Transparently Manipulation Risk Engine

Background, summary findings and key implications

Dr Hamish Macalister †

The Transparently Manipulation Risk Engine [TMRE] is applied to a universe of over 60,000 stocks domiciled and traded in all public markets globally. We present evidence of significant and robust predictive power in manipulation risk scores for future stock performance, and manipulation risk is strongly associated with corporate failure risk. In addition, there is commonly a multi-year lead time between high risk signals and corporate failure. Evidence of predictive power in manipulation risk signals extends to even include periods prior to any market recognition (price falls) of stock problems. These findings support utilizing the TMRE for identification of problematic companies, with high failure risk, and avoiding these for investment purposes, exiting an existing position on relatively favorable terms, or working with management to rectify issues and lower the risk of manipulation and failure.

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† hamish@transparently.ai, https://transparently.ai/

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Background

WorldCom, Enron, Subprime, fraudulent China Nasdaq stocks and the like; these represent a tiny, albeit popularly-known, sample of scandals with their common genesis in accounting manipulation. They also represent the tip of the proverbial iceberg with respect to the financial damage caused by such manipulation. Direct financial losses (equity and debt written off) can be tens of billions of dollars in individual cases. In aggregate we estimate direct financial losses from such events, for listed companies alone, are in the trillions of US dollars over the past few decades, and indirect losses (wider micro and macro effects) are likely multiples of that. Recent academic evidence reports that approximately 40% of companies are engaged in accounting manipulation each year and 10% are committing outright securities fraud.[1] This is costing US investors alone around USD830b per year.

Companies that fail commonly display signs of manipulating their accounts and/or fraud long before the market recognizes problems and long before they actually collapse. That manipulation/fraud represents attempts by management to hide the true state of a company. It also signals poor governance, poor quality and a heightened risk of failure.

It is possible to identify the signs of manipulation, and thus predict the likelihood of eventual failure, often years in advance of that failure. Our particular focus is on the identification of pernicious forms of earnings management/manipulation, that in turn signal poor corporate governance and a significantly heightened risk of subsequent corporate failure.

Manipulation can come in many forms; e.g. management of accruals to hide underlying earnings volatility, recognizing revenue from long term projects up front, manipulating depreciation policies, understatement of bad debts, faking inventory levels, faking cash flows, accelerating sales, investment and asset sale timing, overproduction, use of share transactions to manipulate EPS, use of SPVs and off-balance sheet transactions, manipulating commentaries to provide false impressions, influencing market participants (especially stock analysts) through selective disclosure, etc. Please review Appendix 1 of this paper for a detailed description of accounting manipulation/fraud and types of

[1] Dyck, A., Morse, A. & Zingales, L., 2023, How pervasive is accounting fraud?, *Review of Accounting studies*, https://doi.org/10.1007/s11142-022-09738-5.

manipulation.

The tools and techniques employable by firms to manage their accounts are effectively limitless. Firms may employ any of these techniques for manipulation, and may employ combinations of techniques.

Firms are incentivized to manipulate earnings when the benefits of doing so outweigh the costs. Firms will attempt manipulation in the belief that they can escape detection, and/or obscure the extent of manipulation. In addition, there are many examples of investors exhibiting preferences that incentivize manipulation; e.g. survey results finding high proportions of respondents prefer smooth earnings.

Higher levels of earnings management are associated with substantial negative returns, weaker corporate governance and a higher probability of bankruptcy within a few years. Along with vast direct equity losses come debt holder losses, employee losses, supplier/customer losses, banking system losses, insurer losses, etc. Beyond these are the resulting lost credibility and reputation of exchanges, auditors, rating agencies, regulatory authorities, etc.

When we analyze the characteristics of failed stocks, we find a large proportion exhibit signs of significant accounting manipulation. In addition, total losses to debt holders, employees, suppliers, customers, etc will be multiples of equity losses. It is also important to recognize the substantial reputational damage caused to regulatory and other monitoring agencies by such failures.

Few companies are formally investigated for accounting manipulation and/or fraud. However, we know that many exhibit tell-tale signs of such activity for years prior to the failure event. There are also many zombie companies languishing on exchanges that represent historic failures, yet exchanges have allowed them to remain listed.

Up until now there have been four main solutions available to those exposed to and/or monitoring manipulation and its after-effects:

1. Treat it as an unavoidable risk and budget (and insure) for such losses accordingly;
2. Legal action;

3. Large fines after the event; and,
4. New regulation after the event.

Our solution is to combine the power of advanced AI/ML techniques and big data to identify the tell-tale signs of manipulation far in advance of a failure event.

Companies tend not to fail "out of the blue". Manipulation that presages failure is typically evident years before actual failure occurs (where failure is defined as the collapse of the stock's equity and debt value, and ancillary effects). Hence, we have built a sophisticated engine that can identify manipulation "footprints" and explicitly quantify the risk of corporate failure within the following 2-3 years (and other period lengths depending on system specifications).

The core output from the TMRE is the identification of the most (and least) suspicious companies regarding manipulation and/or fraud, explicit measurement of the resulting risk, and identification of why the firm exhibits the reported risk. Critically, the system is designed to provide explainable AI; it is not a "black box". The TMRE provides detailed explanations of the drivers of manipulation, key parts of the accounts, questions to ask management and specific areas to analyze further.

We take existing concepts such as forensic accounting, activist short seller analytics, credit analytics, equity analysis and machine learning, and combine them to hunt for the fingerprints of adverse manipulation of accounts and fraud. The signals we search for are not obvious to company management, but are clearly identifiable by our algorithms. They are also signals that auditors, stocks analysts, credit analysts, etc fail to notice. However, as we have already seen, the consequences of ignoring these signals can be severe.

Large datasets are employed to identify significant risk signals, derived from a wide variety of characteristics, which in turn are employed to identify clusters of risks, and ultimately an overall risk score. This manipulation risk score represents the joint probability of manipulation and corporate failure resulting from that manipulation. This enables us to identify company risks, where risks are coming from and, when aggregated, wider systemic risks.

The remainder of this paper provides research findings from the application of the TMRE to a dataset composed of over 60,000 stocks globally. Please note that these results represent only a small fraction of the analysis performed by transparently.AI to evaluate the risk engine's effectiveness. Additional tests include evaluation of sub-regions, various time periods, sectors and a range of cross-sectional characteristics.

Dataset

We apply the Transparently Manipulation Risk Engine to a dataset composed of stocks listed and domiciled across all global equity markets, for which required data is available. Most banks and insurers were excluded given manipulation risk estimation would require an alternative model specification (this is a key component of the transparently.AI development pipeline). We include common stocks, foreign shares and ADRs. We include active, delisted and suspended stocks.

Based on these requirements we selected over 60,000 stocks with more than 650,000 stock-years of financial data, extending from January 1994 through to June 2023. All financial data represents full financial year-end accounts. We will incorporate higher frequency data in future system enhancements. All financial data was sourced from Refinitiv. All analysis was performed in R: R Core Team (2020), R Foundation for Statistical Computing, Vienna, Austria, https://www.R-project.org/.

Table 1 provides summary data on country of domicile for the stock universe, including the proportions of stocks that were inactive (e.g. acquired, delisted, etc) versus active/live on exchanges as at the point in time of the data update. Overall, 35% of companies that listed, subsequently delisted, representing 24% of available financial years.

Amongst countries with relatively large numbers of stocks, it should be noted that the China delisting figure is very low by international standards, at just 9%. For most developed markets the proportion that de-listings represent of all historically-listed stocks is 30-50%+. This is not an artifact of the selection process for Chinese stocks employed by this analysis, but rather a feature of the China market in which many companies that effectively failed in the past are permitted to remain listed.

Appendix 3 provides the same analysis by country of incorporation and by country of listing. While all stocks may be domiciled in one country, they may be incorporated elsewhere.

Table 1. Transparently stock coverage by country of domicile

	Tickers			Ticker years		
	Active	Inactive	Ratio	Active	Inactive	Ratio
All stocks	39,944	21,599	0.35	494,478	157,394	0.24
ANGUILLA	1	NA	NA	5	NA	NA
ARGENTINA	67	29	0.30	1,199	191	0.14
AUSTRALIA	1,545	1,278	0.45	17,768	9,290	0.34
AUSTRIA	53	66	0.55	903	387	0.30
AZERBAIJAN	1	NA	NA	16	NA	NA
BAHAMAS	1	NA	NA	5	NA	NA
BAHRAIN	23	4	0.15	219	15	0.06
BANGLADESH	102	3	0.03	772	7	0.01
BARBADOS	1	1	0.50	3	3	0.50
BELGIUM	118	89	0.43	1,734	648	0.27
BERMUDA	44	24	0.35	495	156	0.24
BOSNIA & HERZEGOVINA	56	5	0.08	417	15	0.03
BOTSWANA	17	6	0.26	144	28	0.16
BRAZIL	236	80	0.25	2,161	444	0.17
BULGARIA	158	81	0.34	1,365	344	0.20
BURKINA FASO	1	NA	NA	5	NA	NA
CAMBODIA	1	NA	NA	16	NA	NA
CANADA	2,241	1,787	0.44	20,294	10,937	0.35
CAYMAN ISLANDS	70	26	0.27	428	118	0.22
CHILE	146	66	0.31	2,206	594	0.21
CHINA	5,388	550	0.09	51,280	4,159	0.08
COLOMBIA	30	18	0.38	409	83	0.17
COSTA RICA	1	NA	NA	3	NA	NA
COTE D'IVOIRE	26	1	0.04	319	2	0.01
CROATIA	55	56	0.50	634	346	0.35
CURACAO	1	NA	NA	13	NA	NA
CYPRUS	63	67	0.52	545	275	0.34
CZECH REPUBLIC	8	36	0.82	108	157	0.59
DENMARK	152	142	0.48	2,025	1,139	0.36
EGYPT	214	19	0.08	2,338	131	0.05
ESTONIA	22	4	0.15	235	25	0.10
FALKLAND ISLANDS	1	NA	NA	6	NA	NA
FAROE ISLANDS	2	NA	NA	22	NA	NA
FINLAND	165	81	0.33	2,080	661	0.24
FRANCE	585	613	0.51	8,210	4,131	0.33
GABON	1	NA	NA	22	NA	NA
GERMANY	632	565	0.47	8,336	3,377	0.29
GHANA	14	2	0.12	98	15	0.13
GIBRALTAR	3	2	0.40	27	18	0.40
GREECE	145	205	0.59	2,439	1,870	0.43
GUERNSEY	22	16	0.42	226	125	0.36
HONG KONG	1,330	342	0.20	18,482	3,648	0.16
HUNGARY	31	36	0.54	400	245	0.38
ICELAND	22	11	0.33	176	41	0.19
INDIA	3,123	725	0.19	33,888	4,664	0.12
INDONESIA	619	111	0.15	6,685	770	0.10

Continued overleaf

Table 1. Transparently stock coverage by country of domicile (continued)

	Tickers			Ticker years		
	Active	Inactive	Ratio	Active	Inactive	Ratio
IRAQ	18	NA	NA	103	NA	NA
IRELAND	74	74	0.50	934	528	0.36
ISLE OF MAN	16	25	0.61	164	176	0.52
ISRAEL	499	244	0.33	5,325	1,579	0.23
ITALY	328	218	0.40	3,282	1,550	0.32
JAMAICA	29	2	0.06	184	3	0.02
JAPAN	3,707	1,755	0.32	73,150	19,199	0.21
JERSEY	30	28	0.48	295	201	0.41
JORDAN	141	53	0.27	1,735	306	0.15
KAZAKHSTAN	16	5	0.24	74	14	0.16
KENYA	41	4	0.09	430	21	0.05
KOREA (SOUTH)	2,253	719	0.24	28,934	4,877	0.14
KUWAIT	113	79	0.41	1,572	631	0.29
LATVIA	9	17	0.65	112	166	0.60
LEBANON	3	1	0.25	32	5	0.14
LIECHTENSTEIN	1	1	0.50	2	9	0.82
LITHUANIA	28	17	0.38	334	90	0.21
LUXEMBOURG	50	26	0.34	456	118	0.21
MACAU	16	2	0.11	130	3	0.02
MACEDONIA	20	5	0.20	199	29	0.13
MALAWI	8	NA	NA	61	NA	NA
MALAYSIA	933	425	0.31	15,241	3,789	0.20
MALTA	29	4	0.12	264	17	0.06
MARTINIQUE	1	NA	NA	7	NA	NA
MAURITIUS	50	8	0.14	399	48	0.11
MEXICO	114	63	0.36	1,851	478	0.21
MONACO	8	3	0.27	114	10	0.08
MONGOLIA	4	NA	NA	42	NA	NA
MONTENEGRO	20	1	0.05	126	7	0.05
MOROCCO	55	12	0.18	716	106	0.13
NAMIBIA	6	1	0.14	38	9	0.19
NETHERLANDS	114	150	0.57	1,565	1,041	0.40
NEW ZEALAND	124	97	0.44	1,693	638	0.27
NIGERIA	78	15	0.16	662	84	0.11
NORWAY	228	238	0.51	2,124	1,395	0.40
OMAN	74	17	0.19	729	77	0.10
PAKISTAN	343	35	0.09	4,021	162	0.04
PALESTINE	25	1	0.04	217	4	0.02
PANAMA	1	NA	NA	17	NA	NA
PAPUA NEW GUINEA	2	3	0.60	41	47	0.53
PERU	79	35	0.31	887	135	0.13
PHILIPPINES	213	55	0.21	3,156	430	0.12
POLAND	515	240	0.32	5,140	1,736	0.25
PORTUGAL	40	36	0.47	642	244	0.28
PUERTO RICO	2	NA	NA	15	NA	NA

