



# A Darwinian Approach To Detecting Accounting Irregularities

## Forensic Accounting – The next evolutionary phase of SRI

This is our inaugural publication on forensic accounting. In the coming months, we will be publishing a series of research papers on accounting governance, fraud detection, and financial statement irregularities.

### Accounting governance is critical to investors

Accounting governance, which is rooted within the principle of SRI or ESG investing, has become an increasingly integral component of the investment process. Accounting misstatements can cause severe share price underperformance and damage shareholder value. However, detection of corporate financial misstatements is typically a daunting task. Investors must sift through a multitude of financial statements and company behaviors in hopes of identifying accounting irregularities or anomalies. In this research piece, we discuss two interesting approaches to identify accounting fraud.

### Systematically identifying corporate accounting offenders

The first method is based on statistical analysis. In particular, we study the number distribution of a company's financial statement data items, based on the Benford's law. We find when a firm's accounting data violates the typical distributional property of natural numbers, it suggests a higher probability of accounting irregularity and lower subsequent stock returns. In addition, using the AAER (Accounting and Auditing Enforcement Releases) database, we analyze the characteristics of companies exhibiting accounting irregularities. We further build a logistic regression model to predict accounting fraud. Our logit model can be quite useful to identify extreme underperformers and is uncorrelated with other quality factors.

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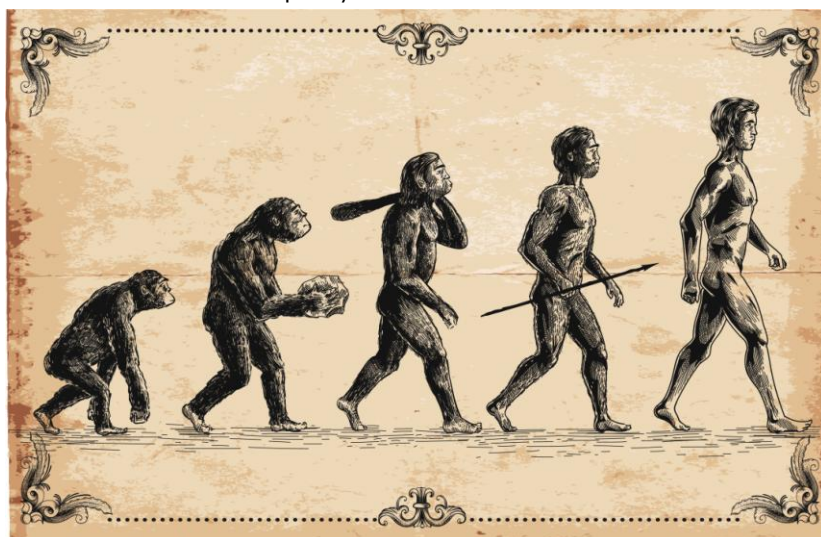
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# A Letter to our readers

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## A pragmatic approach to accounting governance

Social responsible investing (SRI) or environmental, social, and governance (ESG) has become a critical and integral component of the investment process. Our stance on SRI is that, for it to go from tabloid to mainstream, we need to show how ESG principles can impact investment returns. In our previous ESG research papers<sup>1</sup>, we showed the positive impact of ESG screening techniques on investment performance. This research piece extends our previous work on the accounting and corporate governance dimension.

The governance pillar of the ESG investing incorporates the rights and responsibilities of company management, the board, shareholders, and other stakeholders. It typically encompasses: management structure, board makeup, employee relations, diversity, executive compensation, and corporate conduct. However, as quantitative investors, we want to see whether we can include “accounting governance” as an additional component.

Accounting governance is essentially the quality and judiciousness of how companies report their financials. It also encompasses accounting fraud, mishaps, and misstatements. Misstating corporate financials has serious consequences to share price performance and destroys shareholder value.

However, detection of corporate financial misstatements is typically a daunting task. Investors must sift through a multitude of financial statements and comparables in hopes of identifying accounting irregularities or anomalies. In this research, we study two systematic approaches to identify corporate frauds – one based on statistical analysis of financial statement data items, using the Benford’s law and another using the AAER (Accounting and Auditing Enforcement Releases) databases, based on a company’s fundamental characteristics.

Such quantitative techniques can enrich our understanding and awareness of accounting governance, corporate governance, and SRI accountability. Keeping to our principles, in this report, we show the direct financial and investor impact of accounting governance mishaps. In the coming months, we will be publishing more accounting governance, forensics, and ESG specific reports. We hope you enjoy the rest of this paper.

Regards,

Yin, Miguel, Javed, Sheng, Allen, Gaurav, David, and Kevin  
**Deutsche Bank North American Quantitative Strategy**

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<sup>1</sup> See Jussa, et al [2013a, b] and Luo, et al [2014, 2015] for details.



# Darwinian accounting

## Natural number occurring patterns using weather data

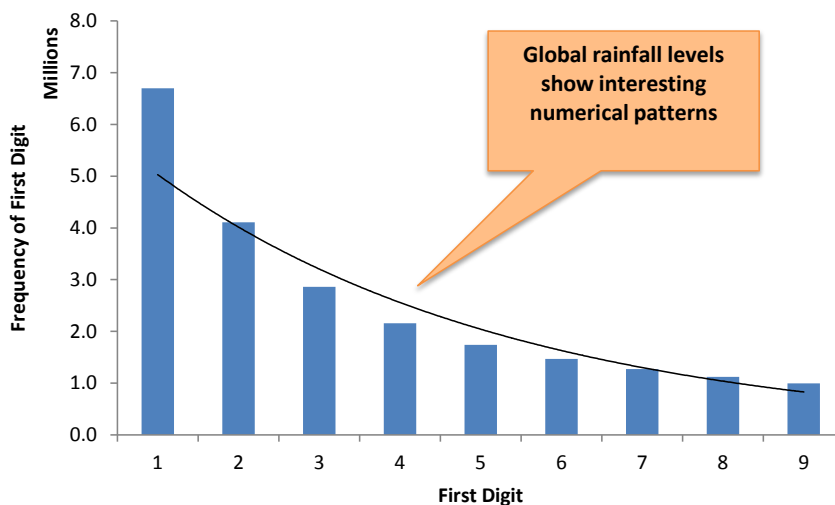
Studies surrounding the identification of accounting irregularities typically begin by discussing sophisticated models that can detect accounting misstatements to some degree of statistical certainty. The classic accruals anomaly pioneered by Richard Sloan offers such an example<sup>2</sup>. However, in this research, we do not begin with this approach. Surprisingly, we start off our theory by analyzing global weather patterns.

*Many analysts may look at weather patterns as a signal of economic strength. We look at weather levels to identify natural occurring patterns or phenomena.*

Many analysts may look at weather patterns as a signal of economic strength. We look at weather levels to identify natural occurring patterns or phenomena. Figure 1 shows the distribution of global rainfall levels. The chart shows the distribution of the first digit of global rainfall levels (e.g., if there was 268ml of rainfall, the chart plots the first digit, the value of "2"). An interesting pattern emerges.

We find that the number "1" occurs more frequently than the number "2". The number "2" appears more often than the number "3", and so on. Why does such a numerical pattern occur? Is this numerical pattern limited to just global rainfall levels or does it apply elsewhere? Let us analyze this further.

Figure 1: Frequency distribution of first digit for global rainfall levels



Source: <http://www.esrl.noaa.gov/psd/data/gridded/data.gpcc.html>, Deutsche Bank Quantitative Strategy

This may be a surprise, but we are not the first ones to discover or even highlight this interesting numerical pattern. In 1938, a physicist named Frank Benford discovered this pattern<sup>3</sup>. This pattern is referred to as the **Benford's Law**, also called the **First-Digit Law**. The Benford's law is known within the scientific community and is typically used in genome mapping, statistical

<sup>2</sup> See Sloan [1996] and Luo, et al [2010] for details.

<sup>3</sup> Although it had been previously stated by Simon Newcomb in 1881.

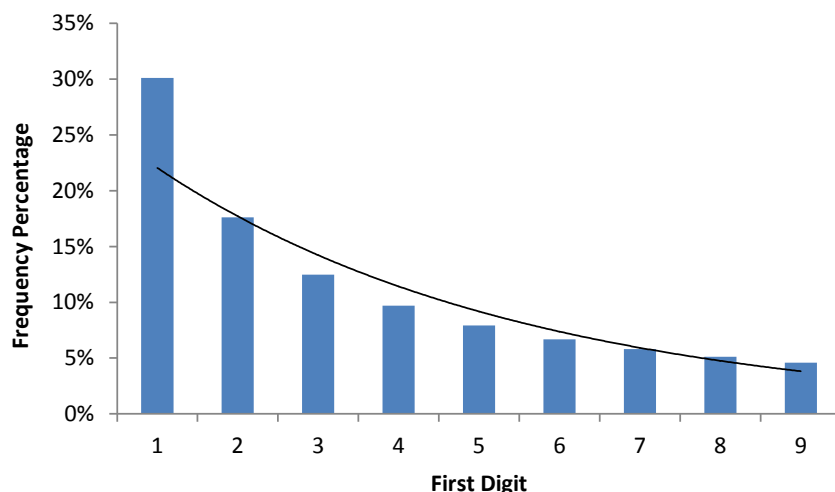


inference analysis, election fraud detection, as well as the detection of accounting fraud and governance.

Hence, the Benford's law follows a theoretical distribution (Figure 2). In the upcoming sections, we will explore the Benford's law in the context of financial statement analysis. Specifically, we investigate whether the Benford's law can be applied to detecting accounting irregularities, misstatements and governance issues.

*In the upcoming sections, we will explore the Benford's law in the context of financial statement analysis. Specifically, we investigate whether Benford's law can be applied to detecting accounting irregularities, misstatements and governance issues.*

Figure 2: Theoretical distribution of the Benford's law



Source: Deutsche Bank Quantitative Strategy

## Natural number distributional properties using financial data

As we alluded to, the Benford's law is not merely limited to weather patterns and genome data analysis. The Benford's law also applies to financial accounting data.

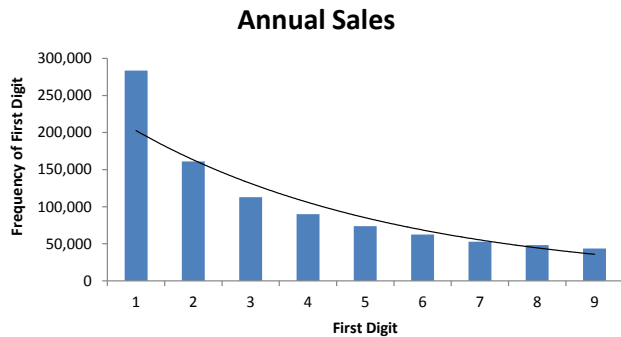
Figure 3 shows the distribution of the first digit of annual sales/revenue data (a key income statement item) for Russell 3000 companies<sup>4</sup>. For the first digit of annual sales/revenue, we find that the same pattern, e.g., number "1" occurs more frequently than the number "2", and so on. We see the same phenomenon in balance sheet data items. Figure 4 shows the distribution of the first digit of total assets (an important balance sheet item) for Russell 3000 companies.

*For the first digit of annual sales, we find that the number 1 occurs more than the number 2. The number 2 occurs more than the number 3 and so on.*

<sup>4</sup> Sales and total asset figures are captured at every month end over a period of approximately twenty years.

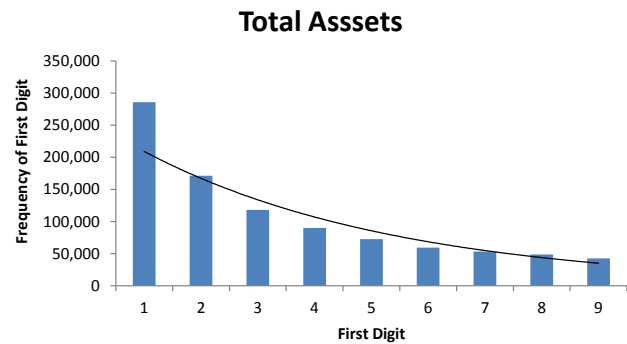


Figure 3: First digit distribution of annual sales



Source: Thomson Reuters, Compustat, IBES, Russell, S&P, Deutsche Bank Quantitative Strategy

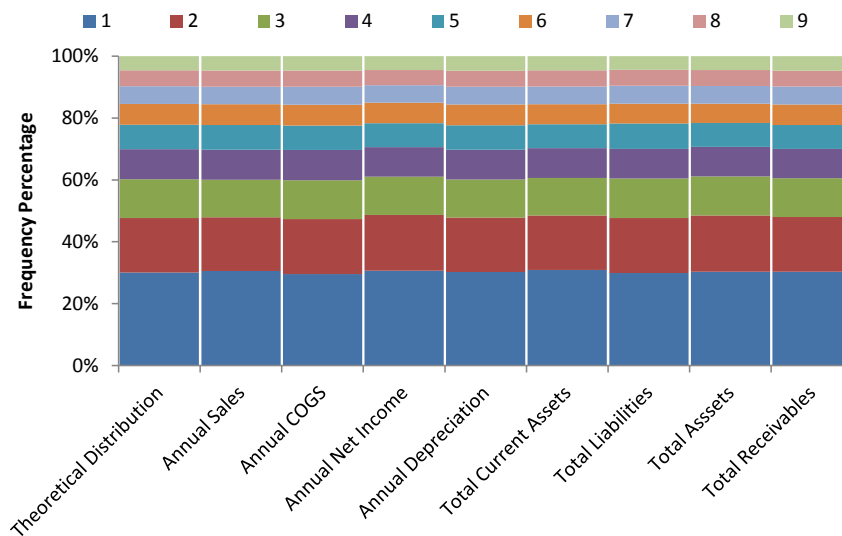
Figure 4: First digit distribution of total assets



Source: Thomson Reuters, Compustat, IBES, Russell, S&P, Deutsche Bank Quantitative Strategy

This same pattern applies for almost every balance sheet and income statement items<sup>5</sup>, including cost of goods sold, net income, depreciation, and even accounts receivables, for US public companies (Figure 5). To ensure that this numerical pattern is not limited to US stocks or biased by regional effects, we also compute the first digit distribution for global firms.

Figure 5: The Benford's law applied to various financial statement figures



Source: Thomson Reuters, Compustat, IBES, Russell, S&P, Deutsche Bank Quantitative Strategy

*This pattern occurs in the US market for several balance sheet and income statement items.*

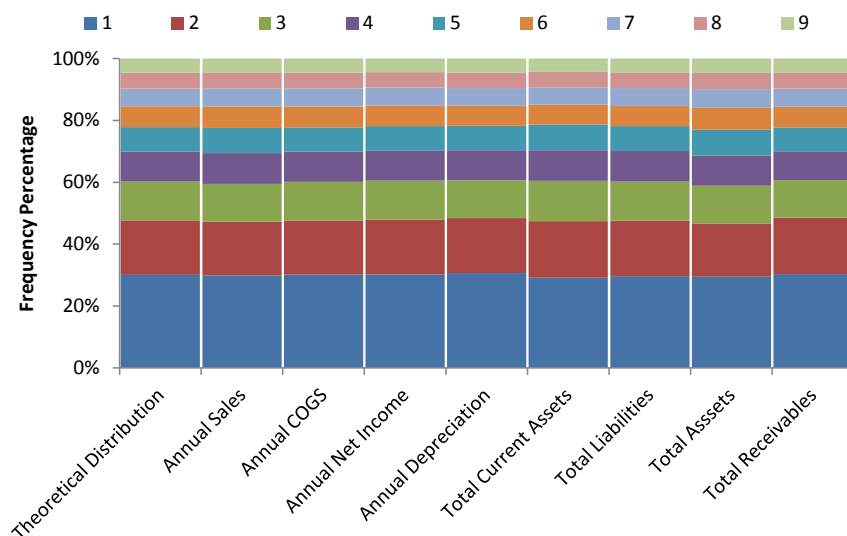
Figure 6 shows the first digit distribution of income statement and balance sheet items for global ex US companies<sup>6</sup>. We see that the Benford's law applies globally.

<sup>5</sup> This distribution is calculated using approximately eight accounting items derived from the income statement, balance sheet, and cash flow statement. The accounting items are captured at every month end over a period of approximately twenty years.

<sup>6</sup> The global ex US universe includes all countries in the MSCI ACWI index (both developed and emerging countries), excluding the US. For global ex US countries, we use the S&P BMI stock universe, which includes both large- and mid-/small-cap stocks.



