17	8	16	10	13
4*	.68	.61	.64	.77	1

Note: 1* = original configured variables, 2* = statistically significant loadings at .05 sig. level, 3* = statistically significant and loadings >.4, 4* = 3* as % of 1*

From the above table, I can claim that the uncorrelated researcher model 1 did a better job than the uncorrelated Basel model 1 in confirming variables under the latent factors. In other words, the uncorrelated researcher model was able to confirm 68 percent of its original variables. In comparison, the uncorrelated Basel model confirmed 61 percent. On the contrary, the Basel model did a better job than the researcher model when the model factors remained correlated. The correlated researcher model 2 was able to confirm only 64 percent of its original variables. In contrast, the correlated Basel model 2 confirmed 77 percent. At this point, you should understand that these figures can change based on how you hypothesize and configure the models.

Additionally, researcher model 3 shows a 100 percent confirmation of the original variables under the latent factors. What is the reason for the 100 percent? The researcher model 3 is designed to offer AML policy experts the optimal model with observed measurable variables (with high factor loadings), confirming and capturing its latent factors. Consequently, based on the results of researcher model 3, I can theoretically and statistically claim that changes in the four hidden factors should explain ML risk for countries. You may ask how? Look back at the 'Method' section above. There, I explain that the concept of 'ML risk' is partitioned into four clusters, which are my latent factors. To provide evidence of this inference, I recommended a potential solution, which is regression analysis. I will elaborate more on this in the conclusion section below.

5.2. Conclusion

How will researcher model 3 be useful for AML policy experts? First, the Financial Action Task Force (FATF - an intergovernmental organization that combats ML), does a peer-review exercise called 'mutual evaluations.' The exercise is done between its member countries to test ML effectiveness and technical compliance. For mutual evaluations, assessors visit the examinee country to collect evidence to test ML effectiveness and technical compliance. During the on-site visit, assessors prepare a scope for the mutual evaluation exercise factoring different elements into consideration (FATF, 2020). In terms of factoring elements for technical compliance, assessors have the FATF's 40 recommendations. At present, to evaluate ML effectiveness, AML experts arbitrarily consider factors elements for their evaluation scope (FATF, 2020). To avoid randomness in selecting scoping elements, I recommend the AML experts at the FATF to consider the 13 observed variables from researcher model 3. AML policy experts can extract the most critical observable variables from researcher model 3, particularly the factors with the highest loadings: 'Rule,' 'TI,' 'Transparency,' 'Auditing,' and 'Quality' (see Table 4.1 above for the highest loaded observed measures). Additionally, these 13 variables capture four hidden ML risk factors. I argue that it would remain sensible to consider my models' observable variables and latent variables for mutual evaluation scoping than making a subjective guess. AML experts can use the other statistically significant observed variables from researcher models 1, 2, and Basel models 1, 2, to write the mutual evaluation scope. Furthermore, these variables can potentially shed light on grey areas currently researched by other AML organizations (e.g., the Financial Transactions and Reports Analysis Centre of Canada (FINTRAC)).

Second, I point out in the 'Discussion' section above that the regression analysis technique can provide evidence of 'inference.' In a pragmatic sense, what does this mean to AML policy experts? AML policy experts can investigate causality (i.e., only provide evidence of causality but not prove causality) by regressing the observed measurable variables in my model(s) against an appropriate dependent variable to explain the relationship in terms of association. For example, AML policy experts can test ML risk worldwide by collecting the number of reported suspicious transactions as the dependent variable and regressing against the observed measurable variables. Likewise, AML policy experts can perform regression analysis by latent factors or as a whole model (with all four latent factors) depending on dependent variables' availability. Further, AML policy experts can design regression analysis models based on a panel or time-series data to find interesting relationships. The main challenge to measure ML risk using regression analysis is the time and cost associated with finding the right dependent variable. For instance, if I have to obtain reported suspicion transactions for regression analysis to measure ML risk. In that case, I have to reach FIUs (e.g., the FINTRAC in Canada). The complexity of getting data depends on what information I will use from the suspicious transaction reports as the dependent variable. For example, information such as the total number of reported suspicious transactions may be easy to obtain. However, if we need the Dollar values in those reports, the process can be lengthy and costly.

