UNIVERSITA' DEGLI STUDI DI PADOVA

DIPARTIMENTO DI SCIENZE ECONOMICHE ED AZIENDALI "M. FANNO"

CORSO DI LAUREA IN ECONOMIA

Analysis of operations against organised crime conducted by EUROJUST

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How did we develop a model that could be able to prevent financial crimes?

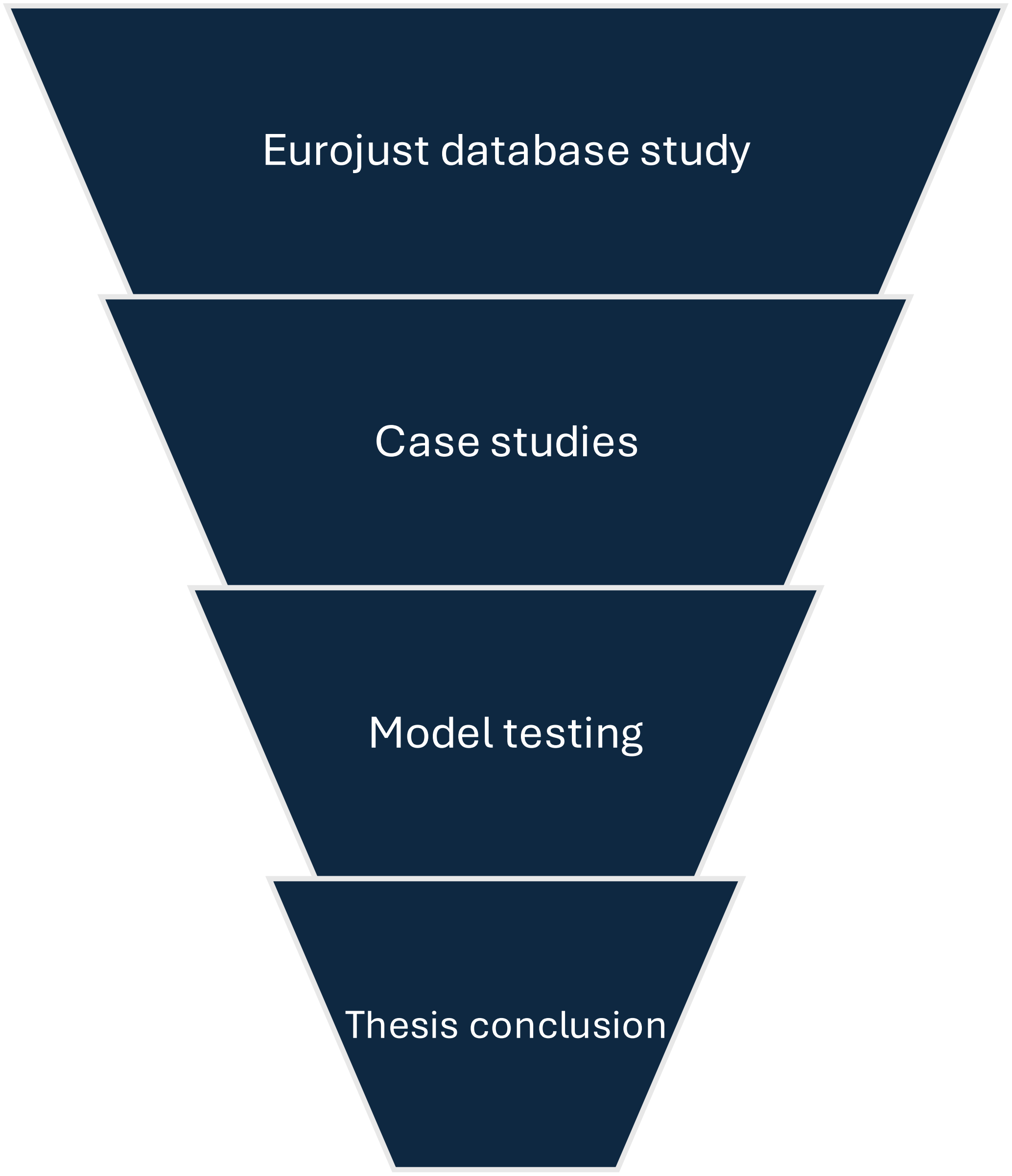
Step 1: Strategy Overview

Collected data for 85k crimes operations to reach our first goal of understanding **how much financial crimes weights on total operations by Eurojust**

Collected data for 37 well documented case studies, in order to build the model able to **classify financial crime risk ex-post**

Tested the model on the 37 cases, **developing an equation** able to classify risk within a matrix of variables, and **attributing risk** through decision tree models

Obtained **significant results in financial crimes prevention strategies** laying foundations for future researches



