Earnings Quality Revisited

Jennifer Bender and Frank Nielsen

Jennifer Bender
is a vice president for research at MSCI in New York, NY.
jennifer.bender@msci.com

Frank Nielsen
is the managing director for research at Fidelity Investments in Boston, MA.
frank.nielsen@fmr.com

Earnings quality as an investment signal has been popular among equity portfolio managers for many years. The basic idea is that stocks with high and increasing accruals tend to have low earnings quality, while stocks with low and decreasing accruals tend to have high earnings quality. Although the importance of understanding the earnings composition has been known since at least Graham and Dodd [1934], for many years investors and analysts seemed to have overlooked the simple fact that cash earnings are worth more than accruals-based earnings. As we show in this article, a simple strategy of going long companies with high earnings quality outperformed a portfolio of stocks with low earnings quality by more than 18 percent, annualized over the last 15 years. Here, we set out to confirm the results and extend the empirical analysis to the present, using commercially available earnings-quality scores. We investigate the following questions:

- Does the accruals anomaly persist, i.e., do stocks with high earnings quality (low accruals) continue to outperform stocks with low earnings quality (high accruals)?
- Is earnings quality an alpha signal, i.e., is the outperformance of a portfolio of high earnings quality driven by the high earnings quality, or does the outperformance come from sector or style[1] biases?
- Is earnings quality a risk factor, i.e., are high earnings-quality stocks consistently more or less risky than their low earnings-quality peers after adjusting for sector and other style characteristics?

In the next two sections, we first review the existing literature and describe the earnings quality definition used in this article.

THE ACCRUALS ANOMALY

Beginning in the 1980s, a wealth of research analyzed the link between accounting measures and stock prices. Researchers found the persistence of a curious stock price anomaly, called the *accruals anomaly*. That is, firms with relatively high (low) levels of accruals experience negative (positive) future abnormal stock returns.

In accounting, accruals are accounts on the balance sheet that represent liabilities and noncash-based assets.[2] These accounts include, among many others, accounts payable, accounts receivable, goodwill, future tax liability, and future interest expense. Before accrual accounting, these statements recorded only cash transactions. The introduction of accruals allowed a company to measure what it will owe, looking forward, and what cash revenue it expects to receive.

Graham and Dodd [1934] and others first recognized that various operating accruals, such as arbitrary reserves and unusual levels of depreciation or amortization, are less likely to recur in future period earnings. Later research—Ou and Penman [1989], Bernard and Thomas [1990], and Sloan [1996]—showed that the low persistence in accruals translated into low persistence in earnings, resulting in lower stock returns. In contrast, companies whose current earnings consist of fewer accruals and more cash tended to experience stronger future earnings and higher stock returns.

All of this suggests that the financial health of companies with high accruals is often overstated. Because higher accruals typically stem from factors that are less likely to persist,[3] it seems reasonable that future earnings are likely to be lower than current earnings, often leading to negative earnings surprises.

In addition, researchers have proposed that high accruals may reflect deliberate earnings management (such as channel stuffing, bond sales timing, or taking one-time charges). In fact, Richardson et al. [2005] showed that less reliable subcategories of accruals[4] (those subject to greater subjectivity in their estimates) lead to lower earnings persistence.

What we have summarized only touches the tip of the iceberg. The accruals literature continues to be a rich area of study. Highlights include:

- The link to mean reversion in sales and earnings (higher-accrual companies have higher trailing sales and ROE, and analysts are over-optimistic in their forecasts); see Mahedy [2005].
- The link, or lack of a link, to earnings revisions (accruals are found to be informative even after accounting for earnings revisions); see Barth and Hutton [2003].
- The link to the value-glamour anomaly (Desai et al. [2004] suggest that the accruals anomaly is the glamour stock phenomenon in disguise).
- The link to idiosyncratic risk (the anomaly is concentrated in firms with high idiosyncratic volatility, low price, and low-volume stocks); see Mashruwala et al. [2006]).

We refer interested readers to De Chow and Schrand [2004], who provide a comprehensive review of the literature.

MEASURING EARNINGS QUALITY

For our study, we look at a measure of earnings quality provided by CFRA (Center for Financial Research & Analysis) called CFRA earnings score.[5] Earnings scores are based on the ratio of accruals to total assets, as reported by Compustat. Accruals are computed as the change from one quarter to the next in total assets, minus cash and equivalents, minus total liabilities, net of current and long-term debt. Total assets are averaged over the last four quarters. CFRA applies an additional proprietary adjustment to the raw accrual scores, based on return on assets.[6] The resulting scores are ranked such that top decile (10th decile) earnings scores are those of firms with a high ratio of accruals to total assets, which are thus stocks with low earnings quality. Conversely, bottom decile earnings scores are from firms with a low ratio of accruals, and so are high earnings-quality stocks.

