Disentangling the sources of cyber risk premia

Cyber-Alp Retreat 2024

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Motivation

- Financial markets and aggregate expectation. . . fundamentals of future cash flow and discount rate (*i.e. risk*).
- Financial econometrics success: yes, there are identified sources of risk that are orthogonal to each other, which determines the prices of assets!
- Can the cyber risk be part of the discount rate?

Existing research

- Florackis et al. (2023); Jamilov et al. (2023); Liu et al. (2022); Jiang et al. (2023); Celeny and Maréchal (2023), all find that *ceteris paribus*, the higher the cyber risk faced by a firm, the lower its valuation *vs.* its fair value, and hence the higher the risk premium $\rightarrow$ consensus.
- The risk premium has the same interpretation as in the insurance context: firms are indifferent between i) facing cyber risk, ii) paying an insurance contract, or iii) paying for cybersecurity.
- Campbell et al. (2003); Gordon et al. (2011); Johnson et al. (2017); Celeny et al. (2024) show how different types of cyber incidents (availability, confidentiality, ransomware, etc.) affect organizations. They all find that not all cyber incidents are equal.
- Thus, there is no reason for investors to discount different cyber risks at the same rate. This is the main caveat of all aforementioned research: they only study cyber risk through the lenses of a single cyber risk score.

Research question and contribution

Comparing description of cyber attacks and annual statements of firms, we can assess if a firm is exposed to cyber risk. We call this degree of exposition, the cyber score of a firm.

- Celeny and Maréchal (2023) constructed a unique cyber score for firms.
- In reality, cyber attacks are not all equally destructive, so they should be different cyber scores for different type of cyber attack.
- Can we decompose the cyber score into several sub-cyber score? Is this decomposition acknowledged on the market? Does it reflect more information than the unique cyber score on the market?

Data

- MITRE ATT&CK: textual database, description of cyber attacks.
- Chicago Research in Security Prices (CRSP), monthly data,adjusted prices and returns, 2007–2023, all US stocks from NYSE, NASDAQ, ARCA...
- Compustat database annual or monthly data, accounting data on US listed firms.
- 10-K filings: yearly frequency but asynchronous textual reports required by the SEC (Securities and Exchange Commission) for all listed firms.

Descriptive statistics: MITRE ATT&CK

Tactic

Tactics represent the "why" of an ATT&CK technique or sub-technique. It is the adversary's tactical goal: the reason for performing an action. For example, an adversary may want to achieve credential access, collect data or run malicious code. $N = 14$

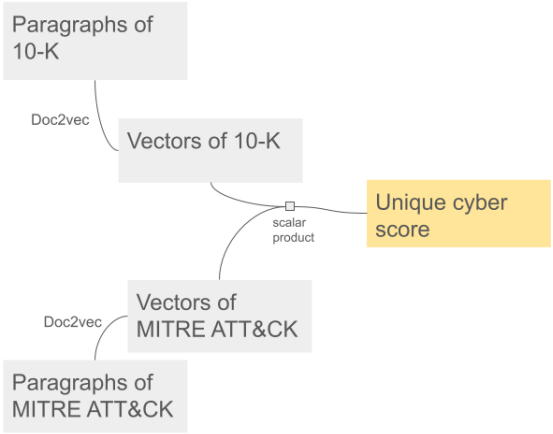
Technique

Techniques represent "how" an adversary achieves a tactical goal by performing an action. For example, an adversary may dump credentials to achieve credential access or may use social engineering to run malicious code. $N = 235$

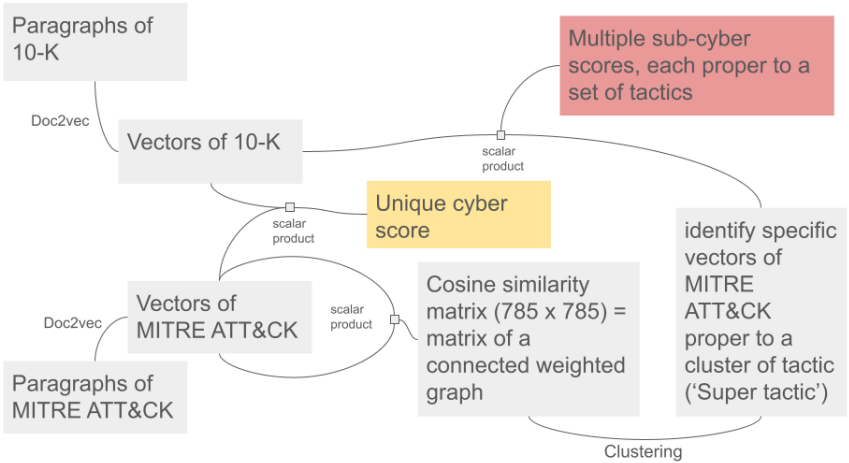
Sub-technique

Sub-techniques describe the different types of a technique. For example, when trying to run malicious code for social engineering, the adversary may use a malicious link, a malicious file or a malicious image for execution. $N = 785$

