Predicting Corporate Collapse with Accounting Quality

Transparently Risk Scores as predictors of Corporate Collapse

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The Transparently Risk Engine [TRE] is applied to a universe of approximately 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 stock 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 TRE for identification of problematic stocks, with high failure risk, and avoiding these for investment purposes, exiting an existing position on relatively favourable terms or working with management to rectify issues and lower the risk of manipulation and failure.

30 April, 2023

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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.

[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.

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. Evaluating the Bloomberg company database, we find direct peak to trough equity losses for failed stocks in excess of USD12 trillion. 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 data science 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 TRE 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.

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 TRE to a dataset comprised of approximately 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 Risk Engine to a dataset comprised of stocks listed and domiciled across all global equity markets, for which required data is available. 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 approximately 60,000 stocks with 640,000 stock-years of financial data, extending from January 1994 through to March 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.

It should be noted that the China figure is very low by international standards. For most developed markets the proportion that de-listings represent of all historically-listed stocks is 40-50%+. This is not an artifact of the selection process for Chinese stocks employed by this analysis. In an earlier study we found the rate of de-listings across all Chinese stocks was the second-lowest out of 50 stock domiciles we investigated.

Table 1. Transparently stock coverage by country of domicile

	Tickers			Ticker years		
	Active	Inactive	Ratio	Active	Inactive	Ratio
China	4,997	615	0.11	47,739	4,294	0.08
Hong Kong	1,353	322	0.19	18,202	3,462	0.16
Singapore	519	388	0.43	6,833	3,544	0.34
United States	5,542	7,547	0.58	62,428	50,015	0.44
All stocks	12,411	8,872	0.42	135,202	61,315	0.27

Source: Transparently Pte Ltd

Table 2. Transparently stock coverage by country of incorporation

	Tickers			Ticker years		
	Active	Inactive	Ratio	Active	Inactive	Ratio
Antigua and Barbuda	1	NA	NA	13	NA	NA
Australia	1	NA	NA	3	NA	NA
Bermuda	444	175	0.28	8,373	2,011	0.19
Canada	29	28	0.49	319	168	0.34
China	4,150	236	0.05	42,463	2,298	0.05
Curacao	1	NA	NA	28	NA	NA
Cayman Islands	1,456	327	0.18	10,764	2,257	0.17
Germany	1	NA	NA	1	NA	NA
United Kingdom	9	2	0.18	36	26	0.42
Guernsey	1	NA	NA	23	NA	NA
Hong Kong	191	49	0.20	3,435	554	0.14
Isle of Man	1	NA	NA	7	NA	NA
Ireland	3	4	0.57	34	32	0.48
Israel	4	NA	NA	15	NA	NA
Jersey	1	2	0.67	12	12	0.50
Liberia	1	NA	NA	22	NA	NA
Marshall Islands	6	6	0.50	37	19	0.34
Mauritius	1	NA	NA	22	NA	NA
Malaysia	1	NA	NA	7	NA	NA
Netherlands	1	NA	NA	1	NA	NA
Panama	1	1	0.50	28	22	0.44
Singapore	473	395	0.46	6,691	3,570	0.35
United States	5,581	7,615	0.58	62,503	50,157	0.45
Virgin Islands (British)	50	29	0.37	334	160	0.32
Virgin Islands (US)	3	NA	NA	31	NA	NA

Source: Transparently Pte Ltd

Note that 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 unfavourable 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.

Table 2 provides data on the country of incorporation for stocks within our sample universe. While all stocks are domiciled in the US, China, Hong Kong and Singapore, they may be incorporated elsewhere. Note that the proportion of stocks removed from listing is substantially higher for all incorporation countries outside of China, which has only 5% of stocks delisted. For stocks incorporated in Singapore and the US the proportions removed from listing are 46% and 58% respectively. 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 China (Shenzhen or Shanghai), Hong Kong, Singapore and the US. Summary listing information is provided in Table 3. In subsequent tables/figures, all relative return calculations are with reference to appropriate benchmarks within each jurisdiction. For reference purposes, Tables 4 and 5 provide summary information for the POC stock universe by Thomson Reuters Business Classification [TRBC] Code economic sector and business sector.