Figure 6: The Benford's law applied to global companies



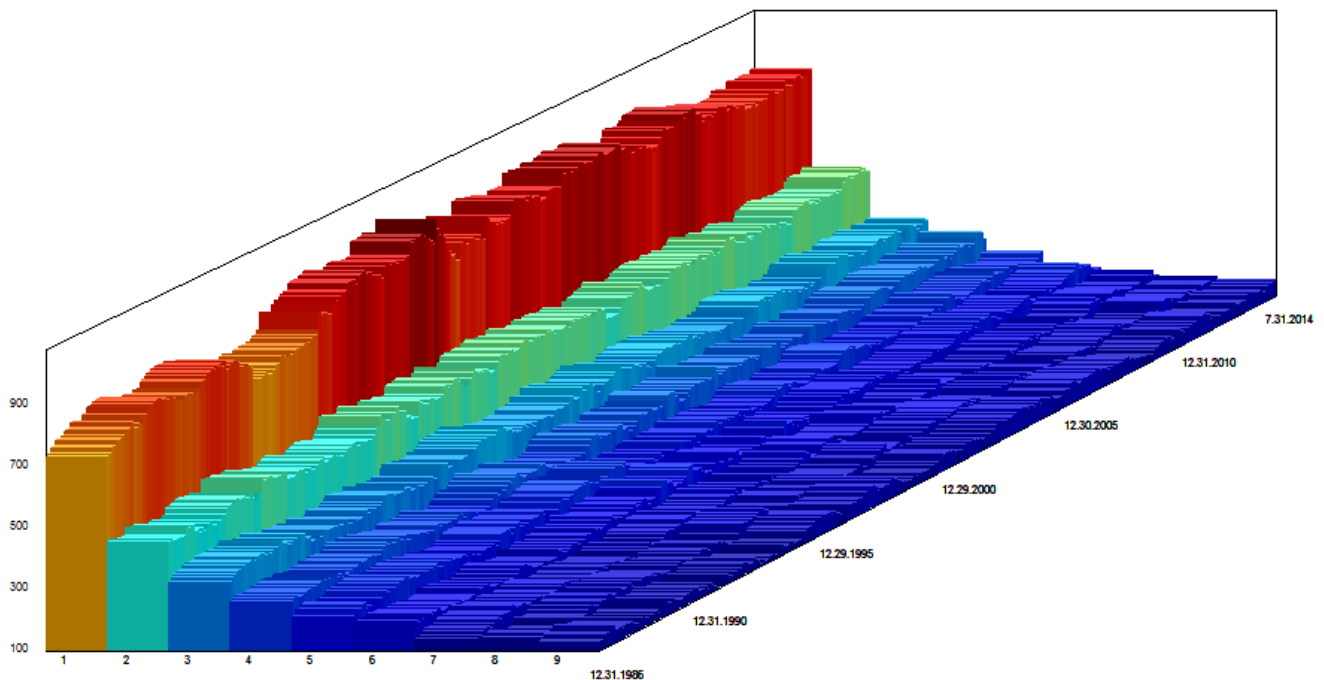
*We see that the Benford's law applies even for global companies.*

Source: Thomson Reuters, Compustat, IBES, Russell, S&P, Deutsche Bank Quantitative Strategy

We also find that the Benford's law is robust over time, albeit there are a few minor variations throughout history (Figure 7). In summary, we find that the Benford's law holds for global financial data and is robust over time. Next, we explore the potential reasons underlying this interesting numerical pattern.



Figure 7: Time series of first digit distribution of total annual sales for Russell 3000 companies



Source: Thomson Reuters, Compustat, IBES, Russell, S&P, Deutsche Bank Quantitative Strategy

## The intuition behind the Benford's law in finance

There are a multitude of explanations and theories attempting to explain the rationale behind the Benford's law. Many of these explanations are based on rather complex statistical and behavioral arguments. Here, we offer a simpler and more intuitive explanation.

We believe that the Benford's law occurs as a natural consequence of company growth and maturity. Let us explain this in more detail. For example, for a company to grow from \$1.0 billion to \$2.0 billion in annual sales/revenue, it would need to double or increase its sales by 100%. Although obvious, we note that the first digit in \$1.0 billion is "1" and the first digit in \$2.0 billion is "2". It is, without a doubt, a challenging feat for a company to double its annual sales figure.

However, for a company to grow from \$8.0 billion to \$9.0 billion would require an increase in sales by approximately 13% - still challenging but a lot more manageable. Therefore, we would extrapolate that a company is more likely to be in a state where its sales are within the \$1.0 billion range than if its sales are in the \$8.0 billion range. As such, a company will stay in a state longer where the first digit is a smaller number than if the first digit were a larger number. Essentially, it is easier for a company to grow its sales when the first digit is a high number than if it were a low number.

*There are a multitude of explanations and theories attempting to explain the rationale of the Benford's law. We look for a simpler and more intuitive explanation.*



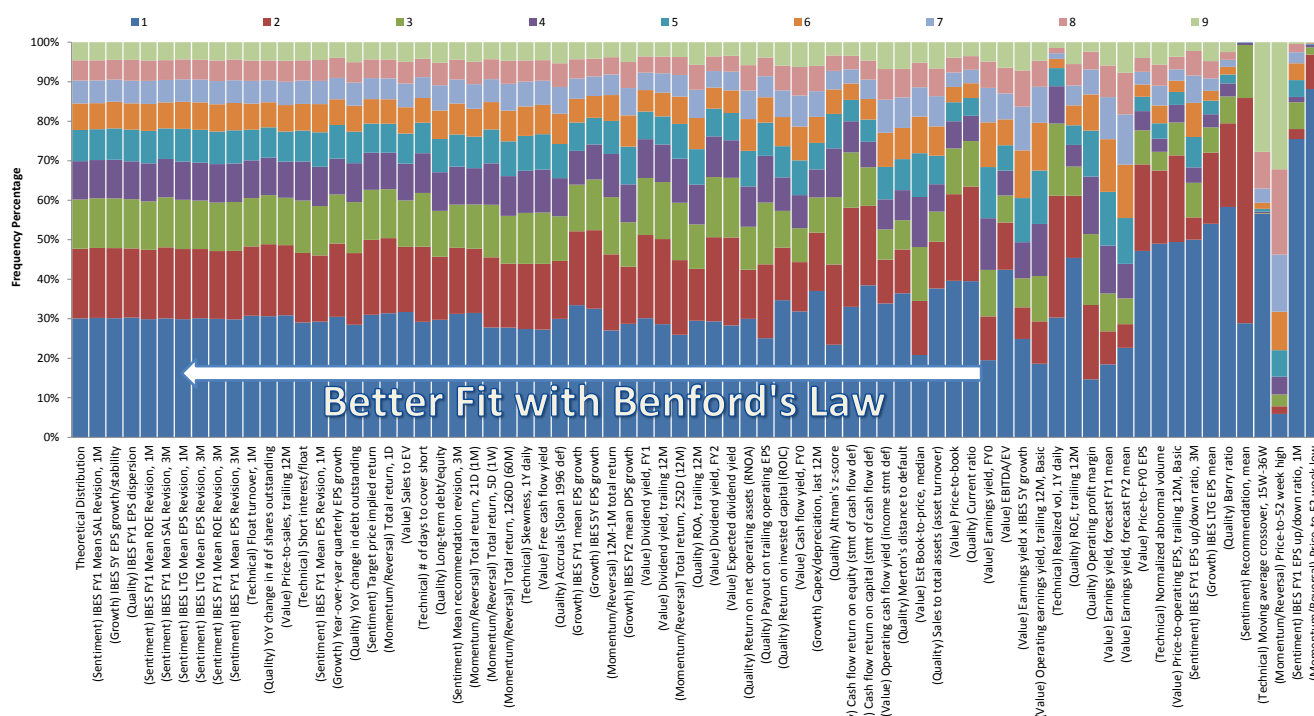
In the above example, we discussed the intuition behind the Benford's law using various accounting metrics. However, this rationale can be extended to other financial statement items including the income statement, balance sheet, and statement of cash flows. This is our explanation for the presence of the Benford's numerical pattern. Now that we have an understanding of the Benford's law, next we analyze whether this phenomenon applies to quantitative factors<sup>7</sup>.

## Quantitative stock-selection factor distribution patterns

Does the Benford's law apply to quantitative factors and financial ratios? To test this, we simply calculate the distribution of the first digit for each of our common 80 quant factors<sup>8</sup>. Figure 8 shows the results for our US quant factors sorted by their conformity to the Benford's law.

*Does the Benford's law or the First Digit Law apply to quantitative factors and financial ratios?*

Figure 8: First distribution of seventy quantitative factors sorted by their fit to the theoretical distribution



Source: Thomson Reuters, Compustat, IBES, Russell, S&P, Deutsche Bank Quantitative Strategy

Interestingly, we find that approximately two thirds of quant factors do conform to the Benford's law. The fact that most quant factors conform to the Benford's law may be expected – they are nothing but derived items based on primarily financial statement data. However, what about the one-third of factors that do not follow the same pattern?

<sup>7</sup> Factors are also often called signals. In recent years, many common stock selection factors are also referred as smart betas.

<sup>8</sup> Please refer to Wang, et al [2014b] for the list and definition of the 80 factors.



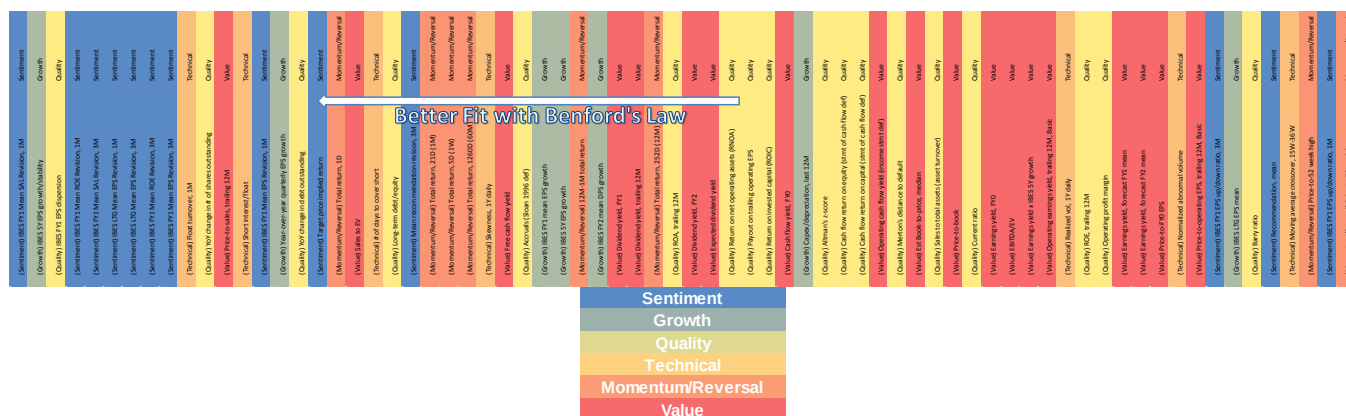
Figure 9 shows the conformity of quant factors by style. Interestingly, we find that on average, sentiment factors conform better whereas price reversal and technical factors show less conformity.

The results are not entirely unexpected – most factors that are based on company financial statements (e.g., valuation ratios, quality factors) follow the Benford's law closely, while variables based on price/volume data do not.

Another potential explanation is likely that certain quant factors may have restricted values due to error checking, winsorization, numerical limits, or even mean reverting behavior (i.e. such as technical or reversal factors). In these instances, where value restrictions may reside (intentionally or unintentionally), quant factor values may not conform to the law of natural numbers and as such will not exhibit the properties of the Benford's law.

In the rest of the paper, we will focus on pure accounting metrics sourced directly from the three standard financial statements. We investigate the application of the Benford's law at the company level and study the implications for stock selection.

Figure 9: First distribution of seventy quantitative factors sorted by their fit to the theoretical distribution



Source: Thomson Reuters, Compustat, IBES, Russell, S&P, Deutsche Bank Quantitative Strategy



# Company evolution

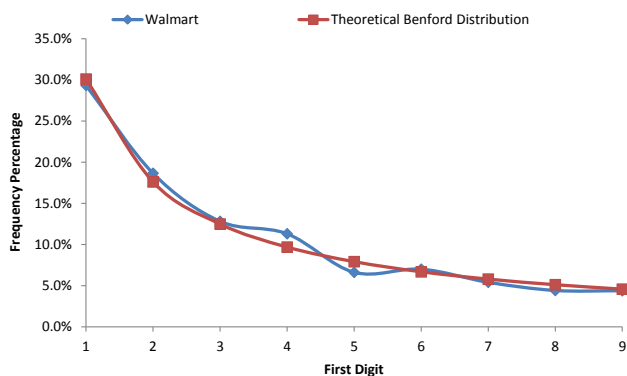
## Company level number distribution

Most equity managers are not directly concerned about global rainfall patterns. Their focus is more on stock selection. In this section, we first show how the Benford's law can be applied at the company level. Figure 10 and Figure 11 show the first digit distribution for Wal-Mart and Enron. The distribution is calculated using approximately 40 accounting items from the income statement, balance sheet, and cash flow statement.

*In this section, we first show how the Benford's law can be applied at the company level.*

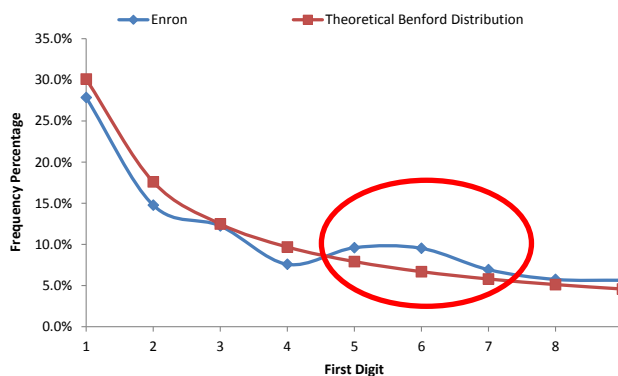
The accounting items are captured on a monthly basis over a period of approximately 20 years. Interestingly, based on charts alone, we see that Wal-Mart conforms fairly tightly to the Benford's distribution, while Enron (which filed for bankruptcy in 2001) does not conform as tightly. Higher numbers like "5", "6", and "7" appear to frequently than natural distribution, which hints at potential data manipulation.

Figure 10: Wal-Mart's conformity to the Benford's law



Source: Thomson Reuters, Compustat, IBES, Russell, S&P, Deutsche Bank Quantitative Strategy

Figure 11: Enron's conformity to the Benford's law



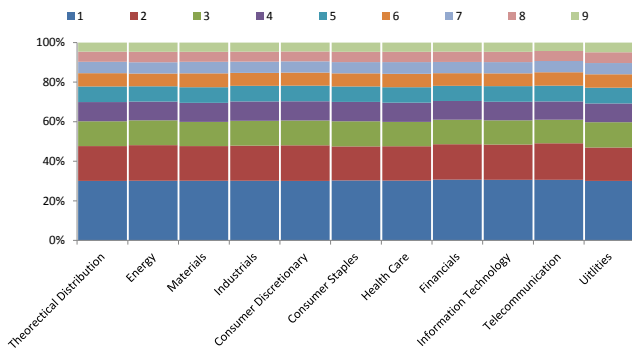
Source: Thomson Reuters, Compustat, IBES, Russell, S&P, Deutsche Bank Quantitative Strategy

Aggregating each company level distributions to the GICS sectors<sup>9</sup>, Figure 12 and Figure 13 show that sectors also conform fairly tightly to the Benford's law. This is of course based on our visual interpretation of the figures. Simple visual analysis to gauge conformity to the Benford's law is sufficient here, but may not necessarily be the most scientific approach. Next, we look at a more systematic approach to measure the conformity to the Benford's law.

<sup>9</sup> This distribution is calculated using approximately 40 accounting items derived from the income statement, balance sheet, and cash flow statement. The accounting items are captured at every month end over a period of approximately 20 years.

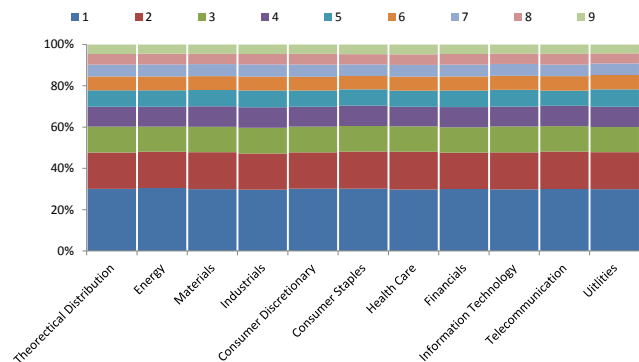


Figure 12: GICS conformity to the Benford's Law (US)



Source: Thomson Reuters, Compustat, IBES, Russell, S&P, Deutsche Bank Quantitative Strategy

Figure 13: GICS conformity to the Benford's Law (Global)



Source: Thomson Reuters, Compustat, IBES, Russell, S&P, MSCI, Deutsche Bank Quantitative Strategy

## MAD Science and kiss statistics

We now discuss two statistics to measure the conformity to the Benford's law: mean absolute deviation (MAD) and Kolmogorov–Smirnov (KS)<sup>10</sup>. The MAD measure is fairly intuitive and is simply calculated by summing the mean absolute difference between the theoretical and empirical distributions of each digit from 1 to 9. Let us walk through an example.

Figure 14 shows a sample balance sheet for a company. We note that the first digit of each accounting item is bolded. Counting the frequency of the first digit for each item in the balance sheet would produce the distribution in Figure 15.

*We discuss two statistics to calculate conformity to the Benford's law: mean absolute deviation (MAD) and Kolmogorov–Smirnov (KS).*

<sup>10</sup> Various other statics can be utilized such as the Z-statistics and Chi-square. For the purposes of this report, we focus on the KS statistic.