- High earnings quality: Low ratio of accruals to total assets (low earnings scores)
- Low earnings quality: High ratio of accruals to total assets (high earnings scores)

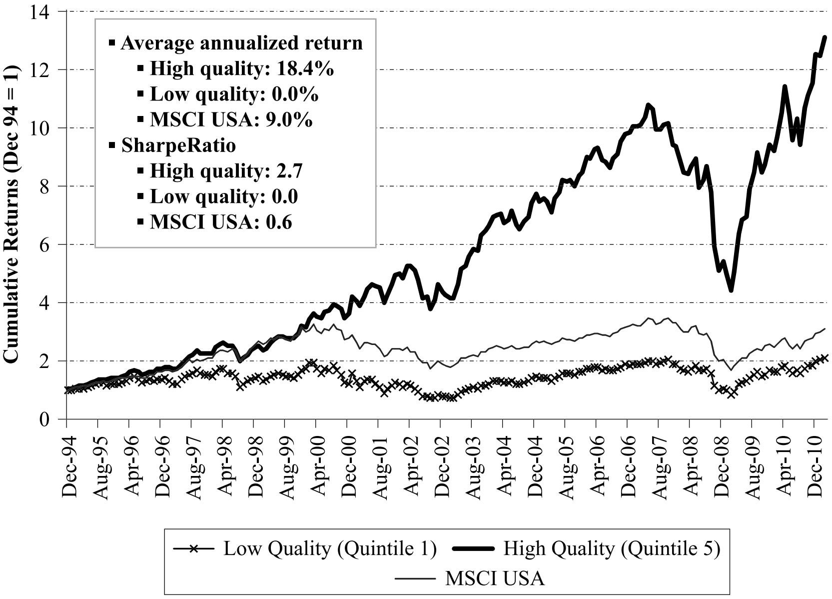
Earnings scores are estimated for North America and companies in EMEA and Asia (World Earnings Scores). The universe consists of companies that have a twelve-month fiscal period reported under U.S. GAAP or IFRS standards, and whose market capitalization is greater than $25 million. The scores cover roughly 6,000 stocks in North America and 5,500 companies outside North America. Quarterly scores start in the first quarter of 1983, our focal point in this study.[7]

DOES EARNINGS QUALITY STILL WORK?

Using earnings scores as our measure of earnings quality, we begin by ranking stocks quarterly (on the date earnings scores are made available)[8] and forming decile portfolios based on these rankings. The stocks are equally weighted within each decile. Do high earnings-quality portfolios outperform low earnings-quality portfolios? Exhibit 1 confirms that the high-quality portfolio exhibits strong long-run performance, with an average annualized return of 18.4 percent since December 1994. Moreover, the Sharpe ratio was 2.7 for this portfolio, reflecting relatively low volatility for that level of return.

EXHIBIT 1

Performance of Top and Bottom Earnings-Quality Deciles (Monthly Returns, December 1994 to March 2011, Deciles Rebalanced Quarterly)



Do the results hold up if we look at cap-weighted deciles or consider alternative groupings? Exhibit 2 shows the robustness of the earnings-quality signal, even as we dilute it by considering less granular grouping and weighting schemes.

However, the strong performance of earnings quality has not been consistent over all periods. In fact, the largest returns are focused in the earlier part of the sample and the most recent two years. As shown in Exhibit 3, during the years 2003 to 2008 it all but disappeared, with 2007 as the year high quality most underperformed low quality. There may be various reasons the quality signal essentially stopped working from 2003 to 2008.

First, this period shortly followed the WorldCom and Enron scandals. Companies may have been more cautious about accounting manipulation after these events. On the reverse side, investors may have been more cautious about investing in stocks where there was a hint of manipulation, which high accruals could signal. High accruals would have then earned a premium. A second reason may have been tied to the popularization of the accruals strategy in the quantitative management space. The years in which earnings quality most underperformed coincided with a period in which accruals research proliferated in the academic and practitioner literature.