Third, there are two areas open in this paper for AML policy experts to work on as future research. 1) My model may not offer some demanding observed measurable variables that may capture certain latent factors of ML risk. For example, cryptocurrencies remain one prominent area that AML policy experts need to focus on to deter ML risk. Unfortunately, I could not find a suitable variable that represented cryptocurrencies, which I could have included in my model(s). Hence, it remains open for AML experts to incorporate such variables, which can increase model fit. My study premises itself at the international/national level as the data comes from the country level. However, two other levels can potentially use CFA to measure ML risk, namely the industry and business unit levels. Future researchers can consider a similar study at the industry level (E.g. banking and finance) or the business unit level (E.g. Casinos) to measure ML risk. The research design will somewhat remain the same; however, the data will be the main element that will change in such studies. A sound recommendation for data collection for such studies can include a questionnaire. 2) If you look at the covariances between the factors in Figure 4.1 above, it shows numbers without high variations (1.02, .88, .92, .94, 1.01, .97), which explains that the factors remain highly correlated. In other words, "if the theory is that a fifth factor causes the correlation between these four factors, then these four first-order factors can serve as latent indicators of the underlying second-order factor" (UCLA Statistical Consulting, 2020). Therefore, this opens room for AML policy researchers to work on nested models to find such hidden dimensions.

In conclusion, what is the contribution of my work to ML and AML literature? If you look at the method used in this paper, it is hardly ever used in policy papers due to the complexity in presenting to general audiences. Most commonly, you find CFA as a structural equation modelling method in psychology and medical research. Additionally, I never came across the application of the CFA method in ML and AML literature. This paper's method offers a potential contribution to the field of ML and AML literature, answering my **research question**: Are the empirically observable measures of money laundering risk identified in the money laundering and anti-money laundering literature captured in the hypothesized latent factors of money laundering risk? Finally, this paper's model serves the purpose of 'generalizability.' As a result, this allows AML policy experts and criminologists to calibrate the model to answer similar research questions. For example, the same method can be used to study hidden factors of terrorist financing risk across countries.

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Appendix A.