Table 3. Transparently stock coverage by country of exchange

	Tickers			Ticker years		
	Active	Inactive	Ratio	Active	Inactive	Ratio
China	4,027	180	0.04	41,023	1,779	0.04
Hong Kong	1,990	412	0.17	22,544	4,049	0.15
Singapore	490	462	0.49	7,012	4,140	0.37
US	5,904	7,818	0.57	64,623	51,347	0.44

Source: Transparently Pte Ltd

Table 4. Transparently stock coverage by TRBC economic sector

	Tickers			Ticker years		
	Active	Inactive	Ratio	Active	Inactive	Ratio
Energy	631	646	0.51	7257	4,547	0.39
Basic Materials	1,178	603	0.34	13,391	4,061	0.23
Industrials	2,364	1,436	0.38	25,935	10,438	0.29
Consumer Cyclicals	1,990	1,461	0.42	23,558	10,375	0.31
Consumer Staples	727	500	0.41	8,468	3,567	0.30
Financials	538	269	0.33	4,259	1,578	0.27
Health Care	1,734	1,264	0.42	16,496	8,669	0.34
Technology	2,085	2,165	0.51	20,521	13,877	0.40
Utilities	296	173	0.37	4,632	1,493	0.24
Real estate	771	285	0.27	9,901	2,347	0.19
Organizations	1	3	0.75	2	20	0.91
Government	1	NA	NA	7	NA	NA
Education	93	40	0.30	771	264	0.26
NA	2	27	0.93	4	79	0.95

Source: Transparently Pte Ltd

Table 5. Transparently stock coverage by TRBC business sector

	Tickers			Ticker years		
	Active	Inactive	Ratio	Active	Inactive	Ratio
Fossil Fuels	513	579	0.53	6,165	4,085	0.40
Renewable Energy	115	64	0.36	1,050	427	0.29
Uranium	3	3	0.50	42	35	0.45
Chemicals	500	179	0.26	5,240	1,362	0.21
Minerals	522	303	0.37	6,209	1,816	0.23
Applied Resources	156	121	0.44	1,942	883	0.31
Industrial Goods	1,160	523	0.31	12,956	4,143	0.24
Ind & Comm Services	933	721	0.44	9,103	4,822	0.35
Transport	271	192	0.41	3,876	1,473	0.28
Autos	324	134	0.29	3,398	961	0.22
Cyclical Cons Prod	645	387	0.38	7,832	2,797	0.26
Cyclical Cons Serv	659	647	0.50	7,613	4,272	0.36
Retail	362	293	0.45	4,715	2,345	0.33
Food & Beverage	490	289	0.37	5,719	2,038	0.26
Pers & Hhold Prod & Serv	100	109	0.52	1,171	706	0.38
Food & Drug Retail	127	94	0.43	1,372	736	0.35
Cons Goods Conglom	10	8	0.44	206	87	0.30
Banking	281	111	0.28	3,062	858	0.22
Real Estate (deprecated)	1	NA	NA	17	NA	NA
Holding Companies	256	158	0.38	1,180	720	0.38
Healthcare Services	600	670	0.53	6,332	4,583	0.42
Pharma & Biotech	1,134	594	0.34	10,164	4,086	0.29
Tech Equipment	871	766	0.47	10,226	5,906	0.37
Software & IT Services	1,014	1,119	0.52	8,551	6,424	0.43
Fintech	81	10	0.11	544	66	0.11
Telecommunications	119	270	0.69	1,200	1,481	0.55
Utilities	296	173	0.37	4,632	1,493	0.24
Real Estate	771	285	0.27	9,901	2,347	0.19
Organizations	1	3	0.75	2	20	0.91
Government	1	NA	NA	7	NA	NA
Education	93	40	0.30	771	264	0.26
NA	2	27	0.93	4	79	0.95

Source: Transparently Pte Ltd

Summary results

The TRE 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.