Figure 14: Example of balance sheet financial statement with first digit highlighted

| Assets                          |                  | Liabilities                                 |                  |
|---------------------------------|------------------|---------------------------------------------|------------------|
| Current Assets                  |                  | Current Liabilities                         |                  |
| Cash                            | \$ 11,874        | Accounts payable                            | \$ 8,060         |
| Short-term investments          | \$ 9,900         | Income taxes payable                        | \$ 6,145         |
| Prepaid Rent                    | \$ 255.00        | Total current liabilities                   | \$ 14,205        |
| Inventory                       | \$ 275.00        | Long-Term Liabilities                       |                  |
|                                 |                  | Long-term debt                              | \$ 5,450         |
| <b>Total current assets</b>     | <b>\$ 22,304</b> | <b>Total long-term liabilities</b>          | <b>\$ 5,450</b>  |
| Fixed (Long-Term) Assets        |                  | Owner's Equity                              |                  |
| Long-term investments           | \$ 1,208         | Owner's investment                          | \$ 7,178         |
| Property, plant, and equipment  | \$ 15,340        | Retained earnings                           | \$ 4,389         |
| (Less accumulated depreciation) | \$ 2,200         | <b>Total owner's equity</b>                 | <b>\$ 11,567</b> |
| <b>Total fixed assets</b>       | <b>\$ 14,348</b> |                                             |                  |
| <b>Total Assets</b>             | <b>\$ 36,652</b> | <b>Total Liabilities and Owner's Equity</b> | <b>\$ 31,222</b> |

Source: Thomson Reuters, Compustat, IBES, Russell, S&P, Deutsche Bank Quantitative Strategy

Figure 15 shows the total occurrence (i.e. frequency distribution) of the first digit as well as the percentage of occurrence. Taking the mean absolute difference between the empirical and theoretical distribution will yield the MAD score<sup>11</sup>. Although easy to calculate, the MAD score has no critical values to test against<sup>12</sup>.

Figure 15: Distribution of first digit in financial statement

| First Digit                                                       | 1    | 2    | 3    | 4    | 5    | 6    | 7    | 8    | 9    |
|-------------------------------------------------------------------|------|------|------|------|------|------|------|------|------|
| Total Occurrences of First Digit                                  | 6    | 4    | 2    | 1    | 2    | 1    | 1    | 1    | 1    |
| Percentage of Occurrences of First Digit (Empirical Distribution) | 0.32 | 0.21 | 0.11 | 0.05 | 0.11 | 0.05 | 0.05 | 0.05 | 0.05 |
| Benford's Law (Theoretical Distribution)                          | 0.30 | 0.18 | 0.12 | 0.10 | 0.08 | 0.07 | 0.06 | 0.05 | 0.05 |

Source: Thomson Reuters, Compustat, IBES, Russell, S&P, Deutsche Bank Quantitative Strategy

On the other hand, the KS statistic has critical values to test against. In general, the KS test is used to determine if two datasets or distributions differ significantly. It is calculated by computing the maximum absolute difference between the empirical and theoretical distribution. The test value is then compared to the critical values to determine conformity<sup>13</sup>.

*The KS statistic is more useful for testing conformity at the company level because it has critical values to compare against.*

<sup>11</sup> We note the calculation takes the difference in the percentage of the empirical distribution and theoretical distribution and divides by the number of non-zero digits being analyzed. This normalization enables us to compare companies with different number of data items and differing amounts of historical data.

<sup>12</sup> Although the MAD score has no critical values to test, Nigrini (2012) showed through simulation that a MAD value of 0.006 or less can likely conform to Benford's distribution.

<sup>13</sup> We note to test significance at a 10% level, the test value is calculated by 1.22 divided by the square root of the total number of non-zero digits being analyzed. To test significance at a 5% level, the test value is calculated by 1.36 divided by the square root of the total number of non-zero digits being analyzed. To test significance at a 1% level, the test value is calculated by 1.63 divided by the square root of the total number of non-zero digits being analyzed.



The KS statistic is more useful for testing conformity at the company level because it has critical values to compare against. As such, going forward, we will use the KS statistic as our company-level factor to measure accounting irregularity.

The formulas for MAD and the KS statistic are below. We note that AD is the actual digit (the empirical frequency) and ED is the expected digit (the theoretical frequency obtained from the Benford's Law).

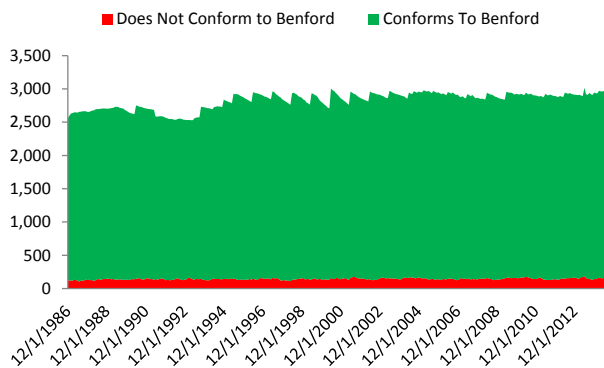
$$MAD = \frac{(\sum_{i=1}^K |AD - ED|)}{K}$$

$$KS = \text{Max}\{|AD_1 - ED_1|, |(AD_1 - AD_2) - (ED_1 - ED_2)|, \dots, |(AD_1 + \dots + AD_9) - (ED_1 + \dots + ED_9)|\}$$

Next, we calculate the KS value for every company in our database at each point in time. Figure 16 shows the time series coverage, numbers of companies that conform and do not conform to the Benford's law<sup>14</sup>, in the Russell 3000 universe. Based on the KS statistics, most companies adhere to the Benford's law. Only approximately 5% of companies do not conform (see Figure 17). This is somewhat expected as most companies are honest about their financial reporting.

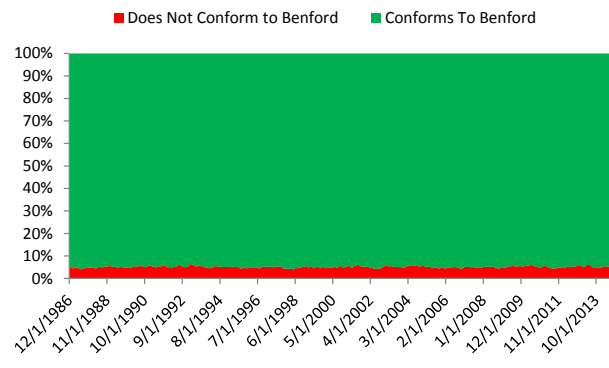
*Based on the KS ratio, most companies adhere to the Benford's law. Only approximately 5% of companies do not conform.*

Figure 16: KS coverage (Russell 3000)



Source: Thomson Reuters, Compustat, IBES, Russell, S&P, Deutsche Bank Quantitative Strategy

Figure 17: KS percentage coverage (Russell 3000)



Source: Thomson Reuters, Compustat, IBES, Russell, S&P, Deutsche Bank Quantitative Strategy

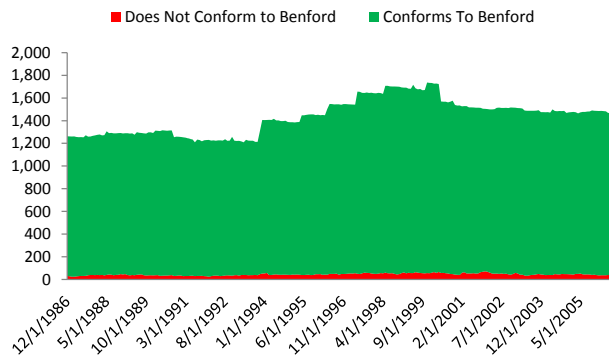
Figure 18 and Figure 19 show the coverage and percentage breakdown for global large-cap companies in the MSCI World universe. We see fairly similar results. Based on the KS ratio, the vast majority of companies adhere to the Benford's law. Interestingly, the percentage of non-conforming companies is slightly higher in the US than it in other countries. Now the question is whether our KS factor can predict future stock returns.

*Interestingly, on a percentage basis, US companies tend to have more accounting irregularities.*

<sup>14</sup> This is based on a 10% level of significance. We note that a significance level of 10% is used for the computation of the KS value throughout the report.

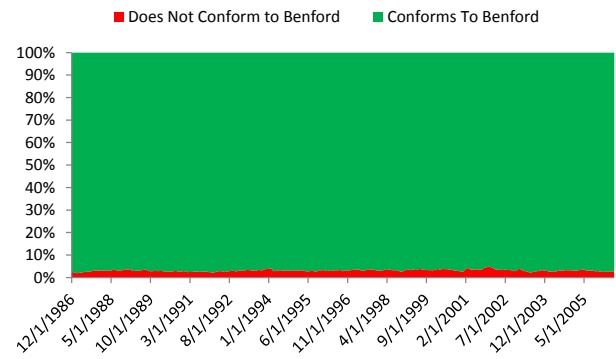


Figure 18: KS coverage (MSCI World)



Source: Thomson Reuters, Compustat, IBES, Russell, S&P, MSCI, Deutsche Bank Quantitative Strategy

Figure 19: KS percentage coverage (MSCI World)



Source: Thomson Reuters, Compustat, IBES, Russell, S&P, MSCI, Deutsche Bank Quantitative Strategy



# Natural selection versus stock selection

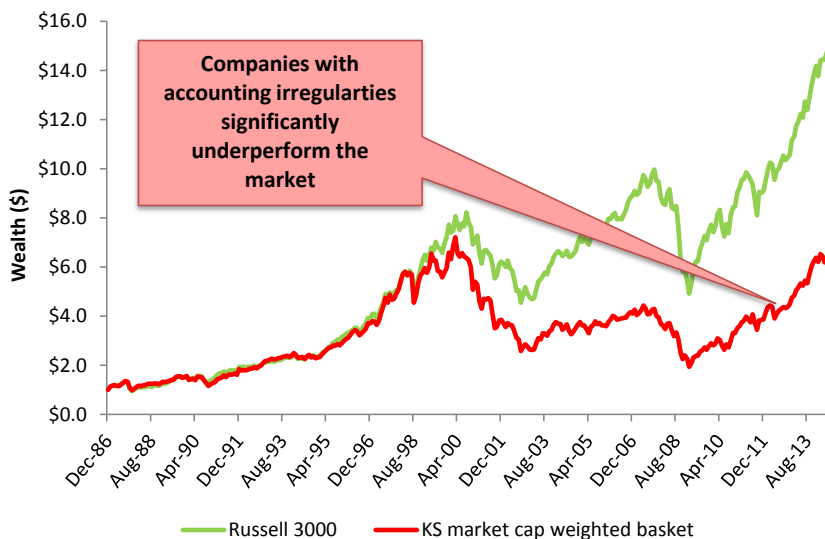
## The evolution of alpha

The Benford's law is an intriguing concept, but the question is now whether it is equally useful in stock selection. Designing and testing a stock selection model based on accounting irregularities is not an easy task. The challenge is that there are very few companies that have accounting irregularities at a given point of time. The lack of breadth means that simple strategies like screening non-conformers from a broad market index may not reap meaningful results. This is because the impact of filtering out a small number of companies from a broader index is minimal.

With this in mind, we start by previewing some of the properties of non-conformers based on our KS factor (hereafter we call it the "KS basket"). Figure 20 shows the wealth curve of the KS basket. Interestingly, stocks with potential accounting irregularities underperform the market significantly.

*Designing and testing a stock selection model based on accounting irregularities is not an easy task. The challenge is that there are very few companies that have accounting irregularities.*

Figure 20: Wealth curve of KS basket in the Russell 3000 universe



*Stocks with potential accounting irregularities underperform the market significantly.*

Source: Thomson Reuters, Compustat, IBES, Russell, S&P, Deutsche Bank Quantitative Strategy

More importantly, companies with accounting irregularities exhibit more severe drawdowns, higher volatility, and lower risk adjusted returns compared to the market portfolio (Figure 21). Keep in mind that non-conformers represent a small subset of companies and as such this portfolio may be concentrated. However, the results show that companies with accounting irregularities should be useful to screen for short candidates or for leverage indexing strategy.

*Beyond wealth curves, companies with accounting irregularities exhibit more severe drawdowns, higher volatility and lower risk adjusted returns compared to the market portfolio.*



Figure 21: Statistics on companies with accounting irregularities within the Russell 3000

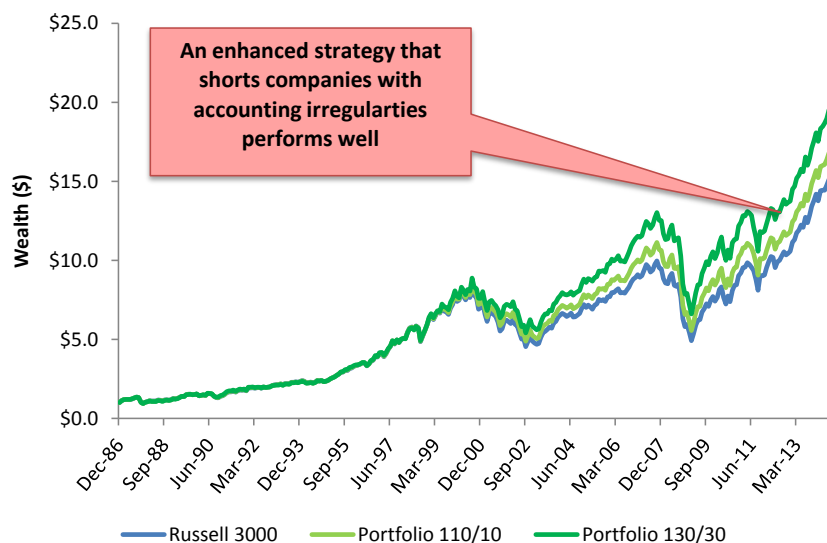
|              | # of Months | Start Date | Cumulative Return | CAGR  | Annual Vol | Sharpe Ratio | Skewness | Kurtosis | Max DD |
|--------------|-------------|------------|-------------------|-------|------------|--------------|----------|----------|--------|
| Russell 3000 | 333         | 12/31/1986 | 14.43             | 10.4% | 15.5%      | 0.67         | (0.91)   | 2.67     | -51%   |
| KS basket    | 333         | 12/31/1986 | 5.68              | 7.1%  | 18.0%      | 0.39         | (0.79)   | 1.64     | -73%   |

Source: Thomson Reuters, Compustat, IBES, Russell, S&P, Deutsche Bank Quantitative Strategy

One such strategy is the 130/30 portfolio. This is a long/short portfolio strategy. Say you have \$100 to invest. You short \$30 in stocks and long \$130 (vis-à-vis leverage) by investing in a market index for example<sup>15</sup>. Now you have \$30 of short exposure and \$130 long only exposure with a 100% net market exposure (i.e. \$130 long minus \$30 short). This is why sometimes these types of portfolios are referred to as beta one strategies. The benefit of this type of strategy is that you can maintain the market exposure while trying to generate alpha from both the long and the short sides.

As a simple demonstration, we simply take 130% long exposure to the market (i.e., the Russell 3000 index) and a 30% short exposure to companies with potential accounting irregularities (i.e. non-conformers). Figure 22 shows the performance of a 130/30 and 110/10 strategy (a less levered and aggressive strategy). The enhanced strategies outperform the benchmark slightly. In practice, we would of course apply some sort of stock selection on both the long and the short sides.

Figure 22: Wealth curve enhanced strategy within Russell 3000



*The benefit of this type of strategy is that you can maintain market exposure while trying to generate alpha from the short leg.*

Source: Thomson Reuters, Compustat, IBES, Russell, S&P, Deutsche Bank Quantitative Strategy

The enhanced strategies show slightly higher Sharpe ratio and lower drawdown (see Figure 23).

<sup>15</sup> Typically the short proceeds are used to fund the additional long position.



Figure 23: Statistics on companies with accounting irregularities within the Russell 3000

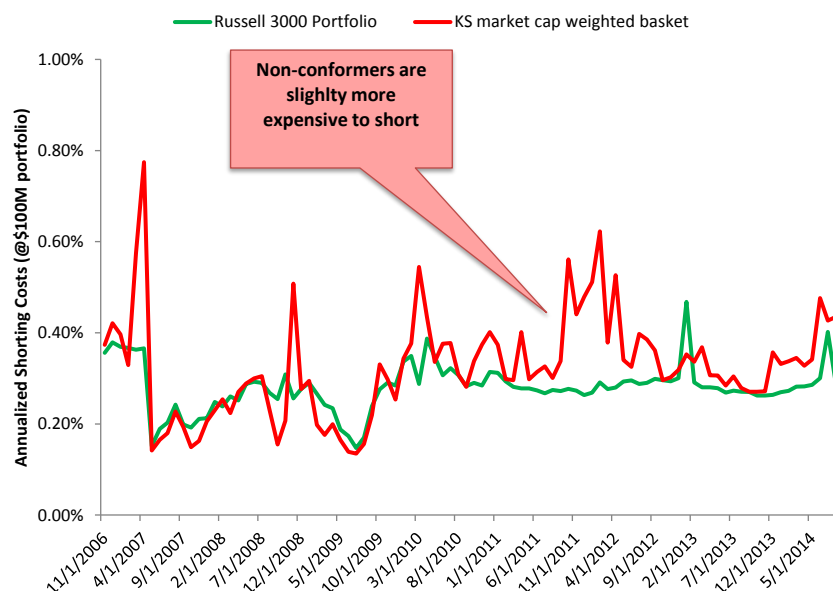
|                  | # of Months | Start Date | Cumulative Return | CAGR  | Annual Vol | Sharpe Ratio | Skewness | Kurtosis | Max DD |
|------------------|-------------|------------|-------------------|-------|------------|--------------|----------|----------|--------|
| Russell 3000     | 333         | 12/31/1986 | 14.43             | 10.4% | 15.5%      | 0.67         | (0.91)   | 2.67     | -50.7% |
| Portfolio 110/10 | 333         | 12/31/1986 | 16.15             | 10.8% | 15.5%      | 0.70         | (0.91)   | 2.81     | -50.1% |
| Portfolio 130/30 | 333         | 12/31/1986 | 18.91             | 11.4% | 15.5%      | 0.73         | (0.88)   | 2.96     | -49.2% |

Source: Thomson Reuters, Compustat, IBES, Russell, S&P, Deutsche Bank Quantitative Strategy

As our KS factor entails shorting stocks, we need to have a better understanding about shorting availability and cost. To address this, we analyze the approximate costs of shorting a basket of such stocks. To get an idea of the shorting costs we utilize the Data Explorers' stock lending database<sup>16</sup>.