Researcher Model 1

```
lavaan 0.6-7 ended normally after 45 iterations

  Estimator                                         ML
  Optimization method                           NLMINB
  Number of free parameters                         50

  Number of observations                           203

Model Test User Model:

  Test statistic                              2452.886
  Degrees of freedom                               275
  P-value (Chi-square)                           0.000

Model Test Baseline Model:

  Test statistic                              3547.294
  Degrees of freedom                               300
  P-value                                        0.000

User Model versus Baseline Model:

  Comparative Fit Index (CFI)                    0.329
  Tucker-Lewis Index (TLI)                       0.268

Loglikelihood and Information Criteria:

  Loglikelihood user model (H0)              -7261.312
  Loglikelihood unrestricted model (H1)      -6034.869

  Akaike (AIC)                               14622.625
  Bayesian (BIC)                             14788.285
  Sample-size adjusted Bayesian (BIC)        14629.872

Root Mean Square Error of Approximation:

  RMSEA                                          0.198
  90 Percent confidence interval - lower         0.190
  90 Percent confidence interval - upper         0.205
  P-value RMSEA <= 0.05                          0.000

Standardized Root Mean Square Residual:

  SRMR                                           0.276
```

```
Parameter Estimates:

  Standard errors                             Standard
  Information                                 Expected
  Information saturated (h1) model          Structured

Latent Variables:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
  f1 =~
    International     0.555    0.106    5.215    0.000    0.555    0.379
    ATMs              0.935    0.084   11.066    0.000    0.935    0.717
    Commercial        0.414    0.058    7.187    0.000    0.414    0.506
    Battle            0.208    0.035    5.957    0.000    0.208    0.428
    AProcedures       0.659    0.110    6.004    0.000    0.659    0.431
    Atime             0.325    0.080    4.071    0.000    0.325    0.301
    ACost             0.430    0.071    6.096    0.000    0.430    0.437
    NProcedures       0.398    0.113    3.514    0.000    0.398    0.261
    Register          0.375    0.115    3.253    0.001    0.375    0.242
    Enforce           0.368    0.118    3.109    0.002    0.368    0.232
    GDP               1.279    0.099   12.856    0.000    1.279    0.799
    Denominations     0.266    0.032    8.273    0.000    0.266    0.570
    Life              1.356    0.113   11.995    0.000    1.356    0.760
  f2 =~
    Egmont            0.330    0.047    6.973    0.000    0.330    0.742
    RemittancesP      0.197    0.075    2.619    0.009    0.197    0.226
    RemittancesR      0.148    0.086    1.729    0.084    0.148    0.149
    Secrecy           0.862    0.153    5.653    0.000    0.862    0.514
    Auditing          0.857    0.163    5.271    0.000    0.857    0.467
  f3 =~
    Freedom           0.391    0.060    6.563    0.000    0.391    0.486
    Rule              1.974    0.143   13.796    0.000    1.974    1.302
    Quality           1.168    0.150    7.809    0.000    1.168    0.592
  f4 =~
    Budget            0.451    0.056    8.092    0.000    0.451    0.562
    disclosure        0.024    0.032    0.756    0.450    0.024    0.057
    TI                1.781    0.141   12.640    0.000    1.781    0.865
    Transparency      1.358    0.110   12.312    0.000    1.358    0.843

Covariances:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
  f1 ~~
    f2                0.000                               0.000    0.000
    f3                0.000                               0.000    0.000
    f4                0.000                               0.000    0.000
  f2 ~~
    f3                0.000                               0.000    0.000
    f4                0.000                               0.000    0.000
  f3 ~~
    f4                0.000                               0.000    0.000

Variances:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
   .International     1.834    0.187    9.799    0.000    1.834    0.856
   .ATMs              0.828    0.100    8.308    0.000    0.828    0.486
```

.Commercial	0.499	0.052	9.509	0.000	0.499	0.744
.Battle	0.193	0.020	9.706	0.000	0.193	0.817
.AProcedures	1.903	0.196	9.699	0.000	1.903	0.814
.Atime	1.067	0.108	9.912	0.000	1.067	0.910
.ACost	0.782	0.081	9.686	0.000	0.782	0.809
.NProcedures	2.169	0.218	9.955	0.000	2.169	0.932
.Register	2.255	0.226	9.973	0.000	2.255	0.941
.Enforce	2.379	0.238	9.982	0.000	2.379	0.946
.GDP	0.927	0.130	7.116	0.000	0.927	0.362
.Denominations	0.147	0.016	9.281	0.000	0.147	0.675
.Life	1.341	0.173	7.769	0.000	1.341	0.422
.Egmont	0.089	0.027	3.259	0.001	0.089	0.450
.RemittancesP	0.720	0.074	9.782	0.000	0.720	0.949
.RemittancesR	0.967	0.097	9.954	0.000	0.967	0.978
.Secrecy	2.072	0.275	7.532	0.000	2.072	0.736
.Auditing	2.638	0.320	8.234	0.000	2.638	0.782
.Freedom	0.496	0.054	9.249	0.000	0.496	0.764
.Rule	-1.598	0.563	-2.837	0.005	-1.598	-0.696
.Quality	2.527	0.314	8.042	0.000	2.527	0.649
.Budget	0.439	0.047	9.251	0.000	0.439	0.684
.disclosure	0.180	0.018	10.069	0.000	0.180	0.997
.TI	1.069	0.312	3.431	0.001	1.069	0.252
.Transparency	0.748	0.186	4.026	0.000	0.748	0.289
f1	1.000				1.000	1.000
f2	1.000				1.000	1.000
f3	1.000				1.000	1.000
f4	1.000				1.000	1.000

Appendix B.