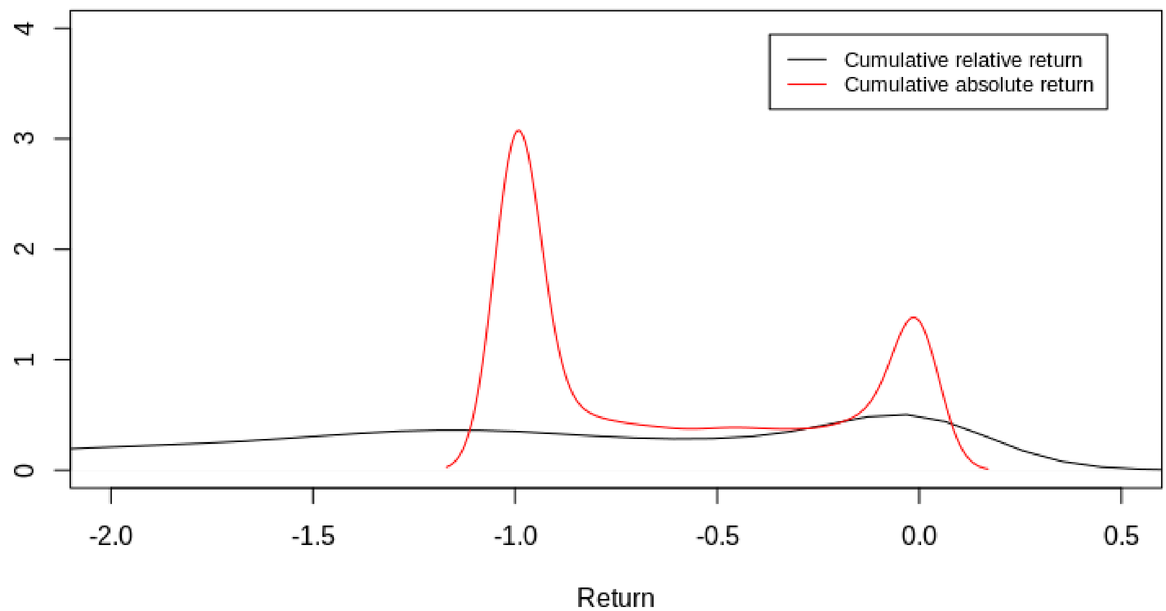
Firstly, for reference purposes, it is important to assess the impact of failed stocks (without identification of manipulation) on stock returns. Figure 1 provides a density plot of the absolute and relative returns (relative to the appropriate country benchmark, determined by the stock's listing location) from the date a stock's price peaks to the date it delists. The mean absolute return is -62.1% and median absolute return is -81.4%. The respective values for relative returns are -121.2% and -99.7%. Evidently, 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, etc. We see a similar pattern to the delisting sample, with reported/suspected manipulation associated with substantial losses (median absolute return of -92.1% and median relative return of -116.8%). 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.

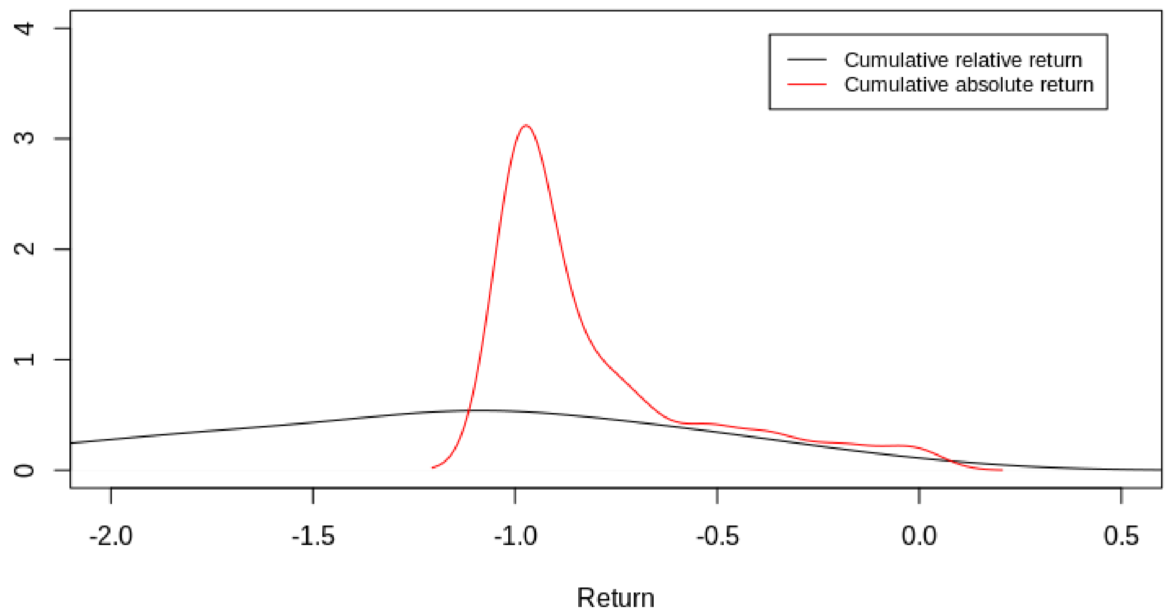
However, such failures can take a considerable period of time to fully play out in market trading. Figure 3 provides a density plot for the number of years from a stock's peak price to its delisting date, for our sample universe. The duration from peak to delisting averages 6.6 years (median 5.3 years), although we can see the distribution peak is closer to 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