Continued overleaf

Table 1. Transparently stock coverage by country of domicile (continued)

	Tickers			Ticker years		
	Active	Inactive	Ratio	Active	Inactive	Ratio
QATAR	35	3	0.08	437	5	0.01
REUNION	2	NA	NA	30	NA	NA
ROMANIA	105	51	0.33	862	264	0.23
RUSSIAN FEDERATION	240	148	0.38	1,911	551	0.22
SAUDI ARABIA	175	5	0.03	1,926	48	0.02
SENEGAL	1	NA	NA	15	NA	NA
SERBIA	29	44	0.60	226	165	0.42
SINGAPORE	545	441	0.45	7,337	4,236	0.37
SLOVAKIA	5	17	0.77	52	90	0.63
SLOVENIA	22	30	0.58	257	180	0.41
SOUTH AFRICA	201	387	0.66	3,243	2,510	0.44
SPAIN	214	120	0.36	2,019	755	0.27
SRI LANKA	190	21	0.10	2,659	124	0.04
SWEDEN	783	374	0.32	7,412	2,449	0.25
SWITZERLAND	219	158	0.42	3,675	1,384	0.27
SYRIA	4	NA	NA	15	NA	NA
TAIWAN	1,906	426	0.18	27,385	2,653	0.09
TANZANIA	10	NA	NA	93	NA	NA
THAILAND	748	148	0.17	9,828	1,266	0.11
TOGO	1	NA	NA	10	NA	NA
TRINIDAD & TOBAGO	12	NA	NA	25	NA	NA
TUNISIA	52	3	0.05	524	33	0.06
TURKEY	374	84	0.18	5,044	759	0.13
UGANDA	5	NA	NA	37	NA	NA
UKRAINE	21	40	0.66	131	115	0.47
UNITED ARAB EMIRATES	71	20	0.22	687	130	0.16
UNITED KINGDOM	1,058	2,383	0.69	14,835	15,926	0.52
UNITED STATES	3,921	4,711	0.55	48,116	34,112	0.41
US VIRGIN ISLANDS	1	1	0.50	9	7	0.44
URUGUAY	3	NA	NA	27	NA	NA
VENEZUELA	5	11	0.69	32	57	0.64
VIETNAM	963	101	0.09	9,027	501	0.05
VIRGIN ISLANDS (BRIT)	12	11	0.48	117	53	0.31
ZAMBIA	16	NA	NA	99	NA	NA

Source: Transparently Pte Ltd

Note that the proportion of stocks removed from listing is substantially higher for all major incorporation countries outside of China, which has only 5% of stocks delisted. For stocks incorporated in the US the proportion removed from listing is 56%. Clearly, incorporation outside of China is a risk marker for removal from listing, relative to incorporation within China. However, this should not be interpreted as an indication of lower quality/higher risk for non-China incorporation. It is more likely that a high proportion of China-incorporated failed companies are permitted to remain listed, resulting in "zombie companies" that are theoretically tradable but exhibit little to no liquidity.

Stocks within our sample universe are listed in all available markets globally (see Appendix 3).

A significant proportion of stocks removed from listing were the targets of acquisitions. Some of these were on positive terms and some represent failed stocks being taken over by related parties, while others were taken over on unfavorable terms (from the perspective of non-purchasing shareholders). Our system accounts for these differences given the latter group is more likely to contain manipulators than the former group.

For reference purposes, Tables 2 and 3 provide summary information for the POC stock universe by Thomson Reuters Business Classification [TRBC] Code economic sector and business sector. There is not a great deal of sector variation in the rate of delistings.

In subsequent tables/figures, all relative return calculations are with reference to appropriate benchmarks within each jurisdiction.

Table 2. Transparently stock coverage by TRBC economic sector

	Tickers			Ticker years		
	Active	Inactive	Ratio	Active	Inactive	Ratio
Energy	1,608	1,366	0.46	20,655	9,092	0.31
Basic Materials	5,956	2,624	0.31	76,266	19,671	0.21
Industrials	7,118	3,734	0.34	94,911	29,963	0.24
Consumer Cyclicals	6,535	3,768	0.37	88,906	28,734	0.24
Consumer Staples	3,094	1,584	0.34	41,851	11,965	0.22
Financials	1,768	1,067	0.38	16,354	5,881	0.26
Health Care	3,779	1,720	0.31	36,790	12,238	0.25
Technology	6,228	3,863	0.38	70,487	27,025	0.28
Utilities	970	473	0.33	13,353	3,711	0.22
Real estate	2,674	1,115	0.29	32,696	8,017	0.20
Education	209	75	0.26	2,161	548	0.20
NA	5	212	0.98	48	593	0.93

Source: Transparently Pte Ltd

Table 3. Transparently stock coverage by TRBC business sector

	Tickers			Ticker years		
	Active	Inactive	Ratio	Active	Inactive	Ratio
Fossil Fuels	1,305	1,236	0.49	17,719	8,301	0.32
Renewable Energy	231	104	0.31	2,167	607	0.22
Uranium	72	26	0.27	769	184	0.19
Chemicals	1,680	542	0.24	22,890	4,498	0.16
Minerals	3,528	1,675	0.32	42,554	11,889	0.22
Applied Resources	748	407	0.35	10,822	3,284	0.23
Industrial Goods	3,135	1,320	0.30	43,628	10,928	0.20
Ind & Comm Services	2,909	1,831	0.39	35,802	14,118	0.28
Transport	1,074	582	0.35	15,481	4,908	0.24
Autos	1,069	332	0.24	15,790	2,893	0.15
Cyclical Cons Prod	2,393	1,256	0.34	32,519	9,352	0.22
Cyclical Cons Serv	2,057	1,532	0.43	26,622	10,947	0.29
Retail	1,016	648	0.39	13,975	5,542	0.28
Food & Beverage	2,151	1,047	0.33	29,139	7,873	0.21
Pers & Hhold Prod & Serv	409	257	0.39	4,746	1,698	0.26
Food & Drug Retail	435	240	0.36	6,095	2,046	0.25
Cons Goods Conglom	99	40	0.29	1,871	348	0.16
Banking	1,254	617	0.33	13,649	4,056	0.23
Real Estate (deprecated)	1	NA	NA	18	NA	NA
Holding Companies	513	450	0.47	2,687	1,825	0.40
Healthcare Services	1,369	877	0.39	13,749	6,448	0.32
Pharma & Biotech	2,410	843	0.26	23,041	5,790	0.20
Tech Equipment	2,706	1,354	0.33	36,173	10,657	0.23
Software & IT Services	2,963	2,062	0.41	28,065	13,519	0.33
Fintech	177	23	0.12	1,161	192	0.14
Telecommunications	382	424	0.53	5,088	2,657	0.34
Utilities	970	473	0.33	13,353	3,711	0.22
Real Estate	2,674	1,115	0.29	32,696	8,017	0.20
Education	209	75	0.26	2,161	548	0.20
NA	5	212	0.98	48	593	0.93

Source: Transparently Pte Ltd

Summary results

The TMRE is trained to identify the probability of accounting manipulation and subsequent corporate failure, employing several hundred sub-models, a variety of time-series and cross-sectional effects within these, and both classical and machine learning estimation systems.

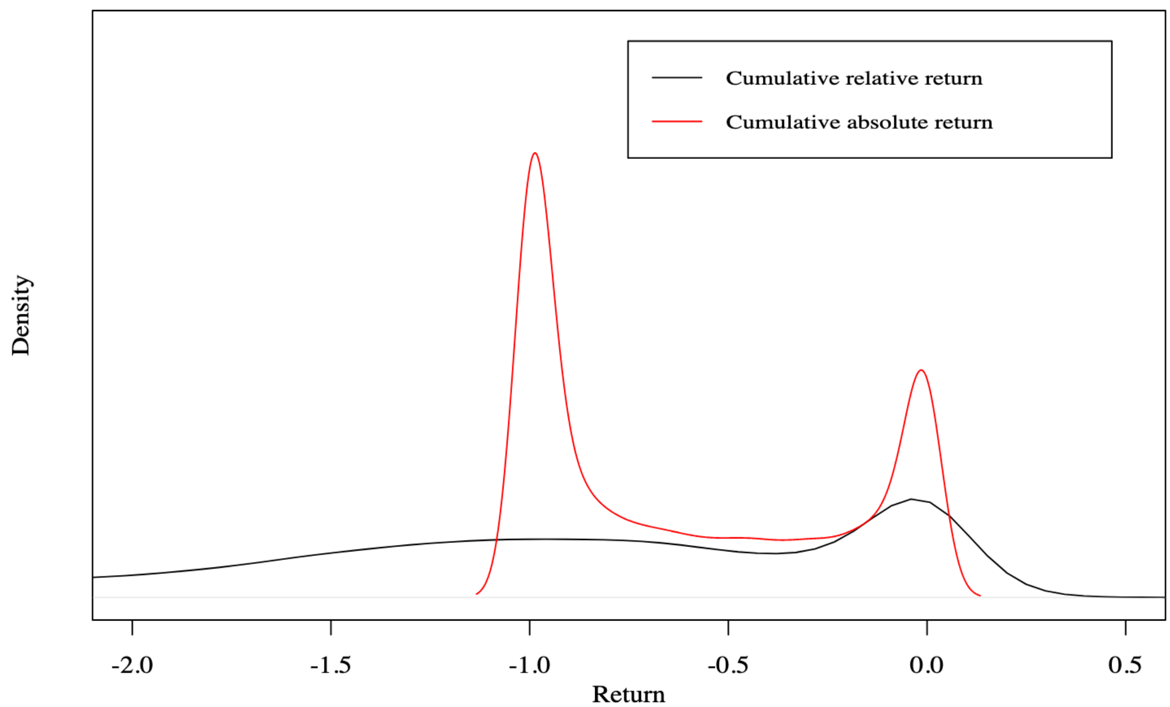
Firstly, for reference purposes, it is important to assess the impact of failed stocks (without identification of manipulation) on stock returns. Figure 1 provides a density plot of the absolute and relative returns (relative to the appropriate country benchmark, determined by the stock's listing location) from the date a stock's price peaks to the date it delists. The mean absolute return is -60.0% and median absolute return is -74.9%. The respective values for relative returns are -122.8% and -95.3%. It is evident that delisting is typically associated with something approaching a near total loss in equity value from a stock's peak.

Figure 2 provides the same form of density plot, but restricted to stocks that have been independently identified as manipulators. Such external verifiers may be regulators, activist short sellers, investment research houses, exchanges, regulators, etc. We see a similar pattern to the delisting sample, with reported/suspected manipulation associated with substantial losses (median absolute return of -94.8% and median relative return of -133.5%). Hence, manipulation is associated with a more adverse absolute return outcome relative to delisting generally.

Overall, it is evident that avoiding such failures could materially benefit an investor's portfolio in terms of both return and risk.

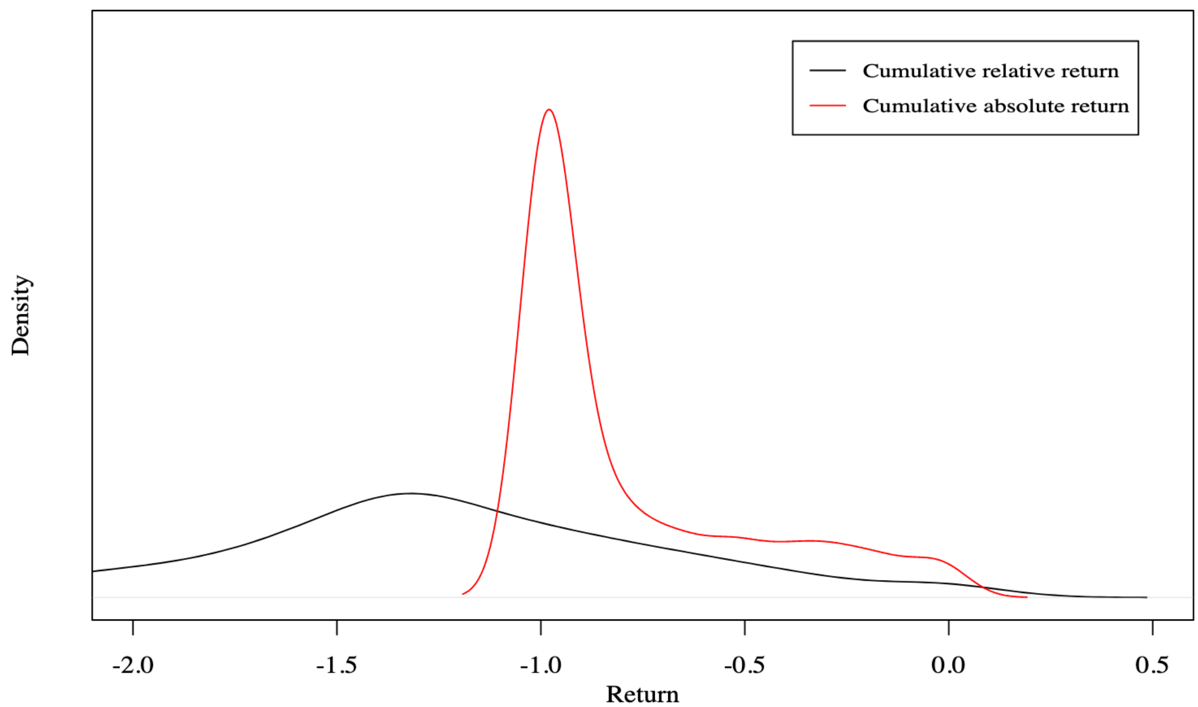
However, such failures can take a considerable period of time to fully play out in market trading. Figure 3 provides a density plot for the number of years from a stock's peak price to its delisting date, for our sample universe. The duration from peak to delisting averages 6.2 years (median 4.7 years), although we can see the distribution peak is at less than 1 year (highlighting a large number of delistings occur shortly after IPOs).