Researcher Model 2

```
lavaan 0.6-7 ended normally after 60 iterations

  Estimator                                         ML
  Optimization method                           NLMINB
  Number of free parameters                         56

  Number of observations                           203

Model Test User Model:

  Test statistic                              1541.234
  Degrees of freedom                               269
  P-value (Chi-square)                           0.000

Model Test Baseline Model:

  Test statistic                              3547.294
  Degrees of freedom                               300
  P-value                                        0.000

User Model versus Baseline Model:

  Comparative Fit Index (CFI)                    0.608
  Tucker-Lewis Index (TLI)                       0.563

Loglikelihood and Information Criteria:

  Loglikelihood user model (H0)              -6805.487
  Loglikelihood unrestricted model (H1)      -6034.869

  Akaike (AIC)                               13722.973
  Bayesian (BIC)                             13908.513
  Sample-size adjusted Bayesian (BIC)        13731.091

Root Mean Square Error of Approximation:

  RMSEA                                          0.153
  90 Percent confidence interval - lower         0.145
  90 Percent confidence interval - upper         0.160
  P-value RMSEA <= 0.05                          0.000

Standardized Root Mean Square Residual:

  SRMR                                           0.103

Parameter Estimates:

  Standard errors                             Standard
```

```
  Information                                      Expected
  Information saturated (h1) model               Structured

Latent Variables:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
  f1 =~
    International     0.514    0.102    5.030    0.000    0.514    0.352
    ATMs              0.863    0.083   10.417    0.000    0.863    0.662
    Commercial        0.352    0.056    6.254    0.000    0.352    0.430
    Battle            0.224    0.033    6.744    0.000    0.224    0.460
    AProcedures       0.710    0.104    6.825    0.000    0.710    0.465
    Atime             0.354    0.076    4.662    0.000    0.354    0.327
    ACost             0.493    0.066    7.433    0.000    0.493    0.501
    NProcedures       0.406    0.108    3.756    0.000    0.406    0.266
    Register          0.445    0.109    4.070    0.000    0.445    0.288
    Enforce           0.380    0.113    3.371    0.001    0.380    0.240
    GDP               1.346    0.092   14.570    0.000    1.346    0.841
    Denominations     0.240    0.031    7.676    0.000    0.240    0.515
    Life              1.302    0.110   11.874    0.000    1.302    0.730
  f2 =~
    Egmont            0.168    0.029    5.825    0.000    0.168    0.379
    RemittancesP      0.241    0.055    4.359    0.000    0.241    0.277
    RemittancesR      0.088    0.061    1.438    0.150    0.088    0.088
    Secrecy           0.744    0.111    6.724    0.000    0.744    0.443
    Auditing          1.251    0.122   10.222    0.000    1.251    0.681
  f3 =~
    Freedom           0.480    0.051    9.397    0.000    0.480    0.596
    Rule              1.431    0.080   17.951    0.000    1.431    0.944
    Quality           1.619    0.113   14.312    0.000    1.619    0.821
  f4 =~
    Budget            0.415    0.053    7.846    0.000    0.415    0.518
    disclosure        0.008    0.030    0.268    0.789    0.008    0.019
    TI                2.010    0.106   18.892    0.000    2.010    0.976
    Transparency      1.195    0.097   12.320    0.000    1.195    0.743

Covariances:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
  f1 ~~
    f2                1.131    0.052   21.650    0.000    1.131    1.131
    f3                0.988    0.015   64.596    0.000    0.988    0.988
    f4                0.913    0.022   41.948    0.000    0.913    0.913
  f2 ~~
    f3                1.134    0.050   22.455    0.000    1.134    1.134
    f4                1.057    0.049   21.585    0.000    1.057    1.057
  f3 ~~
    f4                1.013    0.012   86.395    0.000    1.013    1.013

Variances:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
   .International     1.877    0.188    9.990    0.000    1.877    0.876
   .ATMs              0.957    0.100    9.576    0.000    0.957    0.562
   .Commercial        0.547    0.055    9.937    0.000    0.547    0.815
   .Battle            0.187    0.019    9.911    0.000    0.187    0.789
   .AProcedures       1.834    0.185    9.906    0.000    1.834    0.784
   .Atime             1.047    0.105   10.002    0.000    1.047    0.893
```