Step 2: Collection information about financial crimes

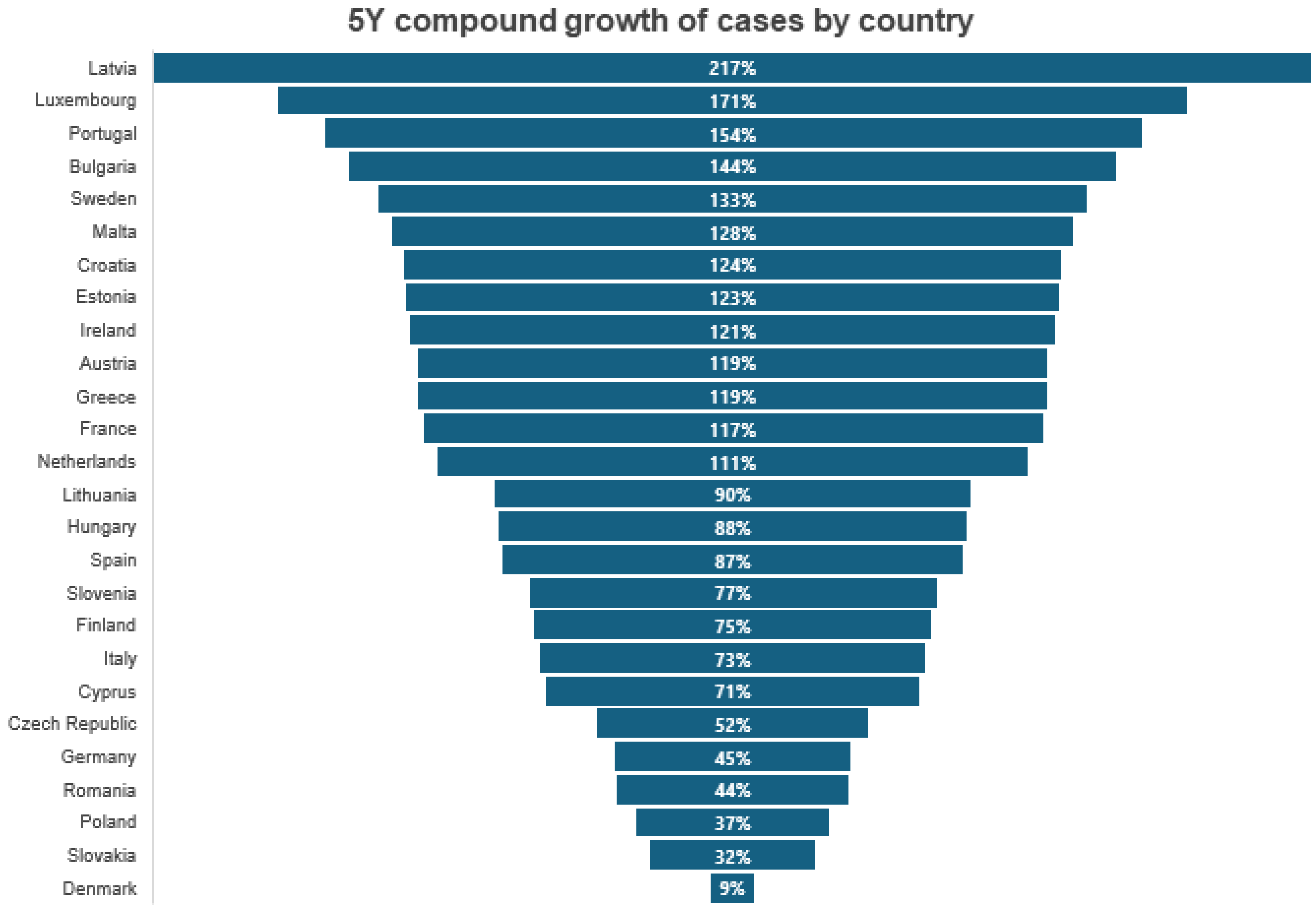
Eurojust operations: financial crimes statistics

56.4%

Financial crimes as % of total crimes

13.5B

Attributed damage over the years for financial crimes



First goal: how much financial crimes weighted on Eurojust total crimes investigation [..]

First result: 56.4% of total crimes in the last 5 years, and about €13B.