Figure 1. Density plot for price peak to final price cumulative return for delisted stocks



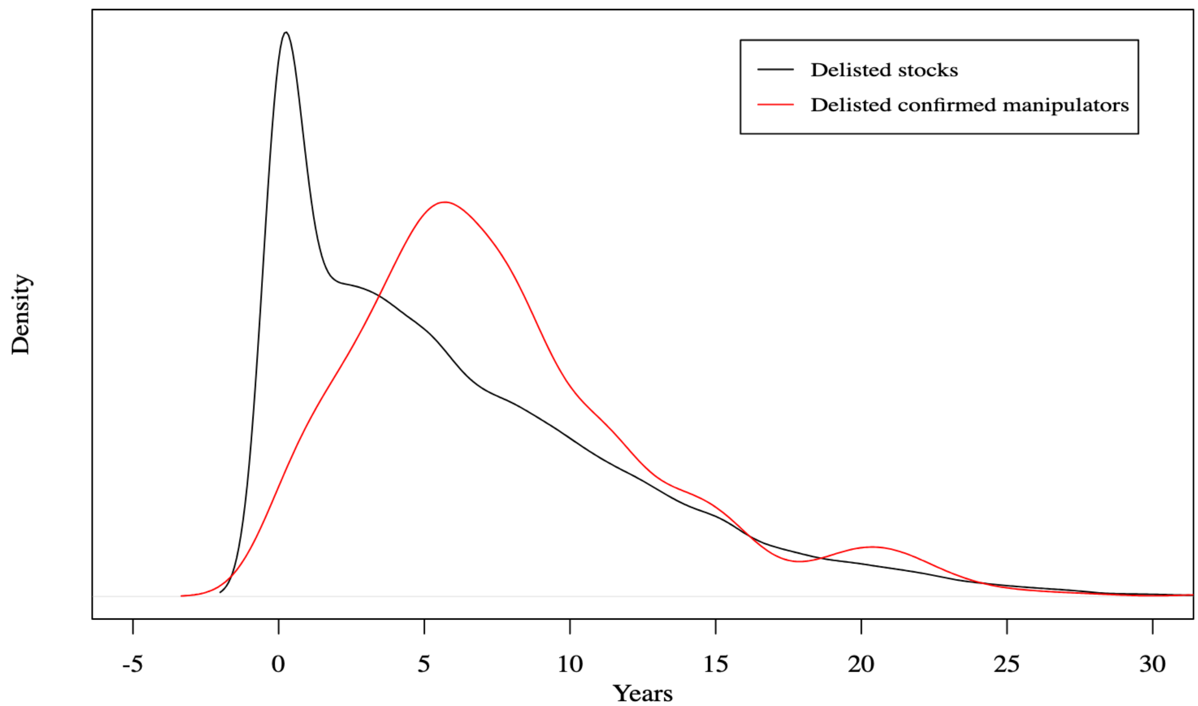
Source: Transparently Pte Ltd

Figure 2. Density plot for price peak to final price cumulative return for manipulators (independently identified)



Source: Transparently Pte Ltd

Figure 3. Density plot for years from peak return to delisting



Source: Transparently Pte Ltd

Figure 3 also provides the same form of distribution for independently identified manipulators that are no longer listed. The mean time from peak to delisting is 7.8 years and the median time is 6.8 years. The distribution peak is around 5 years. This indicates not just that there may be a significant period of time between IPO and failure for manipulators, but is also consistent with the notion of manipulation evolving and building over time to the point at which the company can no longer obscure their actions. Importantly, this distribution indicates there is likely to be a period of time, in which a stock remains actively traded, during which an investor may exit a later failure, and potentially do so on relatively favorable terms.

However, the challenge is advanced identification of such failures. The TMRE focuses on determining the likelihood and extent of serious accounting manipulations that presage such failures. The risk engine is estimated on data extending back to 1990 (results presented for 1994 onwards).

Table 4 provides partial confusion matrix data for in-sample (training) and out-of-sample (testing) datasets. For a range of fitted (for the training set) and predicted (for the testing set) manipulation risk probabilities (MRisk), we record the success rate for manipulation/failure identification. The two datasets contain mutually exclusive data. Note also that the process has been structured to minimize the probability of false positives.

In this context we define stock failure as relative and absolute performance of -80% or worse from a stock's historic peak price. For example, looking at column 1 of Table 4, of stocks the training dataset estimated had a 70%+ probability of manipulation/failure, 100% met that criteria. Applying this estimated model to the test dataset, when the predicted manipulation/failure probability is 70%+, in fact 79% of this test set met the failure criteria. That is, 79% of stocks with a risk score in excess of 70% subsequently collapsed (down 80% in both relative and absolute terms). That proportion increases to 86% for scores above 80% and 97% for scores above 90%. For companies with a risk score in excess of 50%, roughly two thirds subsequently saw their stock prices collapse.

Table 4. Success rates (0-1) for classification of stock manipulation/failure, by manipulation risk score, for in-sample (training) and out-of-sample (test) datasets

Manipulation risk score	>0.9	>0.8	>0.7	>0.6	>0.5	≤0.5	≤0.4	≤0.3	≤0.2	≤0.1
In-sample	1.00	1.00	1.00	0.97	0.92	0.13	0.03	0.00	0.00	0.00
Out-of-sample	0.97	0.86	0.79	0.72	0.65	0.22	0.18	0.13	0.07	0.02

Source: Transparently Pte Ltd

Note that the training set has effectively binary results; 0 or 1. In some situations this might be construed as indicative of an overfitted model, which would consequently have little predictive power. However, this is an artifact of our model specification process. Critically, it is designed to ensure high predictive power. This is evidenced by the results presented in Table 4 for the test dataset. We can see that as the fitted and predicted manipulation probabilities decline, the proportion of actual failure monotonically declines. We can also see a very strong relationship between risk scores and the probability of stock failure. Hence, a higher manipulation probability implies higher certainty over the presence of manipulation and subsequent stock failure, and vice versa for lower manipulation probabilities.

Table 4 employs the full dataset. However, we wish to know how early we can identify such signals. Table 5 provides the same analysis for test and training sets, constrained to periods of time prior to meeting the failure criteria, defined by return performance. Simply, extending periods of time prior to a stock reaching a relative return from its peak of -80% or worse. It should be noted that this analysis is performed with reference to each stock's reporting dates to ensure that only information available to a market participant at that point in time is included.

In section A, where stocks are 1 year before hitting the failure event threshold, we can see there is still a strong monotonic relationship in the out-of-sample test set between predicted manipulation and later failure. For example, a predicted manipulation/failure probability of 70% is associated with 80% of those stocks ultimately meeting the failure threshold.

Panel B provides similar results for stocks 2 years before hitting the failure event threshold. Most importantly, results are virtually identical in Panel C for stocks trading 3 years prior to the failure threshold. Even here we can see that a high predicted manipulation/risk score is associated with a high probability of a stock falling by 80% or more relative to its benchmark (e.g. 73% of the stocks with risk scores greater than 70% subsequently failed). We have also identified statistically significant information in the risk scores even before many stocks have hit their historic peak price (in other words, before there is any market recognition of issues whatsoever).

Table 5. Success rates (0-1) for classification of stock manipulation/failure, by manipulation risk score, for in-sample (training) and out-of-sample (test) datasets – by lagged period returns prior to failure

A. 1 year prior to fail date										
MRisk	>0.9	>0.8	>0.7	>0.6	>0.5	≤0.5	≤0.4	≤0.3	≤0.2	≤0.1
In-sample	1.00	1.00	1.00	0.99	0.94	0.09	0.02	0.00	0.00	0.00
Out-of-sample	1.00	0.90	0.80	0.70	0.60	0.18	0.15	0.11	0.06	0.02
B. 2 years prior to fail date										
MRisk	>0.9	>0.8	>0.7	>0.6	>0.5	≤0.5	≤0.4	≤0.3	≤0.2	≤0.1
In-sample	1.00	1.00	1.00	0.99	0.93	0.08	0.02	0.00	0.00	0.00
Out-of-sample	1.00	0.88	0.77	0.66	0.57	0.17	0.14	0.10	0.06	0.02
C. 3 years prior to fail date										
MRisk	>0.9	>0.8	>0.7	>0.6	>0.5	≤0.5	≤0.4	≤0.3	≤0.2	≤0.1
In-sample	1.00	1.00	1.00	0.98	0.92	0.07	0.02	0.00	0.00	0.00
Out-of-sample	1.00	0.86	0.73	0.63	0.53	0.15	0.13	0.09	0.05	0.01

Source: Transparently Pte Ltd

Appendix 2 provides the same analysis applied to sub-regions, with very similar results: North America ex OTC, Western Europe, Japan, Asia Pacific ex Japan, US OTC and Rest of World.

It is evident that the Transparently Manipulation Risk Engine is able to provide significant information on manipulation/failure rates prior to market recognition of increased failure risk.

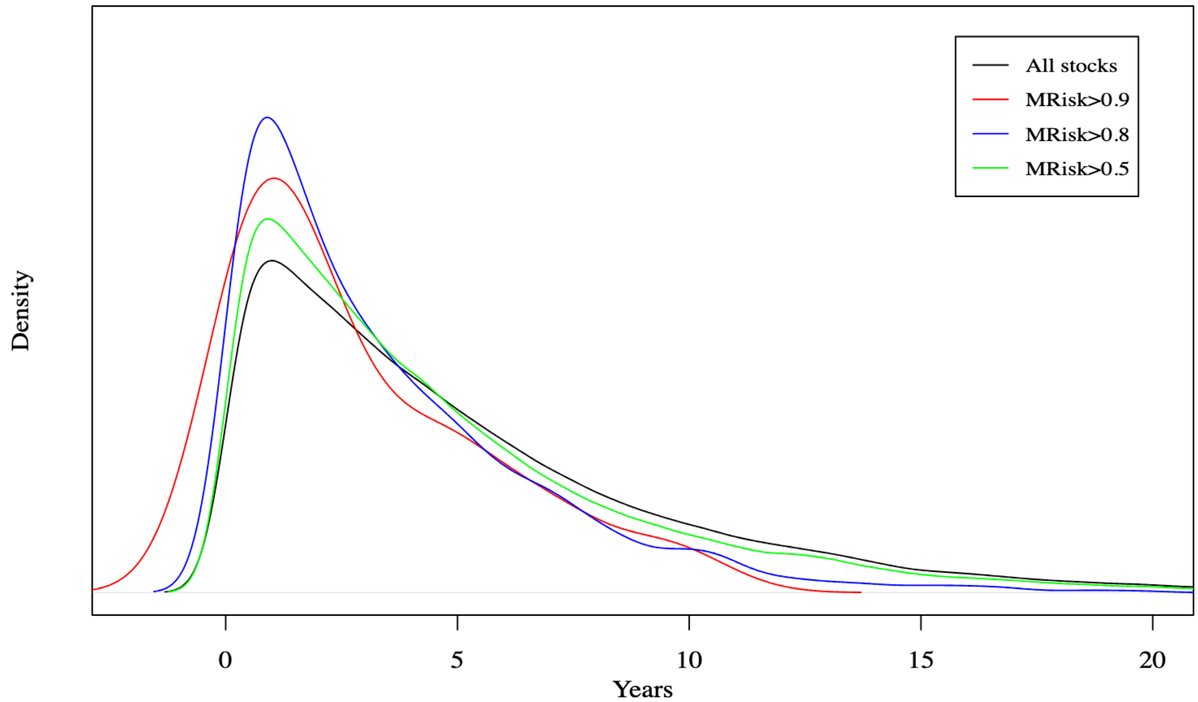
To investigate the expected time for manipulators from peak price to a relative return of -80% or worse, Figure 4 provides a density plot of the duration for our in-sample (training) manipulators. In addition, we include density plots for the subset of these with manipulation/failure risk scores of >50%, >80% and >95%.

Table 6 provides mean and median durations from peak to failure for these groups. For all stocks, the mean duration is 5.1 years and the median is 3.8 years. However, as the manipulation risk score increases, the duration shortens; median 2.5 years for manipulation risk >80% and 2.1 years for manipulation risk >90%. A higher manipulation risk is associated with faster market recognition of that (or other correlated) risk.

Further, in the event a stock is already beginning to underperform, it is helpful to gauge expectations for the extent to which that underperformance could continue. Figure 5 provides a density plot for the peak to last-available-price absolute return performance for manipulators from our in-sample dataset. Summary statistics are provided in Table 7. The median price fall for stocks with scores >50% is -96%%. However, a higher manipulation risk score is associated with a larger price fall. For both >80% and >90% manipulation risk scores the median price fall is around -100%.

Therefore, even in the event that a stock has begun to react negatively, and even if this extends to our relative performance threshold of -80%, manipulators typically see losses extend significantly further. This means an investor may have a window of opportunity (if sufficient liquidity is present) to exit such a holding to prevent further significant portfolio downside.