.ACost	0.725	0.073	9.869	0.000	0.725	0.749
.NProcedures	2.163	0.216	10.029	0.000	2.163	0.929
.Register	2.198	0.219	10.020	0.000	2.198	0.917
.Enforce	2.370	0.236	10.038	0.000	2.370	0.942
.GDP	0.752	0.091	8.286	0.000	0.752	0.293
.Denominations	0.160	0.016	9.852	0.000	0.160	0.735
.Life	1.483	0.159	9.319	0.000	1.483	0.467
.Egmont	0.169	0.017	10.216	0.000	0.169	0.857
.RemittancesP	0.701	0.069	10.207	0.000	0.701	0.923
.RemittancesR	0.981	0.097	10.093	0.000	0.981	0.992
.Secrecy	2.262	0.223	10.134	0.000	2.262	0.803
.Auditing	1.806	0.215	8.411	0.000	1.806	0.536
.Freedom	0.419	0.041	10.123	0.000	0.419	0.645
.Rule	0.248	0.037	6.788	0.000	0.248	0.108
.Quality	1.269	0.130	9.779	0.000	1.269	0.326
.Budget	0.470	0.047	9.975	0.000	0.470	0.731
.disclosure	0.180	0.018	10.075	0.000	0.180	1.000
.TI	0.203	0.080	2.543	0.011	0.203	0.048
.Transparency	1.163	0.119	9.735	0.000	1.163	0.449
f1	1.000				1.000	1.000
f2	1.000				1.000	1.000
f3	1.000				1.000	1.000
f4	1.000				1.000	1.000

Appendix C.

Basel Model 1

```
lavaan 0.6-7 ended normally after 51 iterations

  Estimator                                         ML
  Optimization method                           NLMINB
  Number of free parameters                         25
  Number of equality constraints                     2

  Number of observations                           203

Model Test User Model:

  Test statistic                              1025.379
  Degrees of freedom                                68
  P-value (Chi-square)                           0.000

Model Test Baseline Model:

  Test statistic                              1708.370
  Degrees of freedom                                78
  P-value                                        0.000

User Model versus Baseline Model:

  Comparative Fit Index (CFI)                    0.413
  Tucker-Lewis Index (TLI)                       0.326

Loglikelihood and Information Criteria:

  Loglikelihood user model (H0)              -4363.533
  Loglikelihood unrestricted model (H1)      -3850.843

  Akaike (AIC)                                8773.065
  Bayesian (BIC)                              8849.269
  Sample-size adjusted Bayesian (BIC)         8776.399

Root Mean Square Error of Approximation:

  RMSEA                                          0.263
  90 Percent confidence interval - lower         0.249
  90 Percent confidence interval - upper         0.278
  P-value RMSEA <= 0.05                          0.000

Standardized Root Mean Square Residual:

  SRMR                                           0.308

Parameter Estimates:
```

```
  Standard errors                                 Standard
  Information                                     Expected
  Information saturated (h1) model              Structured

Latent Variables:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
  f1 =~
    FATF              1.000                                1.000    0.452
    Narcotics         0.326    0.159    2.052    0.040    0.326    0.147
    Secrecy           1.698    0.275    6.162    0.000    1.698    1.005
  f2 =~
    CorT              0.343    0.181    1.892    0.058    0.343    0.138
    Auditing          1.718    0.113   15.233    0.000    1.718    0.936
    SecEX             1.364    0.095   14.329    0.000    1.364    0.892
    FinSec            0.826    0.102    8.094    0.000    0.826    0.546
  f3 =~
    Budget     (a)    0.155    0.069    2.232    0.026    0.155    0.193
    disclosure (a)    0.155    0.069    2.232    0.026    0.155    0.361
    Transprncy (a)    0.155    0.069    2.232    0.026    0.155    0.097
  f4 =~
    Freedom           0.391    0.060    6.562    0.000    0.391    0.486
    Quality           1.168    0.150    7.808    0.000    1.168    0.592
    Rule              1.974    0.143   13.795    0.000    1.974    1.302

Covariances:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
  f1 ~~
    f2                0.000                                0.000    0.000
    f3                0.000                                0.000    0.000
    f4                0.000                                0.000    0.000
  f2 ~~
    f3                0.000                                0.000    0.000
    f4                0.000                                0.000    0.000
  f3 ~~
    f4                0.000                                0.000    0.000

Variances:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
   .FATF              3.891    0.477    8.152    0.000    3.891    0.796
   .Narcotics         4.800    0.477   10.057    0.000    4.800    0.978
   .Secrecy          -0.031    0.804   -0.038    0.969   -0.031   -0.011
   .CorT              6.070    0.603   10.058    0.000    6.070    0.981
   .Auditing          0.419    0.204    2.050    0.040    0.419    0.124
   .SecEX             0.476    0.135    3.534    0.000    0.476    0.204
   .FinSec            1.610    0.167    9.663    0.000    1.610    0.702
   .Budget            0.618    0.065    9.468    0.000    0.618    0.963
   .disclosure        0.159    0.027    6.001    0.000    0.159    0.870
   .Transparency      2.524    0.253    9.978    0.000    2.524    0.991
   .Freedom           0.496    0.054    9.249    0.000    0.496    0.764
   .Quality           2.527    0.314    8.042    0.000    2.527    0.649
   .Rule             -1.598    0.563   -2.837    0.005   -1.598   -0.696
    f1                1.000                                1.000    1.000
    f2                1.000                                1.000    1.000
    f3                1.000                                1.000    1.000
    f4                1.000                                1.000    1.000
```