These results beg several questions:

- Is earnings quality an alpha factor, in the sense that it is not readily explained by other well-known factors?
- What changed during the 2003 to 2008 period, when the signal stopped working? Did other fac-

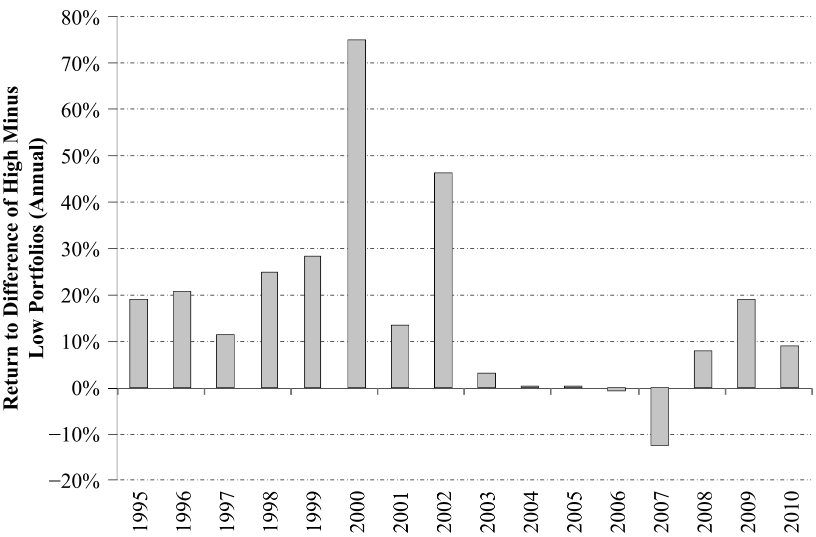
EXHIBIT 2

Performance of Portfolios Sorted on Earnings Quality (December 1994 to March 2011, Deciles Rebalanced Quarterly, Active Return, Benchmark = MSCI USA IMI Index)

	Annualized Active Return		Annualized Information Ratio	
	Low Quality	High Quality	Low Quality	High Quality
Equally Weighted Deciles	−8.99%	9.41%	−1.60	2.53
Cap-Weighted Deciles	−7.84%	1.04%	−1.96	0.41
Equally Weighted Quintiles	−4.84%	8.78%	−0.99	2.84
Cap-Weighted Quintiles	−4.94%	3.21%	−1.51	1.96
Equally Weighted Terciles	−1.89%	8.47%	−0.44	3.04
Cap-Weighted Terciles	−3.42%	3.06%	−1.34	2.28
Equally Weighted Halves	0.27%	7.78%	0.07	2.92
Cap-Weighted Halves	−1.36%	3.19%	−0.76	2.73

EXHIBIT 3

Sub-Period Performance of Top Minus Bottom Earnings-Quality Deciles (Annual Returns, December 1994 to March 2011, Deciles Rebalanced Quarterly)



tors hurt the high-quality portfolio, or did its alpha disappear?

- What has changed in the most recent period, 2009 to 2011? Is the resurgence in the strategy real?

We explore these questions in the next section.

IS EARNINGS QUALITY AN ALPHA SIGNAL?

Clearly earnings quality appears to have had strong return attached to it, both over the long run and more recently. But is it really an alpha factor? Portfolio managers can debate what constitutes a true alpha factor, but a simple interpretation is that an alpha factor should not be easily explained by well-established, systematic sources of return. A good alpha factor will have strong return associated with it, even after well-known factors have been accounted for.

For candidate well-established factors, we turn to the wealth of literature on systematic factors. Beginning with Ross's [1976] arbitrage pricing theory, empirically established by Fama and French [1992, 1993] and others, candidate factors may include value, size, momentum, and other stock characteristics that explain the cross-section of returns. Closely related to this area of the asset-pricing literature is the research focusing on return anomalies. Return anomalies associated with asset growth, earnings revision, earnings surprise, and a host of other characteristics have been empirically identified; see Schwert [2003], Fama and French [2008], and Keim [2008] for a review of financial market anomalies.

In this article, we use the factors in the Barra US Equity Model as our reference set of factors. A good reason for using a multi-factor risk model is that it allows us to quantify the amount of return that is net of (or orthogonal to) the factors in the model. Barra multi-factor risk models are based on cross-sectional regressions, which are similar in spirit to the academic work of Fama and French [1993].[9] The Barra US Equity Model (USE3) identifies 13 style factors and 55 industry factors that meet a certain level of significance in explaining cross-sectional returns. There may be other alpha signals that are not included in this model, as pure alpha signals do not necessarily explain the cross-section of returns. Appendix A additionally considers various well-known alpha signals separately. In sum, we assume the Barra factors are a good benchmark for widely accepted systematic factors.