Figure 4. Density plot for years from peak price to relative return ≤ -80% for in-sample manipulators



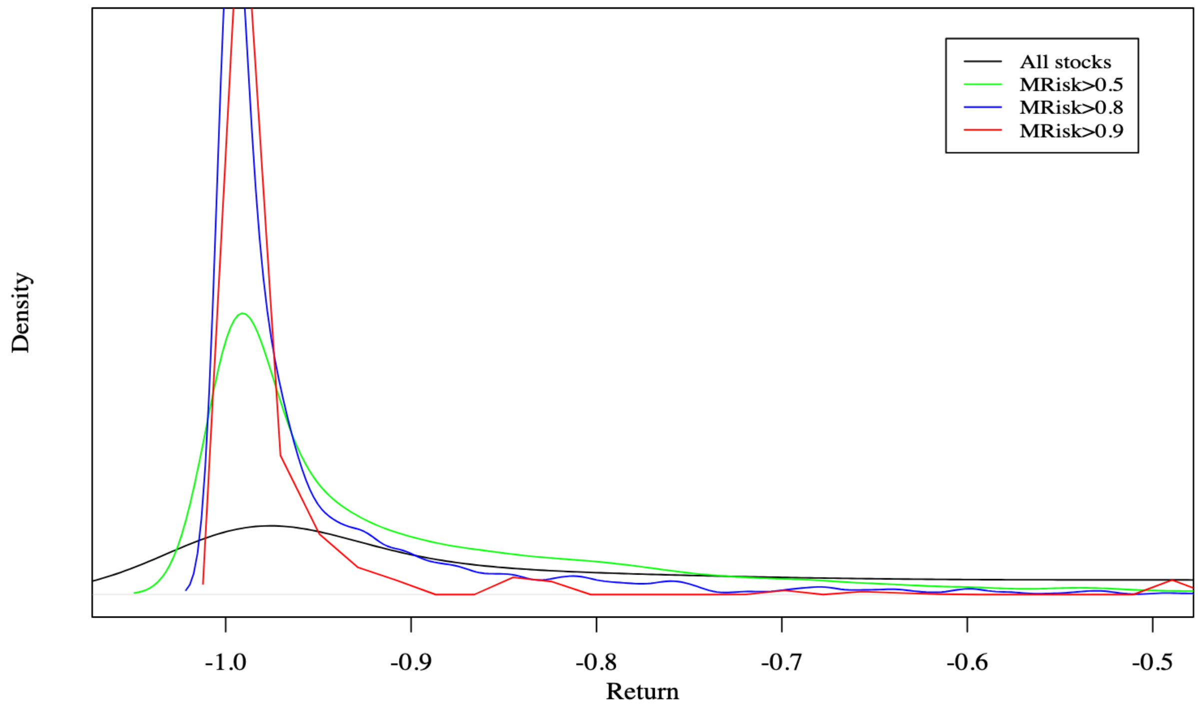
Source: Transparently Pte Ltd

Table 6. Years from peak return to relative return ≤ -80% for in-sample manipulators

	All stocks	MRisk>0.5	MRisk>0.8	MRisk>0.9
Mean	5.1	4.6	3.5	2.9
Median	3.8	3.3	2.5	2.1

Source: Transparently Pte Ltd

Figure 5. Density plot for absolute returns from peak price to last available price for in-sample stocks



Source: Transparently Pte Ltd

Table 7. Absolute returns from peak price to last available price for in-sample stocks (decimal)

	All stocks	MRisk>0.5	MRisk>0.8	MRisk>0.9
Mean	-0.58	-0.88	-0.95	-0.97
Median	-0.68	-0.96	-0.99	-1.00

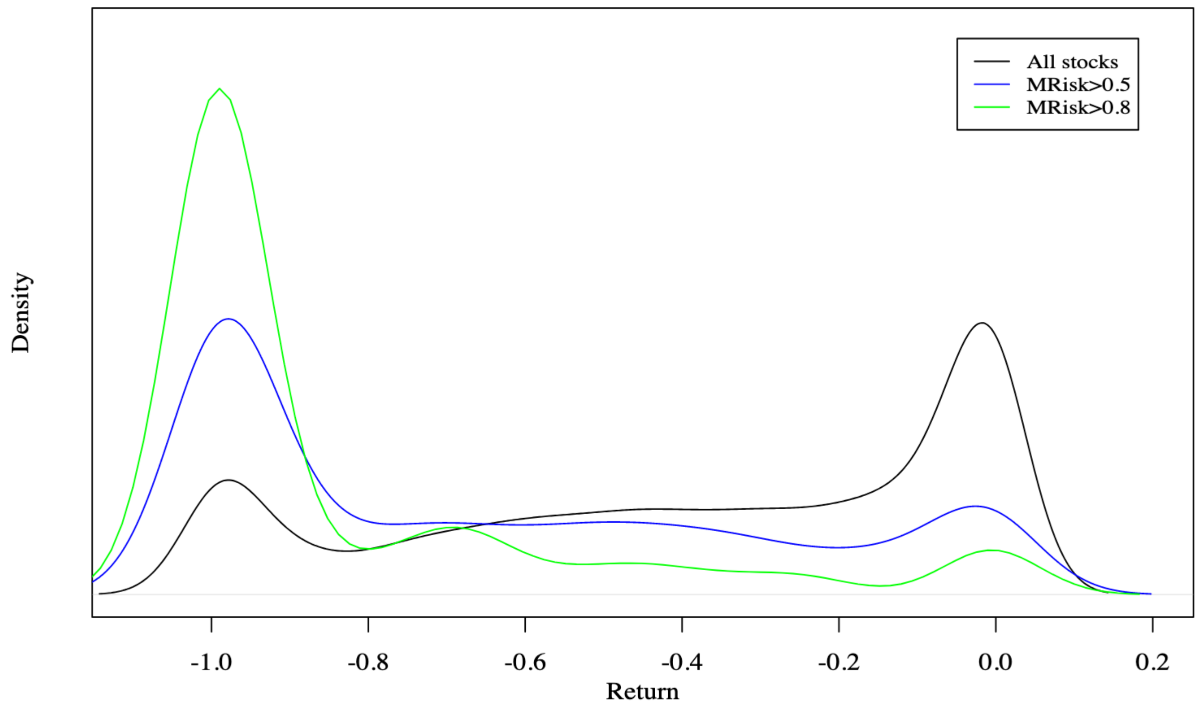
Source: Transparently Pte Ltd

Alternatively, an investor may seek to engage with a stock exhibiting significant manipulation risk to assist management in remedial actions. This is particularly true for large investors, along with regulators, exchanges, auditors, banks and other concerned/interested parties. The time delay between manipulation risk estimation and corporate failure may permit the implementation of rescue plans.

Figure 6 provides the same analysis for the test (out-of-sample) dataset; all stocks and those with a risk score greater than 50% and 80%. For all stocks the distribution has two major peaks; around 0% and 100%, highlighting how stocks tend to exit markets either on very good terms (e.g. positive acquisitions) or on very negative terms (e.g. liquidation). However, we can see that stocks with risk scores >50% and >80% have much fewer positive exit events. The distributions instead very clearly have peaks around -100%. Indeed, the median peal-to-last prices for firms with scores >50% is -76% while it is -99% for firms with scores >80% (Table 8).

Hence, higher manipulation risk scores are strongly associated with substantially worse return outcomes, and are similarly highly effective indicators of corporate collapse.

Figure 6. Density plot for absolute returns from peak price to last available price for out-of-sample stocks



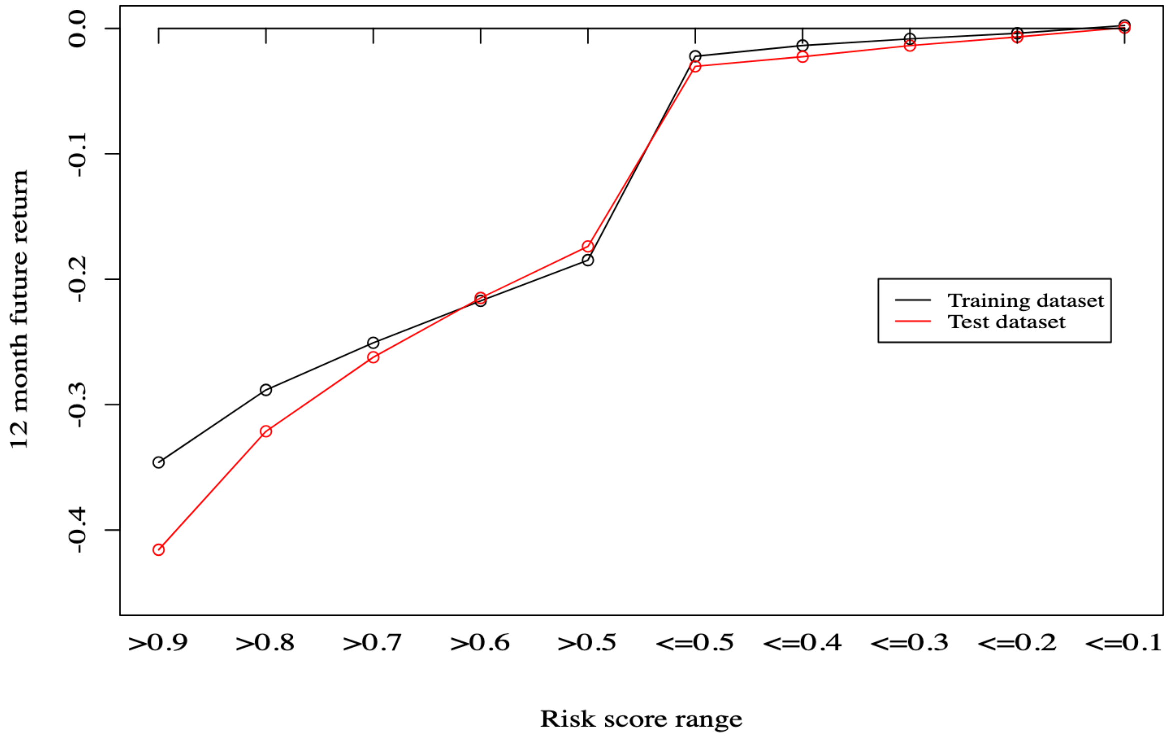
Source: Transparently Pte Ltd

Table 8. Absolute returns from peak price to last available price for out-of-sample stocks (decimal)

	All stocks	MRisk>0.5	MRisk>0.8
Mean	-0.38	-0.65	-0.84
Median	-0.31	-0.76	-0.99

Source: Transparently Pte Ltd

Figure 7. Relationship between manipulation risk score range and 12 month future financial year returns



Source: Transparently Pte Ltd

Table 9. Manipulation risk score range vs median 12 month future financial year returns (%)

MRisk	>0.9	>0.8	>0.7	>0.6	>0.5	≤0.5	≤0.4	≤0.3	≤0.2	≤0.1
In-sample	-34.6	-28.8	-25.1	-21.7	-18.5	-2.2	-1.4	-0.8	-0.4	0.2
Out-of-sample	-41.6	-32.1	-26.2	-21.5	-17.4	-3.0	-2.3	-1.4	-0.7	0.1

Source: Transparently Pte Ltd

To illustrate the benefits of remedial action, Figure 7 and Table 9 highlight the relationship between estimated risk scores and future returns.

The full stock universe is split into risk groups and median returns are calculated for the 12 month financial year after the year generating the risk score. We can see a perfect monotonic relationship between risk bucket and future returns for both the training and test datasets (Figure 8).

As we have already learned, a high risk score is associated with substantial losses. Here we also see that lower risk scores are associated with better future outcomes. The difference between median future annual returns for risk scores >0.9 and risk scores <0.1 is 34.8% for the training dataset and 41.2% for the test dataset. These are extremely large differences.

Appendix 2 provides the same return analysis for North America ex OTC, Western Europe, Japan, Asia Pacific ex Japan, US OTC and Rest of World. The 12 month future return differentials are summarized in Table 10.

Note that this result in fact understates the true difference given it is only calculated for stocks that survive 12 months after the risk score estimation. It excludes failures that occur during that 12 month window, and we saw previously the large price falls associated with failures.