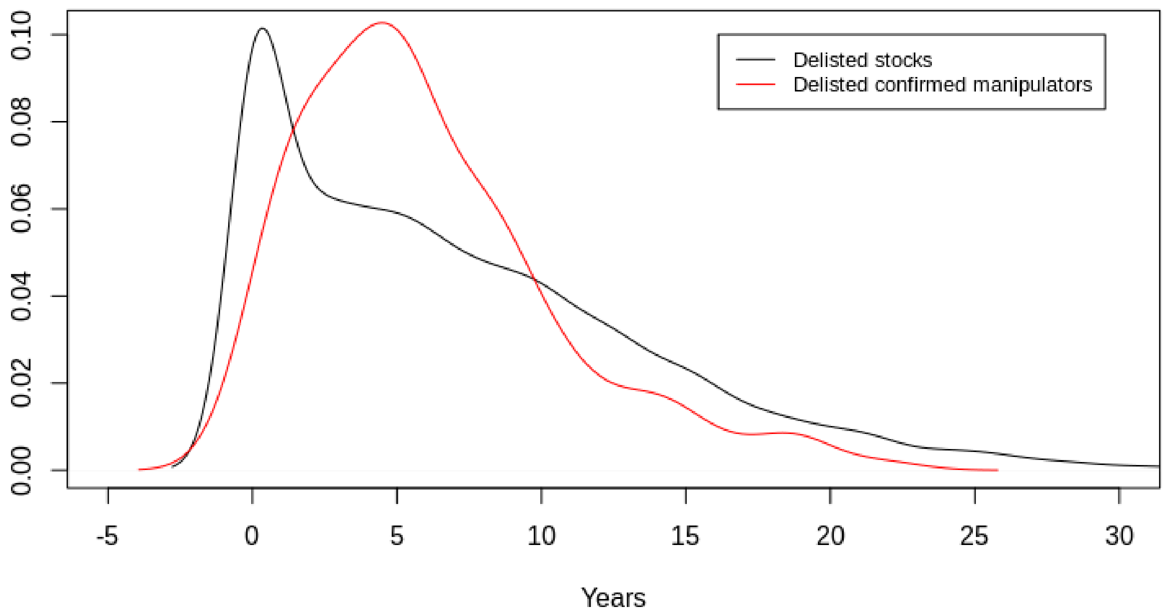
Source: Transparently Pte Ltd

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 6.2 years and the median time is 5.3 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 favourable terms.

However, the challenge is advanced identification of such failures. The TRE 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 6 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 6, 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.

Table 6. 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	0.99	0.94	0.07	0.02	0.00	0.00	0.00
Out-of-sample	0.84	0.81	0.79	0.77	0.72	0.17	0.14	0.10	0.06	0.03

Source: Transparently Pte Ltd

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 6 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 6 employs the full dataset. However, we wish to know how early we can identify such signals. Table 7 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 down no more than 50% from their historic peak, 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 72% of those stocks ultimately meeting the failure threshold.

Panel B provides similar results for stocks down no more than 25% from their historic peak. Most importantly, results are virtually identical in Panel C for stocks trading prior to their price peaking. 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. It is evident that the Transparently Risk Engine is able to provide significant information on manipulation/failure rates prior to any market recognition of increased failure risk.