We first map the CFRA universe of U.S. stocks to the Barra US Equity Model universe. There is an average of 96 percent coverage of names in the CFRA universe from December 1994 to March 2011.[10] We then confine our analysis to the stocks in the MSCI USA IMI Index, which covers large, mid, and small caps (an average of more than 2,000 names). We form earnings-quality deciles based on this universe. Each decile is equally weighted[11] and contains approximately 200 stocks.

Next, we decompose the return of the earnings-quality deciles using the Barra US Equity Model (USE3). A large asset selection (stock selection) component would provide confirmation of earnings quality as an alpha factor. Exhibit 4 shows the results of the attribution on the equally weighted decile portfolios. Of the 18 percent annual spread between the two portfolios' active returns, more than 14 percent came from asset selection.

Remarkably, even when we consider other grouping or weighting schemes, the results are qualitatively similar. Even though the industries have a greater impact

EXHIBIT 4

Annualized Contribution to Return of Top and Bottom Earnings-Quality Deciles (December 1994 to March 2011, Deciles Rebalanced Quarterly, Benchmark = MSCI USA IMI Index

	Low Quality	High Quality	Difference
Total Return	−0.01%	18.39%	18.39%
Benchmark*	8.98%	8.98%	0.00%
Active Return	−8.99%	9.41%	18.39%
Style Factors	−0.43%	2.66%	3.09%
Industry Factors	−1.00%	−0.16%	0.84%
Asset Selection	−7.56%	6.91%	14.47%

**Benchmark is cash plus excess return to the MSCI USA Index.*

on the returns of both high- and low-quality portfolios, the asset selection component still dominates.

What if we drill down into the three subperiods: two periods of strong performance (1995 to 2002 and 2009 to 2011) and one period of poor performance (2003 to 2008)? As seen in Exhibit 5, the specific component for the earnings-quality signal (or alpha) virtually disappeared from 2003 to 2008, and has bounced back since 2009. The same pattern occurs when we use other grouping and weighting schemes. Thus, although the alpha signal did disappear in the middle part of the decade, it has since returned.

Exhibit 5 also highlights some important style and industry effects. The style and industry contributions, though smaller than specific return contributions, are not negligible. Both styles and industries dragged down low-quality portfolio returns (by −5.9 percent and −3.5 percent, respectively) in the first period, but have since disappeared. Curious readers may note the sizable contributions of more than 22 percent from styles to both low- and high-quality portfolios in the most recent period.

Exhibit 6A shows the top three style and industry factors that boosted the high-quality portfolio's return over the whole period. A bias towards small caps (captured by the size factor) was the predominant style contributor; an overweight to technology stocks was the leading industry contributor. The former had a much stronger effect than the latter.

Regarding the sub-period results, two observations stand out. First, the small-cap tilt consistently had a positive effect, particularly from 2009 to 2011. And from 2009 to 2011, the effect of momentum and volatility tilts also became much bigger, resulting in the phenomenal contribution from styles we saw in Exhibit 5. Second, the technology overweight consistently remained the top contributor to the high-quality portfolio's returns, except from 2003 to 2008. In that period, none of the industries had any notable effect.

Exhibit 6B focuses on the styles and industries that contributed most to the return difference between high and low quality. The earnings yield factor had the largest effect among style factors; both low- and high-quality portfolios were negatively exposed to this strongly performing factor, but high-quality stocks were less exposed.

In the most recent period, however, high-quality stocks have actually been hurt by being more underweight towards high E/P stocks. The growth factor has also had an interesting effect over time. A positive growth tilt in the low-quality portfolio hurt performance in the first two sub-periods, but helped in the most recent period. In general, the high-quality portfolio benefited from a low P/E tilt, low volatility tilt, and anti-growth tilt, mostly during the first sub-period. Among industry drivers, the story is still the same: the technology tilt was the only one of note.

Although the style and industry contributions are interesting, the main story is the large specific (or alpha) contributions. We would like to know more about the

EXHIBIT 5

Annualized Return Contribution for Top and Bottom Earnings Quality Equally Weighted Deciles (Deciles Rebalanced Quarterly, Benchmark = MSCI USA IMI Index)

	1995–2002		2003–2008		2009–2011 (March)	
	Low Quality	High Quality	Low Quality	High Quality	Low Quality	High Quality
Total	−11.7%	19.9%	3.5%	3.7%	44.8%	62.3%
Benchmark	9.7%	9.7%	3.1%	3.1%	23.5%	23.5%
Active (Ex-Benchmark)	−21.4%	10.2%	0.3%	0.6%	21.4%	38.9%
Style	−5.9%	−0.5%	0.4%	1.2%	25.8%	22.6%
Industry	−3.5%	−0.2%	1.6%	−1.0%	2.5%	4.0%
Specific	−12.0%	10.9%	−1.7%	0.4%	−6.9%	12.3%

