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Avoid Value Traps using Quantitative Nowcasting Techniques

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Value Signals have a Time Mismatch

In this research report, we develop a new technique to improve the performance of value or "1/P" strategies. We show that the time mismatch generates value traps or situations when low prices are matched with high fundamentals that do not incorporate recent information. Our analysis suggests the potential for value traps to impact valuation measures is large: the average time lag is three months between when a monthly portfolio is rebalanced and firms' fiscal period ends.

What is Nowcasting and how can it be applied to Stock Selection?

Perfect foresight value signals (non-tradable) that use future fundamentals considerably out-performs the standard 1/P signals. Using 45 different variables, we estimate future fundamental values utilizing a machine learning lasso technique. As we show, our nowcasting model has high predictive power, with R^2 that are as high as 0.9 for estimating certain fundamentals.

Why does Value Nowcasting work?

We find that our nowcasting measures that use forecasted fundamentals in place of current lagged fundamentals generate a **28% - 31% improvement in value composite strategy Sharpe ratios**. Even after controlling for systematic factor exposures such as forward analyst forecasts, we find meaningful enhancements in risk-adjusted performance. Our results suggest that taking a structural approach to estimating future fundamentals used for constructing value metrics helps resolve the lack of timeliness of past fundamental data.

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Letter to Our Readers

The concept of value investing can be traced back to Graham and Dodd, who popularized the concept in their 1934 book titled Security Analysis. In that text, they suggest public securities that trade at discounts to book value, have high dividend yields, low price-to-earnings and price-to-sales multiples have higher expected returns. Since then, certain academic research starting with Fama and French (1992, 1993) and Lakonishok, Shleifer and Vishny (1994) find evidence that relative price strategies that scale various fundamentals by price explain the cross-section of average returns. Since the publication of these articles and many that have followed, we find evidence that value investing influences fundamental investing, traditional quantitative alpha models, risk models and long-only smart beta investment products.

In this paper, we extend the literature on value investing by highlighting the time mismatch between prices which are measured in real-time and fundamentals which are measured with a considerable lag. Our findings compliment and provide a solution to Kok, Ribando and Sloan (2017) who suggest that value strategies systematically identify companies with temporarily inflated accounting numbers by adjusting fundamentals in real-time. Additionally, our work builds on Asness and Frazzini (2013) who find more robust value premiums when using current price to estimate HML (Fama/French value factor) instead of lagged price as of December-end. Specifically, the fundamental forecasting model that we design builds on our and other researchers' previous works (See for example Deutsche Bank research by Jussa et al (2011), and academic work by So (2013) and Fama and French (2000)) by incorporating new quantitative insights and leveraging more sophisticated forecasting techniques, i.e. machine learning.

Nowcasting involves forecasting of near and future quantities that cannot be measured accurately in real-time. The majority of nowcasting techniques involves using statistical models to explain macro fundamentals. We extend this analysis to estimating firm-specific information.

The results we present indicate that scaling expected future fundamentals by price improves risk-adjusted returns associated with a generic strategy based traditional value metrics. Our findings suggest that investors can capture the value premium and avoid value traps (stocks with low multiples due to an expectation of future fundamental deterioration) as an alternative solution to that provided by Fisher, Shah and Titman (2016) who suggest the use of momentum to avoid purchases of stocks with declining prices or Novy-Marx (2013) who advises on conditioning on profitability to refine a value strategy. Our results contrast other work that tries to project financial ratios as we focus on not forecasting the price which can already be measured accurately in real-time.

We are happy to speak at length about our empirical findings and opinions – for those that want more details or clarity on our analysis, please do not hesitate to reach out to set-up a meeting in-person, over the phone. You can reach a member of the team by contacting DBEQS.AMERICAS@DB.com or reaching out to your Deutsche Bank sales contact.