Data Explorers contains the average shorting cost for stocks on a daily basis from 2006 onwards. Figure 24 compares the annual shorting costs of the KS basket to the Russell 3000 universe, based on a \$100M portfolio.

Figure 24: Annual shorting cost assuming \$100M portfolio at each month end



Source: Thomson Reuters, Compustat, IBES, Russell, S&P, Data Explorers, Deutsche Bank Quantitative Strategy

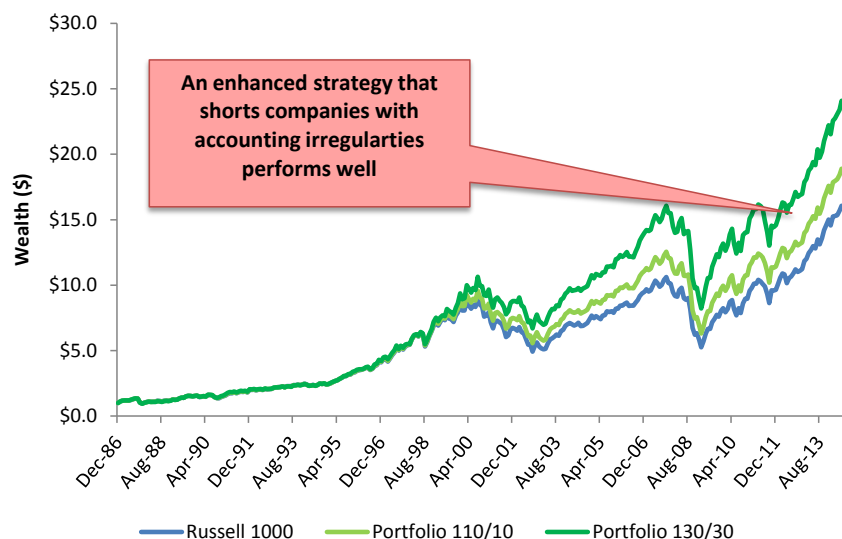
The costing analysis shows that at times, shorting the non-conformers can be slightly more expensive than normal companies. However, the shorting costs are generally in line with other companies. We explore the impact of shorting costs in more detail in the next section.

Another method to combat shorting costs is to apply our strategy to a large cap universe. Therefore, we apply the same enhanced strategy, but limit stocks to the Russell 1000 universe for both the market index as well as the short basket. Figure 25 and Figure 26 shows that our enhanced strategy performs reasonably well within large cap stocks.

<sup>16</sup> We analyzed Data Explorers' database in two of our previous research papers – see Cahan, et al [2011a] and LeBinh, et al [2011].



Figure 25: Wealth curve enhanced strategy within Russell 1000



Our enhanced large cap strategy also exhibits higher annualized returns and Sharpe ratios as compared to the Russell 1000 benchmark.

Source: Thomson Reuters, Compustat, IBES, Russell, S&P, Deutsche Bank Quantitative Strategy

Our enhanced large cap strategy also exhibits higher annualized returns and Sharpe ratios than the Russell 1000 benchmark.

Figure 26: Statistics on companies with accounting irregularities within the Russell 1000

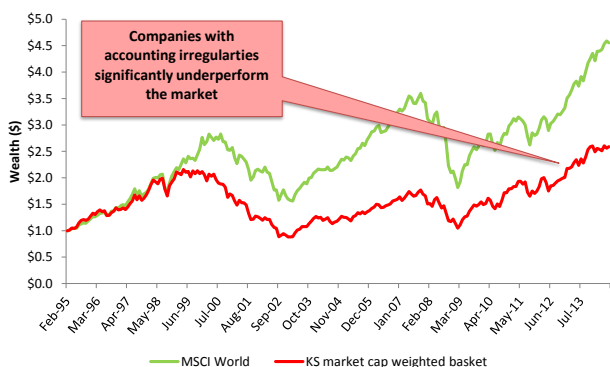
|                  | # of Months | Start Date | Cumulative Return | CAGR  | Annual Vol | Sharpe Ratio | Skewness | Kurtosis | Max DD |
|------------------|-------------|------------|-------------------|-------|------------|--------------|----------|----------|--------|
| Russell 1000     | 333         | 12/31/1986 | 15.44             | 10.6% | 15.4%      | 0.69         | (0.86)   | 2.52     | -50.5% |
| Portfolio 110/10 | 333         | 12/31/1986 | 18.34             | 11.3% | 15.3%      | 0.73         | (0.85)   | 2.62     | -49.8% |
| Portfolio 130/30 | 333         | 12/31/1986 | 23.60             | 12.2% | 15.4%      | 0.79         | (0.81)   | 2.72     | -48.9% |

Source: Deutsche Bank

Interestingly, we find similar results for global companies within the MSCI World universe (see Figure 27 to Figure 29).

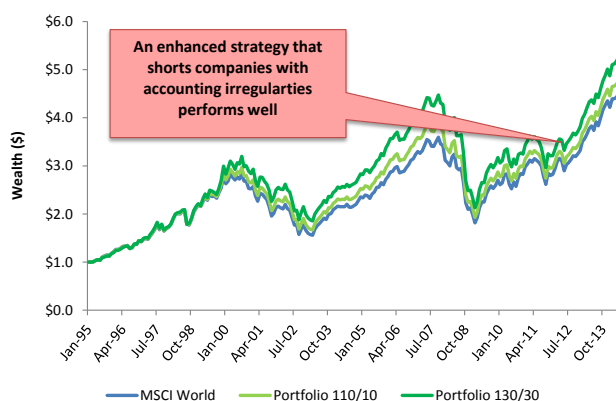
Performance improvement appears better for US companies.

Figure 27: Wealth curve of KS basket in the MSCI World universe



Source: Thomson Reuters, Compustat, IBES, Russell, S&P, MSCI, Deutsche Bank Quantitative Strategy

Figure 28: Wealth curve enhanced strategy within MSCI World



Source: Thomson Reuters, Compustat, IBES, Russell, S&P, MSCI, Deutsche Bank Quantitative Strategy



Figure 29: Statistics on companies with accounting irregularities within MSCI World

|                  | # of Months | Start Date | Cumulative Return | CAGR  | Annual Vol | Sharpe Ratio | Skewness | Kurtosis | Max DD |
|------------------|-------------|------------|-------------------|-------|------------|--------------|----------|----------|--------|
| MSCI World       | 332         | 1/31/1995  | 3.55              | 8.06% | 14.3%      | 0.56         | (0.83)   | 1.17     | -49.5% |
| Portfolio 110/10 | 332         | 1/31/1995  | 3.83              | 8.39% | 14.5%      | 0.58         | (0.85)   | 1.35     | -50.8% |
| Portfolio 130/30 | 332         | 1/31/1995  | 4.33              | 8.93% | 15.0%      | 0.60         | (0.85)   | 1.56     | -52.5% |

Source: Thomson Reuters, Compustat, IBES, Russell, S&P, MSCI, Deutsche Bank Quantitative Strategy

These leveraged index strategies seem to be a viable option for investor to exploit accounting irregularities. Stock with accounting irregularities are potentially good shorting candidates. But how does this strategy stand up to other short bias strategies. We explore this next.

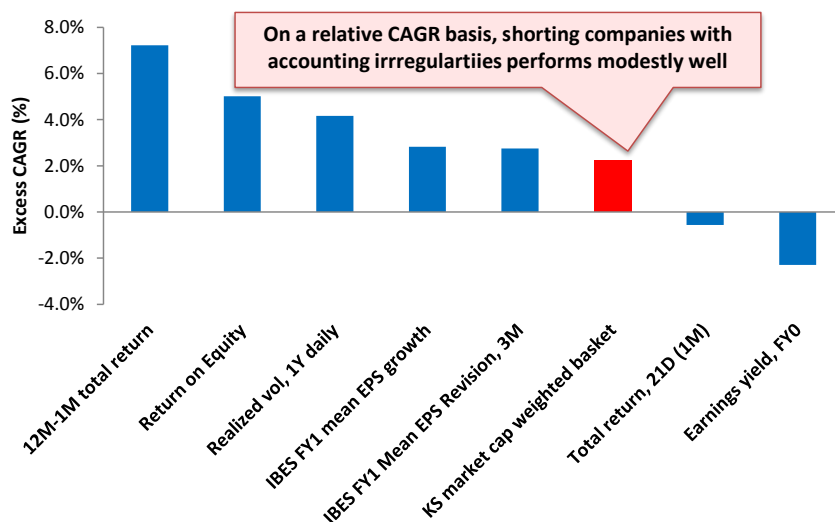
*Our enhanced large cap strategy also exhibits higher annualized returns and Sharpe ratios as compared to the Russell 1000 benchmark*

## Some short analysis on short baskets

Let us compare how our short portfolio basket of companies with accounting irregularities (i.e., the KS basket) stacks up to other popular short strategies. To do this, we compare the excess market performance of shorting our KS basket with other portfolios<sup>17</sup> based on common quantitative factors such as price momentum, quality, earnings growth, etc.

We create the common quant short portfolios by shorting the bottom decile of stocks based on factors within the Russell 3000 universe. Our benchmark is also the Russell 3000 stock index. Figure 24 shows that low momentum stocks are the best short candidates based on CAGR. On a relative basis, our irregularities basket performs modestly well.

Figure 30: Comparison of short baskets based on CAGR



*On a relative basis, our irregularities basket performs modestly well*

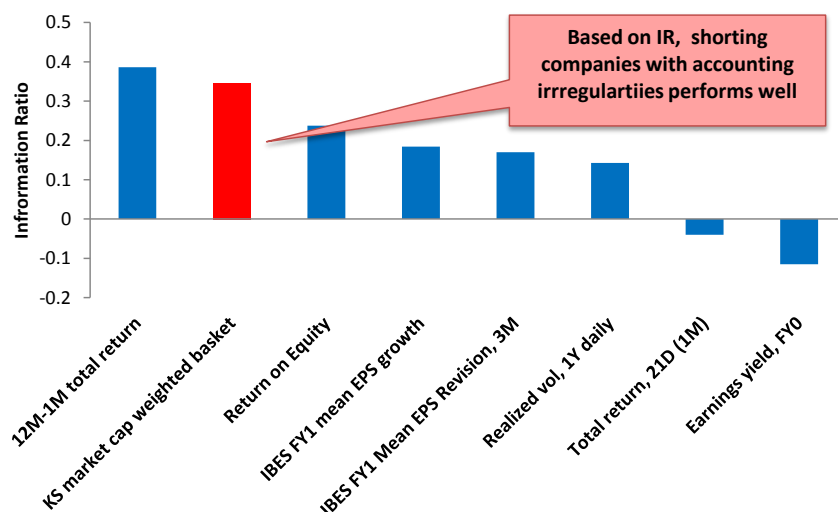
Source: Thomson Reuters, Compustat, IBES, Russell, S&P, Deutsche Bank Quantitative Strategy

However, on a risk adjusted basis, our irregularities basket performs significantly better. Figure 31 compares the Sharpe ratio of our irregularities short basket to other quantitative short baskets. It ranks second only to price momentum.

<sup>17</sup> All portfolios are weighted on each stock's market cap.



Figure 31: Comparison of short baskets based on Information Ratio



*On a risk adjusted basis, our irregularities basket performs significantly better*

Source: Thomson Reuters, Compustat, IBES, Russell, S&P, Deutsche Bank Quantitative Strategy

Not only does our irregularity short basket perform well based on the Sharpe ratio, it also has less negative skewness, smaller excess kurtosis, and significantly lower maximum drawdown (Figure 32). These results are encouraging.

Figure 32: Statistics on short portfolios

| Portfolio                            | Information Ratio | Skew        | Kurtosis    | Max DD      |
|--------------------------------------|-------------------|-------------|-------------|-------------|
| <b>KS market cap weighted basket</b> | <b>0.35</b>       | <b>0.20</b> | <b>0.93</b> | <b>-21%</b> |
| Return on Equity                     | 0.24              | 0.11        | 3.05        | -65%        |
| IBES FY1 mean EPS growth             | 0.18              | 0.06        | 3.31        | -46%        |
| Realized vol, 1Y daily               | 0.14              | (0.35)      | 3.54        | -76%        |
| IBES FY1 Mean EPS Revision, 3M       | 0.17              | (0.59)      | 4.73        | -48%        |
| Earnings yield, FY0                  | (0.11)            | (0.82)      | 5.45        | -73%        |
| 12M-1M total return                  | 0.39              | (1.03)      | 4.32        | -50%        |
| Total return, 21D (1M)               | (0.04)            | (1.77)      | 13.68       | -55%        |

Source: Thomson Reuters, Compustat, IBES, Russell, S&P, Deutsche Bank Quantitative Strategy

*Not only does our irregularity short basket perform well based on information ratio, it also has less negatively skewed returns, less excess kurtosis, and lower maximum drawdown's*

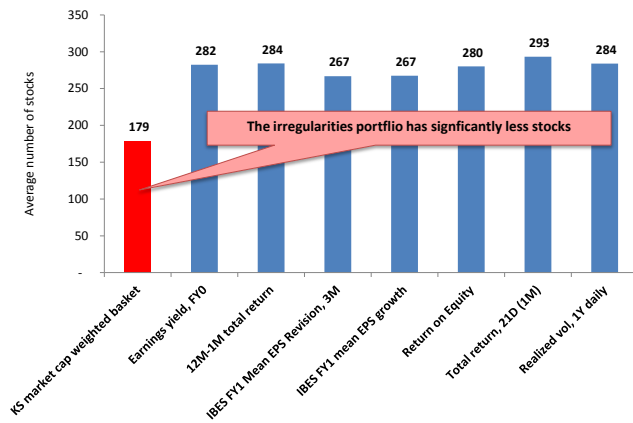
The results are even more promising when considering that the irregularities portfolio has fewer numbers of stocks than the quant short baskets formed from the decile portfolios (Figure 33). Few numbers of stocks offers less diversification benefit.

For a more comparable analysis, we form the quant short portfolios based on vigintiles instead of deciles. Note that deciles divide a series in 10 equal-sized groups whereas vigintiles divide a series into 20 such groups<sup>18</sup>. Figure 34 shows the average number of stocks based on vigintiles portfolios. The average number of stocks based on the vigintiles portfolios is more comparable to our KS basket.

<sup>18</sup> To avoid data mining and over fitting, we setup vigintiles portfolios rather than form matching portfolios containing the same number of stocks.

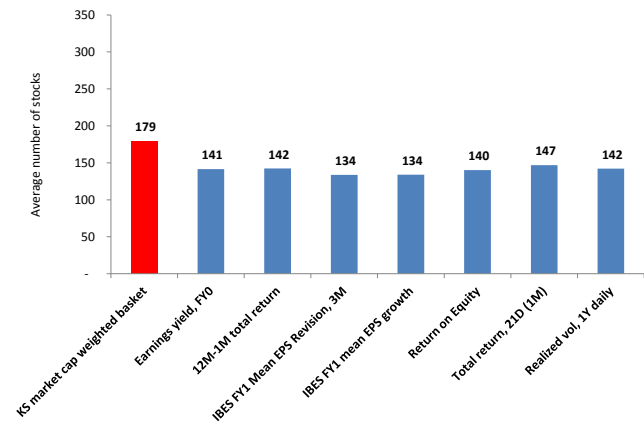


Figure 33: Number of stocks based on decile portfolios



Source: Thomson Reuters, Compustat, IBES, Russell, S&P, MSCI, Deutsche Bank Quantitative Strategy

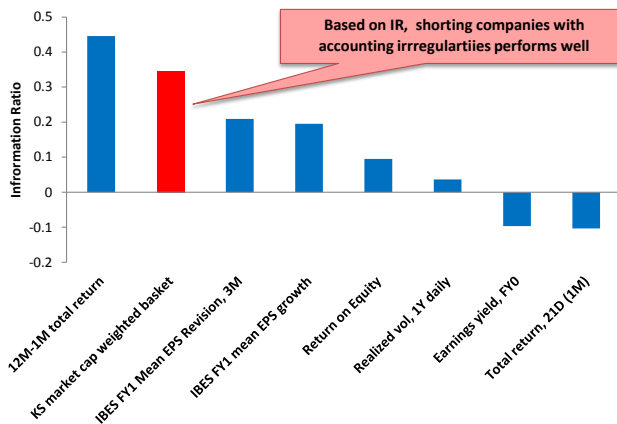
Figure 34: Number of stocks based on vigintiles portfolios



Source: Thomson Reuters, Compustat, IBES, Russell, S&P, MSCI, Deutsche Bank Quantitative Strategy

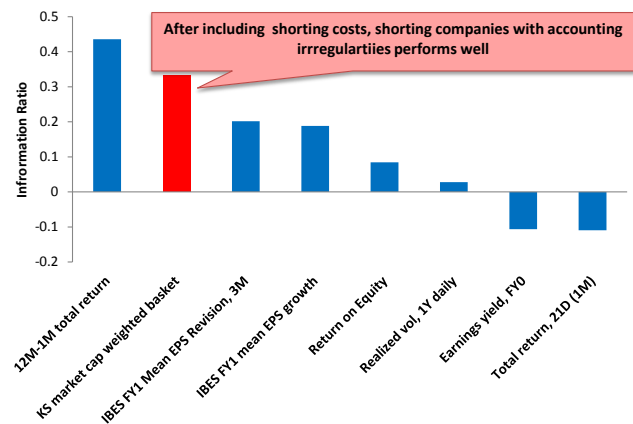
Re-running the backtesting based on vigintiles portfolios yields similar results to the decile portfolios. On a risk adjusted basis, our KS basket performs strongly (Figure 35). The results are also robust to shorting costs. Figure 36 shows the Sharpe ratio after including shorting costs from 2006 onwards<sup>19</sup>. After the inclusion of shorting costs, our KS basket outperforms strongly based on risk adjusted performance.