Step 3: Case studies analysis to detect red flags

Samples: financial crimes categories

Fraud	Money Laundering	Corruption
Financial crimes as % of total crimes	Financial crimes as % of total crimes	Financial crimes as % of total crimes

Samples: companies on which we collected informations

Corruption

Alstom
Gazprom
Glencore
HP
Huawei
JBS
Odebrecht
Petrobras
RBS GRG
SBM Offshore
Siemens AG
SNC-Lavalin
Unaoil

Fraud

1MDB
Banco Espírito Santo
Carillion
FTX Exchange
Nissan
OneCoin
Steinhoff International
Toshiba
Wirecard AG

Money Laundering

ABLV Bank
ABN AMRO
Banco Santander
Bank of Cyprus
Brazil Bank
Credit Suisse
Danske Bank
Deutsche Bank
FBME Bank
Liberty Reserve
N26 Bank GmbH
NatWest Group
Rabobank
Standard Chartered Bank
Swedbank

Samples: descriptive rating parameteres (not model-relevant)

- **Crypto** – 0 or 1 attributed if the case involved crypto
- **Country** – country of origin of the company involved
- **OGC** – 0 or 1 attributed if the case involved organized group crime
- **Source** – who investigated on the case

Samples: fundamental rating parameteres (model-relevant)

- **Estimated impact** – Monetary dimension of the impact, estimated using a scenario valuation
- **Impact parameter** – A parameter that goes from 1 to 7, summarizing the different type of impact on the company for each case
- **Flag categories** – the red flags detected in each cases divided into variables, subvariables and subcategories

Step 4: Obtaining empirical results

The analysis of **37 well documented** companies cases formed ‘patterns’ of informations

Which I also confronted **with external contributors**

External contributors empirical thesis

Davide Moles

(Re-Lender S.P.A.)

Dan McCrum

(Financial Times)

Saajan Sharma Nepal

(YoungPlatform)

RE-LENDER

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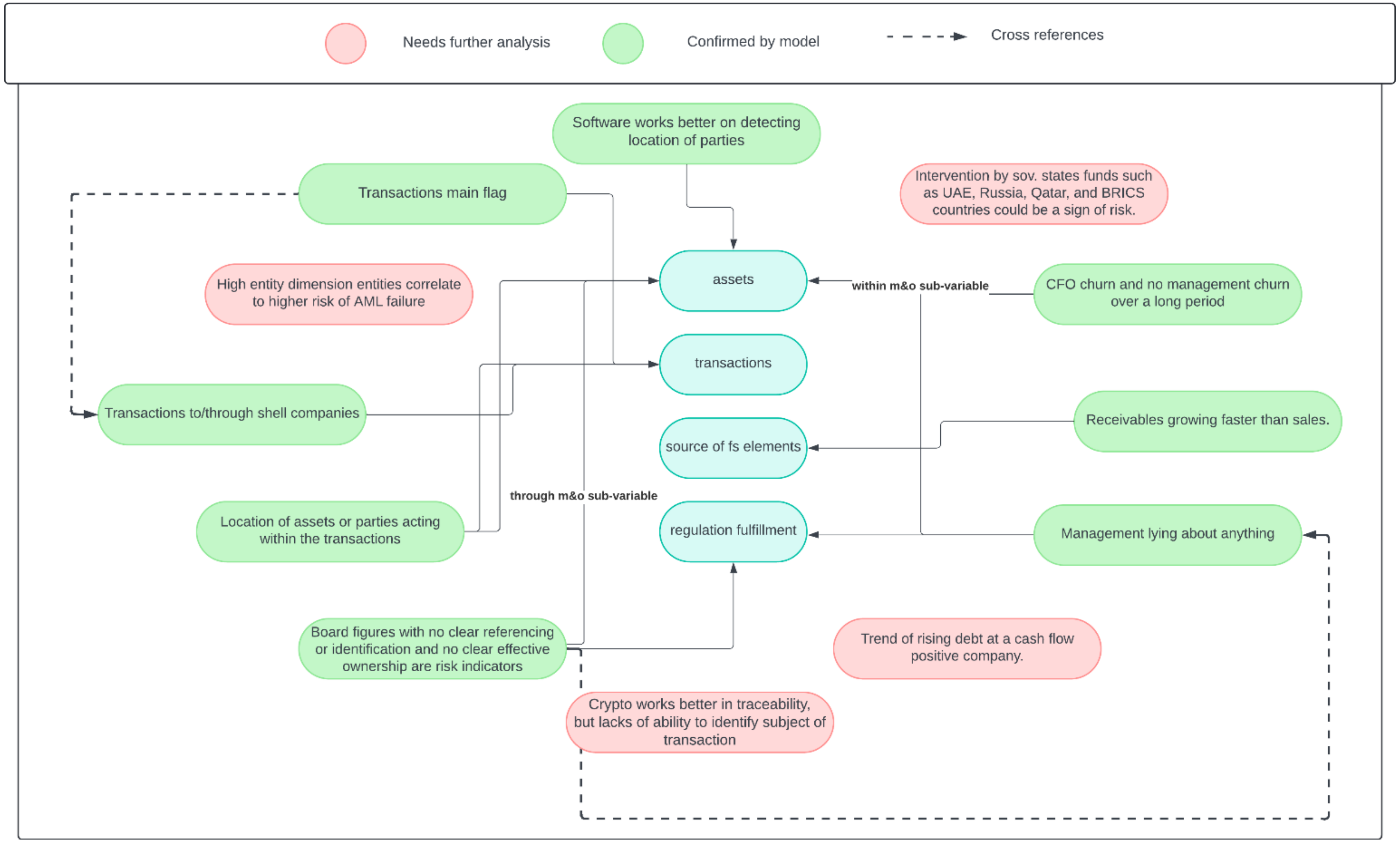


Step 5: Building the model

The model merges two valuations:

1. Binary choice

Has the variable been detected?