Table 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 – by lagged period returns prior to failure

A. Stock has not yet fallen (relative) by 50% or more relative to peak										
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	0.06	0.02	0.00	0.00	0.00
Out-of-sample	1.00	0.84	0.72	0.63	0.51	0.08	0.07	0.06	0.04	0.02
B. Stock has not yet fallen (relative) by 25% or more relative to peak										
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	0.06	0.02	0.00	0.00	0.00
Out-of-sample	NA	0.82	0.70	0.62	0.49	0.07	0.06	0.05	0.04	0.02
C. Prior to stock price peak										
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	0.95	0.05	0.02	0.00	0.00	0.00
Out-of-sample	1.00	0.84	0.73	0.62	0.52	0.08	0.07	0.05	0.04	0.02

Source: Transparently Pte Ltd

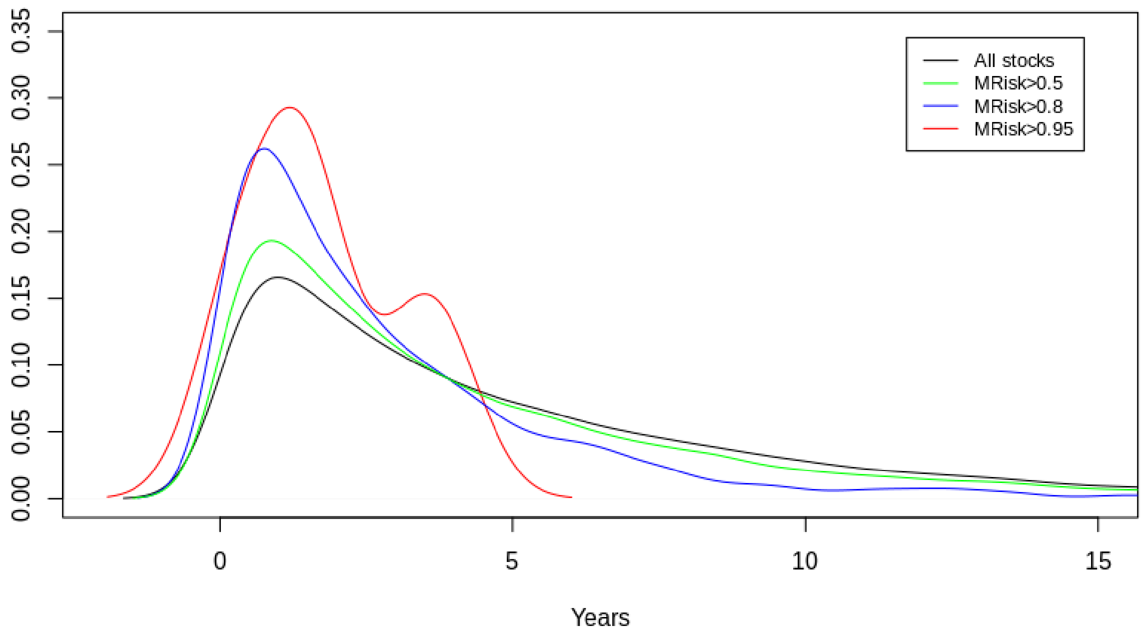
To investigate the expected time for manipulators from peak price to a relative return of -80% or worse, Figure 4 provides a density plot of the duration for our in-sample (training) manipulators. In addition, we include density plots for the subset of these with manipulation/failure risk scores of >50%,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

Table 8 provides mean and median durations from peak to failure for these groups. For all stocks, the mean duration is 4.7 years and the median is 3.3 years. However, as the manipulation risk score increases, the duration shortens; median 1.9 years for manipulation risk>80% and 1.4 years for manipulation risk>95%. 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 9. The median price fall is -82%. 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