Figure 35: Comparison of short baskets, Sharpe ratio of vigintiles portfolios, excluding shorting costs



Source: Thomson Reuters, Compustat, IBES, Russell, S&P, MSCI, Deutsche Bank Quantitative Strategy

Figure 36: Comparison of short baskets, Sharpe ratio of vigintiles portfolios, including shorting costs



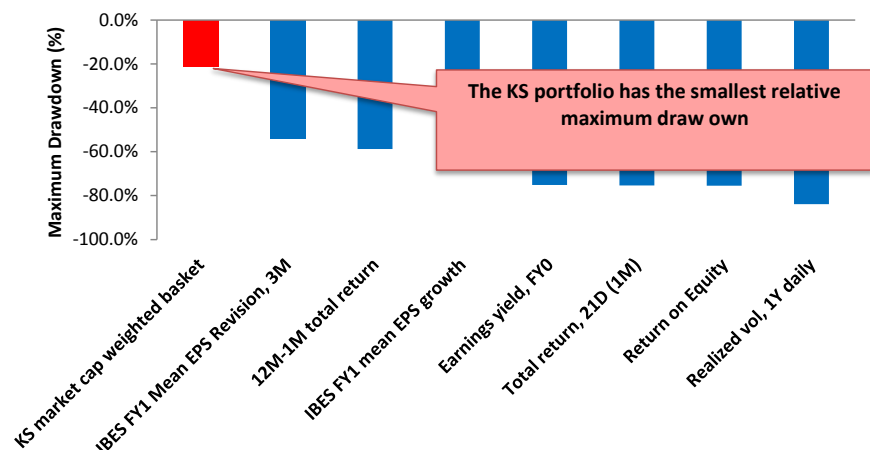
Source: Thomson Reuters, Compustat, IBES, Russell, S&P, MSCI, Deutsche Bank Quantitative Strategy

Lastly, we want to point out that our KS basket has the lowest maximum drawdown of any other short portfolio (Figure 37)

<sup>19</sup> Note that the back test is from 1986 onwards and the shorting costs are applied from 2006 onwards.



Figure 37: Comparison of short baskets, maximum drawdown, including shorting costs



Source: Thomson Reuters, Compustat, IBES, Russell, S&P, Deutsche Bank Quantitative Strategy

Now that we have shown the viability of using accounting irregularities within a tradable investment strategy, the next logical step is to understand the source of this accounting irregularity premia

## Evolutionary sources

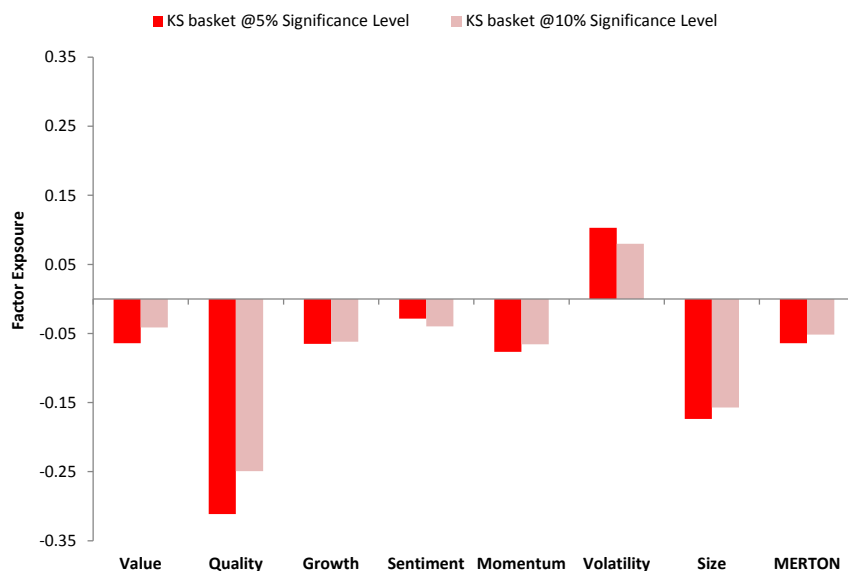
In order to pinpoint the sources of the negative KS premia, we calculate the factor exposures of companies exhibiting accounting irregularities. The goal is to better understand the fundamental characteristics of such companies. This in turn will help explain the sources of premia, to some extent.

To do this, we start by compiling a diverse blend of factors. In particular, we look at factors such as size, quality, value, growth, etc. We calculate the average factor score<sup>20</sup> for each company that shows accounting irregularities. Figure 38 shows that companies exhibiting accounting irregularities are on average: lower quality, smaller size, higher volatility, and slower growth. Additionally, these companies exhibit poorer analyst sentiment and greater default risk.

<sup>20</sup> Similar to Luo, et al [2015], all factors are normalized using our proprietary data transformation technique, so they all roughly follow a standard normal distribution. Therefore, an average score of 0.1 means it is 0.1x standard deviation above the mean of all companies in the investment universe.



Figure 38: Factor exposure of companies with accounting irregularities



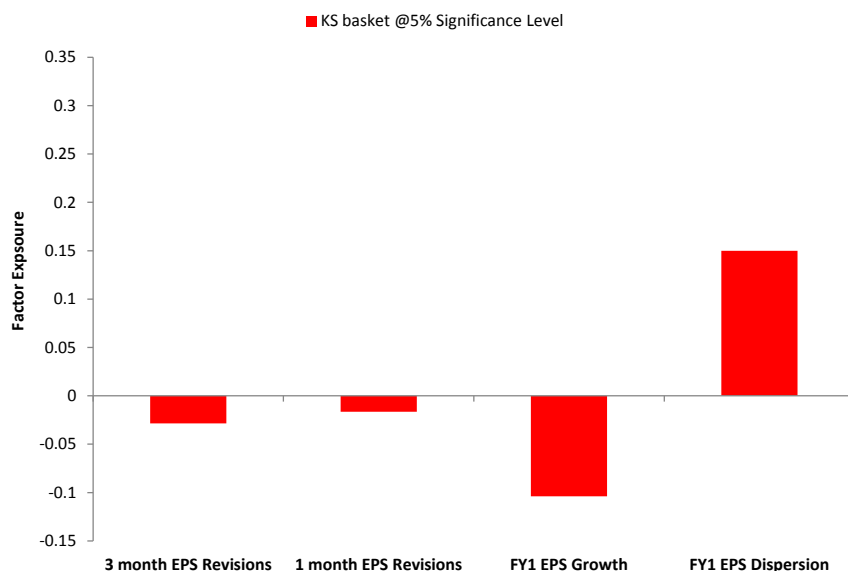
Source: Thomson Reuters, Compustat, IBES, Russell, S&P, Deutsche Bank Quantitative Strategy

*Companies exhibiting accounting irregularities are on average: lower quality, smaller market cap, higher volatility, and slower growth. Additionally, these companies exhibit poorer analyst sentiment and greater default risk.*

Digging deeper, as shown in Figure 39, we also find that companies exhibiting accounting irregularities have lower analyst projected FY1 EPS growth as well as greater FY1 EPS dispersion (i.e., greater uncertainty in expected earnings).



Figure 39: Detailed factor exposure of companies with accounting irregularities

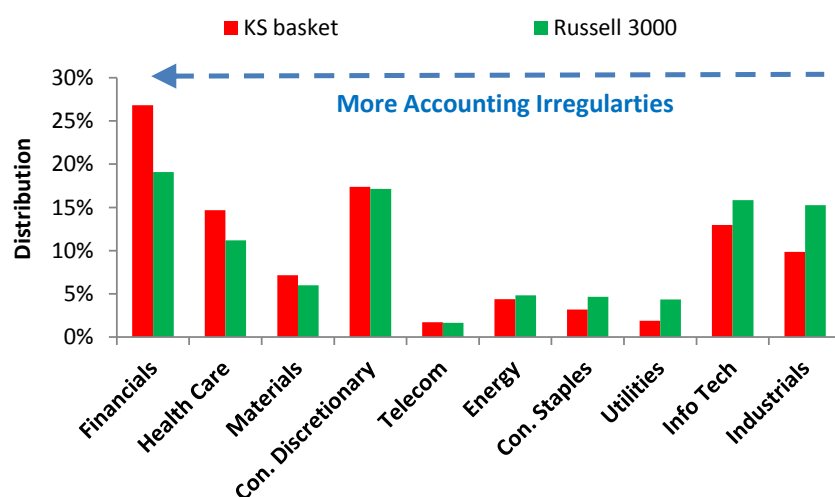


Source: Thomson Reuters, Compustat, IBES, Russell, S&P, Deutsche Bank Quantitative Strategy

*We also find that companies exhibiting accounting irregularities have lower analyst projected FY1 EPS growth as well as greater FY1 EPS dispersion (i.e. greater uncertainty in expected earnings).*

Searching for sector effects, we find that companies in which accounting irregularities manifest are on average concentrated in the financials, health care, and materials sectors (Figure 40). It is worthwhile to note that the accounting rules tend to be more complex in these sectors. Next we explore the relationship between accounting irregularities and corporate governance.

Figure 40: Sector exposure of companies exhibiting accounting irregularities



Source: Thomson Reuters, Compustat, IBES, Russell, S&P, Deutsche Bank Quantitative Strategy

*Searching for sector effects, we find that companies in which accounting irregularities manifest are on average concentrated in the financial, health care, and material sectors.*



## SRI and Accounting Irregularities

In our previous ESG research<sup>21</sup>, we created a list of ESG metrics and factors (see Figure 41). We illustrated the efficacy of ESG factor in forecasting future stock returns. In this section, we show the relationship between ESG factors and companies exhibiting accounting irregularities.

*We show the relationship between ESG factors and companies exhibiting accounting irregularities.*

Figure 41: ESG factors

| Factor Mnemonic                    | Description                                                | Factor Groups                                         | Start Date | Backtesting Period (months) |
|------------------------------------|------------------------------------------------------------|-------------------------------------------------------|------------|-----------------------------|
| SCORE                              | Overall ESG Score                                          |                                                       | 10/29/1999 | 160                         |
| NUMERIC_RATING                     | Numeric Rating such (7=AAA, 6=AA ... 1=CCC)                |                                                       | 10/29/1999 | 160                         |
| ENV_WGT                            | Environmental Weight                                       | Raw Factors                                           | 1/31/2007  | 73                          |
| ENV_SCORE                          | Environmental Score                                        |                                                       | 11/30/2004 | 99                          |
| SOCIAL_WGT                         | Social Weight                                              |                                                       | 1/31/2007  | 73                          |
| SOCIAL_SCORE                       | Social Score                                               |                                                       | 11/30/2004 | 99                          |
| GOV_WGT                            | Governance Weight                                          |                                                       | 1/31/2007  | 73                          |
| GOV_SCORE                          | Governance Score                                           |                                                       | 11/30/2004 | 99                          |
| Size_Adj_NUMERIC_RATING            | Size Adjusted Numeric Rating                               | Size Adjusted Factors                                 | 10/29/1999 | 160                         |
| Size_Adj_SCORE                     | Size Adjusted Overall ESG Score                            |                                                       | 10/29/1999 | 160                         |
| Size_Adj_ENV_SCORE                 | Size Adjusted Environmental Score                          |                                                       | 11/30/2004 | 99                          |
| Size_Adj_SOCIAL_SCORE              | Size Adjusted Social Score                                 |                                                       | 11/30/2004 | 99                          |
| Size_Adj_GOV_SCORE                 | Size Adjusted Governance Score                             |                                                       | 11/30/2004 | 99                          |
| SizeBetaVol_Adj_NUMERIC_RATING     | Size, Vol, & Beta Adjusted Numeric Rating                  | Size, Volatility, & Beta Adjusted Factors             | 10/29/1999 | 160                         |
| SizeBetaVol_Adj_SCORE              | Size, Vol, & Beta Adjusted Overall ESG Score               |                                                       | 10/29/1999 | 160                         |
| SizeBetaVol_Adj_ENV_SCORE          | Size, Vol, & Beta Adjusted Environmental Score             |                                                       | 11/30/2004 | 99                          |
| SizeBetaVol_Adj_SOCIAL_SCORE       | Size, Vol, & Beta Adjusted Social Score                    |                                                       | 11/30/2004 | 99                          |
| SizeBetaVol_Adj_GOV_SCORE          | Size, Vol, & Beta Adjusted Governance Score                |                                                       | 11/30/2004 | 99                          |
| Mom_NUMERIC_RATING                 | Momentum of Numeric Rating                                 | Momentum of Raw Factors                               | 10/31/2000 | 148                         |
| Mom_SCORE                          | Momentum of Overall ESG Score                              |                                                       | 10/31/2000 | 148                         |
| Mom_ENV_SCORE                      | Momentum of Environmental Score                            |                                                       | 11/30/2005 | 87                          |
| Mom_SOCIAL_SCORE                   | Momentum of Social Score                                   |                                                       | 11/30/2005 | 87                          |
| Mom_GOV_SCORE                      | Momentum of Governance Score                               |                                                       | 11/30/2005 | 87                          |
| Mom_Size_Adj_NUMERIC_RATING        | Momentum of Size Adjusted Numeric Rating                   | Momentum of Size Adjusted ESG Factors                 | 10/31/2000 | 148                         |
| Mom_Size_Adj_SCORE                 | Momentum of Size Adjusted Overall Score                    |                                                       | 10/31/2000 | 148                         |
| Mom_Size_Adj_ENV_SCORE             | Momentum of Size Adjusted Environmental Score              |                                                       | 11/30/2005 | 87                          |
| Mom_Size_Adj_SOCIAL_SCORE          | Momentum of Size Adjusted Social Score                     |                                                       | 11/30/2005 | 87                          |
| Mom_Size_Adj_GOV_SCORE             | Momentum of Size Adjusted Governance Score                 |                                                       | 11/30/2005 | 87                          |
| Mom_SizeBetaVol_Adj_NUMERIC_RATING | Momentum of Size, Vol, & Beta Adjusted Numeric Rating      | Momentum of Size, Volatility, & Beta Adjusted Factors | 10/31/2000 | 148                         |
| Mom_SizeBetaVol_Adj_SCORE          | Momentum of Size, Vol, & Beta Adjusted Overall ESG Score   |                                                       | 10/31/2000 | 148                         |
| Mom_SizeBetaVol_Adj_ENV_SCORE      | Momentum of Size, Vol, & Beta Adjusted Environmental Score |                                                       | 11/30/2005 | 87                          |
| Mom_SizeBetaVol_Adj_SOCIAL_SCORE   | Momentum of Size, Vol, & Beta Adjusted Social Score        |                                                       | 11/30/2005 | 87                          |
| Mom_SizeBetaVol_Adj_GOV_SCORE      | Momentum of Size, Vol, & Beta Adjusted Governance Score    |                                                       | 11/30/2005 | 87                          |

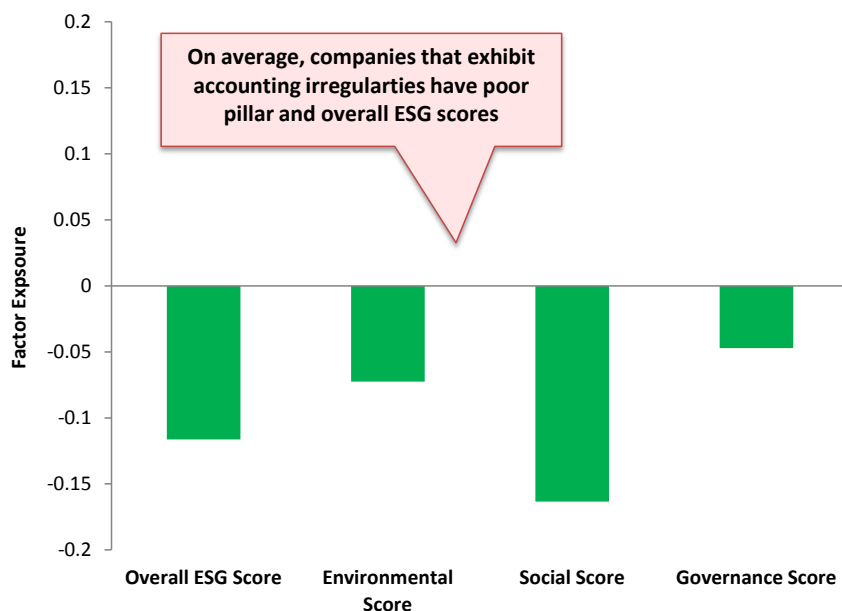
Source: Thomson Reuters, MSCI ESG Research, Compustat, IBES, Russell, S&P, Deutsche Bank Quantitative Strategy

Figure 42 shows the baseline ESG factor exposure for companies that have potential accounting irregularities (i.e., the KS basket). Interestingly, on average, companies that exhibit potential accounting irregularities also rate poorly on mostly ESG metrics, with below average governance, social, and environmental scores.