Appendix D.

Basel Model 2

```
lavaan 0.6-7 ended normally after 43 iterations

  Estimator                                         ML
  Optimization method                           NLMINB
  Number of free parameters                         31

  Number of observations                           203

Model Test User Model:

  Test statistic                               631.016
  Degrees of freedom                                60
  P-value (Chi-square)                           0.000

Model Test Baseline Model:

  Test statistic                              1708.370
  Degrees of freedom                                78
  P-value                                        0.000

User Model versus Baseline Model:

  Comparative Fit Index (CFI)                    0.650
  Tucker-Lewis Index (TLI)                       0.545

Loglikelihood and Information Criteria:

  Loglikelihood user model (H0)              -4166.351
  Loglikelihood unrestricted model (H1)      -3850.843

  Akaike (AIC)                                8394.702
  Bayesian (BIC)                              8497.412
  Sample-size adjusted Bayesian (BIC)         8399.196

Root Mean Square Error of Approximation:

  RMSEA                                          0.217
  90 Percent confidence interval - lower         0.201
  90 Percent confidence interval - upper         0.232
  P-value RMSEA <= 0.05                          0.000

Standardized Root Mean Square Residual:

  SRMR                                           0.127

Parameter Estimates:

  Standard errors                             Standard
```

```
  Information                                      Expected
  Information saturated (h1) model               Structured

Latent Variables:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
  f1 =~
    FATF              1.000                               1.000    0.480
    Narcotics         0.442    0.181    2.436    0.015    0.442    0.200
    Secrecy           1.117    0.141    7.925    0.000    1.117    0.674
  f2 =~
    CorT              0.235    0.174    1.350    0.177    0.235    0.094
    Auditing          1.831    0.096   19.095    0.000    1.831    1.003
    SecEX             1.267    0.089   14.208    0.000    1.267    0.832
    FinSec            0.764    0.100    7.650    0.000    0.764    0.505
  f3 =~
    disclosure        0.005    0.032    0.160    0.873    0.005    0.012
    Budget            0.478    0.055    8.663    0.000    0.478    0.599
    Transparency      1.250    0.109   11.429    0.000    1.250    0.783
  f4 =~
    Freedom           0.495    0.051    9.626    0.000    0.495    0.618
    Quality           1.537    0.115   13.319    0.000    1.537    0.788
    Rule              1.450    0.078   18.639    0.000    1.450    0.972


Covariances:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
  f1 ~~
    f2               -0.451    0.086   -5.219    0.000   -0.451   -0.451
    f3                0.657    0.100    6.571    0.000    0.657    0.657
    f4               -0.773    0.076  -10.199    0.000   -0.773   -0.773
  f2 ~~
    f3               -0.713    0.057  -12.516    0.000   -0.713   -0.713
    f4                0.738    0.037   19.899    0.000    0.738    0.738
  f3 ~~
    f4               -0.913    0.046  -19.982    0.000   -0.913   -0.913

Variances:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
   .FATF              3.337    0.365    9.139    0.000    3.337    0.769
   .Narcotics         4.699    0.474    9.911    0.000    4.699    0.960
   .Secrecy           1.495    0.267    5.602    0.000    1.495    0.545
   .CorT              6.132    0.609   10.075    0.000    6.132    0.991
   .Auditing         -0.020    0.120   -0.168    0.866   -0.020   -0.006
   .SecEX             0.711    0.091    7.832    0.000    0.711    0.307
   .FinSec            1.703    0.170   10.013    0.000    1.703    0.745
   .disclosure        0.181    0.018   10.074    0.000    0.181    1.000
   .Budget            0.408    0.046    8.940    0.000    0.408    0.641
   .Transparency      0.989    0.174    5.681    0.000    0.989    0.388
   .Freedom           0.396    0.041    9.746    0.000    0.396    0.618
   .Quality           1.446    0.161    8.973    0.000    1.446    0.379
   .Rule              0.123    0.062    1.989    0.047    0.123    0.055
    f1                1.000                               1.000    1.000
    f2                1.000                               1.000    1.000
    f3                1.000                               1.000    1.000
    f4                1.000                               1.000    1.000
```