2. Impact ratio

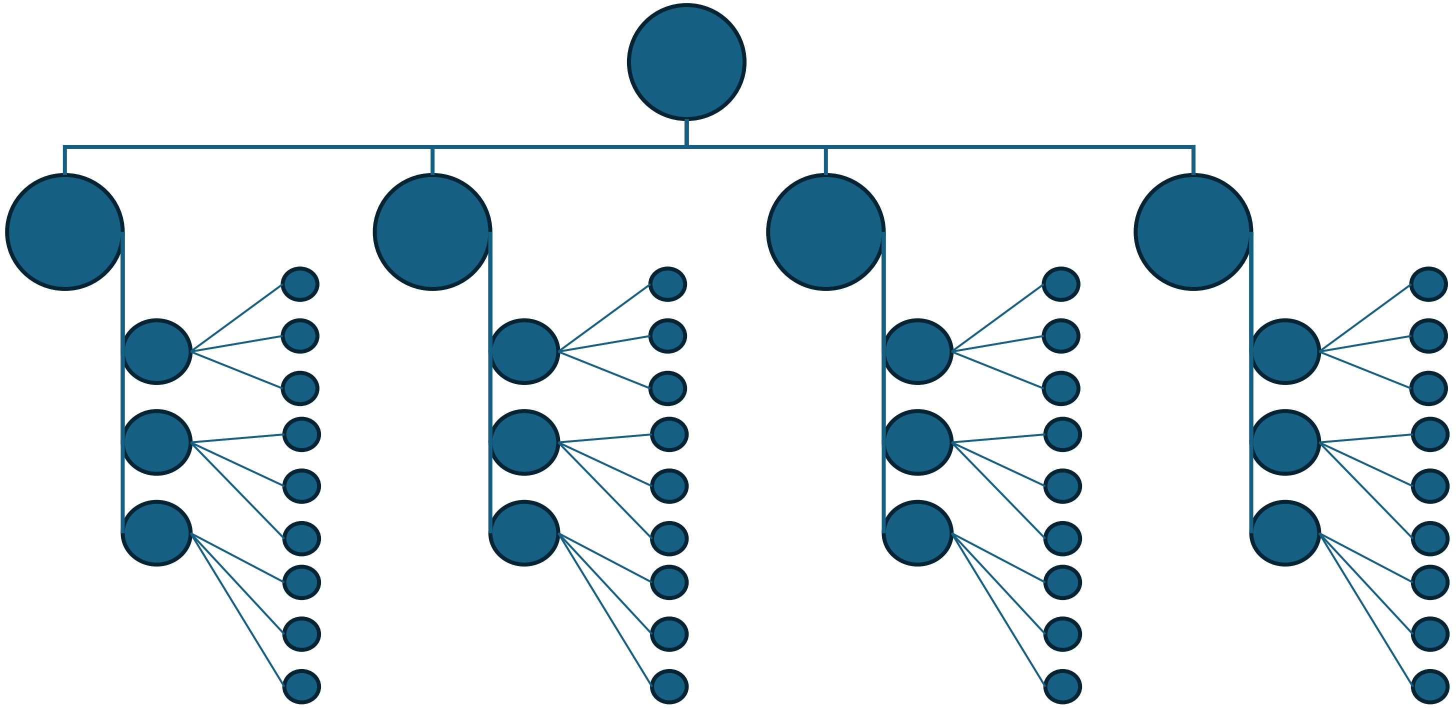
What impact the variable detected has?

Result: Model

Variable-based financial crime risk model

This is the model we built for risk(y), considering:

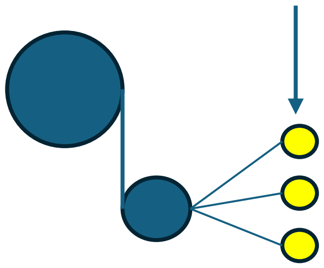
I) variables; II) sub-variables; III) sub-categories.