Regards,

Ronnie, Steve, George, David, Alex and the global quant team

Deutsche Bank Quantitative Strategy

Dimensions of Value

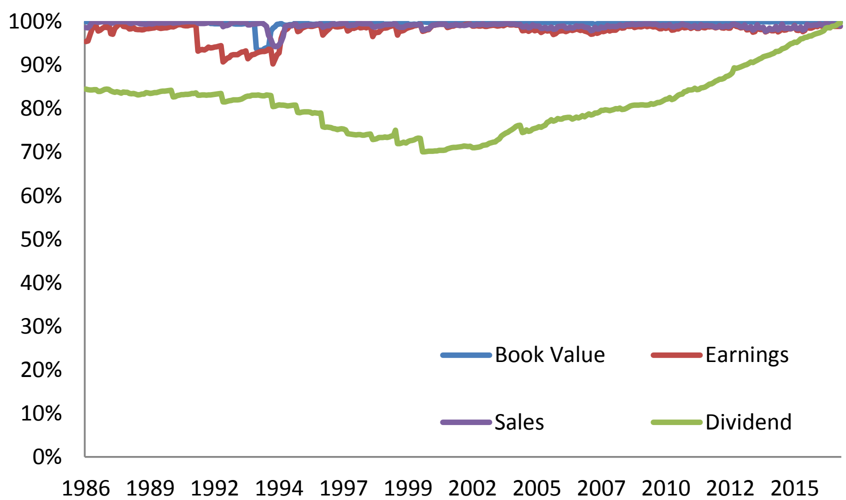
A high level review of traditional value strategies

Typical value metrics scale a variety of fundamentals such as book equity, earnings, sales and dividends by price. High fundamental-to-price metrics imply a firm is value-oriented, while lower ratios dictate a growth-orientation. There are various explanations provided by academic literature why price-scaled strategies explain differences in average returns. Fama and French (1992, 1993) suggest value stocks are riskier than growth stocks and therefore have higher expected returns. Lakonishok, Shleifer and Vishny (1995) in contrast hold the view that investors make mistakes when assigning earnings and sales expectations for growth stocks which lead to their under-performance relative to value stocks.

The time-mismatch involves information differences between prices and fundamentals.

Our focus for this paper is not the theoretical underpinning explanations for why value strategies work but rather how to think about identifying relevant fundamental information when scaling by price. Specifically, we explore how time mismatches cause differences between real-time prices and lagged fundamentals. In this section, we explore and evaluate the performance of certain factor construction decisions when designing value factor strategies.

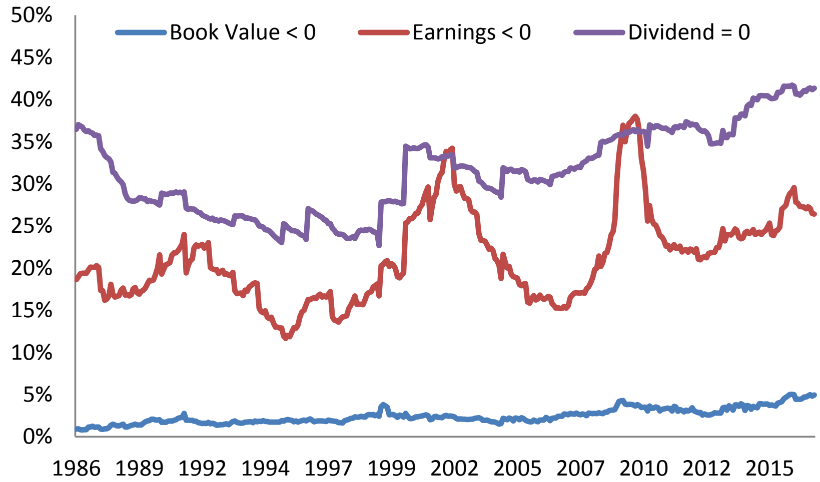
Figure 1: Data Item Coverage for Russell 3000 Firms



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

Figure 1 displays the number of firms with non-missing fundamentals including Book Equity B, Earnings E, Sales S and Dividends D for Russell 3000 firms from December 1986 to March 2017. As we show, non-dividend fundamental coverage is high, exceeding 90% over the sample period. Dividend information is far less prevalent – as approximately 20% of the firms in our sample do not report whether or not they issue a dividend.

Figure 2: % of Russell 3000 with Zero Dividends, Negative Book Equity and Negative Earnings

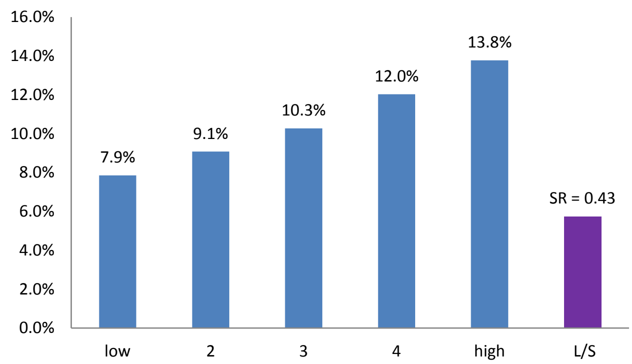


Source: Deutsche Bank Quantitative Strategy, Thomson Reuters, Compustat, IBES, Russell