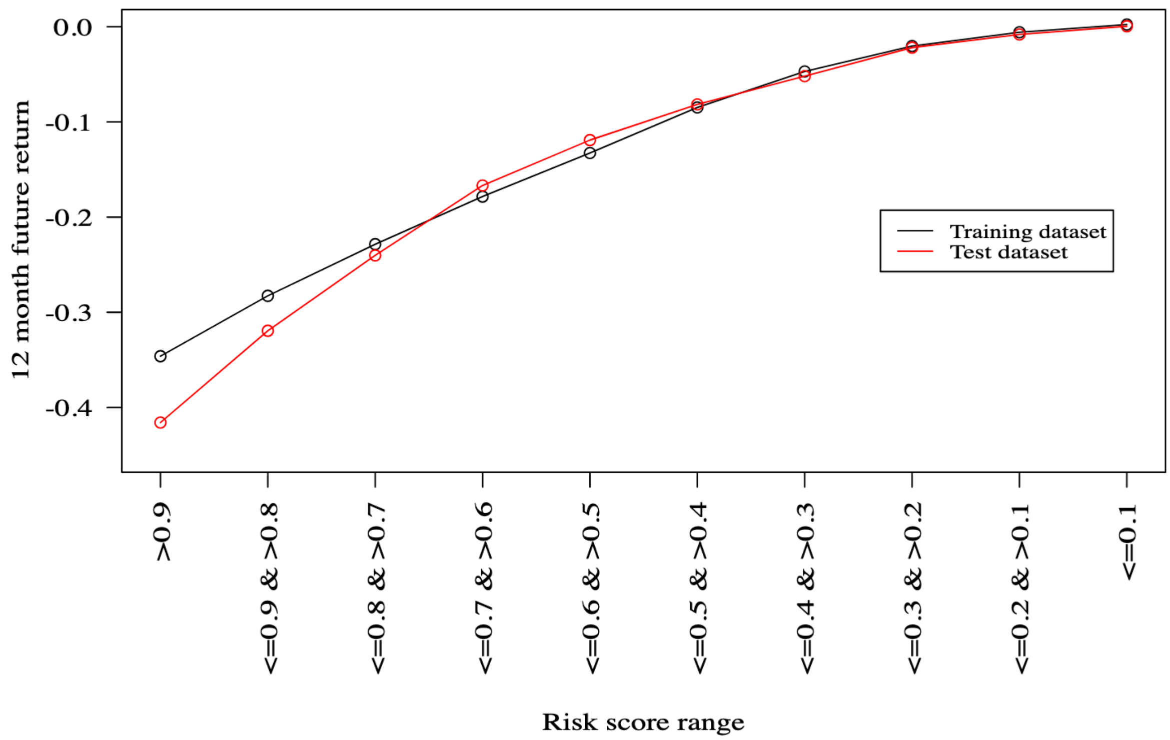
Nonetheless, even ignoring that underestimation, it is evident that the benefits of working with management to remedy stock issues (to shift from, say, a manipulation score of 0.9 to one of 0.1) can be substantial. It should also be noted this difference implies significant potential for a long-short investment strategy driven by relative manipulation scores.

Table 10. Manipulation risk score range vs median 12 month future financial year returns (%), regions

	Training datasets	Test dataset
World	34.8	41.2
North America ex OTC	29.4	35.0
Western Europe	32.9	30.6
Japan	20.4	16.0
Asia Pacific ex Japan	37.1	49.1
Rest of World	34.8	41.7
US OTC	54.4	33.5

Source: Transparently Pte Ltd

Figure 8. Relationship between manipulation risk score range and 12 month future financial year returns



Source: Transparently Pte Ltd

Table 11. Manipulation risk score range vs median 12 month future financial year returns (%)

MRisk	>0.9	≤0.9, >0.8	≤0.8, >0.7	≤0.7, >0.6	≤0.6, >0.5	≤0.5, >0.4	≤0.4, >0.3	≤0.3, >0.2	≤0.2, >0.1	≤0.1
In-sample	-34.6	-28.3	-22.8	-17.8	-13.3	-8.5	-4.7	-2.0	-0.6	0.2
Out-of-sample	-41.6	-31.9	-24.0	-16.7	-11.9	-8.2	-5.2	-2.2	-0.8	0.1

Source: Transparently Pte Ltd

Overall, we find:

- Evidence of significant and robust predictive power in the Transparently Manipulation Risk Engine for future stock performance, with manipulation risk strongly associated with stock failure risk;
- Evidence of a lengthy (multi-year) lead time between high risk signals and corporate failure;
- The lead time, on average, decreases as manipulation risk becomes more extreme;
- Evidence of predictive power in manipulation risk signals for failure risk even prior to any market recognition (price falls) of stock issues;
- Higher manipulation risk is strongly associated with more adverse return outcomes; and,
- Lower manipulation risk is strongly associated with better return outcomes.

Concluding Remarks

We apply the Transparently Manipulation Risk Engine to a dataset composed of over 60,000 stocks globally. These include both currently active and historically delisted companies. The risk engine is designed to provide signals regarding the probability and extent of various forms of accounting and business manipulation. The risk engine underpins all analytics within our cloud-server visualization application; access to which is available under contract with Transparently.AI.

This paper illustrates a selection of key research findings derived from Transparently's validation of the utility of the risk engine. Please note that these results represent only a small fraction of the analysis performed by Transparently to evaluate the risk engine's effectiveness. Additional tests include evaluation of sub-regions, various time periods, sectors and a range of additional cross-sectional characteristics.

We present evidence of:

- Significant and robust predictive power in the Transparently Manipulation Risk Engine for future stock performance, with manipulation risk strongly associated with stock failure risk;
- A multi-year lead time between moderate-to-high risk signals and corporate failure;
- A lead time that, on average, decreases as manipulation risk becomes more extreme;
- Predictive power in manipulation risk signals for failure risk even prior to any market recognition (price falls) of stock issues;
- Higher manipulation risk strongly associated with more adverse return outcomes; and,
- Lower manipulation risk is strongly associated with more positive return outcomes.

These findings support utilizing the Transparently Manipulation Risk Engine for identification of problematic stocks, with high failure risk, and avoiding these for investment purposes, exiting an existing position on relatively favorable terms or working with management to rectify issues and lower the risk of manipulation and failure. This report presents evidence of substantial portfolio return and risk benefits from application of the risk engine to stocks.

Appendix 1.0

Defining Accounting Manipulation

Almost everyone has a fair idea what is meant by accounting fraud. It occurs when accounting records, financial statements or tax returns are manipulated to make a company's financial condition appear better than it actually is. It's pretty simple, or is it?

Upon deeper inspection, accounting fraud is difficult to pin down because different agents have different interpretations of what it actually means. Since fraud is a criminal activity, some like to focus on a narrow legal definition of accounting fraud. Others, notably investors and creditors, take a wider view because all types of account manipulation, whether legal or not, are typically detrimental to a company's future performance. Most financial market participants, therefore, interpret excessive manipulation as fraudulent, regardless of its legality.

For those taking a wider interpretation, accounting fraud is difficult to put neatly in a box because accounting is part science and part art.[2] Every company has considerable discretion in the way it reports its numbers. Just as everybody lies, even if only a little bit, all companies massage their numbers to a certain extent. Some massage their numbers more than others. This is accepted practice but there is general understanding that a distinction exists between aggressive accounting and accounting fraud. There is a line that signifies the boundary between the two. That line, however, varies considerably among investors and creditors. Some are more tolerant of account manipulation than others. As a consequence, there is no precise taxonomy of accounting fraud once we move beyond a strict legal interpretation. It becomes a judgment call.

Even those who adopt a strict legal interpretation will find that the line between aggressive accounting and accounting fraud is blurred because the law itself is nuanced. Although most companies charged with accounting violations agree to pay fines, very few are ever indicted, put on trial, and jailed.

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[2]https://www.iedunote.com/how-accounting-art-science#:~:text=Accounting%20is%20an%20art,-The%20term%20%E2%80%9CArt&text=Art%20is%20using%20the%20skills,universally%20accepted%20method%20(GAAP).

Relative to the known prevalence of accounting fraud, in which one in ten public companies are thought to commit securities fraud each year, admission of guilt is rare and criminal charges even rarer.[3]

This pattern applies to all areas of white-collar crime. According to the US Department of Justice, the annual losses from white-collar crimes are estimated at between US$426 billion and US$1.7 trillion per year. Meanwhile, the FBI estimates that property crime, otherwise known as street crime, costs a mere US$16 billion per year. In a nation with a prison population of more than 1.2 million, there were only 4,180 white-collar prosecutions in 2022. The vast majority of these were for employee theft, money laundering or embezzlement, not for accounting manipulation.

In the whole of 2022, the US Department of Justice tried just 72 individuals for fraud and convicted 56 at trial. On our best efforts, we could find only one case of accounting fraud leading to incarceration, that being Frank Okanuk, the former CFO of the PR firm Weber Shandwick. However, this case was more about embezzlement than account manipulation.

Of course, the FTX saga was major news in 2022 and Sam Bankman-Fried was indicted. But once again, this case looks to be more about embezzlement than account manipulation.

The point we are trying to make is simply this: if one sticks to a strict legal interpretation of accounting fraud, meaning a criminal act that leads to prosecution and incarceration, one is drawn to the conclusion that criminal accounting fraud virtually never happens. Only the direst cases leading to corporate collapse typically result in criminal charges.

Once we move away from a strict legal interpretation, it matters little whether or not a company is breaking the law because only in exceptional cases will we ever know for certain. What really matters is the extent to which a company's accounts distort its true financial condition.

Coming to terms with financial fraud is a journey of discovery. The assessment of accounting fraud is never black and white. It is a matter of degree, a probabilistic investigation requiring the exercise of considerable judgment. This is what makes the field so fascinating to those engaged in it.

[3] https://www.nytimes.com/2023/01/14/business/dealbook/how-common-is-corporate-fraud.html

The definition of criminal accounting fraud

If asked, most people would probably say that a company commits accounting fraud when it begins to engage in illegal accounting practices. Most would likely want to change this definition upon learning that up to 40% of public companies commit accounting violations each and every year.[4]

Illegal accounting practices consist of either misstatement arising from fraudulent financial reporting or misstatement arising from misappropriation of assets. In serious cases of fraud, the two will co-exist.

According to the Public Company Accounting Oversight Board (PCAOB), the arbiter of correct international accounting practice, misstatements arising from fraudulent financial reporting are:

> *"intentional misstatements or omissions of amounts or disclosures in financial statements designed to deceive financial statement users where the effect causes the financial statements not to be presented, in all material respects, in conformity with generally accepted accounting principles (GAAP)."*

Misstatements can include:

- Manipulation, falsification, or alteration of accounting records or supporting documents from which financial statements are prepared;
- Misrepresentation in or intentional omission from the financial statements of events, transactions, or other significant information; or
- Intentional misapplication of accounting principles relating to amounts, classification, manner of presentation, or disclosure.

Once again deferring to the PCAOB, misstatements arising from misappropriation of assets, "*involve the theft of an entity's assets where the effect of the theft causes the financial statements not to be presented, in all material respects, in conformity with GAAP.*"

[4] https://link.springer.com/article/10.1007/s11142-022-09738-5

Misappropriation of assets can include:

- Embezzling receipts;
- Stealing assets; or
- Causing an entity to pay for goods or services that have not been received.

Misappropriation of assets is essentially theft and is far easier to prosecute than fraudulent financial reporting, where a material misstatement might be rationalized as an aggressive rather than indefensible interpretation of complex accounting rules, or as an error. Thus, for example, in the ongoing Wirecard and FTX cases prosecutors will likely pursue evidence of misappropriation of assets with greater vigor than fraudulent accounting.

In the eyes of the law, the mere fact that accounts have been "indefensibly misstated" does not mean that criminal accounting fraud has taken place.

To be subject to criminal prosecution, prosecutors must demonstrate that the manipulation was a) deliberate, and b) undertaken for personal or corporate financial gain. In other words, a successful prosecution needs to demonstrate reasonable evidence of intent and this usually requires motive and hence evidence of material gain.

The standard defense in a fraud case is not that fraud did not happen; it is that the perpetrator did not know they were breaking the law.

Given the complexity of accounting rules, it is exceptionally difficult to prove intent. Thus, even in the case of Marvell Technology the Department of Justice did not press criminal charges even though the company admitted fault in the matter of the backdating of options and restated earnings by more than US$300 million.

Unless fraud leads to collapse, proving fraudulent financial reporting in a strict legal sense is equivalent to proving the existence of ghosts. Enron, FTX and Wirecard all resulted in criminal charges because these companies collapsed. Once a company collapses, liquidating auditors can dissect a company's books, uncovering evidence that financial statement auditors can only dream of.

When offenders are indicted, they are not charged on the basis that they breached a particular accounting rule, they are charged on a breach of the criminal code, which varies from country to country. In the US for example, prosecutors rely on securities law, and the wire fraud and bank fraud statutes within the criminal code. Cases involving misappropriation of assets can be prosecuted as embezzlement under State or Federal law, sometimes both, depending on ease of likely prosecution.

For example, the former Chairman and CEO of Enron was charged with conspiracy to commit securities fraud, four counts of securities fraud, two counts of wire fraud, one count of bank fraud and three counts of making false statements to a bank.

Securities fraud occurs when an agent induces investors to make purchase or sale decisions on the basis of false information. Wire fraud occurs when a person intentionally and voluntarily uses a communication device that sends information over state lines as part of a scheme to defraud another out of money or other valuables. It can involve the use of a landline telephone, cell phone, computer, or any electronic device. Bank fraud includes any "scheme or artifice" intended to "defraud a financial institution," or the use of deceptive means to obtain something of value that a financial institution owns or controls.

In every legal action involving accounting fraud, the original accounting infringement(s) are quickly lost in legal technicality and the process of law.

In 99.9% of cases, companies pay fines when caught (and a clear infringement occurred) but unless a misappropriation of assets can be demonstrated, indictment is exceptionally rare.

In summary, the legal definition of accounting fraud as applied by auditors is not directly relevant if prosecutors wish to press criminal charges. Offenders are never prosecuted for illegal accounting practices. In every jurisdiction, individuals are charged under separate criminal codes and statutes that were not designed for the complexity of accounting. Rather, they were designed for the complexity of the law. To be sure, accounting law is taken into consideration, but perpetrators of accounting fraud are not tried on accounting regulation.

Even in law, accounting fraud is a much broader concept than the illegal misstatement of financial accounts. It is a question of intent to deceive, the extent of damage inflicted by the deception and the monetary gain sought and received by the perpetrators.

Under the strict definition of accounting fraud, the extent of fraud does not matter. What matters is how a company misstates its accounts. A company that inflates earnings by 0.1% might have committed accounting fraud under a strict interpretation whereas a company with more aggressive accounting that inflated earnings by 200% might not have committed accounting fraud.

However, if both of these companies were to collapse you can bet that a law court would be more likely to find the latter guilty of fraud than the former.