$$\begin{bmatrix} a \to \begin{bmatrix} l \to [lag] \\ mo \to \begin{bmatrix} brf \\ cfc \\ mfc \\ bfd \ast \\ eot \ast \\ emi \end{bmatrix} \end{bmatrix} \\ t \to \begin{bmatrix} it \to \begin{bmatrix} tts^{*} \\ itu^{*} \end{bmatrix} \\ ot \to \begin{bmatrix} tsc \\ tfs \ast \\ hpi \\ thl \end{bmatrix} \\ ar \to \begin{bmatrix} lau \\ aic \end{bmatrix} \\ fm \to \begin{bmatrix} nfd \\ ntf \end{bmatrix} \end{bmatrix} \\ s \to \begin{bmatrix} em \to \begin{bmatrix} nsi \\ hce \\ hds \end{bmatrix} \\ rm \to [vma] \end{bmatrix} \\ r \to [fi \to [amy]] \end{bmatrix}$$

Mathematical terms: sub-categories

Sub-categories



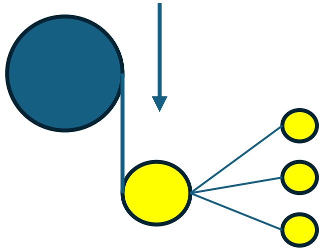
$$\textit{value ratio to magnutude }(VRM)\colon \left\{ \begin{array}{c} \dfrac{sanction}{dimension} > 1 \textit{ then } 1 \\ \dfrac{sanction}{dimension} < 1 \textit{ then } \dfrac{sanction}{dimension} * \textit{impact of the case} * \textit{relevance to the case} \end{array} \right\}$$

$$\textit{VRM to max}\colon \frac{VRM}{(max\ VRM)}$$

$$\textit{impact ratio}\colon \textit{VRM to max} * \left(1 + \frac{f_{sottocat}}{\textit{casi totali}}\right)$$

Mathematical terms: sub-variables

Sub-variables

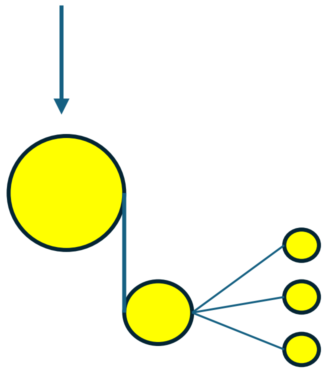


$$sub - variable):\left\{\begin{matrix} \mathbf{1} \rightarrow case\ detected \\ \mathbf{0} \rightarrow case\ not\ detected \end{matrix}\right\}$$

Mathematical terms: variables

Sub-variables

$$impact\ ratio\ of\ variable\ (y)\ =\ |average\,(rr, sr, sd, scc, sfc, scm)|\ *\ gr$$



cross references: number of cross references between the variable and the others.
This parameter is used to assess the relative relevance (**rr**).

leading variable risk: normalized value of frequency as main red-flag.
This parameter is used to assess the severity of the variable (**sr**).

damage dimension when leading variable: the generated dimension of damage in cases where the variable was leasing variable
This parameter is used to assess the severity of the damage (**sd**).

var to cat (corruption) – actualized to impact: impact of the variable related to the corruption cases it was detected, weighted for the corruption category impact ratio.
This parameter is used to assess the severity of the variable, related to the corruption category (**scc**).

var to cat (fraud) – actualized to impact: impact of the variable related to the fraud cases it was detected, weighted for the fraud category impact ratio.
This parameter is used to assess the severity of the variable, related to the fraud category (**sfc**).

var to cat (money laundering) – actualized to impact: impact of the variable related to the money laundering cases it was detected, weighted for the money laundering category impact ratio.
This parameter is used to assess the severity of the variable, related to the money laundering category (**scm**).

% of frequency: % of cases that shows the variable as red-flag.
This parameter is used to assess the general relevance (**gr**).