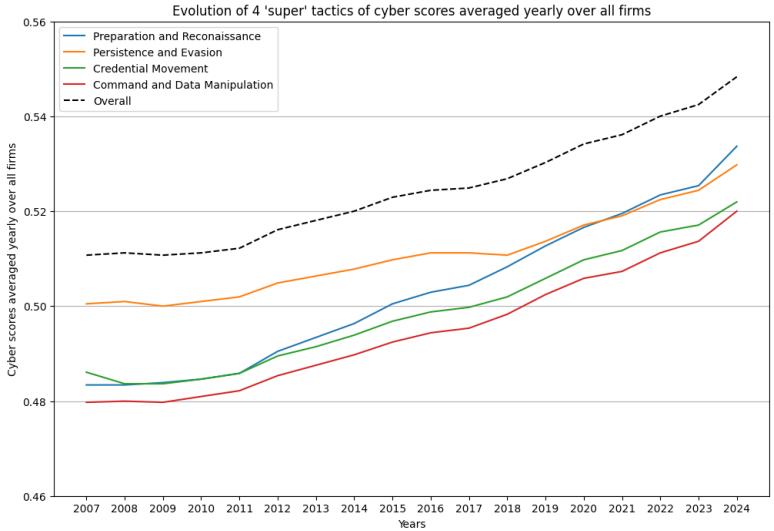
How to obtain the cyber scores?



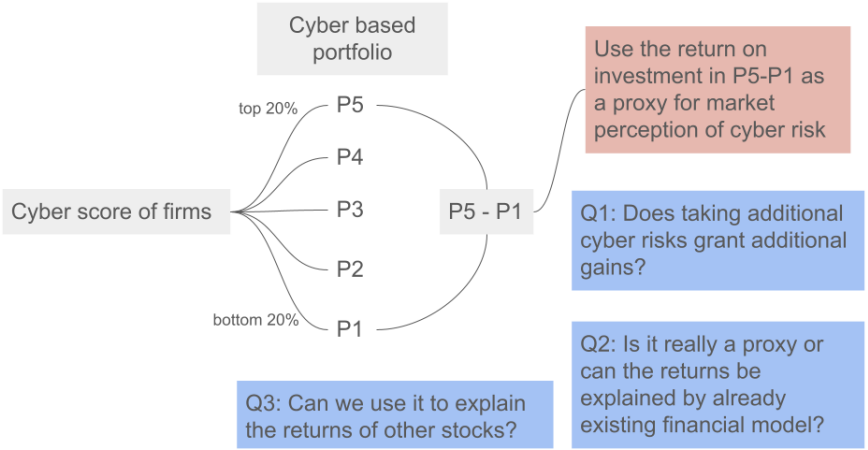
How to obtain the cyber scores?



Descriptive statistics: super tactics



How to use the cyber scores?



Asset pricing model: How to assess relevance?

- for one asset (stock return) $R^e = \alpha + \beta_1 F_1 + \beta_2 F_2 + \beta_3 F_3 + ... + \epsilon$

- F_i are pricing factors
- α is the part of the return R^e that can NOT be explained by the F_i.
- Q2 : If R^e is cyber score based (R^e = P5 for example), is α statistically significant ($\alpha \neq 0$) when not accounting for cyber based factors and accounting for well known pricing factors?
- Q3 : Is our additional factor, $F = P5 - P1$, improving the explained variance in stocks returns? Are α's generally tending toward 0 ?

Asset pricing: R_e is cyber based, can we generate $\alpha \neq 0$?

	P1	P2	P3	P4	P5	P5-P1
A. Portfolios sorted by cyber score						
avg. excess ret.	**0.82*****	**0.93*****	**1.04*****	**1.22*****	**1.44*****	**0.62****
	[3.27]	[3.46]	[3.65]	[4.65]	[4.54]	[2.05]
CAPM alpha	**-0.18**	**-0.12**	**-0.08**	**0.14**	**0.36****	**0.54**
	[-0.85]	[-0.93]	[-0.84]	[1.47]	[2.14]	[1.49]
FFC alpha	**-0.09**	**-0.05**	**0.0**	**0.15***	**0.27*****	**0.36****
	[-0.88]	[-0.57]	[0.04]	[1.71]	[3.04]	[2.2]
FF5 alpha	**-0.14**	**-0.1**	**0.0**	**0.13**	**0.29*****	**0.44*****
	[-1.57]	[-1.18]	[0.01]	[1.47]	[3.16]	[2.88]
B. Characteristics						
Nb. firms	628.48	629.1	629.01	629.1	629.67	-
Avg. cyber score	0.49	0.51	0.52	0.53	0.57	-
Sharp Ratio	0.61	0.69	0.72	0.88	1.02	0.68

Average monthly excess returns and alphas (in percent) using the overall cyber score

Asset pricing: R_e is cyber based, can we generate $\alpha \neq 0$?