<sup>21</sup> See Jussa, et al [2013a, b] for details.



Figure 42: ESG exposure for companies exhibiting accounting irregularities



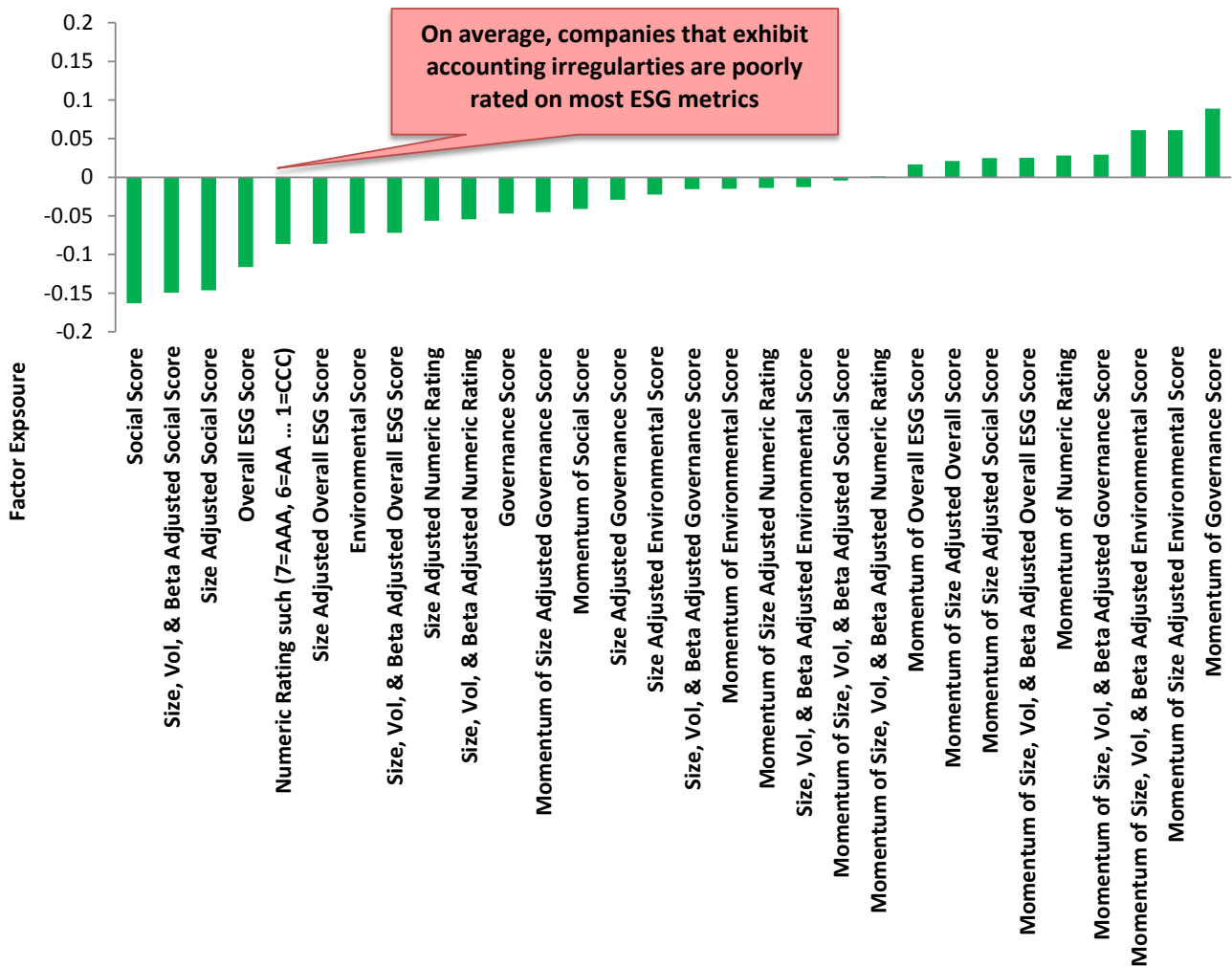
*Interestingly, on average, companies that exhibit accounting irregularities also rate poorly on ESG metrics. These companies have below average governance, social, and environmental scores.*

Source: Thomson Reuters, MSCI ESG Research, Compustat, IBES, Russell, S&P, Deutsche Bank Quantitative Strategy

We also analyze the exposures of the KS basket for a larger set of ESG factors (Figure 43). On average, most companies exhibiting potential accounting irregularities have below average scores along most ESG dimensions.



Figure 43: Detailed ESG factor exposure for companies exhibiting potential accounting irregularities



Source: Thomson Reuters, MSCI ESG Research, Compustat, IBES, Russell, S&P, Deutsche Bank Quantitative Strategy

In summary, we find that companies with potential accounting irregularities rank poorly in terms of quality, volatility, sentiment, credit risk, earnings uncertainty, ESG, and governance metrics.

Next, we analyze companies that have been penalized by the SEC for accounting misrepresentations. The goal is to determine the characteristics of companies with potential accounting irregularities that warrant further investigation.

*On average, most companies exhibiting potential accounting irregularities have below average scores along most ESG dimensions.*



# Beyond statistics

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## Introducing the AAER database

An investigation or even a simple inquiry by the regulators like the SEC can be an unnerving experience for the subject company, its management, and shareholders. The SEC can launch an investigation into a company for a number of reasons. The Accounting and Auditing Enforcement Releases (AAER) database is compiled by the SEC during or at the end of an investigation into a corporate entity or its directors for alleged accounting misconduct<sup>22</sup>.

Accounting manipulation can lead to significant share price underperformance, bankruptcy, expensive litigation costs, and reputational risks (e.g. Tyco, Enron, and WorldCom). The SEC launches investigations into companies that are allegedly manipulating their earnings or shadowing expenses. Non-conformity with GAAP, earnings restatements, and significant write-offs are potential red flags from the SEC's perspective<sup>23</sup>. The SEC also relies on whistleblowers, insiders, and individuals who voluntarily come forward revealing their suspicions on corporate accounting misconduct.

The SEC records and archives all corporate accounting misconduct investigations and enforcements into the AAER database. The database is fairly comprehensive, but also has its own limitations. One key drawback is sample selection bias. With the SEC's limited budget, they typically focus their efforts on companies where they suspect gross or egregious accounting misconduct, receive numerous investor complaints, or when an accounting misconduct or manipulation is highly publicized in the media or public domain<sup>24</sup>.

There are alternative data sources that provide financial misstatement information, which we will explore in the future<sup>25</sup>. Figure 44 shows the time series coverage of AAER accounting misstatements by calendar year – number of accounting misstatements (not number of firms). The dataset contains approximately 1,800 misstatements from 1980 onward. Data is provided on a yearly basis.

As expected, the majority of the misstatements occurred during and after the technology bubble years in the late 1990s, when the SEC significantly ramped up its efforts in investigating corporate accounting misconduct.

*The SEC launches investigations into companies who are allegedly manipulating their earnings or shadowing expenses. Non-conformity with GAAP, earnings restatements, and significant write-offs are potential red flags from the SEC's perspective.*

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<sup>22</sup> The AAER dataset also contains investigations against auditors.

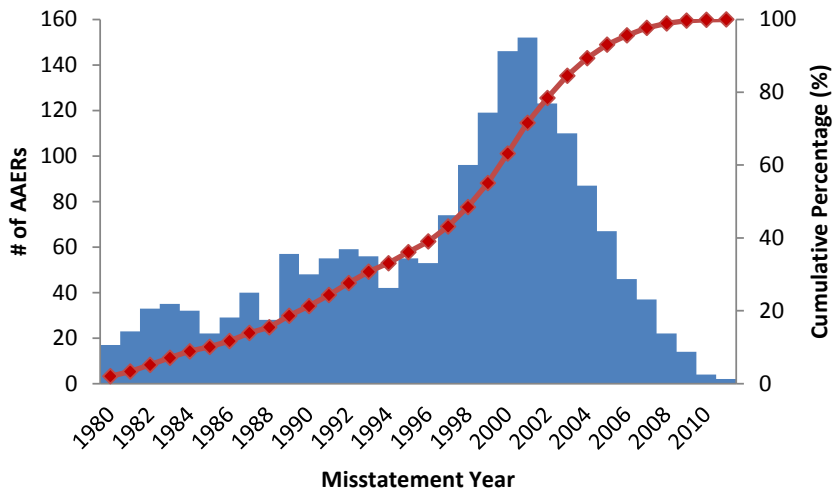
<sup>23</sup> See Dechow et al. [2010] for more information on AAER and the SEC's investigation practices.

<sup>24</sup> See Dechow et al. [2010] for more information some unintended shortcomings of the AAER dataset.

<sup>25</sup> For example, in our forthcoming research, DB Handbook of Event-Driven Strategies, Part II, we will use the Capital IQ's key development and future events (KDFE) database to study late filings, SEC investigations, and other accounting misconducts.



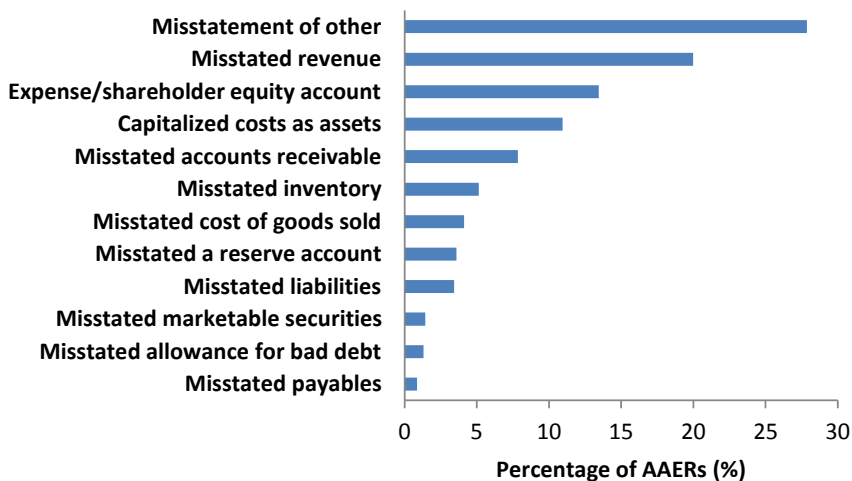
Figure 44: Number of AAER accounting misstatements, by calendar year



Source: Thomson Reuters, Compustat, IBES, Russell, S&P, AAER, Deutsche Bank Quantitative Strategy

The AAER database also records the misstatement type. Figure 45 shows the percentage distribution by misstatement type. Interestingly, the majority of accounting misconduct seems to be the result of revenue misstatement, expense manipulation, or the mishandling of off-balance sheet assets.

Figure 45: Percentage of AAERs by misstatement type



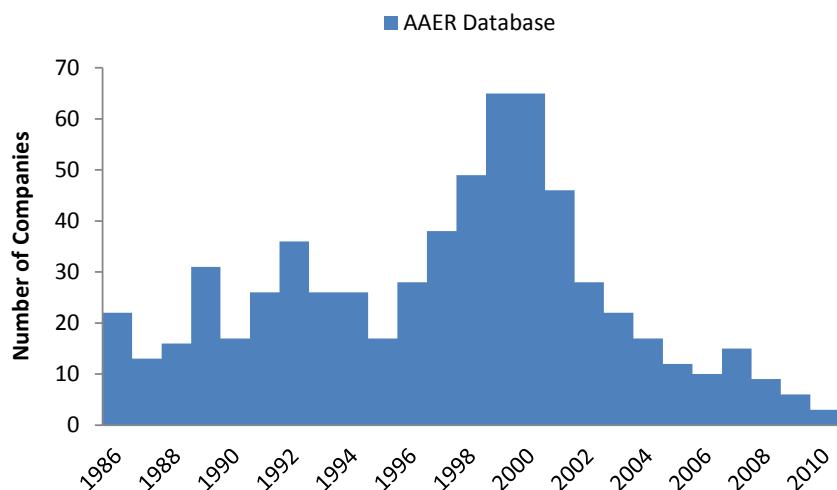
*The majority of accounting misconduct is a result of revenue misstatement, expense manipulation, or the mishandling of off-balance sheet assets.*

Source: Thomson Reuters, Compustat, IBES, Russell, S&P, AAER, Deutsche Bank Quantitative Strategy

Figure 46 shows the number of firms that have committed accounting misstatements in the AAER database. There are approximately 650 firms that have committed at least one accounting misstatement in the archived AAER database. The breadth of coverage is somewhat limited. However, this is expected as most listed companies are unlikely to breach accounting practice.



Figure 46: Company time series coverage in the AAER database

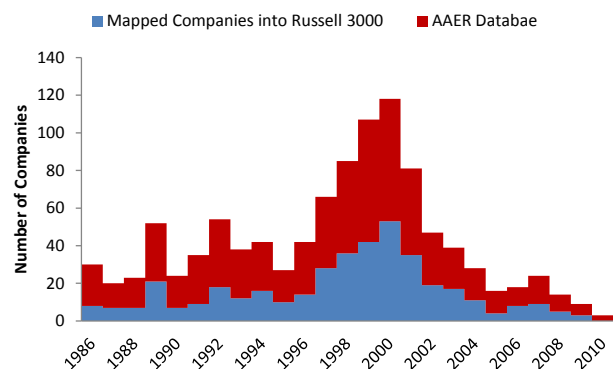


*Most listed companies do not egregiously breach accounting standards and practices.*

Source: Thomson Reuters, Compustat, IBES, Russell, S&P, AAER, Deutsche Bank Quantitative Strategy

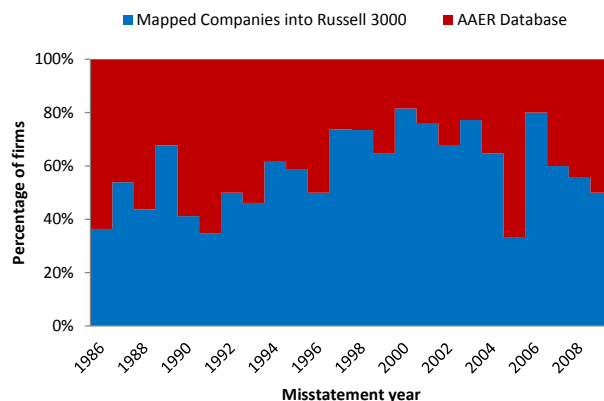
Many companies committing such accounting breaches in the AAER database are also in the Russell 3000 index (see Figure 47 and Figure 48). The breadth of the coverage is limited, which poses a big challenge. We shall address the coverage issue shortly.

Figure 47: Coverage of AAER within Russell 3000



Source: Thomson Reuters, Compustat, IBES, Russell, S&P, AAER, Deutsche Bank Quantitative Strategy

Figure 48: Percentage coverage of AAER in Russell 3000

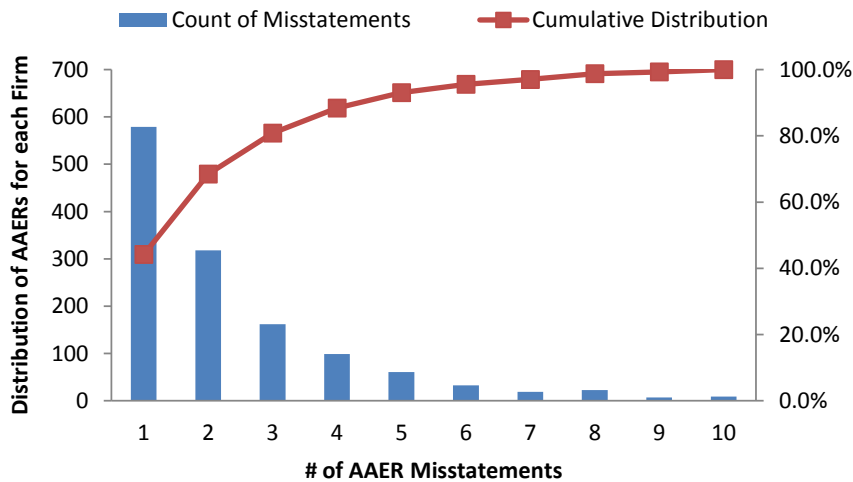


Source: Thomson Reuters, Compustat, IBES, Russell, S&P, AAER, Deutsche Bank Quantitative Strategy

Companies can commit multiple accounting breaches spanning many years. The AAER dataset also records multiple offenders. Figure 49 shows the distribution by the number of AAER misstatements. Most companies commit one to two accounting breaches.



Figure 49: Distribution of companies by number of misstatements



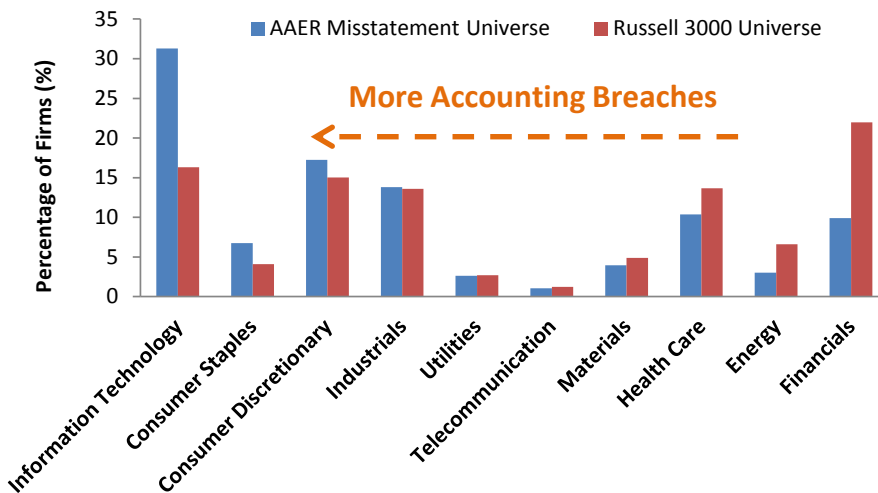
*Most companies commit one to two accounting breaches.*

Source: Thomson Reuters, Compustat, IBES, Russell, S&P, AAER, Deutsche Bank Quantitative Strategy

Analyzing accounting breaches by sector, Figure 50 shows that many accounting breaches are focused in a few sectors such as the information technology, consumer staples, consumer discretionary, and industrials.