Thus, while accounting fraud is a legal concept used by regulators to charge companies and individuals for illegal accounting practices, it is not used to prosecute fraud under criminal law. Under criminal law, aggressive accounting might be considered illegal if it intentionally deceived investors or creditors, if it harmed investors or creditors, or if it delivered specific financial benefit to the offenders.

Accounting fraud in the world of finance

In the world of finance, agents do not care about legal distinctions between aggressive accounting and accounting fraud, they care about the extent to which account manipulation affects the risk of investing in or lending to a company.

Since account manipulation artificially raises current profit at the expense of future profit, absorbs working capital and hides balance sheet weakness, it always affects the risk of investing in or lending to a company. It is deceptive and always represents a risk of accounting fraud.

Moreover, companies that pursue aggressive accounting practices can follow the letter of the law while deviating widely from the spirit of accounting rules. In this era of socially responsible investing, account manipulation is an ethical concern and a matter of trust to professional investors and creditors. It is much more than a legal issue.

If we accept that a company can be ethically fraudulent before it breaches a legal technicality, we must also accept that the line between aggressive accounting and fraudulent accounting is meaningless. In the world of finance, all account manipulation is undesirable and more manipulation is worse than less.

The danger, from the perspective of a creditor or investor, is that account manipulation can be a slippery slope. The fear is that minor manipulation today will lead to greater manipulation in subsequent years.

We see this pattern of escalation time and again in some of the biggest cases of accounting fraud over the past half century; good companies turning bad partly due to increasingly aggressive accounting practices. Enron, WorldCom, Parmalat, Tesco, and Valeant Pharmaceuticals are good examples of this pattern. The list is long.

Neurological research supports the contention that aggressive accounting can be a gateway drug to accounting fraud. Physiological studies of the brain show that lying becomes easier the more we lie and thus lying tends to be habit forming.[5]

The study of lying within organizations is comparatively new. Psychologists have tended to focus on the study of deception in children. Anyone with a child will understand why. Interestingly, the first systematic observations of lying were undertaken by Charles Darwin on his own child. He was fascinated by his child's incessant lying.

Nevertheless, a growing body of evidence suggests that a pattern of lying, even small lies, by an organization's leader can have a big impact on the organization's culture. In other words, small lies tend to encourage dishonesty.[6]

Research in accounting has typically focussed on the 'fraud triangle'.[7] Under the fraud triangle, corporate fraud requires each of the following circumstances to prevail: (i) motivation/pressure; (ii) opportunity and (iii) rationalization of actions.

In the context of the fraud triangle, even a small amount of manipulation will tend to foster increasing future manipulation because opportunity and rationalization become easier as a corporate culture becomes desensitized to dishonesty. Moreover, motivation/pressure will build over time because every accounting manipulation technique boosts current profit at the expense of future profit.

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[5] https://www.nature.com/articles/nn.4426
[6] https://www.nationalgeographic.com/magazine/article/lying-hoax-false-fibs-science
[7] https://www.accountingtools.com/articles/fraud-triangle

Financial markets are lubricated with trust. Once a company is suspected of account manipulation, investors will typically extrapolate the problem. Accenture's Competitive Agility Index — a 7,000-company, 20-industry analysis, has been used to quantify how a decline in stakeholder trust impacts a company's financial performance. Following a material drop in trust, a company's agility index score fell 2 points on average, negatively impacting revenue growth by 6% and EBITDA by 10% on average.[8]

To summarize, in the world of finance all accounting manipulation represents a risk of accounting fraud. It boosts current profit at the expense of future profit and is undesirable because it lowers sustainability, raises financial risk and sets a precedent which can lead to increasingly severe manipulation over time.

How much account manipulation is excessive?

A zero-tolerance approach to account manipulation is impractical because all companies manipulate earnings to some degree. Companies need investors. The role of the CEO is to present the financial performance of a company in the best possible light so as to attract investors. This practice is well understood and accepted. Were it not so, investor relations would not report to the CFO.

In their efforts to present their company in the best available light, CFOs can use a variety of perfectly legal methods to allow premature revenue recognition, defer costs and lower the apparent cost of funding assets. The list of options is long and a good CFO can often pursue these options simultaneously within the letter of GAAP.

However, the more a company manipulates revenue or expenses, the more its future results will be affected and thus the more a company is misrepresenting its true financial position. The more a company manipulates today, the greater the pressure to manipulate even more in the future.

Accounting fraud is a matter of degree. The more aggressive a company's accounting, the more it manipulates accounts, the greater the risk that a company will be a poor investment or credit risk.

[8] https://hbr.org/2019/02/4-ways-lying-becomes-the-norm-at-a-company

In practical terms, a company might be considered fraudulent when we stop investing in or lending to it for fear its account manipulation might have undesirable financial consequences. This is a matter of judgment.

A priori, an external observer cannot say which companies are breaking legal technicalities. However, forensic accounting can assess whether a company shows evidence of potential manipulation across a number of fronts. Using forensic accounting and the number crunching ability of modern data science, software can compare the risk of fraud across companies.

Any company displaying above average account manipulation risk on an accounting fraud detection platform has potentially crossed the line from aggressive to fraudulent accounting. Every investor or analyst will have varying appetites for accounting manipulation risk and each can employ their own judgment.

Examples of accounting fraud - manipulation

Accounting fraud can occur anywhere in a company's financial statements but is most commonly occurs in the income statement and the balance sheet. In other words, revenue, expenses, assets and liabilities are the items most commonly affected.

There are many, many types of accounting fraud and we can't examine them all here. Our intention is simply to give a sense of what accounting fraud looks like.

From the outset, we must distinguish between account manipulation and account misstatement.

Account manipulation occurs when accounting discretion is used to improve or change the impression given by a company's accounts, for example, to boost earnings. Done properly, account manipulation is perfectly legal. Done improperly, account manipulation becomes account misstatement.

Account misstatement is an incorrect statement or the giving of false information. It is a factual error in the accounts which could be accidental or intentional.

Many forms of account manipulation reflect accounting decisions that are perfectly allowable within the rules of GAAP. Frequent forms of manipulation relate to the timing of revenue or expense recognition, the re-valuation of assets and obligations, the treatment of income from related businesses, the treatment of non-cash expenses such as depreciation and amortization, and the reporting of related party transactions.

For example, a company might use accruals to recognize revenue before a product has been delivered. Property companies are a great example. They typically book sales well before apartment construction is completed. In fact, in China they often book sales before construction has even started. This is a great way to boost earnings because revenue is recognized sometimes years before the expense associated with the sale is recorded. As you can imagine, this inflates earnings and gross margin to a wondrous extent. The practice works well in a growing real estate market but typically leads to dire results in a property market downturn. This is why real estate companies the world over collapse with great regularity. This example also illustrates how account manipulation weakens a company's true financial situation. Anything that makes the accounts look better today, will cause them to be worse in the future.

Asset valuations are another popular avenue for account manipulation, especially equity investments using the equity accounting method.

When a company invests in a new product or buys another business it can choose to buy it entirely and incorporate the business within its own accounts, buy more than 50% and run it as a subsidiary, or it can acquire between 20% and 50% and keep it as an equity investment on its accounts. In Asia it is very common for entrepreneurs to invest alongside their companies in equity investments.

The choice of acquisition methods typically says volumes about the way a company manages its accounts. Companies with conservative accounting will typically just fold acquisitions and investment in innovations into their existing business. Companies with aggressive accounting will prefer to keep investments at arms-length, either as subsidiaries or as equity investments; like to develop new businesses as a JV or some other kind of start-up.

Companies that practice aggressive accounting will typically use the equity accounting method for subsidiaries (where it is optional) and equity investments (where it is compulsory). Under equity accounting, the initial investment is recorded at cost and each reporting period adjustments are made depending on the assessed value of the investment at the end of the period. Any profit or income on the investment will also be reflected in changes in the value of the investment in direct proportion to the ownership percentage.

As you might imagine, this kind of set-up allows tremendous scope for account manipulation. Think of how many songs you have heard in your entire life, multiply by 1,000, and this will approach the number of options for creative accounting available to an enterprising CFO.

In its filing for the December quarter of 2020, for example, the Chinese eCommerce giant Alibaba reported quarterly net income of US$12.2 billion. This figure included valuation gains (asset write-ups) worth a staggering US$5.7 billion. Separately, the company reported income of US$735 million under equity method accounting from its 33% stake in Ant Group. In other words, the revaluation of assets and reporting of income from equity investments represented more than half the company's reported earnings.

From the time of its IPO in September 2014 until December 2020, Alibaba reported more than US$60 billion of asset write-ups, representing almost three quarters of its retained earnings at the time. Based on its accounts, Alibaba was essentially a private equity investor with a sideline in e-Commerce.

Alibaba was a market darling for many years. Investors, bankers and analysts did not care that so much of the company's reported income and indeed that so much of its balance sheet was concentrated in assets that nobody except the senior management at Alibaba were in a position to value. From the outside, this situation was cheered by analysts and investors alike. It reflected extremely aggressive accounting by any standard but was perfectly legal. Judging by the high level of "Buy" recommendations, analysts were no doubt surprised when Alibaba chose to "restructure" its assets a few short years later.

Companies with aggressive accounting practices frequently control a large number of separate entities. By late 2020 Alibaba had more than 350 subsidiaries and innumerable equity investments. You can imagine how difficult it might be for an auditor to track the value, income and potential related party transactions of such a complex entity. Typically, the smaller the company, the more aggressive the accounting. Equity accounting effectively allows a company to outsource its account manipulation.

We have shown two simple examples of account manipulation. In these examples, companies used discretionary accounting decisions to paint their financials in the best available light. Alibaba, for example, could have chosen to revalue its equity investments more conservatively. Chinese property companies did not have to use accruals quite so aggressively.

A high level of equity investment typically lead to a high volume of related party transactions. Prior to its aborted IPO, Ant Group generated about 60% of net income from related party transactions with Alibaba and other related groups. As noted, 33% of this net income was then reported as profit for Alibaba, reflecting its ownership share. This all makes for highly complex accounts and tremendous opportunity for massaging of the accounts. This is account manipulation, which is perfectly legal if not withing the spirit oif accounting guidelines.

Examples of accounting fraud - misstatement

Account misstatement is an incorrect statement or the giving of false information. It is a factual error in the accounts which could be accidental or intentional. Material misstatement occurs when the financial statements presented by a client are not in conformity with Generally Accepted Accounting Principles in all material respects, and indicate the auditor's belief that the financial statements, taken as a whole, are materially misstated.

In other words, account misstatement occurs when the accounts are either fabricated or just plain wrong for some reason.

There are a million possibilities for account misstatement. Examples would include overstating revenue, understating expense, fictitious sales and expenses, incorrect timing of revenue or expenses, concealment of liabilities or obligations, improper or inadequate disclosures, and misappropriations.

To pick one of these, fictitious revenue involves claiming sales that did not occur. Common examples would include dDouble-counting sales, creating phantom customers or overstating or otherwise altering the legitimate invoices of existing customers. Companies that undertake this kind of fraud sometimes reverse the false sales at the end of the reporting period to help conceal the deceit. Remarkably, this is what Wells Fargo did in a fraud case that surfaced in 2016. Wells Fargo employees were given impossible sales goals. To meet targets, employees created millions of checking and savings accounts on behalf of clients — but without their consent. The accounts were then canceled after the reporting period.

A good example of a somewhat more elaborate misstatement is channel stuffing, in which a company ships more goods to distributors and retailers along its distribution channel than end-users are likely to buy in a normal inventory cycle. This is usually achieved by offering deep discounts, rebates, and extended payment terms, to persuade distributors and retailers to buy quantities in excess of their current needs. In most cases, distributors retain the right to return any unsold inventory which makes it dubious that a final sale has occurred.

Unless fully documented, channel stuffing is considered illegal. It helps to boost sales and profit numbers, sometimes for as long as 6 to 9 months. It is typically evidenced by a sharp jump in accounts receivable. Since channel stuffing comes at the expense of future sales it always leads to a deterioration in financial performance.

A very simple example of expense misstatement would be to an operating expense as capex. Thus, the expense is capitalized and becomes a depreciation expense, realized slowly over time, rather than an operating expense that is recognized immediately. Agricultural businesses, miners and companies with a lot of R&D have been notorious for this kind of expense manipulation in the past.

Concluding thoughts

In summary, companies can manipulate their accounts in many ways. Manipulation can be legal or illegal. If it breaks the principles of GAAP or involves misstatement, it will be considered illegal. Only rarely can we detect when a company is engaged in misstatement from examining its public records. However, evidence of aggressive account manipulation can be observed by careful analysis of a company's statements. The more conservative is a company's accounting, the less likely it is that it will be engaged in accounting fraud. The more aggressive the account manipulation, the greater the risk of fraud because aggressive accounting worsens a company's financial condition over time and conditions management and employees to engage in dishonest practices. Forensic accountants are able to uncover companies with a high risk of account manipulation. Fraud detection software can perform the same task but by looking at thousands of companies at once.