Appendix E.

Researcher Model 3

```
lavaan 0.6-7 ended normally after 52 iterations

  Estimator                                         ML
  Optimization method                           NLMINB
  Number of free parameters                         32

  Number of observations                           203

Model Test User Model:

  Test statistic                               449.162
  Degrees of freedom                                59
  P-value (Chi-square)                           0.000

Model Test Baseline Model:

  Test statistic                              2167.513
  Degrees of freedom                                78
  P-value                                        0.000

User Model versus Baseline Model:

  Comparative Fit Index (CFI)                    0.813
  Tucker-Lewis Index (TLI)                       0.753

Loglikelihood and Information Criteria:

  Loglikelihood user model (H0)              -3292.570
  Loglikelihood unrestricted model (H1)      -3067.989

  Akaike (AIC)                                6649.140
  Bayesian (BIC)                              6755.162
  Sample-size adjusted Bayesian (BIC)         6653.778

Root Mean Square Error of Approximation:

  RMSEA                                          0.180
  90 Percent confidence interval - lower         0.165
  90 Percent confidence interval - upper         0.196
  P-value RMSEA <= 0.05                          0.000

Standardized Root Mean Square Residual:

  SRMR                                           0.073

Parameter Estimates:

  Standard errors                             Standard
```

```
  Information                                      Expected
  Information saturated (h1) model               Structured

Latent Variables:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
  f1 =~
    Commercial        0.391    0.056    6.938    0.000    0.391    0.478
    GDP               1.414    0.091   15.507    0.000    1.414    0.883
    Denominations     0.254    0.031    8.080    0.000    0.254    0.545
    Life              1.295    0.111   11.636    0.000    1.295    0.726
    ATMs              0.898    0.083   10.825    0.000    0.898    0.689
  f2 =~
    Egmont            0.201    0.032    6.346    0.000    0.201    0.453
    Auditing          1.440    0.135   10.638    0.000    1.440    0.784
  f3 =~
    Freedom           0.484    0.051    9.489    0.000    0.484    0.601
    Rule              1.416    0.080   17.588    0.000    1.416    0.934
    Quality           1.627    0.113   14.398    0.000    1.627    0.825
  f4 =~
    Budget            0.419    0.053    7.927    0.000    0.419    0.523
    TI                2.011    0.106   18.926    0.000    2.011    0.976
    Transparency      1.190    0.097   12.251    0.000    1.190    0.739

Covariances:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
  f1 ~~
    f2                0.922    0.062   14.917    0.000    0.922    0.922
    f3                0.944    0.021   44.978    0.000    0.944    0.944
    f4                0.878    0.026   33.839    0.000    0.878    0.878
  f2 ~~
    f3                1.011    0.059   17.129    0.000    1.011    1.011
    f4                0.972    0.058   16.833    0.000    0.972    0.972
  f3 ~~
    f4                1.020    0.012   85.932    0.000    1.020    1.020

Variances:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
   .Commercial        0.517    0.053    9.791    0.000    0.517    0.772
   .GDP               0.564    0.090    6.283    0.000    0.564    0.220
   .Denominations     0.153    0.016    9.669    0.000    0.153    0.703
   .Life              1.501    0.167    8.978    0.000    1.501    0.472
   .ATMs              0.895    0.097    9.196    0.000    0.895    0.526
   .Egmont            0.157    0.016    9.654    0.000    0.157    0.795
   .Auditing          1.299    0.270    4.802    0.000    1.299    0.385
   .Freedom           0.415    0.041   10.121    0.000    0.415    0.639
   .Rule              0.292    0.041    7.180    0.000    0.292    0.127
   .Quality           1.245    0.128    9.699    0.000    1.245    0.320
   .Budget            0.467    0.047    9.977    0.000    0.467    0.727
   .TI                0.198    0.078    2.542    0.011    0.198    0.047
   .Transparency      1.175    0.120    9.758    0.000    1.175    0.454
    f1                1.000                                1.000    1.000
    f2                1.000                                1.000    1.000
    f3                1.000                                1.000    1.000
    f4                1.000                                1.000    1.000
```