EXHIBIT 6

Annualized Return Contribution from USE3 Style and Industry Factors for Top and Bottom Earnings Quality Equally Weighted Deciles (Deciles Rebalanced Quarterly, Benchmark = MSCI USA IMI Index)

	Whole Period		1995–2002		2003–2008		2009–2011 (March)	
	Low Quality	High Quality	Low Quality	High Quality	Low Quality	High Quality	Low Quality	High Quality
Panel A: Factors Selected Based on the Largest Contribution to the High-Quality Portfolio								
Top Style Contributors to High Quality								
Size	5.2%	5.9%	4.1%	5.6%	3.4%	3.4%	17.5%	18.4%
Momentum	1.9%	1.4%	2.2%	0.8%	0.6%	0.7%	3.9%	6.8%
Volatility	0.2%	0.9%	−1.5%	−0.4%	0.1%	0.1%	11.9%	11.5%
Top Industry Contributors to High Quality								
Technology	−1.3%	0.8%	−2.8%	1.0%	0.2%	0.3%	1.6%	2.2%
Industrials	0.0%	0.2%	0.0%	0.0%	−0.1%	0.1%	0.5%	1.3%
Commercial Services	0.1%	−0.3%	0.4%	−0.1%	−0.1%	−0.6%	0.9%	1.2%
Panel B: Factors Selected Based on the Largest Contribution to the Spread between High- and Low-Quality Portfolios								
Top Style Contributors to Spread between High and Low Quality								
Earnings Yield	−4.0%	−2.3%	−6.5%	−3.3%	−1.2%	−1.2%	−1.4%	−3.7%
Growth	−0.8%	0.0%	−1.3%	0.1%	−1.3%	0.1%	3.4%	−0.7%
Volatility	0.2%	0.9%	−1.5%	−0.4%	0.1%	0.1%	11.9%	11.5%
Top Industry Contributors to Spread between High and Low Quality								
Technology	−1.3%	0.8%	−2.8%	1.0%	0.2%	0.3%	1.6%	2.2%
Consumer Non-Cyclicals	−0.3%	0.1%	−0.4%	0.1%	0.1%	0.2%	−1.4%	−1.2%
Industrials	0.0%	0.2%	0.0%	0.0%	−0.1%	0.1%	0.5%	1.3%

stocks responsible for the alpha component. We therefore analyze whether stock selection worked better in some sectors, rather than across the whole universe.

In Exhibit 7, we show the specific return contributions from securities within each sector.[12] High-quality stocks within the technology and health care sectors appear to contain more alpha than other sectors, and low-quality stocks within the technology, commercial services, and consumer cyclicals sectors contributed strongly to the high negative specific return of the low-quality decile portfolio.

These results suggest it might be worth exploring within-sector earnings quality portfolios. A strategy that goes long the top decile and short the bottom decile within just the technology sector, for example, earned 24.5 percent annually over the whole period.[13]

One critical aspect we do not address here is the implementation of such an earnings-quality strategy. Specifically, we have not considered transaction costs in our analysis. The average annual one-way turnover of the low- and high-quality portfolios is extremely high, at 165 percent and 190 percent, respectively.

Moreover, the tilt towards small-cap stocks for the high-quality portfolio implies higher costs, compared to the benchmark. Mashruwala et al. [2006] highlight these implementation issues, showing that the accrual anomaly is concentrated in firms with high idiosyncratic volatility, low price and low volume. Their results suggest that arbitrage obstacles and transaction costs may impose barriers to exploiting accrual mispricing.

IS EARNINGS QUALITY A RISK FACTOR?

Last but not least, we look at earnings quality as a risk factor. So far we have seen evidence that earnings quality passes the sniff test for an alpha factor. But does it constitute a good risk factor? A good risk factor will be important for explaining stock returns and exhibit

EXHIBIT 7

Contributions to Specific Return by Sector (December 1994 to March 2011, Deciles Rebalanced Quarterly)