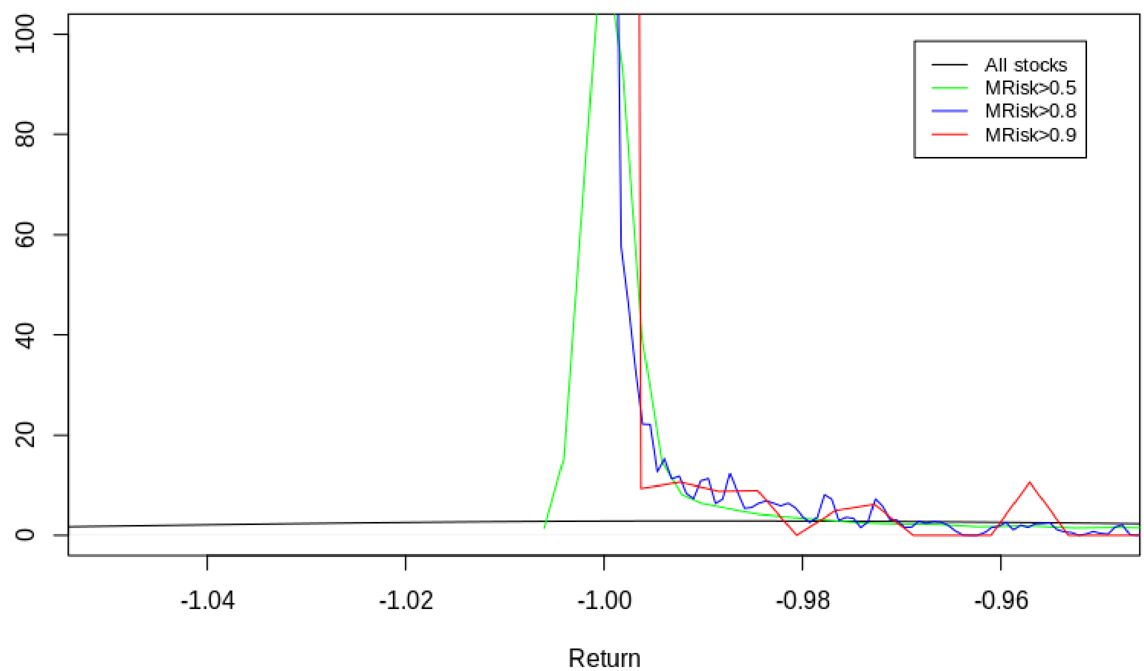
Source: Transparently Pte Ltd

Table 8. Years from peak return to relative return≤-80% for in-sample manipulators

	All stocks	MRisk>0.5	MRisk>0.8	MRisk>0.95
Mean	4.7	4.1	2.9	1.8
Median	3.3	2.8	1.9	1.4

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 9. Absolute returns from peak price to last available price for in-sample stocks

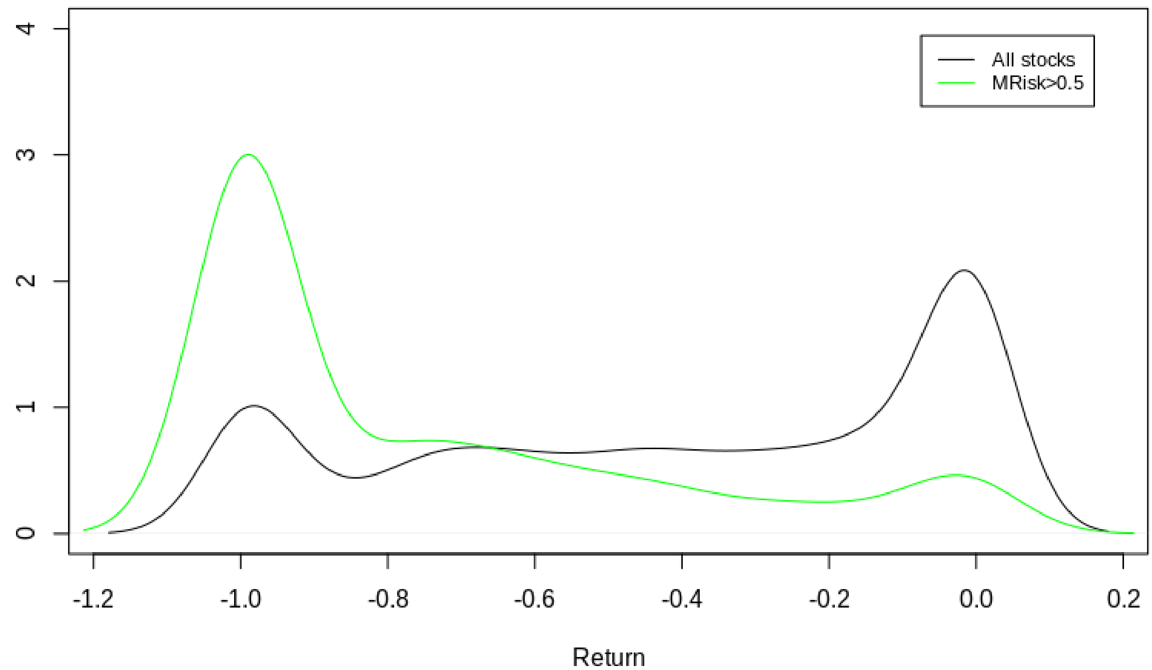
	All stocks	MRisk>0.5	MRisk>0.8	MRisk>0.9
Mean	-0.63	-0.97	-0.99	-1.00
Median	-0.82	-1.00	-1.00	-1.00

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%. For all stocks the distribution peak is at zero, reflecting how stocks tend to trend higher over time. However, we can see the strong peak around -100% for test stocks with a risk score over 50%. For these stocks the median return from peak to last available price is -96% (-100% for higher risk scores; see Table 10).