	P1	P2	P3	P4	P5	P5-P1
A. Portfolios sorted by cyber score						
avg. excess ret.	**0.88*****	**0.9*****	**1.04*****	**1.13*****	**1.49*****	**0.61****
	[3.63]	[3.51]	[3.5]	[4.34]	[4.66]	[2.06]
CAPM alpha	**-0.12**	**-0.14**	**-0.1**	**0.07**	**0.4****	**0.52**
	[-0.6]	[-1.01]	[-1.16]	[1.11]	[2.31]	[1.48]
FFC alpha	**-0.04**	**-0.07**	**-0.02**	**0.09**	**0.3*****	**0.34****
	[-0.41]	[-0.76]	[-0.29]	[1.4]	[3.09]	[2.07]
FF5 alpha	**-0.1**	**-0.11**	**-0.02**	**0.08**	**0.33*****	**0.43*****
	[-1.15]	[-1.25]	[-0.32]	[1.23]	[3.19]	[2.74]
B. Characteristics						
Nb. firms	628.48	629.1	629.01	629.1	629.67	-
Avg. cyber score	0.46	0.48	0.49	0.51	0.54	-
Sharp Ratio	0.66	0.67	0.72	0.83	1.04	0.69

Average monthly excess returns and alphas (in percent) using the credential movement cyber score

Asset pricing: GRS, $\alpha_i \to 0 \quad \forall i$?

	GRS	p value	$\overline{R2}$	GRS	p value	$\overline{R2}$
	Sorted on cyber risk			Sorted on size		
FF5	1.451	0.107	0.868	0.737	0.783	0.876
FF5 + CyberFactor	1.088	0.367	0.888	0.833	0.671	0.877
	Sorted on market beta			Sorted on book-to-market		
FF5	1.541	0.075	0.793	1.240	0.229	0.891
FF5 + CyberFactor	1.495	0.090	0.806	1.021	0.441	0.895

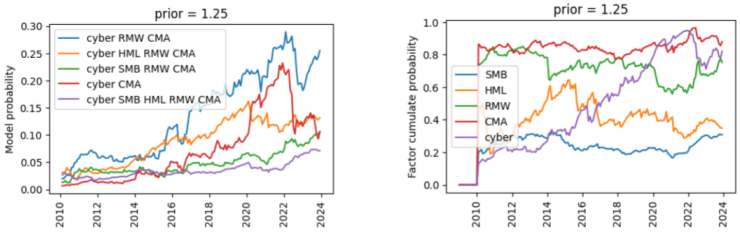
GRS test for overall cyber score

Asset pricing: GRS, $\alpha_i \to 0 \quad \forall i$?

	GRS	p value	$\overline{R2}$	GRS	p value	$\overline{R2}$
	Sorted on cyber risk			Sorted on size		
FF5	1.539	0.076	0.864	0.737	0.783	0.876
FF5 + CyberFactor	1.192	0.268	0.884	0.770	0.746	0.877
	Sorted on market beta			Sorted on book-to-market		
FF5	1.541	0.075	0.793	1.240	0.229	0.891
FF5 + CyberFactor	1.441	0.111	0.804	0.997	0.469	0.895

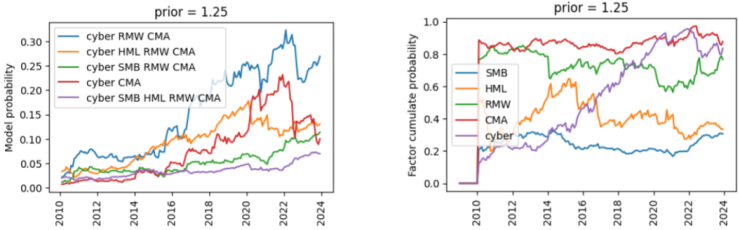
GRS test for credential movement

Asset pricing: BGRS, Are models better as pricing factors when cyber based factors are included ?



Factor model posterior probabilities using overall cyber score

Asset pricing: BGRS, Are models better as pricing factors when cyber based factors are included ?



Factor model posterior probabilities using credential movement cyber score

Conclusion

Win:

- We identify cosine similarity based structure in MITRE ATT&CK, 4 "super-tactics" were identified using clustering methods.
- We show that our cyber factors (unique and super-tactics based) were useful to explain the return of different stocks on the market.
- Similarly, we showed that making an investment in a firm that is cyber risky grant additional reward. Additional reward can not be explained by traditional pricing factors.

Loss:

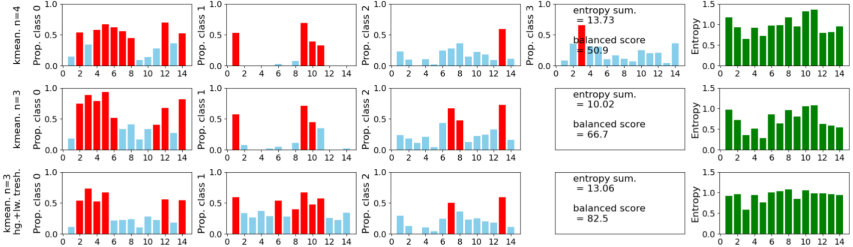
- P5 - P1 are statistically too similar for all cyber scores. Investor are not informed enough to differentiate the sources of cyber risk. However, from 2024 onwards, the law required that all firms report their cyber risk in the 10-K. This could drastically improve our study in the future.