Now that we have a grasp of the AAER dataset, we investigate some of the firm level characteristics of companies that have accounting misstatements in the AAER database.

Figure 50: Distribution of AAER misstatements by sector



*Accounting breaches are focused in a few particular sectors including information technology, consumer staples, consumer discretionary, and industrials.*

Source: Thomson Reuters, Compustat, IBES, Russell, S&P, AAER, Deutsche Bank Quantitative Strategy

## Characteristics of accounting offenders

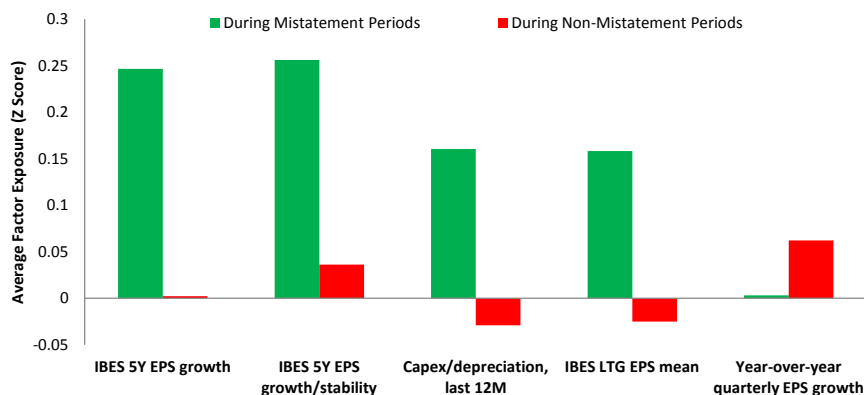
In this section, we analyze the fundamental characteristics of firms during misstatement and non-misstatement years. This will enable us to better gauge the fundamental repercussions of firms when they manipulate accounting



metrics. We start by analyzing the impact of accounting misstatement on growth metrics.

As shown in Figure 51, almost all growth measures “appear” superior during misstatement years as compared to non-misstatement years. This is expected as the one of the primary purposes for accounting manipulation is to maintain glorious growth prospect.

Figure 51: Growth factors

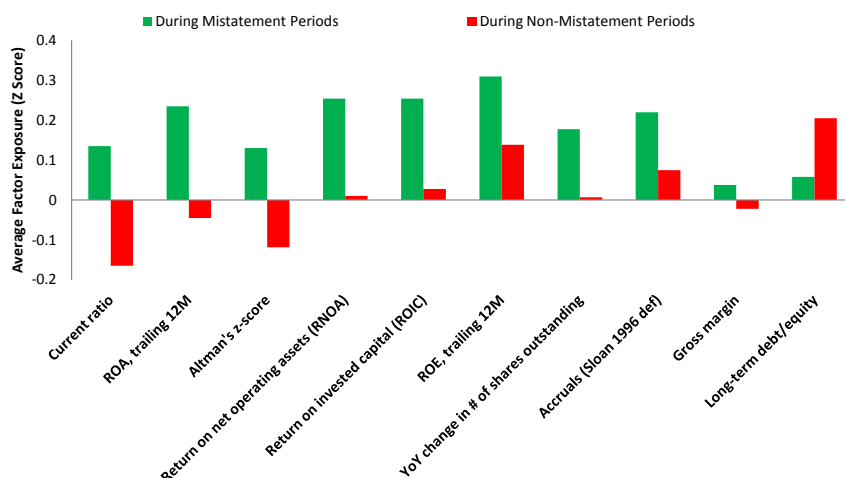


Source: Thomson Reuters, Compustat, IBES, Russell, S&P, AAER, Deutsche Bank Quantitative Strategy

*We find that all fundamental growth measures “appear” superior during misstatement years as compared to non-misstatement years.*

Diving into the quality dimension (see Figure 52), firms during the misstatement years tend to be more profitable, have better liquidity and lower financial leverage, than during normal years, but probably only on paper. The higher level of accruals gives us a hint of potential problems.

Figure 52: Quality factors



Source: Thomson Reuters, Compustat, IBES, Russell, S&P, AAER, Deutsche Bank Quantitative Strategy

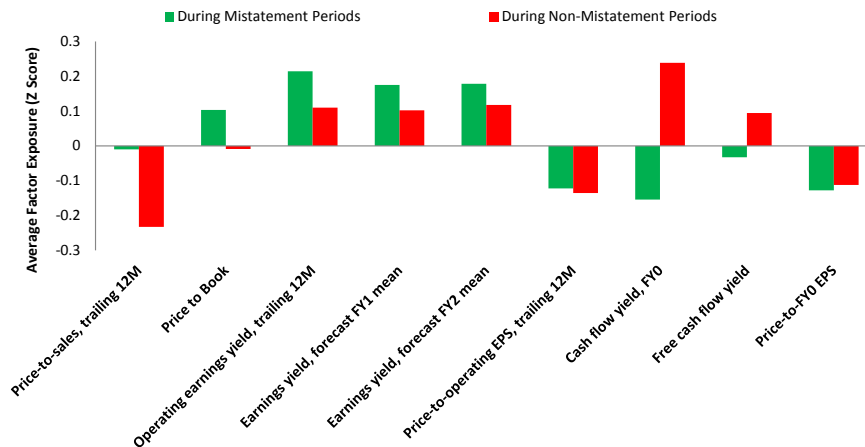
*During misstatement years, quality, liquidity, and leverage ratios appear strong. This paints a very different picture as compared to non-misstatement years.*

The valuation aspect shows mixed results (see Figure 53). The offenders appear to be cheap on earnings (e.g., earnings yield), but expensive on cash flows or free cash flows (e.g., cash flow yield). Obviously, company management has more discretion on how to compute earnings, but much less



so on cash flows, which is the fundamental theory behind the accruals-based earnings quality study (see Sloan [1996] and Luo, et al [2010] for details).

Figure 53: Value factors

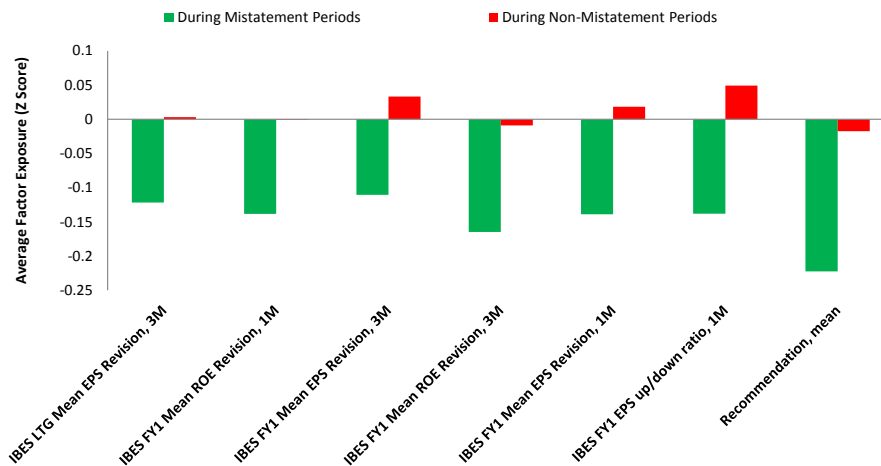


Many valuation factors appear more favorable during misstatement years.

Source: Thomson Reuters, Compustat, IBES, Russell, S&P, AAER, Deutsche Bank Quantitative Strategy

The most notable finding is along the analyst sentiment dimension (Figure 54). Interestingly, most sentiment factors are more negative during misstatement years than non-misstatement years. Could analysts have a better sense at detecting accounting irregularities?

Figure 54: Sentiment factors



Interestingly, most sentiment factors showed poorer metrics during misstatement years than non-misstatement years. Could analysts have a better sense at detecting accounting irregularities or misstatements?

Source: Thomson Reuters, Compustat, IBES, Russell, S&P, AAER, Deutsche Bank Quantitative Strategy

As we have shown, financial metrics can appear fairly lofty during misstatement years. As such, it is prudent for investors to be able to detect which companies may be accounting offenders. Next, we discuss a model based approach to tackle this.



## Misstatement modeling

In this section, we investigate whether we can forecast accounting misstatements. This is undoubtedly a difficult task for many reasons. Accounting misstatements are rare events, so the sample size is fairly small<sup>26</sup>. We are also limited to analyzing accounting misstatements that have been identified by the SEC, while arguably there are frauds that have never been reported. Furthermore, accounting metrics for offenders are potentially inaccurate and misleading. As such, our model may be riddled with messy input data.

However, a quantitative model can still be useful, even if it is only roughly correct. Indeed, as Warren Buffett once said “it is better to be approximately right than precisely wrong”. Accounting fraud can have serious consequences for stock returns.

We develop a logistic regression model that uses quantitative factors (both fundamental and pricing) as the independent or explanatory variables<sup>27</sup>. We also include the KS statistics developed in the previous section as an independent variable. The dependant variable (a binary variable<sup>28</sup>) is whether the SEC has identified that the company has misstated its accounting metrics (i.e., whether does the company exist in the AAER database). Following convention, we run a balanced logit model, i.e., the number of misstatement firms is matched to the number of comparable firms. We select non-misstatement firms at random and run 25 simulations to ensure that our beta coefficients are robust. For each misstatement firm, we randomly select a matched firm in the same value (based on book-to-market) and size (market cap) quintile.

We start with a pool of approximately 70 independent variables. We run a backward stepwise logistic regression, which eliminates any variables that are not statistically significant. Figure 55 shows (in the order of importance) the factors that are most predictive of accounting misstatements<sup>29</sup>.

Interestingly, we find that companies with more short interest<sup>30</sup>, increased abnormal volume, negative skewness, and those prices that are far away from their 52-week lows, and higher credit risk (as measured by the Merton’s distance to default model) have a higher probability of an accounting misstatement. In addition, our KS statistic based on the Benford’s law, has the expected sign, i.e., a higher reading of the KS statistics suggests a higher probability of accounting problem, but not on the top of the list<sup>31</sup>.

*Accounting misstatements are rare events, so the sample size is fairly limited. We are also limited to analyzing accounting misstatements that have been identified by the SEC.*

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<sup>26</sup> In a sense, fraud detection models are similar to takeover prediction models, as they both attempt to forecast rare events. Please see detailed discussion in our takeover prediction model white paper, Cahan, et al [2011b].

<sup>27</sup> This is similar to our takeover prediction model (see Cahan, et al [2011b]) and dividend growth prediction model (see Wang, et al [2014a]).

<sup>28</sup> We note that a 1 is an accounting misstatement and a 0 is no misstatement. The regression is done using the entire dataset.

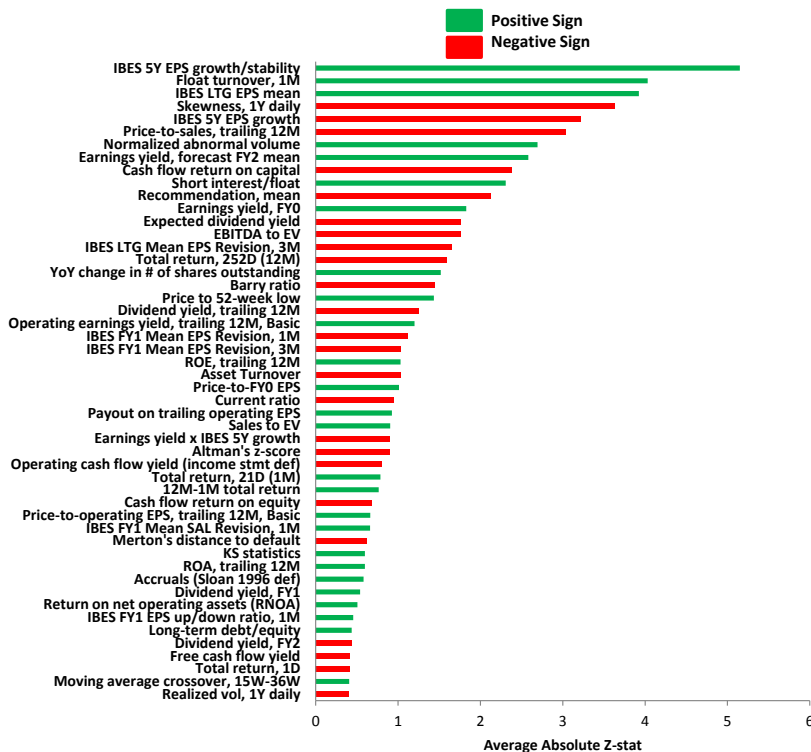
<sup>29</sup> Note that the figure shows the weighted Z-stat. It’s weighted based on the number of simulations where a factor is significant. So a factor that is only significant in one simulation is penalized as compared to a factor that is significant in all simulations.

<sup>30</sup> Similar to what we showed in Cahan, et al [2011a] and Luo, et al [2014], short sellers are likely to be more informed; therefore, stocks that are heavily shorted are likely to have some issues.

<sup>31</sup> This does suggest that our logit model and the KS model are somewhat uncorrelated.



Figure 55: Top fifty factors explains accounting misstatements



*We find that companies with more short interest, increased abnormal volume, and those that are nearing their price to 52 week lows have a higher probability of an accounting misstatement.*

Source: Thomson Reuters, Compustat, IBES, Russell, S&P, AAER, Deutsche Bank Quantitative Strategy

The output of our logit model is the probability of accounting fraud<sup>32</sup>:

$$Probability = \frac{e^{\text{Predicted Value}}}{1 + e^{\text{Predicted Value}}}$$

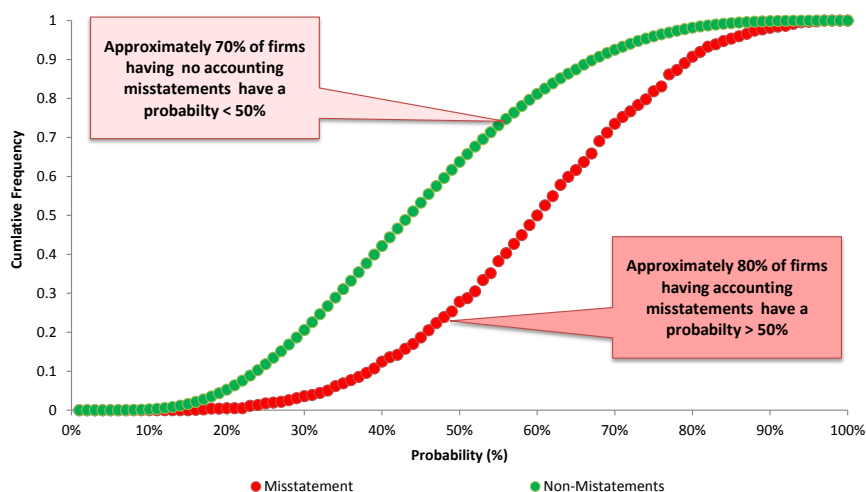
Although the coverage breadth of the AAER database is small, our model has an estimated probability of accounting misstatement for every company in our universe.

To assess the hit rate and accuracy of our model, Figure 56 shows the cumulative distribution of probabilities for misstatement (as determined by AAER) and non-misstatement firms. Over 80% of firms that have an accounting misstatement (as identified by the SEC) have a probability of a misstatement greater than 50% (based on our model). On the flip side, approximately 70% of firms having no accounting misstatements in the AAER database have a probability of less than 50% based on our model.

<sup>32</sup> We calculate the probability at each simulation. Then we take the average probability across all simulations. Note that there are 25 simulations in total.



Figure 56: The effectiveness of our misstatement model

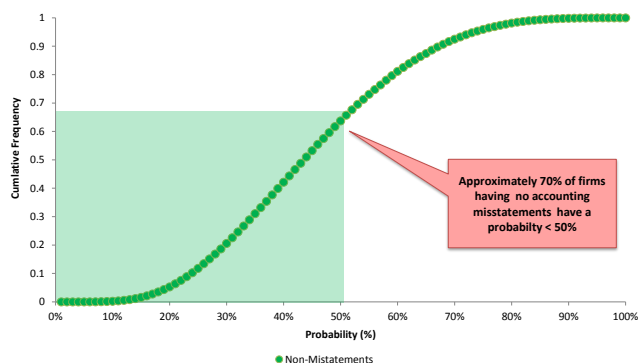


*80% of firms that have an accounting misstatement as identified by the SEC have a probability of a misstatement greater than 50% based on our model.*

Source: Thomson Reuters, Compustat, IBES, Russell, S&P, AAER, Deutsche Bank Quantitative Strategy

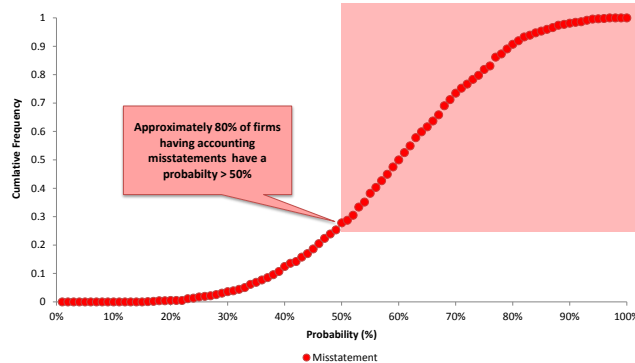
This can be seen more clearly by separately analyzing the results of the offenders versus non-offenders (see Figure 57 and Figure 58).