Appendix 2.1

North America ex OTC

Table A2.1. Success rates (0-1) for classification of stock manipulation/failure, by manipulation risk score, for in-sample (training) and out-of-sample (test) datasets

A. All stocks										
MRisk	>0.9	>0.8	>0.7	>0.6	>0.5	≤0.5	≤0.4	≤0.3	≤0.2	≤0.1
In-sample	1.00	1.00	1.00	0.96	0.90	0.12	0.03	0.00	0.00	0.00
Out-of-sample	0.93	0.91	0.85	0.78	0.71	0.13	0.09	0.07	0.04	0.02
B. 1 year prior to fail date										
MRisk	>0.9	>0.8	>0.7	>0.6	>0.5	≤0.5	≤0.4	≤0.3	≤0.2	≤0.1
In-sample	1.00	1.00	1.00	0.97	0.90	0.07	0.01	0.00	0.00	0.00
Out-of-sample	0.93	0.90	0.83	0.70	0.59	0.10	0.08	0.06	0.03	0.02
C. 2 years prior to fail date										
MRisk	>0.9	>0.8	>0.7	>0.6	>0.5	≤0.5	≤0.4	≤0.3	≤0.2	≤0.1
In-sample	1.00	1.00	1.00	0.96	0.88	0.06	0.01	0.00	0.00	0.00
Out-of-sample	0.91	0.88	0.80	0.66	0.54	0.10	0.08	0.06	0.03	0.02
D. 3 years prior to fail date										
MRisk	>0.9	>0.8	>0.7	>0.6	>0.5	≤0.5	≤0.4	≤0.3	≤0.2	≤0.1
In-sample	1.00	1.00	1.00	0.95	0.85	0.06	0.01	0.00	0.00	0.00
Out-of-sample	0.89	0.86	0.77	0.62	0.50	0.09	0.08	0.06	0.03	0.02

Source: Transparently Pte Ltd

Table A2.2. Manipulation risk score range vs median 12 month future financial year returns (%)

MRisk	>0.9	>0.8	>0.7	>0.6	>0.5	≤0.5	≤0.4	≤0.3	≤0.2	≤0.1
In-sample	-30.9	-29.3	-26.1	-23.6	-20.3	-1.5	-0.9	-0.7	-0.8	-1.5
Out-of-sample	-35.7	-34.6	-30.8	-27.0	-23.2	-1.6	-1.1	-0.6	-0.2	-0.7

Source: Transparently Pte Ltd

Appendix 2.2

Western Europe

Table A2.3. Success rates (0-1) for classification of stock manipulation/failure, by manipulation risk score, for in-sample (training) and out-of-sample (test) datasets

E. All stocks										
MRisk	>0.9	>0.8	>0.7	>0.6	>0.5	≤0.5	≤0.4	≤0.3	≤0.2	≤0.1
In-sample	1.00	1.00	1.00	1.00	0.95	0.11	0.02	0.00	0.00	0.00
Out-of-sample	NA	0.73	0.72	0.66	0.58	0.20	0.16	0.12	0.06	0.02
F. 1 year prior to fail date										
MRisk	>0.9	>0.8	>0.7	>0.6	>0.5	≤0.5	≤0.4	≤0.3	≤0.2	≤0.1
In-sample	1.00	1.00	1.00	1.00	0.97	0.08	0.01	0.00	0.00	0.00
Out-of-sample	NA	0.75	0.79	0.69	0.56	0.16	0.13	0.10	0.05	0.01
G. 2 years prior to fail date										
MRisk	>0.9	>0.8	>0.7	>0.6	>0.5	≤0.5	≤0.4	≤0.3	≤0.2	≤0.1
In-sample	1.00	1.00	1.00	1.00	0.97	0.07	0.01	0.00	0.00	0.00
Out-of-sample	NA	0.71	0.76	0.66	0.52	0.15	0.12	0.09	0.05	0.01
H. 3 years prior to fail date										
MRisk	>0.9	>0.8	>0.7	>0.6	>0.5	≤0.5	≤0.4	≤0.3	≤0.2	≤0.1
In-sample	1.00	1.00	1.00	1.00	0.96	0.07	0.01	0.00	0.00	0.00
Out-of-sample	NA	0.71	0.73	0.62	0.48	0.14	0.11	0.08	0.05	0.01

Source: Transparently Pte Ltd

Table A2.4. Manipulation risk score range vs median 12 month future financial year returns (%)

MRisk	>0.9	>0.8	>0.7	>0.6	>0.5	≤0.5	≤0.4	≤0.3	≤0.2	≤0.1
In-sample	-11.7	-29.5	-24.9	-21.3	-17.9	-0.8	0.5	1.4	2.5	3.4
Out-of-sample	NA	-31.1	-25.7	-21.6	-17.0	-1.3	-0.1	1.2	1.9	0.5

Source: Transparently Pte Ltd

Appendix 2.3

Japan

Table A2.5. Success rates (0-1) for classification of stock manipulation/failure, by manipulation risk score, for in-sample (training) and out-of-sample (test) datasets

I. All stocks										
MRisk	>0.9	>0.8	>0.7	>0.6	>0.5	≤0.5	≤0.4	≤0.3	≤0.2	≤0.1
In-sample	1.00	1.00	1.00	0.98	0.96	0.11	0.05	0.01	0.00	0.00
Out-of-sample	0.99	0.89	0.82	0.74	0.64	0.16	0.14	0.11	0.07	0.03
J. 1 year prior to fail date										
MRisk	>0.9	>0.8	>0.7	>0.6	>0.5	≤0.5	≤0.4	≤0.3	≤0.2	≤0.1
In-sample	1.00	1.00	1.00	0.99	0.97	0.09	0.04	0.01	0.00	0.00
Out-of-sample	1.00	0.94	0.87	0.79	0.68	0.14	0.12	0.10	0.06	0.03
K. 2 years prior to fail date										
MRisk	>0.9	>0.8	>0.7	>0.6	>0.5	≤0.5	≤0.4	≤0.3	≤0.2	≤0.1
In-sample	1.00	1.00	1.00	0.98	0.96	0.08	0.04	0.00	0.00	0.00
Out-of-sample	1.00	0.93	0.85	0.77	0.66	0.14	0.12	0.09	0.06	0.03
L. 3 years prior to fail date										
MRisk	>0.9	>0.8	>0.7	>0.6	>0.5	≤0.5	≤0.4	≤0.3	≤0.2	≤0.1
In-sample	1.00	1.00	1.00	0.98	0.96	0.08	0.04	0.00	0.00	0.00
Out-of-sample	1.00	0.91	0.83	0.75	0.63	0.13	0.11	0.09	0.06	0.03

Source: Transparently Pte Ltd

Table A2.6. Manipulation risk score range vs median 12 month future financial year returns (%)

MRisk	>0.9	>0.8	>0.7	>0.6	>0.5	≤0.5	≤0.4	≤0.3	≤0.2	≤0.1
In-sample	-20.9	-15.2	-12.3	-12.1	-10.3	-1.7	-1.3	-0.8	-0.5	-0.5
Out-of-sample	-16.3	-20.3	-16.1	-15.3	-11.0	-1.9	-1.7	-1.3	-0.9	-0.3

Source: Transparently Pte Ltd

Appendix 2.4

Asia Pacific ex Japan

Table A2.7. Success rates (0-1) for classification of stock manipulation/failure, by manipulation risk score, for in-sample (training) and out-of-sample (test) datasets

M. All stocks										
MRisk	>0.9	>0.8	>0.7	>0.6	>0.5	≤0.5	≤0.4	≤0.3	≤0.2	≤0.1
In-sample	1.00	1.00	1.00	0.97	0.92	0.11	0.02	0.00	0.00	0.00
Out-of-sample	0.88	0.79	0.77	0.72	0.67	0.24	0.19	0.13	0.07	0.02
N. 1 year prior to fail date										
MRisk	>0.9	>0.8	>0.7	>0.6	>0.5	≤0.5	≤0.4	≤0.3	≤0.2	≤0.1
In-sample	1.00	1.00	1.00	0.99	0.94	0.08	0.01	0.00	0.00	0.00
Out-of-sample	1.00	0.91	0.81	0.72	0.63	0.19	0.15	0.10	0.05	0.01
O. 2 years prior to fail date										
MRisk	>0.9	>0.8	>0.7	>0.6	>0.5	≤0.5	≤0.4	≤0.3	≤0.2	≤0.1
In-sample	1.00	1.00	1.00	0.99	0.94	0.07	0.01	0.00	0.00	0.00
Out-of-sample	1.00	0.90	0.78	0.68	0.60	0.18	0.14	0.10	0.05	0.01
P. 3 years prior to fail date										
MRisk	>0.9	>0.8	>0.7	>0.6	>0.5	≤0.5	≤0.4	≤0.3	≤0.2	≤0.1
In-sample	1.00	1.00	1.00	0.99	0.93	0.06	0.01	0.00	0.00	0.00
Out-of-sample	1.00	0.88	0.75	0.65	0.56	0.07	0.16	0.09	0.04	0.01

Source: Transparently Pte Ltd

Table A2.8. Manipulation risk score range vs median 12 month future financial year returns (%)

MRisk	>0.9	>0.8	>0.7	>0.6	>0.5	≤0.5	≤0.4	≤0.3	≤0.2	≤0.1
In-sample	-36.3	-28.3	-24.1	-21.1	-18.6	-2.9	-1.9	-1.4	-0.6	0.8
Out-of-sample	-47.4	-25.8	-22.7	-18.9	-15.6	-4.1	-3.3	-2.1	-0.7	1.7

Source: Transparently Pte Ltd

Appendix 2.5

Rest of World

Table A2.9. Success rates (0-1) for classification of stock manipulation/failure, by manipulation risk score, for in-sample (training) and out-of-sample (test) datasets

Q. All stocks										
MRisk	>0.9	>0.8	>0.7	>0.6	>0.5	≤0.5	≤0.4	≤0.3	≤0.2	≤0.1
In-sample	1.00	1.00	1.00	0.97	0.92	0.13	0.03	0.00	0.00	0.00
Out-of-sample	0.97	0.86	0.79	0.72	0.65	0.22	0.18	0.13	0.07	0.02
R. 1 year prior to fail date										
MRisk	>0.9	>0.8	>0.7	>0.6	>0.5	≤0.5	≤0.4	≤0.3	≤0.2	≤0.1
In-sample	1.00	1.00	1.00	0.99	0.94	0.09	0.02	0.00	0.00	0.00
Out-of-sample	1.00	0.90	0.80	0.70	0.60	0.18	0.15	0.11	0.06	0.02
S. 2 years prior to fail date										
MRisk	>0.9	>0.8	>0.7	>0.6	>0.5	≤0.5	≤0.4	≤0.3	≤0.2	≤0.1
In-sample	1.00	1.00	1.00	0.99	0.93	0.08	0.02	0.00	0.00	0.00
Out-of-sample	1.00	0.88	0.77	0.66	0.57	0.17	0.14	0.10	0.06	0.02
T. 3 years prior to fail date										
MRisk	>0.9	>0.8	>0.7	>0.6	>0.5	≤0.5	≤0.4	≤0.3	≤0.2	≤0.1
In-sample	1.00	1.00	1.00	0.98	0.92	0.07	0.02	0.00	0.00	0.00
Out-of-sample	1.00	0.86	0.73	0.63	0.53	0.15	0.13	0.09	0.05	0.01

Source: Transparently Pte Ltd

Table A3.0. Manipulation risk score range vs median 12 month future financial year returns (%)

MRisk	>0.9	>0.8	>0.7	>0.6	>0.5	≤0.5	≤0.4	≤0.3	≤0.2	≤0.1
In-sample	-34.6	-28.8	-25.1	-21.7	-18.5	-2.2	-1.4	-0.8	-0.4	0.2
Out-of-sample	-41.6	-32.1	-26.2	-21.5	-17.4	-3.0	-2.3	-14	-0.7	0.1

Source: Transparently Pte Ltd

Appendix 2.6

US OTC stocks

Table A3.1. Success rates (0-1) for classification of stock manipulation/failure, by manipulation risk score, for in-sample (training) and out-of-sample (test) datasets

U. All stocks										
MRisk	>0.9	>0.8	>0.7	>0.6	>0.5	≤0.5	≤0.4	≤0.3	≤0.2	≤0.1
In-sample	1.00	1.00	0.98	0.92	0.89	0.00	0.00	0.00	0.00	NA
Out-of-sample	0.85	0.81	0.79	0.78	0.77	0.19	0.18	0.00	NA	NA
V. 1 year prior to fail date										
MRisk	>0.9	>0.8	>0.7	>0.6	>0.5	≤0.5	≤0.4	≤0.3	≤0.2	≤0.1
In-sample	1.00	1.00	0.98	0.92	0.88	0.00	0.00	0.00	0.00	NA
Out-of-sample	0.80	0.77	0.73	0.70	0.67	0.13	0.10	0.00	NA	NA
W. 2 years prior to fail date										
MRisk	>0.9	>0.8	>0.7	>0.6	>0.5	≤0.5	≤0.4	≤0.3	≤0.2	≤0.1
In-sample	1.00	1.00	0.98	0.90	0.85	0.00	0.00	0.00	0.00	NA
Out-of-sample	0.77	0.73	0.69	0.66	0.64	0.13	0.10	0.00	NA	NA
X. 3 years prior to fail date										
MRisk	>0.9	>0.8	>0.7	>0.6	>0.5	≤0.5	≤0.4	≤0.3	≤0.2	≤0.1
In-sample	1.00	1.00	0.98	0.88	0.82	0.00	0.00	0.00	0.00	NA
Out-of-sample	0.73	0.70	0.65	0.62	0.59	0.11	0.07	0.00	NA	NA

Source: Transparently Pte Ltd

Table A3.2. Manipulation risk score range vs median 12 month future financial year returns (%)

MRisk	>0.9	>0.8	>0.7	>0.6	>0.5	≤0.5	≤0.4	≤0.3	≤0.2	≤0.1
In-sample	-35.3	-32.1	-31.6	-31.0	-30.1	-1.8	-2.9	0.7	19.1	NA
Out-of-sample	-37.0	-32.7	-29.8	-28.6	-27.7	-5.3	-2.1	-3.5	NA	NA