Appendix

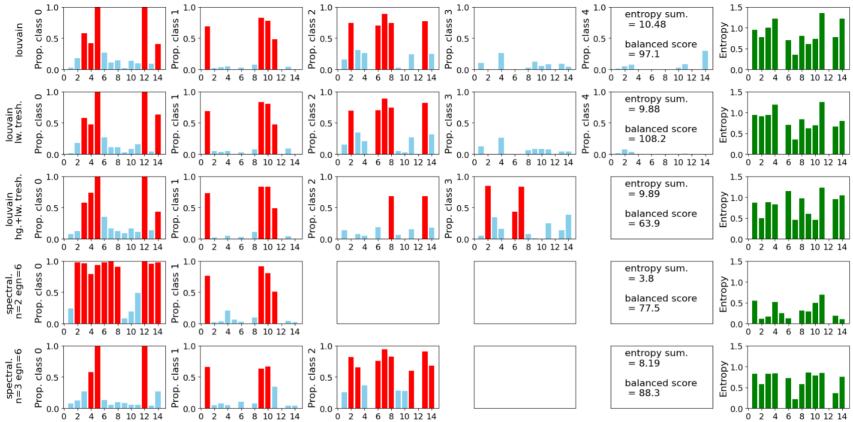
- CMA (Conservative Minus Aggressive): Difference in returns between firms with low investment (conservative) and high investment (aggressive).
- SMB (Small Minus Big): Difference in returns between small-cap and large-cap stocks.
- HML (High Minus Low): Difference in returns between value stocks (high book-to-market) and growth stocks (low book-to-market).
- RMW (Robust Minus Weak): Difference in returns between firms with high profitability (robust) and low profitability (weak).
- UMD (Up Minus Down): Difference in returns between stocks with high past returns (winners) and low past returns (losers).

- Preparation and Reconaissance includes : Impact, Initial Access, Resource Development, Reconnaissance, Discovery
- Persistence and Evasion includes : Persistence, Privilege Escalation, Execution, Defense Evasion
- Credential Movement includes : Credential Access, Lateral Movement
- Command and Data Manipulation includes : Command and Control, Collection, Exfiltration

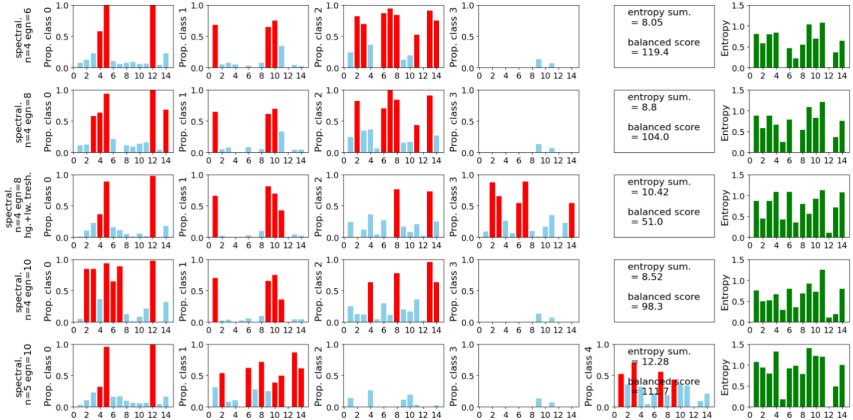
Appendix


kmean, n=4
kmean, n=3
kmean, n=3
hg+iw, tresh.
Prop. class 0
Prop. class 1
Prop. class 2
Prop. class 3
Entropy
entropy sum.
= 13.73
balanced score
= 50.9
entropy sum.
= 10.02
balanced score
= 66.7
entropy sum.
= 13.06
balanced score
= 82.5

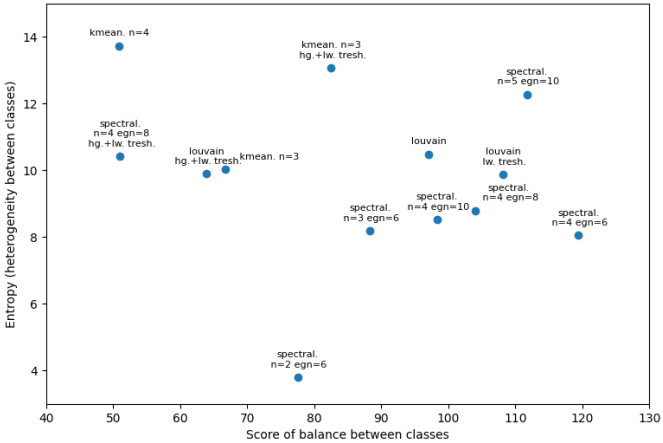
Appendix


louvain
louvain lw. tresh.
louvain hg. tkw. tresh.
spectral- n=2_eig=-6
spectral- n=3_eig=-6
Prop. class 0
Prop. class 1
Prop. class 2
Prop. class 3
Prop. class 4
Entropy
entropy sum. = 10.48
balanced score = 97.1
entropy sum. = 9.88
balanced score = 108.2
entropy sum. = 9.89
balanced score = 63.9
entropy sum. = 3.8
balanced score = 77.5
entropy sum. = 8.19
balanced score = 88.3