Mathematical terms: model

Model

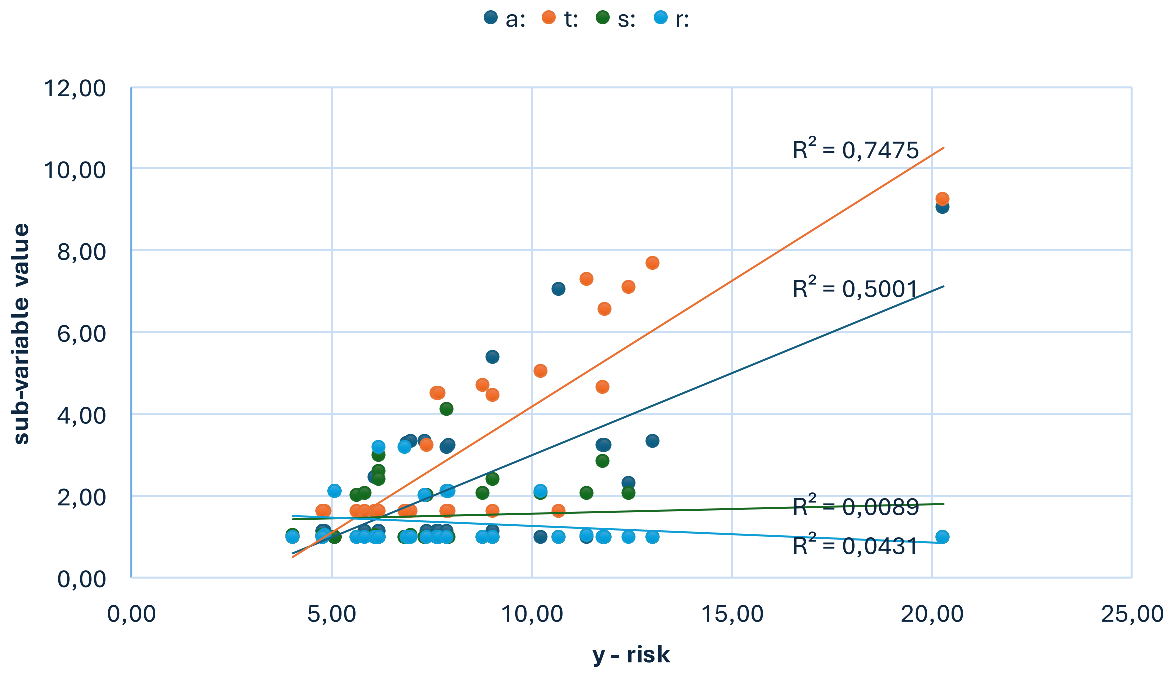
$$y = \begin{bmatrix} a : (1 + \boldsymbol{a_{ir}}) * \{[1 + \boldsymbol{l} * (1 + \boldsymbol{lag})] + [(1 + \boldsymbol{mo} * [(1 + \boldsymbol{cfc}) * (1 + \boldsymbol{mfc}) * (1 * \boldsymbol{emi}) * (1 * \boldsymbol{bfd})]]\} \\ t : (1 + \boldsymbol{t_{ir}}) * \{(1 + \boldsymbol{it}) + [(1 + \boldsymbol{ot} * [(1 + \boldsymbol{tsc}) * (1 + \boldsymbol{hpi}) * (1 + \boldsymbol{thl})]] + [(1 + \boldsymbol{ar} * [(1 + \boldsymbol{lau}) * (1 + \boldsymbol{aic})]] + [(1 + \boldsymbol{fm} * [(1 + \boldsymbol{nfd}) * (1 + \boldsymbol{ntf})]]\} \\ s : (1 + \boldsymbol{s_{ir}}) * \{[(1 + em * [(1 + \boldsymbol{nsi}) * (1 + \boldsymbol{hce}) * (1 + \boldsymbol{hds})] + [(1 + \boldsymbol{rm} * [(1 + \boldsymbol{vam})]\} \\ r : (1 + \boldsymbol{r_{ir}}) * \{[1 + \boldsymbol{fi} * [(1 + \boldsymbol{amy})]]\} \end{bmatrix}$$

Step 6: Results of the model

Second goal: Detect red flags that signal the presence of a financial crime, by developing a standardized model

Second result: We detected that assets, transactions, source of financial statements and regulations fulfillments are the four main concerns of risk valuation within a financial crime [..]

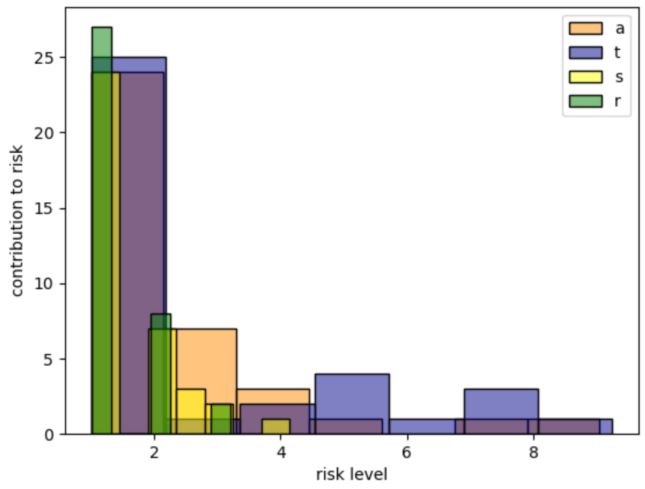
Results: Significant Variables (target of thesis)



- **Significant Variables**: **Transactions emerged as the most significant risk variable**, followed by **assets.** This was corroborated by expert opinions and data analysis, indicating transactions as a primary indicator of risk, especially in cases involving fraud or corruption

Results: Significant Variables (target of thesis)

% of damage	**65,72%**	**34%**
average t	0,41	0,32
average a	0,23	0,26
average s	0,24	0,21
average r	0,12	0,21