Appendix F.

Variable Description

Table 1 - Description of the Indicator Variables

Indicator Variables	Description
1. International	International migrant stock
2. Life	Life expectancy at birth
3. Egmont	Egmont group member
4. Freedom	Freedom House: Freedom in the World and Freedom and the Media
5. TI	Transparency International corruption score
6. ATMs	Automated teller machines (per 100,000 adults)
7. Battle	Battle-related deaths (deaths in the past 20 years)
8. Commercial	Commercial bank branches (per 100,000 adults)
9. AProcedures	Starting a business - Procedures (average for men women)
10. ATime	Starting a business - Time (average for men and women)
11. ACost	Starting a business - Cost - (% of income per capita) (average- men and women)
12. NProcedures	Registering property - Procedures
13. Register	Registering property - Time (days)
14. Enforce	Enforcing contracts - Time (days)
15. GDP	Per capita GDP US$
16. RemittencesP	Personal remittances, paid (US$)
17. RemittancesR	Personal remittances, received (US$)
18. Transparency	World Bank transparency, accountability, and corruption in the public-sector
19. Rule	World Justice Project, Rule of Law index (Central bank independence)
20. Secrecy	Financial secrecy index
21. Denominations	Denominations by country (equivalent and/or greater than US$100)
22. Disclosure	International IDEA Political Finance Database - Political disclosure
23. Budget	International Budget Partnership Open Budget Index - Budget transparency
24. Auditing	WEF Global Competitiveness Report - Strength of auditing and reporting
25. Quality	WEF Global Competitiveness Report - Institutional pillar
26. FATF	FATF Mutual Evaluation Reports
27. Narcotics	US State Department International Narcotics Control Strategy Report (INCSR)
28. CorT	Doing Business ranking (World Bank) Business extent of corporate transparency
29. SecEX	WEF Global Competitiveness Report - Regulation of securities exchanges
30. FinSec	World Bank IDA Resource Allocation Index - Financial sector regulations

Note: All 30 variables account for the year 2017.