Source: Transparently Pte Ltd

Appendix 3.0

Table A3.3. Transparently stock coverage by country of incorporation

	Tickers			Ticker years		
	Active	Inactive	Ratio	Active	Inactive	Ratio
Anguilla	1	NA	NA	5	NA	NA
Antigua & Barbuda	1	NA	NA	13	NA	NA
Argentina	66	28	0.30	1,194	184	0.13
Australia	1,545	1,283	0.45	17,748	9,295	0.34
Austria	52	66	0.56	897	387	0.30
Bahamas	1	3	0.75	5	23	0.82
Bahrain	23	4	0.15	219	15	0.06
Bangladesh	102	3	0.03	772	7	0.01
Barbados	1	NA	NA	3	NA	NA
Belgium	116	89	0.43	1,726	646	0.27
Bermuda	507	235	0.32	9,162	2,424	0.21
Bosnia & Herzegovina	56	5	0.08	417	15	0.03
Botswana	16	6	0.27	143	28	0.16
Brazil	224	78	0.26	2,140	438	0.17
Bulgaria	158	81	0.34	1,365	344	0.20
Burkina Faso	1	NA	NA	5	NA	NA
Canada	2,322	1,836	0.44	20,924	11,297	0.35
Cayman Islands	1,816	445	0.20	13,018	2,617	0.17
Chile	143	66	0.32	2,179	594	0.21
China	4,588	250	0.05	45,937	2,511	0.05
Colombia	28	17	0.38	389	79	0.17
Cote d'Ivoire	26	1	0.04	319	2	0.01
Croatia	55	56	0.50	634	346	0.35
Curacao	2	2	0.50	42	28	0.40
Cyprus	63	68	0.52	531	277	0.34
Czechia	8	34	0.81	108	134	0.55
Denmark	149	140	0.48	2,001	1,137	0.36
Egypt	214	19	0.08	2,338	131	0.05
Estonia	22	4	0.15	229	25	0.10
Falkland Islands	1	1	0.50	6	9	0.60
Faroe Islands	2	NA	NA	22	NA	NA
Finland	166	80	0.33	2,084	650	0.24
France	587	613	0.51	8,249	4,154	0.33
Gabon	1	NA	NA	22	NA	NA
Germany	616	560	0.48	8,245	3,360	0.29
Ghana	14	2	0.12	98	15	0.13
Gibraltar	3	3	0.50	27	19	0.41
Greece	127	198	0.61	2,262	1,834	0.45
Guernsey	28	24	0.46	300	155	0.34
Hong Kong	209	66	0.24	3,607	704	0.16
Hungary	32	36	0.53	410	245	0.37
Iceland	22	11	0.33	176	41	0.19
India	3,120	725	0.19	33,855	4,664	0.12
Ireland	69	78	0.53	942	534	0.36

Continued overleaf

Table A3.4. Transparently stock coverage by country of incorporation (continued)

	Tickers			Ticker years		
	Active	Inactive	Ratio	Active	Inactive	Ratio
Indonesia	618	111	0.15	6,674	770	0.10
Iraq	18	NA	NA	103	NA	NA
Isle of Man	20	45	0.69	187	280	0.60
Israel	491	244	0.33	5,239	1,587	0.23
Italy	322	218	0.40	3,203	1,550	0.33
Jamaica	29	2	0.06	184	3	0.02
Japan	3,705	1,751	0.32	73,165	19,192	0.21
Jersey	50	79	0.61	541	450	0.45
Jordan	140	52	0.27	1,728	302	0.15
Kazakhstan	15	4	0.21	73	8	0.10
Kenya	41	4	0.09	430	21	0.05
Kuwait	113	79	0.41	1,572	631	0.29
Latvia	9	17	0.65	112	166	0.60
Lebanon	3	1	0.25	32	5	0.14
Liberia	2	NA	NA	37	NA	NA
Liechtenstein	1	1	0.50	2	9	0.82
Lithuania	27	17	0.39	326	90	0.22
Luxembourg	58	36	0.38	529	168	0.24
Malawi	8	NA	NA	61	NA	NA
Malaysia	889	404	0.31	14,915	3,662	0.20
Malta	27	3	0.10	248	11	0.04
Marshall Islands	37	16	0.30	381	89	0.19
Mauritius	53	8	0.13	427	48	0.10
Mexico	112	63	0.36	1,836	478	0.21
Monaco	1	1	0.50	20	2	0.09
Montenegro	20	1	0.05	126	7	0.05
Morocco	55	12	0.18	716	106	0.13
Namibia	7	2	0.22	51	11	0.18
Netherlands	146	155	0.51	1,791	1,052	0.37
New Zealand	122	100	0.45	1,689	675	0.29
Nigeria	78	15	0.16	662	84	0.11
North Macedonia	20	5	0.20	199	29	0.13
Norway	227	232	0.51	2,127	1,358	0.39
Oman	74	17	0.19	729	77	0.10
Pakistan	343	35	0.09	4,021	162	0.04
Palestine, State of	25	1	0.04	210	4	0.02
Panama	4	1	0.20	72	4	0.05
Papua New Guinea	2	9	0.82	41	89	0.68
Peru	78	33	0.30	877	128	0.13
Philippines	214	55	0.20	3,178	430	0.12
Poland	516	239	0.32	5,154	1,732	0.25
Portugal	40	35	0.47	642	243	0.27
Puerto Rico	1	NA	NA	9	NA	NA
Qatar	35	3	0.08	437	5	0.01
Romania	104	51	0.33	857	264	0.24
Russian Federation	239	145	0.38	1,895	537	0.22

Continued overleaf

Table A3.4. Transparently stock coverage by country of incorporation (continued)

	Tickers			Ticker years		
	Active	Inactive	Ratio	Active	Inactive	Ratio
Saudi Arabia	175	6	0.03	1,926	52	0.03
Senegal	1	NA	NA	15	NA	NA
Serbia	29	44	0.60	226	165	0.42
Singapore	502	439	0.47	7,275	4,203	0.37
Slovakia	5	17	0.77	52	90	0.63
Slovenia	22	30	0.58	257	180	0.41
South Africa	195	381	0.66	3,172	2,467	0.44
South Korea	2,254	717	0.24	28,929	4,866	0.14
Spain	210	117	0.36	1,983	742	0.27
Sri Lanka	193	21	0.10	2,703	124	0.04
Sweden	785	374	0.32	7,395	2,452	0.25
Switzerland	210	153	0.42	3,570	1,348	0.27
Syria	4	NA	NA	15	NA	NA
Taiwan	1,846	410	0.18	26,898	2,563	0.09
Tanzania	9	NA	NA	77	NA	NA
Thailand	741	148	0.17	9,791	1,261	0.11
Trinidad & Tobago	12	NA	NA	25	NA	NA
Tunisia	52	3	0.05	524	33	0.06
Turkey	374	84	0.18	5,044	759	0.13
Uganda	5	NA	NA	37	NA	NA
Ukraine	16	37	0.70	83	94	0.53
United Arab Emirates	66	16	0.20	663	97	0.13
United Kingdom	1,034	2,314	0.69	14,560	15,654	0.52
United States	3,686	4,611	0.56	47,154	33,580	0.42
Venezuela	5	11	0.69	32	57	0.64
Vietnam	961	100	0.09	9,008	496	0.05
Virgin Islands (British)	93	53	0.36	680	266	0.28
Virgin Islands (US)	1	NA	NA	9	NA	NA
Zambia	16	NA	NA	99	NA	NA

Source: Transparently Pte Ltd

Table A3.5. Transparently stock coverage by country of exchange

	Tickers			Ticker years		
	Active	Inactive	Ratio	Active	Inactive	Ratio
Argentina	66	28	0.30	1,194	184	0.13
Australia	1,579	1,306	0.45	17,969	9,459	0.34
Austria	47	62	0.57	817	358	0.30
Bahrain	23	4	0.15	219	15	0.06
Bangladesh	102	3	0.03	772	7	0.01
Belgium	115	90	0.44	1,701	628	0.27
Bosnia & Herzegovina	56	5	0.08	417	15	0.03
Botswana	17	6	0.26	144	28	0.16
Brazil	225	74	0.25	2,141	405	0.16
Bulgaria	157	81	0.34	1,360	344	0.20
Canada	2,291	1,830	0.44	20,430	11,092	0.35
Chile	143	66	0.32	2,179	594	0.21
China	4,473	201	0.04	44,696	2,085	0.04
Colombia	28	18	0.39	389	89	0.19
Cote d'Ivoire	27	1	0.04	328	2	0.01
Croatia	55	56	0.50	634	346	0.35
Cyprus	46	59	0.56	343	221	0.39
Czechia	8	35	0.81	108	150	0.58
Denmark	136	138	0.50	1,993	1,117	0.36
Egypt	214	19	0.08	2,338	131	0.05
Estonia	21	4	0.16	221	25	0.10
Finland	162	77	0.32	2,063	648	0.24
France	604	633	0.51	8,467	4,257	0.33
Germany	644	599	0.48	8,551	3,649	0.30
Ghana	14	2	0.12	98	15	0.13
Greece	126	197	0.61	2,249	1,831	0.45
Hong Kong	2,103	457	0.18	23,790	4,282	0.15
Hungary	31	36	0.54	400	245	0.38
Iceland	21	11	0.34	162	41	0.20
India	3,119	724	0.19	33,835	4,663	0.12
Indonesia	618	111	0.15	6,674	770	0.10
Iraq	18	NA	NA	103	NA	NA
Ireland	15	47	0.76	221	325	0.60
Israel	417	194	0.32	4,624	1,267	0.22
Italy	329	209	0.39	3,321	1,516	0.31
Jamaica	30	2	0.06	187	3	0.02
Japan	3,703	1,751	0.32	73,152	19,199	0.21
Jordan	140	53	0.27	1,728	306	0.15
Kazakhstan	15	4	0.21	73	8	0.10
Kenya	41	4	0.09	430	21	0.05
Kuwait	113	79	0.41	1,572	631	0.29
Latvia	9	17	0.65	112	166	0.60
Lebanon	3	1	0.25	32	5	0.14
Lithuania	26	16	0.38	318	85	0.21
Luxembourg	7	12	0.63	105	50	0.32
Malawi	8	NA	NA	61	NA	NA

Continued overleaf

Table A3.5. Transparently stock coverage by country of exchange (continued)

	Tickers			Ticker years		
	Active	Inactive	Ratio	Active	Inactive	Ratio
Malaysia	891	409	0.31	14,946	3,699	0.20
Malta	18	2	0.10	171	7	0.04
Mauritius	47	7	0.13	368	46	0.11
Mexico	111	61	0.35	1,833	466	0.20
Montenegro	20	1	0.05	126	7	0.05
Morocco	55	12	0.18	716	106	0.13
Namibia	6	1	0.14	38	9	0.19
Netherlands	92	122	0.57	1,382	880	0.39
New Zealand	113	96	0.46	1,615	672	0.29
Nigeria	78	15	0.16	662	84	0.11
North Macedonia	20	5	0.20	199	29	0.13
Norway	268	259	0.49	2,465	1,518	0.38
Oman	74	17	0.19	729	77	0.10
Pakistan	343	35	0.09	4,021	162	0.04
Palestine	26	1	0.04	224	4	0.02
Peru	79	33	0.29	887	128	0.13
Philippines	214	54	0.20	3,178	421	0.12
Poland	535	249	0.32	5,308	1,777	0.25
Portugal	41	35	0.46	656	243	0.27
Qatar	35	3	0.08	437	5	0.01
Romania	106	51	0.32	866	264	0.23
Russian Federation	239	144	0.38	1,895	536	0.22
Saudi Arabia	175	5	0.03	1,926	48	0.02
Serbia	29	44	0.60	226	165	0.42
Singapore	513	509	0.50	7,630	4,774	0.38
Slovakia	5	16	0.76	52	80	0.61
Slovenia	22	30	0.58	257	180	0.41
South Africa	205	388	0.65	3,294	2,502	0.43
South Korea	2,271	728	0.24	29,030	4,924	0.15
Spain	208	117	0.36	1,960	739	0.27
Sri Lanka	193	21	0.10	2,703	124	0.04
Sweden	808	382	0.32	7,494	2,499	0.25
Switzerland	190	143	0.43	3,431	1,285	0.27
Syria	4	NA	NA	15	NA	NA
Taiwan	1,951	434	0.18	27,718	2,689	0.09
Tanzania	9	NA	NA	77	NA	NA
Thailand	739	147	0.17	9,761	1,260	0.11
Trinidad & Tobago	12	NA	NA	25	NA	NA
Tunisia	52	3	0.05	524	33	0.06
Turkey	374	84	0.18	5,044	759	0.13
Uganda	5	NA	NA	37	NA	NA
Ukraine	16	37	0.70	83	94	0.53
United Arab Emirates	66	16	0.20	663	111	0.14
United Kingdom	1,169	2,576	0.69	16,156	16,993	0.51
United States	4,390	4,882	0.53	51,785	35,231	0.40

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Table A3.5. Transparently stock coverage by country of exchange (continued)

	Tickers			Ticker years		
	Active	Inactive	Ratio	Active	Inactive	Ratio
Venezuela	5	11	0.69	32	57	0.64
Vietnam	962	100	0.09	9,023	496	0.05
Zambia	15	NA	NA	89	NA	NA

Source: Transparently Pte Ltd

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