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



Source: Transparently Pte Ltd

Table 10. Absolute returns from peak price to last available price for out-of-sample stocks

	All stocks	MRisk>0.5	MRisk>0.8	MRisk>0.9
Mean	-0.40	-0.76	-0.98	-1.00
Median	-0.36	-0.96	-1.00	-1.00

Source: Transparently Pte Ltd

To illustrate the benefits of remedial action, Figure 7 and Table 11 highlight the relationship between estimated risk scores and future returns.

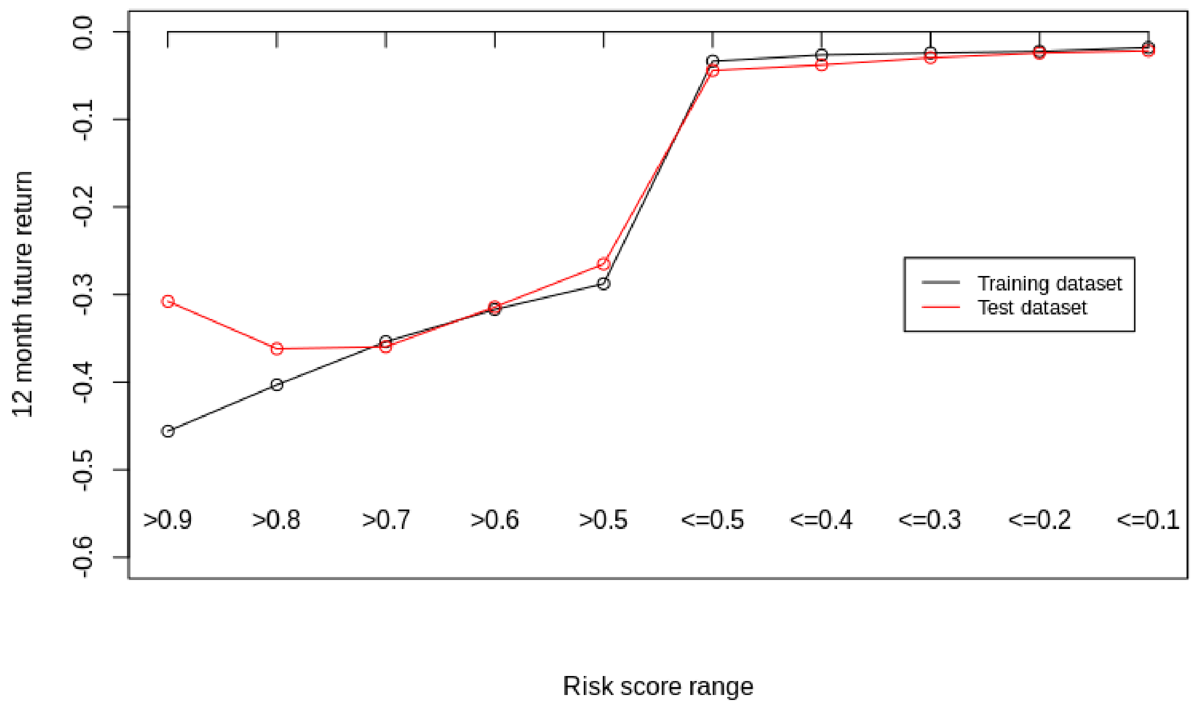
The full stock universe is split into risk groups and median are calculated for the 12 month financial year after the year generating the risk score. We can see a monotonic relationship between risk bucket and future returns for the training dataset and what is almost a monotonic relationship for the test dataset (the only exception being for the highest risk category which has a very small sample size in the test dataset).

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 43.8% for the training dataset and 28.7% for the test dataset. These are extremely large differences.

Note that this result in fact <u>understates</u> 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.