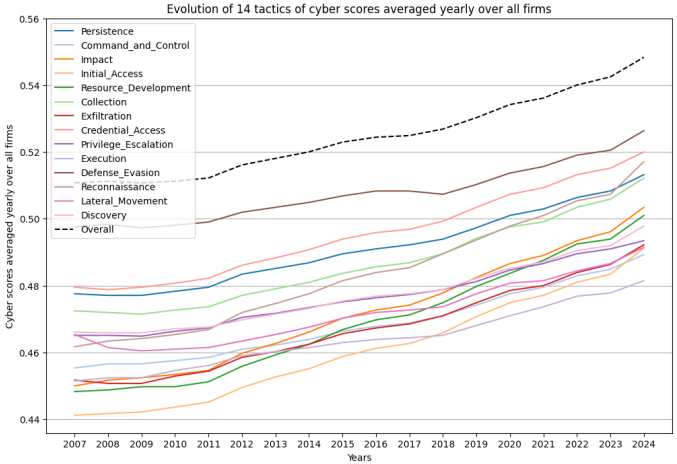
Appendix


spectral, n=4 eqn=6
spectral, n=4 eqn=8
spectral, n=4 eqn=8 hg.+lw. tresh.
spectral, n=4 eqn=10
spectral, n=5 eqn=10
Prop. class 0
Prop. class 1
Prop. class 2
Prop. class 3
Prop. class 4
entropy sum. = 8.05
balanced score = 119.4
entropy sum. = 8.8
balanced score = 104.0
entropy sum. = 10.42
balanced score = 51.0
entropy sum. = 8.52
balanced score = 98.3
entropy sum. = 12.28
balanced score = 111.7
Entropy

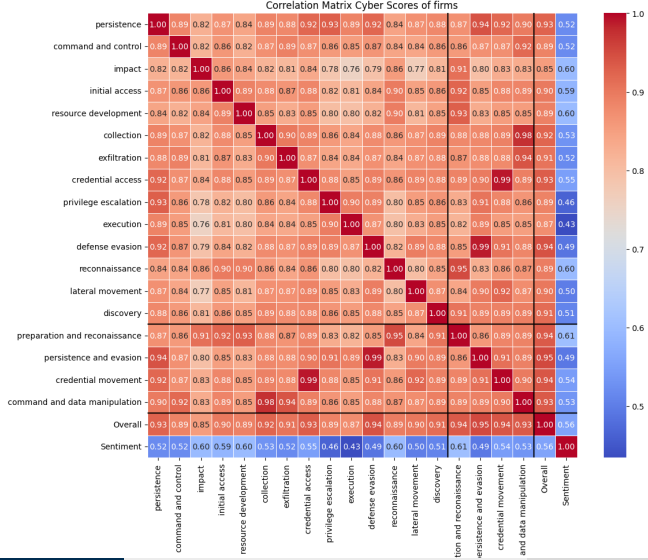
Appendix


kmean. n=4
kmean. n=3
hg.+lw. tresh.
spectral.
n=5 egn=10
spectral.
n=4 egn=8
hg.+lw. tresh.
louvain
louvain
hg.+lw. tresh.
kmean. n=3
louvain
lw. tresh.
spectral.
n=4 egn=8
spectral.
n=4 egn=10
spectral.
n=3 egn=6
spectral.
n=4 egn=6
spectral.
n=2 egn=6
Entropy (heterogeneity between classes)
Score of balance between classes
14
12
10
8
6
4
40
50
60
70
80
90
100
110
120
130

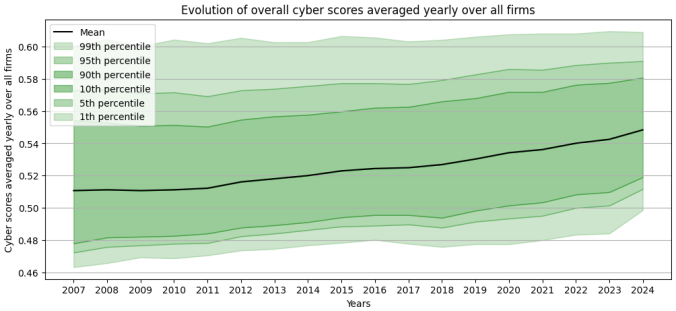
Appendix


Evolution of 14 tactics of cyber scores averaged yearly over all firms
Cyber scores averaged yearly over all firms
Years
0.56
0.54
0.52
0.50
0.48
0.46
0.44
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017
2018
2019
2020
2021
2022
2023
2024
Persistence
Command_and_Control
Impact
Initial_Access
Resource_Development
Collection
Exfiltration
Credential_Access
Privilege_Escalation
Execution
Defense_Evasion
Reconnaissance
Lateral_Movement
Discovery
Overall

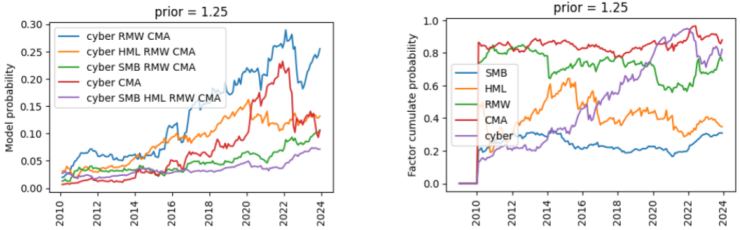
Appendix


Correlation Matrix Cyber Scores of firms
persistence
command and control
impact
initial access
resource development
collection
exfiltration
credential access
privilege escalation
execution
defense evasion
reconnaissance
lateral movement
discovery
preparation and reconaissance
persistence and evasion
credential movement
command and data manipulation
Overall
Sentiment
1.0
0.9
0.8
0.7
0.6
0.5