	Low Quality	High Quality
Basic Materials	−0.4%	0.3%
Energy	−0.6%	0.2%
Consumer Non-Cyclicals	−0.1%	0.2%
Consumer Cyclicals	−1.3%	0.5%
Consumer Services	−0.7%	0.4%
Industrials	−0.5%	0.5%
Utility	0.0%	0.1%
Transport	−0.2%	0.0%
Health Care	−0.2%	1.6%
Technology	−1.9%	2.3%
Telecommunications	−0.5%	0.2%
Commercial Services	−1.4%	0.6%
Financials	0.1%	0.3%
Total	−7.6%	6.9%

moderate-to-high volatility over time. We refer to the literature, beginning with Rosenberg [1972] and Fama and French [1992]. Miller [2006] provides a more recent update on the topic. Thus, we first look for a risk factor to be statistically significant. Second, the factor must exhibit a certain amount of volatility. Third, the factor should be persistent over time. In the fundamental factor framework, we are therefore looking for:

- High absolute t-statistics over time
- A large number of months where the t-stat is significant (indicates the factor is persistent)
- High volatility over time

We first look at the average cross-sectional correlation of CFRA Earnings Scores to USE3 style factor exposures.[14] (Note that we include financials in this exercise, as well as in the analysis that follows, given that the Barra USE3 model contains financials.) Given the sizable contribution from stock selection we saw earlier, we do not expect earnings scores to be highly correlated with any of the existing factors. Exhibit 8 confirms this. (Keeping with intuition, the factor with which the earnings scores have the highest correlation is growth, but even here the correlation is only 0.29 over the whole period.)

Next, we add earnings quality as a factor in the US Equity risk model. We add earnings scores to the model's existing factors and rerun the multivariate regression.[15] Recall the fundamental framework, where the exposures are our known independent variables and we estimate the factor returns. If there is indeed an earnings-quality risk factor, the estimated factor in either regression should have a t-statistic greater than 2 in most months. On average over time, the factor would exhibit at least a moderate amount of volatility.

Exhibit 9 summarizes the results of the regression using the same estimation universe as Barra's US Equity risk model. We test different weighting schemes in the weighted least squares (WLS) regression. For both equal-weighting and cap-weighting schemes, the average absolute t-statistic is less than 2. The percentage of months in which the t-statistic for earnings quality was more than 2 or less than −2 is also low, ranging from 22 percent to 33 percent. Finally, the volatility of the earnings quality factor is low: 1.45 percent and 2.21 percent. For reference, the volatilities of other style factors range between 1.8 percent and 7.0 percent (see Appendix C).

We graph the factor's return and volatility over time in Exhibit 10. It was most volatile during the Internet bust in 2000 to 2002 and has since been relatively quiet.

EXHIBIT 8

Average Cross-Sectional Correlation (December 1994 to March 2011)

	1994–1999	2000–2005	2006–2010	Whole Period
Volatility	0.22	0.14	0.04	0.14
Momentum	0.01	−0.01	0.01	0.00
Size	−0.12	−0.05	−0.03	−0.06
Size Nonlinearity	−0.10	−0.05	−0.01	−0.05
Trading Activity	0.14	0.11	0.02	0.10
Growth	0.35	0.26	0.24	0.29
Earnings Yield	0.06	0.08	0.02	0.05
Value	−0.14	−0.09	0.02	−0.07
Earnings Variation	−0.12	−0.05	−0.05	−0.07
Leverage	0.08	0.06	0.01	0.05
Currency Sensitivity	0.02	0.04	0.04	0.03
Yield	−0.19	−0.07	−0.03	−0.10
Non-Estimation Universe	0.09	0.02	0.01	0.04

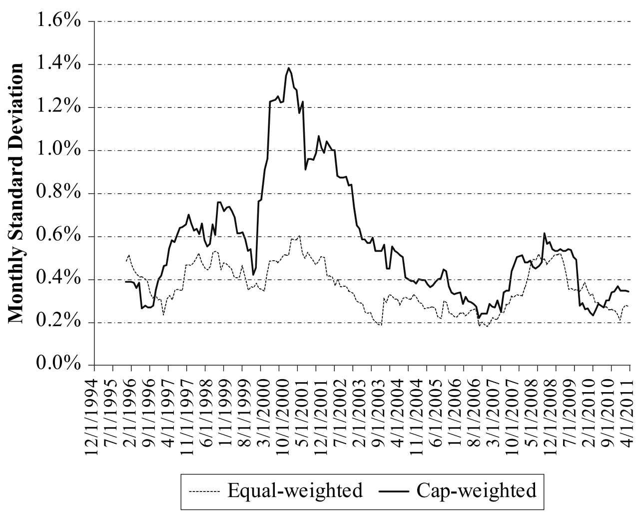
EXHIBIT 9

Is Earnings Quality a Risk Factor? Results of Cross-Sectional Multivariate Regressions (December 1994 to March 2011)