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



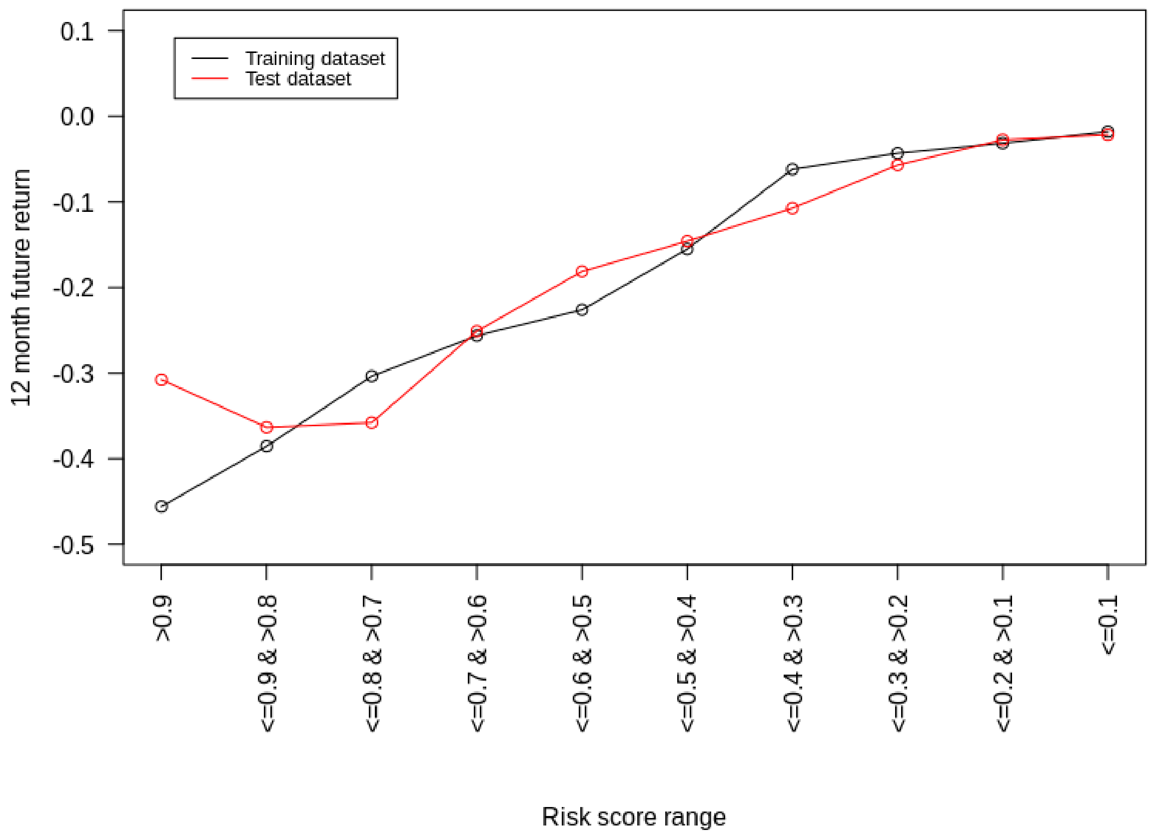
Source: Transparently Pte Ltd

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

MRisk	>0.9	>0.8	>0.7	>0.6	>0.5	≤0.5	≤0.4	≤0.3	≤0.2	≤0.1
In-sample	-45.6	-40.3	-35.4	-31.7	-28.8	-3.3	-2.6	-2.4	-2.2	-1.8
Out-of-sample	-30.8	-36.2	-35.9	-31.4	-26.5	-4.4	-3.8	-2.9	-2.4	-2.1

Source: Transparently Pte Ltd

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



Source: Transparently Pte Ltd

Table 12. 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	-45.6	-38.5	-30.4	-25.6	-22.6	-15.5	-6.2	-4.3	-3.1	-1.8
Out-of-sample	-30.8	-36.3	-35.8	-25.1	-18.1	-14.6	-10.7	-5.7	-2.7	-2.1

Source: Transparently Pte Ltd

Overall, we find:

- Evidence of significant and robust predictive power in the Transparently 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 Risk Engine to a dataset comprised of approximately 21,000 US, China, Hong Kong and Singapore-domiciled stocks. 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.

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 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 strongly associated with more positive return outcomes.

These findings support utilizing the Transparently Risk Engine for identification of problematic stocks, with high failure risk, and avoiding these for investment purposes, exiting an existing position on relatively favourable 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.