Appendix


Evolution of overall cyber scores averaged yearly over all firms
Mean
99th percentile
95th percentile
90th percentile
10th percentile
5th percentile
1th percentile
Cyber scores averaged yearly over all firms
0.60
0.58
0.56
0.54
0.52
0.50
0.48
0.46
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017
2018
2019
2020
2021
2022
2023
2024
Years

Appendix



Factor model posterior probabilities using overall cyber score

Appendix

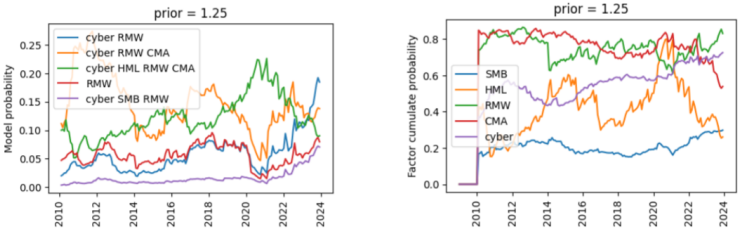
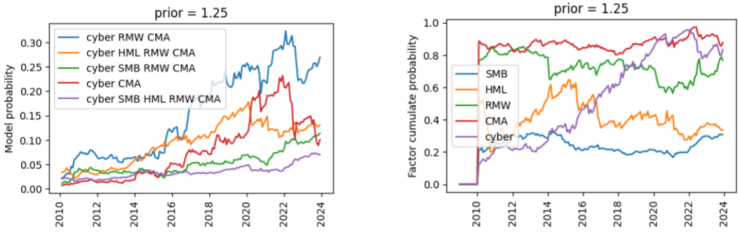


Figure 5.13: **Factor model posterior probabilities using cyber sentiment score**

Appendix



Factor model posterior probabilities using credential movement cyber score

Appendix

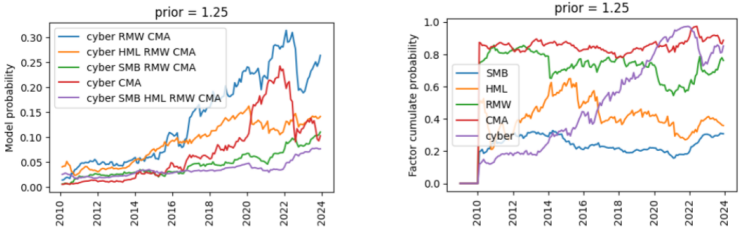


Figure 5.14: **Factor model posterior probabilities using command and data manipulation cyber score**

Appendix

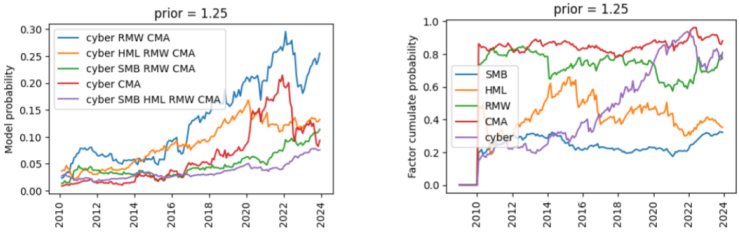


Figure 5.16: **Factor model posterior probabilities using persistence and evasion cyber score**

Appendix

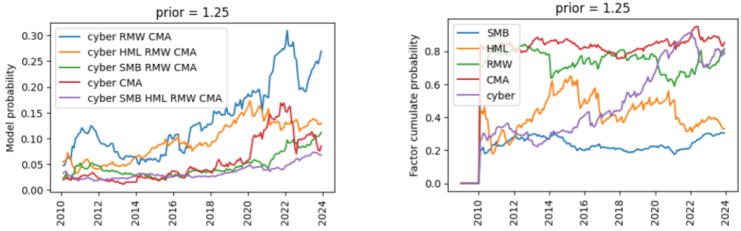


Figure 5.17: **Factor model posterior probabilities using preparation and reconaissance cyber score**

Appendix

	GRS	p value	$\overline{R2}$	GRS	p value	$\overline{R2}$
	Sorted on cyber risk			Sorted on size		
FF5	1.451	0.107	0.868	0.737	0.783	0.876
FF5 + CyberFactor	1.088	0.367	0.888	0.833	0.671	0.877
	Sorted on market beta			Sorted on book-to-market		
FF5	1.541	0.075	0.793	1.240	0.229	0.891
FF5 + CyberFactor	1.495	0.090	0.806	1.021	0.441	0.895

GRS test for overall cyber score

Appendix

	GRS	p value	$\overline{R2}$	GRS	p value	$\overline{R2}$
	Sorted on cyber risk			Sorted on size		
FF5	1.254	0.218	0.854	0.737	0.783	0.876
FF5 + CyberFactor	1.198	0.263	0.864	0.748	0.771	0.877
	Sorted on market beta			Sorted on book-to-market		
FF5	1.541	0.075	0.793	1.240	0.229	0.891
FF5 + CyberFactor	1.488	0.093	0.796	1.188	0.271	0.892

Table 5.22: **GRS test for cyber sentiment score**

Appendix

	GRS	p value	$\overline{R2}$	GRS	p value	$\overline{R2}$
	Sorted on cyber risk			Sorted on size		
FF5	1.539	0.076	0.864	0.737	0.783	0.876
FF5 + CyberFactor	1.192	0.268	0.884	0.770	0.746	0.877
	Sorted on market beta			Sorted on book-to-market		
FF5	1.541	0.075	0.793	1.240	0.229	0.891
FF5 + CyberFactor	1.441	0.111	0.804	0.997	0.469	0.895