	Equal-Weighted	Cap-Weighted
Annualized return of factor	2.61%	1.87%
Annualized stdev of factor	1.45%	2.21%
Sharpe ratio	1.80	0.85
Average absolute *t*-stat over all months	1.22	1.70
% months |t| > 2	22%	33%

EXHIBIT 10

Estimated Earnings Quality Factor (Monthly Standard Deviation, December 1994 to March 2011)



CONCLUSION

The accruals anomaly has been well studied in the academic literature and often confirmed in practitioner studies. We revisit this topic using a measure of earnings quality developed by CFRA and based on the seminal accrual anomaly research by Richard Sloan and Scott Richardson. Stocks with high increases in accruals have low earnings quality, while stocks with low and decreasing accruals have high earnings quality.

We find several interesting and somewhat unexpected results. Earnings quality as a strategy stopped working in the mid-2000s, but since the end of 2008 has staged a remarkable rebound. In the periods when it worked, the strategy was largely driven by stock selection, suggesting that earnings quality is indeed an alpha signal. Furthermore, it worked very well in some sectors, in particular technology, suggesting that further research may focus on within-sector implementations of an earnings-quality strategy.

We did not consider transaction costs, nor did we try to minimize turnover when forming the decile portfolios, as we wanted to analyze the earnings-quality effect in its purest form. Considering transaction costs or managing turnover would be relevant for the actual implemetation of such a strategy, and was beyond the scope of this article.

Our tests also indicate that earnings quality is not a good risk factor, which means that earnings quality may really be that rare example of a pure-alpha factor.

APPENDIX A

PERFORMANCE OF WELL-KNOWN ALPHA SIGNALS

The factors in the Barra USE3 multi-factor model are those that best explain the cross-section of returns. They are *systematic risk factors*. As mentioned in the paper, alpha signals can lack great explanatory power for the cross-section, but still have information about future returns. We consider a set of well-known alpha signals that are part of the Barra

EXHIBIT A1

Earnings Quality and Other Alpha Signals (Decile Portfolios, December 1994 to March 2011)

	Top Decile	Bottom Decile	Top Minus Bottom Decile
Earnings Quality	18.39%	−0.01%	18%
Cash Plow Back	6.56%	18.03%	11%
Normalized E/P	8.68%	17.10%	8%
Relative Strength	6.79%	14.32%	8%
Predicted E/P	7.93%	13.98%	6%
Residual Reversal	10.46%	11.59%	1%
Neglect	11.87%	10.86%	−1%
Estimate Changes	12.37%	11.26%	−1%
Estimate Revision	12.19%	9.86%	−2%
Earnings Momentum	11.66%	9.27%	−2%
Sector Momentum	15.93%	12.88%	−3%
Dividend Discount	13.00%	9.07%	−4%

Exhibit B1

Monthly Correlation of Long-Short Earnings Quality Portfolio (High Minus Low) with Barra USE3 Model Factors (December 1994 to March 2011)

	Correlation (Whole Period)	1995–2002	2003–2008	2009–March 2011
Volatility	−0.50	−0.68	−0.25	0.24
Momentum	0.02	0.05	−0.17	0.01
Size	−0.02	−0.02	0.12	−0.26
Size-Nonlinearity	0.12	0.19	−0.29	0.26
Trading Activity	−0.27	−0.36	−0.21	0.15
Growth	−0.31	−0.36	−0.19	−0.34
Earnings Yield	0.38	0.48	−0.03	−0.12
Value	0.07	−0.02	0.27	0.11
Earnings Variability	−0.21	−0.19	−0.29	−0.28
Leverage	0.14	0.17	0.05	−0.23
Currency Sensitivity	−0.13	−0.16	0.13	−0.36
Yield	0.11	0.01	0.31	0.03
Non-Estimation Universe	−0.07	−0.02	−0.14	−0.19

Alphabuilder model. These include signals such as earnings momentum and predicted earnings-to-price ratios.

Exhibit A1 shows the performance of the high- and low-quality portfolios, relative to the top and bottom deciles for each of the signals. For consistency, we use the same universe (MSCI USA IMI Index) that we used for earnings quality. The portfolios are rebalanced quarterly on the same day as the earnings-quality portfolios. Also for consistency, financials are included here (unlike the results in the main article), as we do not want to exclude them from the other signals.

Over the period in question, the high-quality portfolio outperformed all other decile portfolios. More striking is the spread between high- and low-quality portfolios, which is far higher than any of the other spreads.