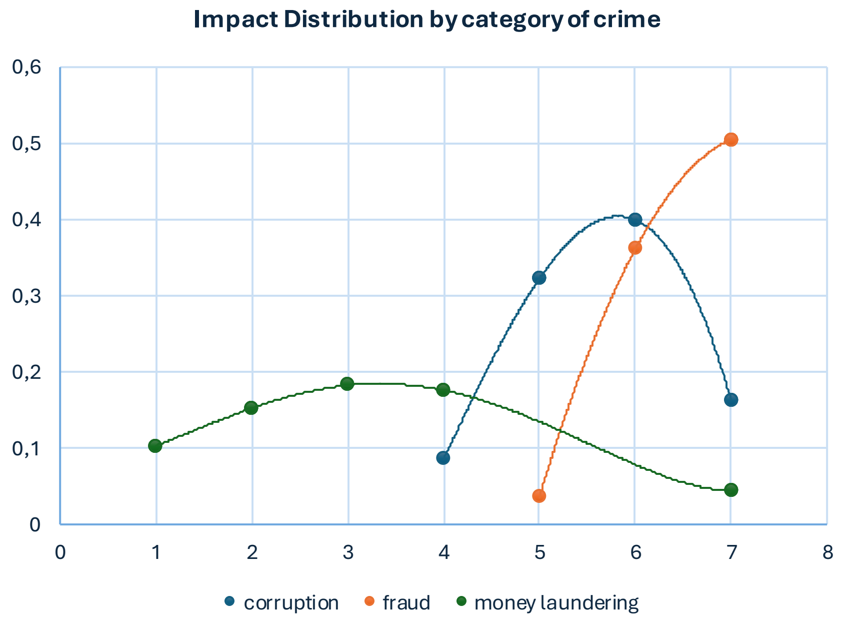
- **1st relationship observation: average contribution of t** is almost half of total explanation of risk for the cases that **generated 66% of total damages**, decreasing to 0.32 for the remaining 34% of cases

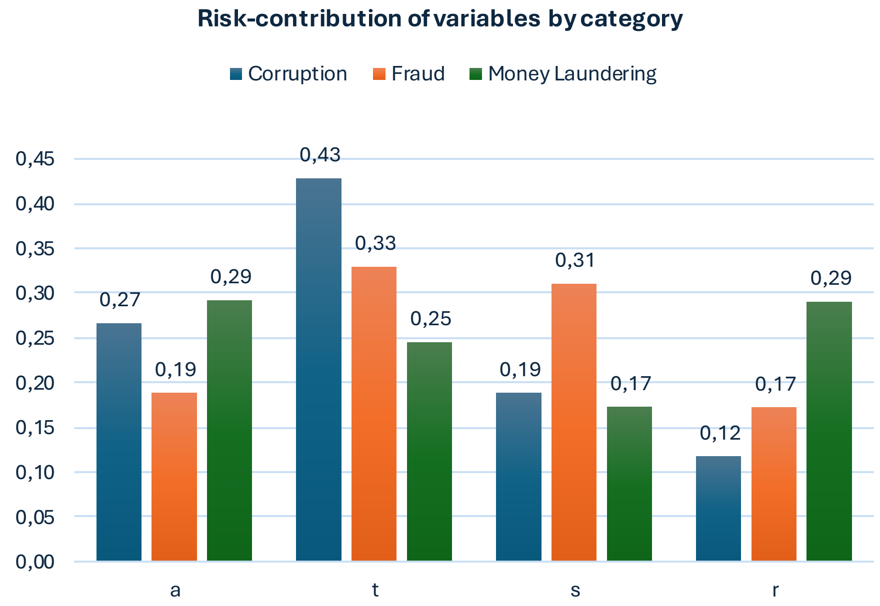
- **2nd relationship observation:** to test the proof of transactions as leading risk variable we tested the distribution of the model results, which shows two things:
  - on average, the distribution is (as in the 1 results bullet point) **skewed towards lower values of risk contribution**
  - **tail risk values** show a **predominance of transaction** contribution

Results: Significant Variables (target of thesis)

- by connecting the 2-relationship observation, we didn’t observe the mere frequency of the variable flagged by the model, but we instead **obtained good evidence** to assume that **transactions**, when found, **increase risk expectation**.