GRS test for credential movement

Appendix

	GRS	p value	$\overline{R2}$	GRS	p value	$\overline{R2}$
	Sorted on cyber risk			Sorted on size		
FF5	1.558	0.070	0.855	0.737	0.783	0.876
FF5 + CyberFactor	1.119	0.335	0.877	0.844	0.657	0.877
	Sorted on market beta			Sorted on book-to-market		
FF5	1.541	0.075	0.793	1.240	0.229	0.891
FF5 + CyberFactor	1.472	0.099	0.807	1.026	0.436	0.895

Table 5.23: **GRS test for command and data manipulation cyber score**

Appendix

	GRS	p value	$\overline{R2}$	GRS	p value	$\overline{R2}$
	Sorted on cyber risk			Sorted on size		
FF5	1.465	0.101	0.868	0.737	0.783	0.876
FF5 + CyberFactor	1.128	0.326	0.890	0.884	0.608	0.878
	Sorted on market beta			Sorted on book-to-market		
FF5	1.541	0.075	0.793	1.240	0.229	0.891
FF5 + CyberFactor	1.500	0.088	0.806	1.021	0.441	0.896

Table 5.25: **GRS test for persistence and evasion cyber score**

Appendix

	GRS	p value	$\overline{R2}$	GRS	p value	$\overline{R2}$
	Sorted on cyber risk			Sorted on size		
FF5	1.516	0.083	0.861	0.737	0.783	0.876
FF5 + CyberFactor	1.216	0.248	0.879	0.807	0.703	0.877
	Sorted on market beta			Sorted on book-to-market		
FF5	1.541	0.075	0.793	1.240	0.229	0.891
FF5 + CyberFactor	1.546	0.073	0.807	0.990	0.477	0.896

Table 5.26: **GRS test for preparation and reconaissance cyber score**

Appendix

	GRS	p value	$\overline{R2}$	GRS	p value	$\overline{R2}$
	Sorted on cyber risk			Sorted on size		
FF5	1.516	0.083	0.861	0.737	0.783	0.876
FF5 + CyberFactor	1.216	0.248	0.879	0.807	0.703	0.877
	Sorted on market beta			Sorted on book-to-market		
FF5	1.541	0.075	0.793	1.240	0.229	0.891
FF5 + CyberFactor	1.546	0.073	0.807	0.990	0.477	0.896

Table 5.26: **GRS test for preparation and reconaissance cyber score**

Appendix

	P1	P2	P3	P4	P5	P5-P1
A. Portfolios sorted by cyber score						
avg. excess ret.	**0.82*****	**0.93*****	**1.04*****	**1.22*****	**1.44*****	**0.62****
	[3.27]	[3.46]	[3.65]	[4.65]	[4.54]	[2.05]
CAPM alpha	**-0.18**	**-0.12**	**-0.08**	**0.14**	**0.36****	**0.54**
	[-0.85]	[-0.93]	[-0.84]	[1.47]	[2.14]	[1.49]
FFC alpha	**-0.09**	**-0.05**	**0.0**	**0.15***	**0.27*****	**0.36****
	[-0.88]	[-0.57]	[0.04]	[1.71]	[3.04]	[2.2]
FF5 alpha	**-0.14**	**-0.1**	**0.0**	**0.13**	**0.29*****	**0.44*****
	[-1.57]	[-1.18]	[0.01]	[1.47]	[3.16]	[2.88]
B. Characteristics						
Nb. firms	628.48	629.1	629.01	629.1	629.67	-
Avg. cyber score	0.49	0.51	0.52	0.53	0.57	-
Sharp Ratio	0.61	0.69	0.72	0.88	1.02	0.68

Average monthly excess returns and alphas (in percent) using the overall cyber score

Appendix

	P1	P2	P3	P4	P5	P5-P1
A. Portfolios sorted by cyber score						
avg. excess ret.	**0.99*****	**1.08*****	**1.24*****	**1.15*****	**1.14*****	**0.14**
	[3.92]	[4.61]	[4.78]	[3.94]	[3.88]	[1.21]
CAPM alpha	**-0.03**	**0.04**	**0.19***	**0.02**	**0.05**	**0.08**
	[-0.27]	[0.31]	[1.91]	[0.31]	[0.59]	[0.58]
FFC alpha	**0.0**	**0.05**	**0.17***	**0.04**	**0.05**	**0.05**
	[0.02]	[0.48]	[1.78]	[0.59]	[0.66]	[0.45]
FF5 alpha	**-0.03**	**-0.02**	**0.12**	**0.07**	**0.1**	**0.12**
	[-0.41]	[-0.18]	[1.31]	[1.15]	[1.17]	[1.15]
B. Characteristics						
Nb. firms	628.48	629.1	629.01	629.1	629.67	-
Avg. cyber score	0.46	0.49	0.51	0.53	0.57	-
Sharp Ratio	0.75	0.8	0.92	0.81	0.82	0.3

Table 5.4: **Average monthly excess returns and alphas (in percent) using the cyber sentiment score**