Appendix B

CORRELATIONS WITH BARRA USE3 FACTORS

Exhibit B1 shows the correlation of the returns from the long/short quality-tilted strategy (high-quality portfolio minus low-quality portfolio) with the risk factor returns in the USE3 model. Note that the quality portfolio is not factor neutral, unlike the USE3 factors, which are factor neutral by construction.

Appendix C

ADDITIONAL REGRESSION OUTPUT

Exhibit C1 shows statistics similar to those shown in Exhibit 10 for all factors included in the regression (all USE3 factors except size nonlinearity). We show the results for the equally weighted regression. Additional results for other weighting schemes are available upon request.

Exhibit C1

Summary of Regression Output (Cross-Sectional Multivariate Regressions, December 1994 to March 2011)

	Annualized Return of Factor	Annualized Standard Deviation Factor	Sharpe	Average Absolute *t*-Stat Over All Months
Volatility	1.9%	7.0%	0.27	2.9
Momentum	−0.6%	5.8%	−0.11	2.9
Size	−1.5%	3.4%	−0.43	2.0
Trading Activity	0.2%	2.8%	0.07	1.6
Growth	−0.2%	1.8%	−0.11	1.2
Earnings Yield	2.5%	3.5%	0.71	1.9
Value	0.8%	2.2%	0.37	1.4
Earnings Variability	−0.8%	2.1%	−0.38	1.2
Leverage	0.7%	2.3%	0.28	1.5
Currency Sensitivity	0.1%	1.9%	0.04	1.4
Yield	−0.5%	2.0%	−0.27	1.1

ENDNOTES

[1]Styles include stock characteristics that explain commonalities across equities. For example, size, value, and momentum are characteristics that explain significant parts of portfolio performance.

[2]Specifically, accruals in the earnings literature are typically defined as operating income (after depreciation) minus operating cash flows. Debt in current liabilities is typically excluded, because it relates to financing transactions as opposed to operating transactions. Income taxes payable is also typically excluded.

[3]Researchers have found that higher accruals tend to be related to slower customer payment collection; slower inventory movement, relative to production or inventory orders; lower recognition of estimated provisions; increased capitalization of operating costs as "other current assets;" and increased capitalization of investment activities.

[4]For instance, accounts receivable and intangible assets are generally measured with more uncertainty than categories such as marketable securities and short-term debt.

[5]The methodology was first developed by Criterion, LLC, with input by Scott Richardson more than a decade ago.

[6]Because accruals naturally occur for growing firms, a high level of accruals may not be a major concern. The adjustment is made to differentiate cases where high accruals are less of a concern and cases where earnings manipulations are more likely to be behind the high accrual levels.

[7]Monthly scores are also available, beginning in January 2005.

[8]Earnings scores are available monthly, beginning in January 2005. Prior to that, they were made available quarterly on February 5, May 5, August 5, and November 5. Note that we exclude financials from our universe, though they are covered by CFRA, because the demarcation between operating and financing activities is not clear in these firms. This follows Sloan's [1996] original research.

[9]In the Barra multi-factor model framework, the exposures (or betas) are pre-specified, while the factors themselves are cross-sectionally estimated. Bender and Nielsen [2012] provide an overview of the model. In contrast, in the Fama and French [1993] approach, portfolios are constructed that reflect these characteristics and the betas are estimated via time-series regressions.

[10]Additional detail on the mapping of names is available upon request.

[11]Market-cap weighting the deciles produces qualitatively similar results, which are available upon request.

[12]Barra sectors are shown here, the default sector scheme in Aegis Performance Analyst.

[13]Additional results are available upon request.

[14]We reverse the sign on the earnings scores, to make this a measure of earnings quality.

[15]We exclude size nonlinearity in this regression for parsimony; qualitatively, the results with the factor included are minimally different. The non-estimation universe factor is not an independent variable to begin with. Therefore, there are 67 factors in the model we are testing. We use the same estimation universe as in USE3. The estimation universe in the USE3 model is comprised of the largest 1,500 U.S. stocks, plus smaller stocks that are added to ensure an adequate basis for estimating industry returns. Stocks with prices of less than $5 are usually excluded, but S&P 500 members are always included. Timely fundamental data must be available and turnover is limited by grandfathering rules. The resulting universe contains approximately 2,000 names, relatively similar to the MSCI USA IMI Index constituents on which we based our earlier analysis. We remove outlier earnings scores at more than 10 and less than -10. We standardize the earnings scores and truncate the resulting exposures to 5 and -5. This is similar to what is done in the USE3 model.

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