Figure 57: Effectiveness on model on non-misstatements



Source: Thomson Reuters, Compustat, IBES, Russell, S&P, AAER, Deutsche Bank Quantitative Strategy

Figure 58: Effectiveness on model on misstatements



Source: Thomson Reuters, Compustat, IBES, Russell, S&P, AAER, Deutsche Bank Quantitative Strategy

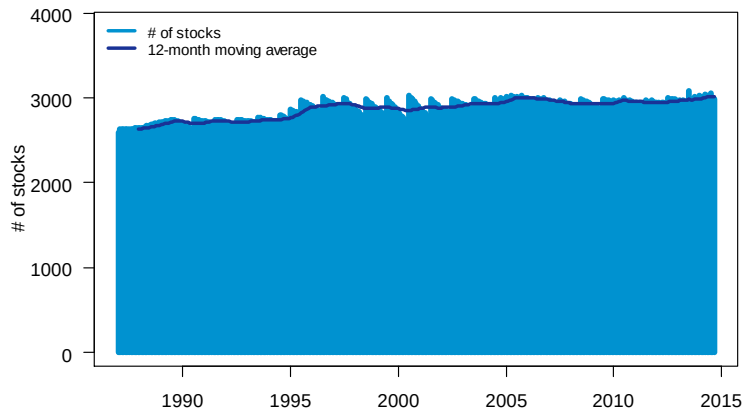
Our logit model appears to be able to differentiate the offenders from the other companies. Next, we explore whether we can utilize this framework for alpha modeling.

## Alpha modeling

The probability of a misstatement that we calculated in the previous section could also be a potential alpha factor. Again, although the AAER has a limited coverage, the logit model produces a probability estimate for every company in our research universe (see Figure 59).



Figure 59: Coverage of probability misstatement factor



Source: Thomson Reuters, Compustat, IBES, Russell, S&P, AAER, Deutsche Bank Quantitative Strategy

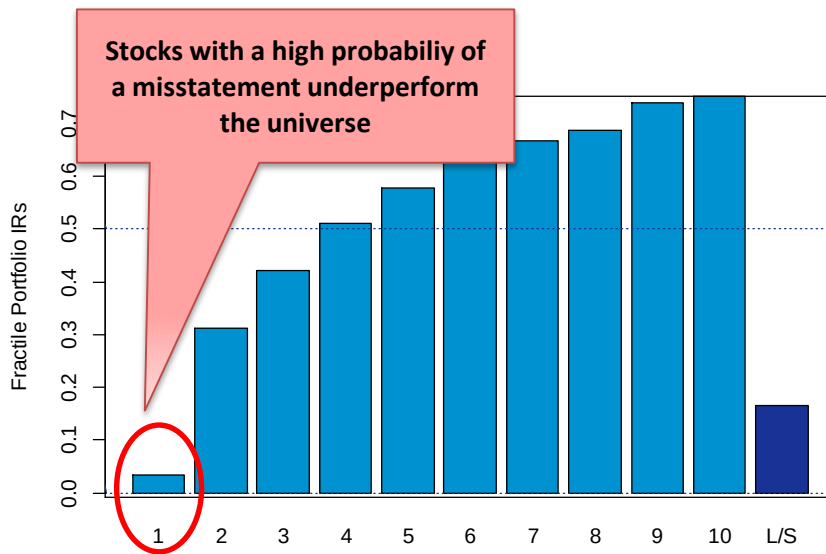
Next, we backtest the logit model in the Russell 3000 universe. We form equally weighted decile portfolios on a monthly basis. Naturally, we take a long position in stocks with low probabilities of a misstatement and a short position in stocks with high probabilities. We rebalance our portfolio on a monthly basis.

The results are interesting and intuitive. Figure 60 shows the Sharpe ratio of each decile portfolios. Stocks with the high probabilities of a misstatement (in decile one) significantly underperform the rest of the universe. Naturally, as our logit model attempts to predict accounting fraud and those offenders' share prices tend to fall sharply, if our model is indeed effective in predicting accounting misconduct, it should be useful in identifying extreme underperformers.

*The probability of a misstatement could also be a potential alpha factor*



Figure 60: Sharpe ratio of misstatement factor

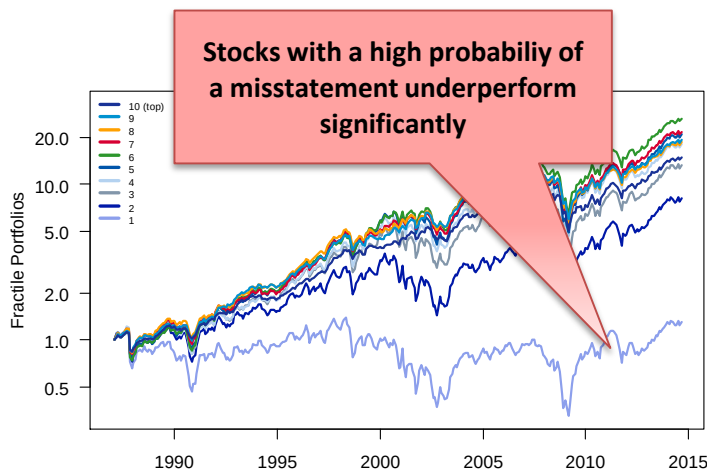


Source: Thomson Reuters, Compustat, IBES, Russell, S&P, AAER, Deutsche Bank Quantitative Strategy

This can be seen more clearly by analyzing the wealth curve (Figure 61). The results again show that stocks with the highest probabilities of a misstatement (decile 1) significantly underperform the rest of the universe.



Figure 61: Wealth curve of probability of misstatement factor



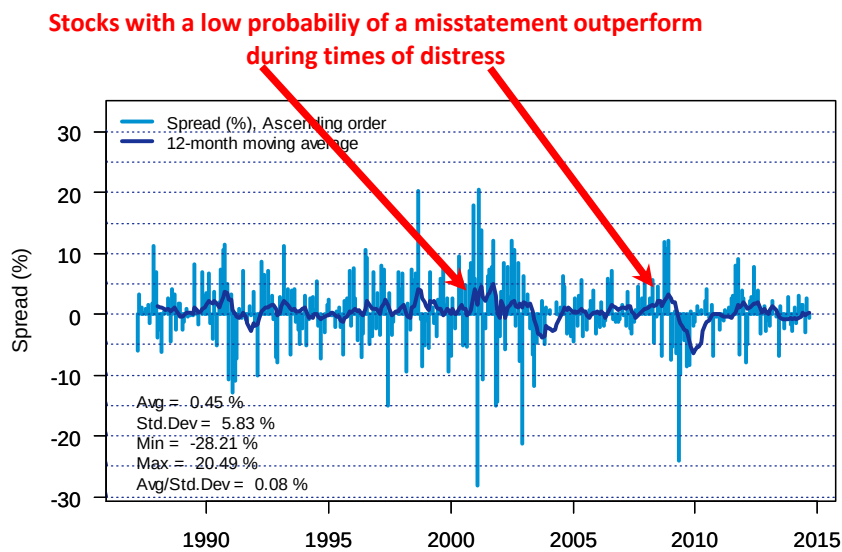
The results again show that stocks with a high probability of a misstatement (decile 1) significantly underperform the rest of the universe.

The results reiterate are previous findings thought the report that stocks with a high probability of a misstatement are potential short candidates

Source: Thomson Reuters, Compustat, IBES, Russell, S&P, AAER, Deutsche Bank Quantitative Strategy

Analyzing the time series performance of our logit model, Figure 62 shows that our model works well during market stress times, e.g., in the years subsequent to tech bubble and during the 2008-global financial crisis.

Figure 62: Long/short portfolio return of probability of misstatement factor



Our probability of misstatement factor performs strongly when markets are in a distressed state

Source: Thomson Reuters, Compustat, IBES, Russell, S&P, AAER, Deutsche Bank Quantitative Strategy

Although investors may expect our logit model as another proxy for quality, in fact, it is somewhat uncorrelated and at times, negatively correlated to other common quality factors (see Figure 63). The results indicate that the inclusion of the probability of accounting misstatement factor into a standard quality focused quantitative or fundamental strategy may reap some additional diversification benefit.

In fact, our probability misstatement factor is somewhat uncorrelated and at times, negatively correlated to our standard quality factors



Figure 63: Correlation matrix between probability of misstatement and other quality factors

|                                | Probability of Misstatement | Berry Ratio | Capex to Dep | YoY change in debt outstanding | Current ratio | Long-term debt to equity | Gross margin | IBES FY1 EPS dispersion | Merton | ROA  | ROE  | Asset Turnover | ROIC |
|--------------------------------|-----------------------------|-------------|--------------|--------------------------------|---------------|--------------------------|--------------|-------------------------|--------|------|------|----------------|------|
| Probability of Misstatement    | 100%                        |             |              |                                |               |                          |              |                         |        |      |      |                |      |
| Berry Ratio                    | 62%                         | 100%        |              |                                |               |                          |              |                         |        |      |      |                |      |
| Capex to Dep                   | 51%                         | 31%         | 100%         |                                |               |                          |              |                         |        |      |      |                |      |
| YoY change in debt outstanding | -22%                        | -34%        | 4%           | 100%                           |               |                          |              |                         |        |      |      |                |      |
| Current ratio                  | -57%                        | -73%        | -42%         | 19%                            | 100%          |                          |              |                         |        |      |      |                |      |
| Long-term debt to equity       | -32%                        | -58%        | -47%         | 14%                            | 80%           | 100%                     |              |                         |        |      |      |                |      |
| Gross margin                   | 31%                         | 39%         | 4%           | -19%                           | -13%          | 14%                      | 100%         |                         |        |      |      |                |      |
| IBES FY1 EPS dispersion        | 76%                         | 56%         | 35%          | -24%                           | -30%          | -3%                      | 53%          | 100%                    |        |      |      |                |      |
| Merton                         | 74%                         | 60%         | 25%          | -28%                           | -27%          | 6%                       | 59%          | 86%                     | 100%   |      |      |                |      |
| ROA                            | 65%                         | 87%         | 34%          | -33%                           | -69%          | -44%                     | 56%          | 72%                     | 71%    | 100% |      |                |      |
| ROE                            | 70%                         | 90%         | 41%          | -36%                           | -76%          | -53%                     | 50%          | 71%                     | 71%    | 98%  | 100% |                |      |
| Asset Turnover                 | -41%                        | -3%         | -38%         | 7%                             | 5%            | 17%                      | 2%           | -18%                    | -14%   | -2%  | -6%  | 100%           |      |
| ROIC                           | 68%                         | 87%         | 37%          | -34%                           | -71%          | -46%                     | 53%          | 73%                     | 72%    | 99%  | 99%  | -4%            | 100% |

Source: Thomson Reuters, Compustat, IBES, Russell, S&P, AAER, Deutsche Bank Quantitative Strategy

Next, we explore whether our logit model, which was trained based on SEC investigations of US companies, can be extrapolated to firms outside of the US market.

## Regional effects of accounting misstatements

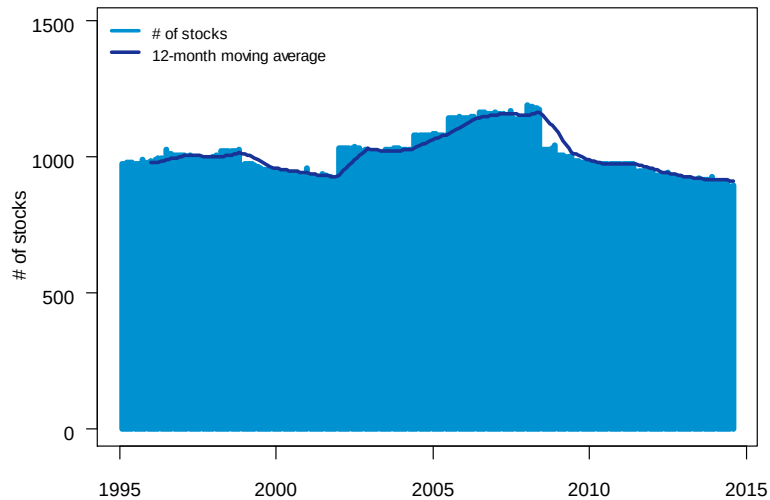
Here we investigate whether accounting offenders have common traits or characteristics across countries. To test this we utilize our logit model developed in the previous section. We apply the same factors and beta coefficients from our logistic model trained using the AAER dataset onto the MSCI World ex US stock universe. Arguably, we make a few strong assumptions:

- There are some common traits among accounting fraud across countries, and more importantly,
- The market reacts to potential accounting offenders similarly across countries

Next, we backtest the logit model. We form equally weighted decile portfolios on a monthly basis. Naturally, we take a long position in stocks with low probabilities of a misstatement and a short position in stocks with high probabilities. We rebalance our portfolio on a monthly basis. Figure 64 shows the coverage of our probability of misstatement factor for MSCI World ex US.



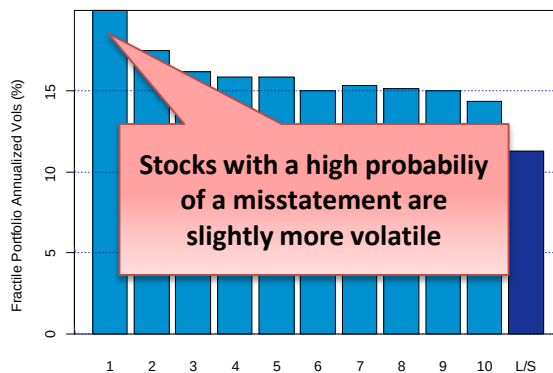
Figure 64: Coverage of probability misstatement factor for MSCI World ex US



Source: Thomson Reuters, Compustat, IBES, Russell, S&P, AAER, Deutsche Bank Quantitative Strategy

Figure 65 shows the annualized volatility of each decile portfolios. Stocks with the highest probabilities of a misstatement (in decile one) are meaningfully more volatile than the rest of the universe.

Figure 65: Annualized vol of misstatement factor for MSCI World ex US

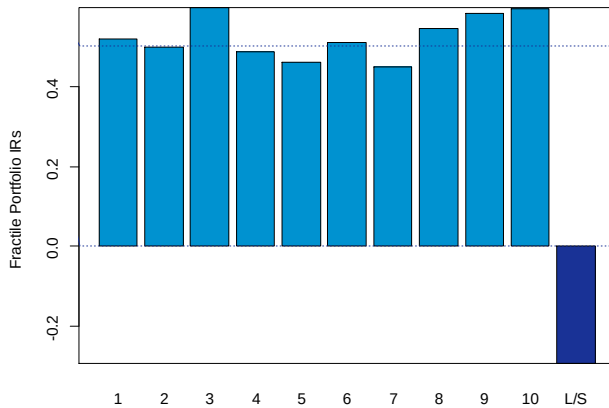


Source: Thomson Reuters, Compustat, IBES, Russell, S&P, AAER, Deutsche Bank Quantitative Strategy

However, the extrapolated logit model does not appear to predict future stock returns. Indeed, the payoff pattern for the decile portfolio is not very monotonic (see Figure 66). Although the low fraud probability decile (i.e., decile 10) has slightly higher Sharpe ratio than the high fraud probability portfolio (i.e., decile one), the long/short spread is slightly negative (see Figure 67).

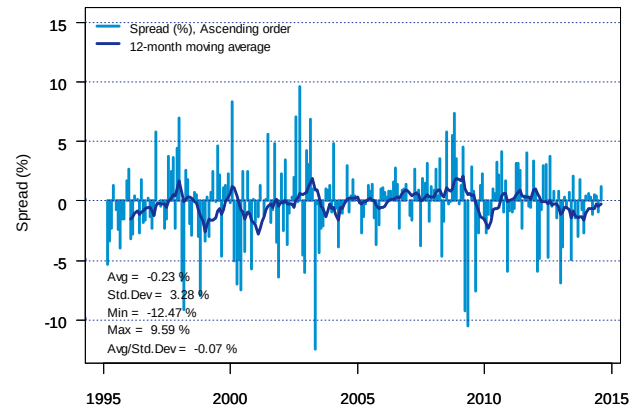


Figure 66: Sharpe ratio of misstatement factor for MSCI World ex US



Source: Thomson Reuters, Compustat, IBES, Russell, S&P, AAER, Deutsche Bank Quantitative Strategy

Figure 67: Long/short portfolio return of probability of misstatement factor for MSCI World ex US



Source: Thomson Reuters, Compustat, IBES, Russell, S&P, AAER, Deutsche Bank Quantitative Strategy

The results are interesting and seem to suggest that detecting accounting fraud may be more region specific than globally standardized. This could be a result of many factors including the vast differences in accounting and auditing standards, accounting data quality and reporting frequencies, and the advancement and enforcement of governing and regulatory bodies across regions. It might also be due to how the market reacts to accounting offenders differently across countries.



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# Appendix 1

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