Appendix

	P1	P2	P3	P4	P5	P5-P1
A. Portfolios sorted by cyber score						
avg. excess ret.	**0.88*****	**0.9*****	**1.04*****	**1.13*****	**1.49*****	**0.61****
	[3.63]	[3.51]	[3.5]	[4.34]	[4.66]	[2.06]
CAPM alpha	**-0.12**	**-0.14**	**-0.1**	**0.07**	**0.4****	**0.52**
	[-0.6]	[-1.01]	[-1.16]	[1.11]	[2.31]	[1.48]
FFC alpha	**-0.04**	**-0.07**	**-0.02**	**0.09**	**0.3*****	**0.34****
	[-0.41]	[-0.76]	[-0.29]	[1.4]	[3.09]	[2.07]
FF5 alpha	**-0.1**	**-0.11**	**-0.02**	**0.08**	**0.33*****	**0.43*****
	[-1.15]	[-1.25]	[-0.32]	[1.23]	[3.19]	[2.74]
B. Characteristics						
Nb. firms	628.48	629.1	629.01	629.1	629.67	-
Avg. cyber score	0.46	0.48	0.49	0.51	0.54	-
Sharp Ratio	0.66	0.67	0.72	0.83	1.04	0.69

Average monthly excess returns and alphas (in percent) using the credential movement cyber score

Appendix

	P1	P2	P3	P4	P5	P5-P1
A. Portfolios sorted by cyber score						
avg. excess ret.	**0.84*****	**0.95*****	**1.04*****	**1.11*****	**1.49*****	**0.64****
	[3.35]	[3.61]	[3.75]	[4.44]	[4.54]	[2.01]
CAPM alpha	**-0.18**	**-0.08**	**-0.03**	**0.05**	**0.39****	**0.58**
	[-0.86]	[-0.54]	[-0.39]	[0.66]	[2.16]	[1.53]
FFC alpha	**-0.1**	**0.01**	**0.03**	**0.08**	**0.29*****	**0.39****
	[-0.89]	[0.13]	[0.38]	[1.47]	[2.9]	[2.23]
FF5 alpha	**-0.15**	**-0.05**	**0.03**	**0.05**	**0.33*****	**0.48*****
	[-1.66]	[-0.78]	[0.5]	[0.78]	[3.09]	[2.97]
B. Characteristics						
Nb. firms	628.48	629.1	629.01	629.1	629.67	-
Avg. cyber score	0.48	0.49	0.5	0.52	0.55	-
Sharp Ratio	0.61	0.71	0.76	0.82	1.03	0.67

Table 5.7: **Average monthly excess returns and alphas (in percent) using the persistence and evasion cyber score**

Appendix

	P1	P2	P3	P4	P5	P5-P1
A. Portfolios sorted by cyber score						
avg. excess ret.	**0.81*****	**0.91*****	**1.12*****	**1.17*****	**1.46*****	**0.65***
	[3.18]	[3.35]	[4.31]	[4.55]	[4.33]	[1.94]
CAPM alpha	**-0.22**	**-0.13**	**0.06**	**0.05**	**0.39****	**0.6**
	[-0.94]	[-1.07]	[0.75]	[0.61]	[2.01]	[1.49]
FFC alpha	**-0.11**	**-0.07**	**0.1****	**0.04**	**0.3*****	**0.42****
	[-1.0]	[-0.77]	[2.18]	[0.5]	[2.69]	[2.12]
FF5 alpha	**-0.16**	**-0.12**	**0.11****	**0.03**	**0.33*****	**0.49*****
	[-1.66]	[-1.35]	[2.01]	[0.37]	[2.76]	[2.61]
B. Characteristics						
Nb. firms	628.48	629.1	629.01	629.1	629.67	-
Avg. cyber score	0.46	0.48	0.49	0.5	0.54	-
Sharp Ratio	0.59	0.68	0.82	0.82	1.04	0.71

Table 5.5: **Average monthly excess returns and alphas (in percent) using the command and data manipulation cyber score**

Appendix

	P1	P2	P3	P4	P5	P5-P1
A. Portfolios sorted by cyber score						
avg. excess ret.	**0.86*****	**0.85*****	**1.15*****	**1.11*****	**1.43*****	**0.57****
	[3.54]	[3.13]	[4.22]	[3.94]	[4.69]	[1.97]
CAPM alpha	**-0.09**	**-0.23**	**0.02**	**0.02**	**0.37****	**0.46**
	[-0.44]	[-1.97]	[0.2]	[0.29]	[2.39]	[1.34]
FFC alpha	**-0.02**	**-0.16**	**0.07**	**0.04**	**0.28*****	**0.3***
	[-0.14]	[-2.45]	[1.23]	[0.56]	[3.07]	[1.75]
FF5 alpha	**-0.09**	**-0.19**	**0.11***	**0.01**	**0.3*****	**0.38****
	[-0.95]	[-3.08]	[1.76]	[0.19]	[3.17]	[2.42]
B. Characteristics						
Nb. firms	628.48	629.1	629.01	629.1	629.67	-
Avg. cyber score	0.47	0.48	0.5	0.51	0.54	-
Sharp Ratio	0.67	0.61	0.8	0.8	1.03	0.69

Table 5.8: **Average monthly excess returns and alphas (in percent) using the preparation and reconaissance cyber score**