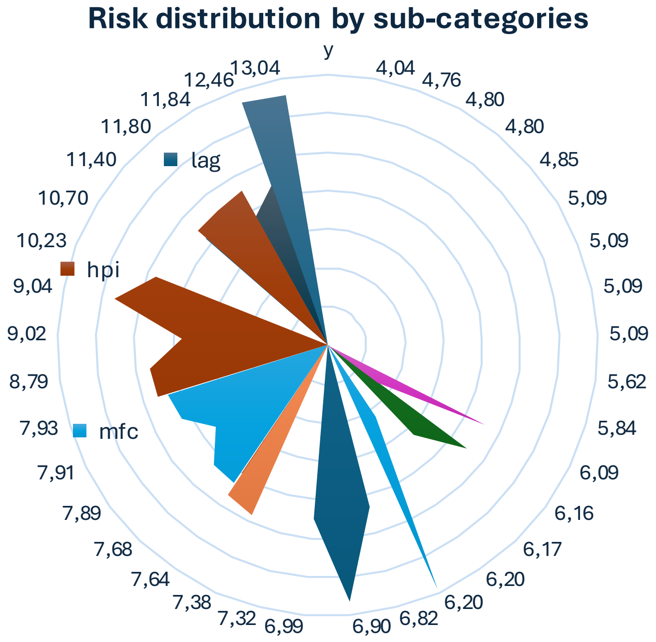
Results: Category Impact





- Category Impact: **Corruption** and **fraud** are the categories of crime with the **highest expected damage and impact**. Risk is particularly associated with outbound transactions to shell companies and politically involved individuals. We noted that, **corruption risk is strictly related to transactions.**

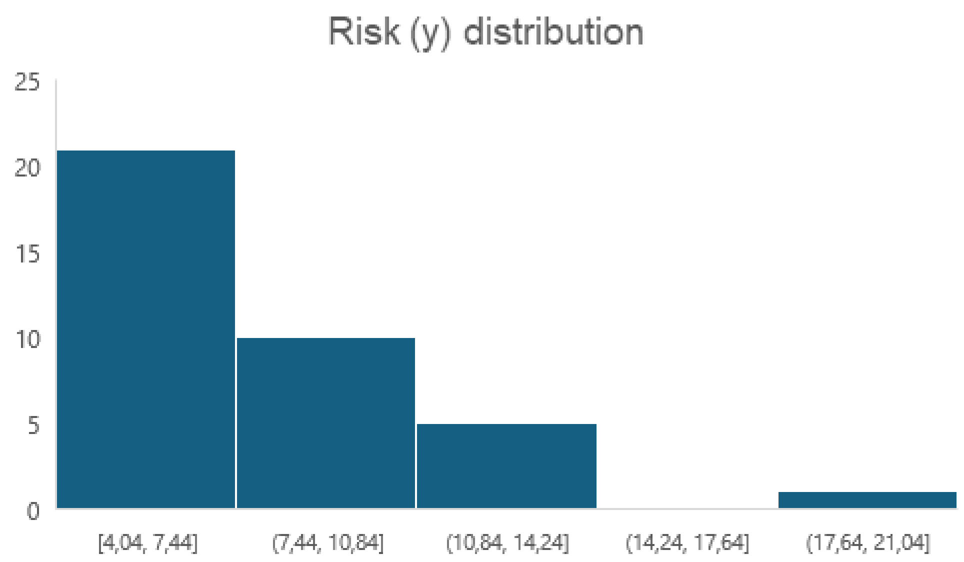
Results: Category Impact



subcat	avg impact
hpi	0,33316725
lag	0,30608827
mfc	0,29396162
tsc	0,1045258
hds	0,09893706
thl	0,06659239
cfc	0,06378933
amy	0,05724463
bfd	0,05647768
lau	0,04958315
vma	0,04684812
hce	0,0447892
brf	0,04235428
emi	0,03909376
ntf	0,03473444
nfd	0,03145344
aic	0,02609563
nsi	0,01161043

- **Sub-category Analysis**: The most frequent sub-categories include **management misreporting**, **high political involvement**, and the **location of assets in high-risk areas**. Each has a distinct impact on overall risk.

Results: Risk distribution



- **Risk Distribution**: **56.7%** of companies fall within the **low to medium risk range** (4.04 to 7.44), 27% within medium to high risk (7.44 to 10.84), 13.5% in high risk range10.84 and 14.24, and less than 0.1% in the tail risk scenario.

Step 7: Conclusion

Conclusions

1. Results showed that assets, transactions, source of financial statements and regulations fulfillments are the four main concerns of risk valuation within a financial crime, with conclusive evidence of **transactions being the most risk-related factor**, with strong emphasis of companies with **high political involvement**, and assets in high-risk location especially when cross referenced to **outbound transactions.**

2. Per each crime category, there's a leading variable in signaling financial crime risk:
   1. For **corruption** cases we look at **transactions**
   2. For **fraud** cases we look at **source of financial statements**
   3. For **money laundering** cases we look at (AML) **regulations fulfillment** and **assets**.

3. Results open the door to further research and studies in the context of financial crime prevention and underline the **importance for regulators** to **focus** more **on making transactions** more transparent and reliable, because **AML processes** are easily **bypassed**

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