When forming price-scaled value factors, one consideration is how to treat negative or zero fundamental values which is an issue for signals that use book equity, earnings and dividends information. For earnings, a firm that has negative earnings in perpetuity should have a market value of zero. Firms with negative book equity generally have had losses in previous years. Given these challenges, in our analysis that follows we exclude those firms that have negative book equity, negative earnings or have zero dividends. These exclusions reduce the breadth of the strategies we consider as displayed in Figure 2. As we show, 32.0% of stocks in our sample do not pay dividends, 21.0% have negative earnings and 2.5% have negative book values.

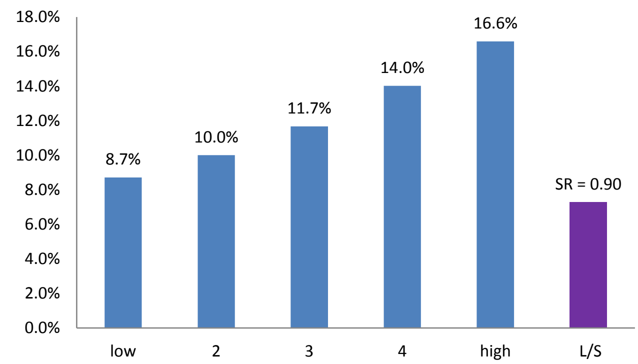
We start our main analysis in this section by sorting Russell 3000 stocks into five equal groups based on different fundamental-to-price ratios: Book-to-Price (B/P), Sales-to-Price (S/P), Earnings-to-Price (E/P). Given the high proportion of firms in our sample that report zero dividends for dividend-to-price metrics we report zero dividends separately and then sort the remaining dividend-paying stocks into four equal groups. For each of the price-scaled variables, we sector neutralize cross-sectionally by subtracting each ratio by the mean of all ratios in the same GICs sector and divide by the standard deviation of the ratios from same grouping of firms. This procedure removes any sector bias associated with the different value signals we consider, which enables us to focus on the predictive power for explaining returns within stocks from the same sector. Due to data limitations particularly analyst estimates for variables we use in our forecasting model, our analysis begins in April 1996 and ends in March 2017.

Figure 3: Returns for portfolios formed on B/P



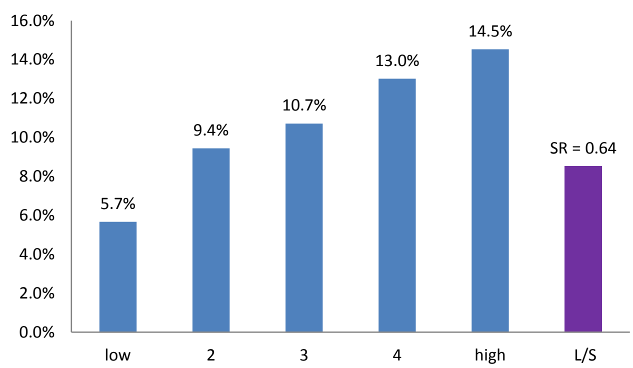
Source: Deutsche Bank Quantitative Strategy, Thomson Reuters, Compustat, IBES, Russell

Figure 4: Returns for portfolios formed on E/P



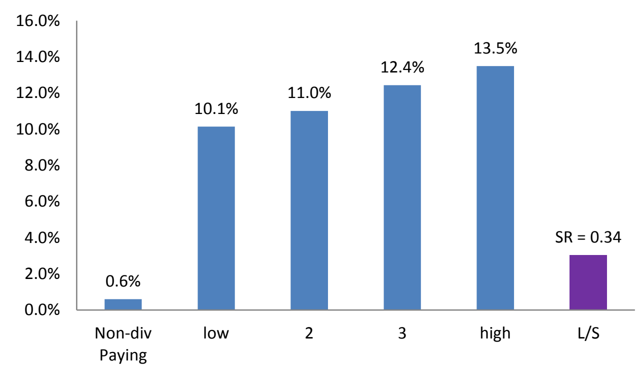
Source: Deutsche Bank Quantitative Strategy, Thomson Reuters, Compustat, IBES, Russell

Figure 5: Returns for portfolios formed on S/P



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

Figure 6: Returns for portfolios formed on D/P



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

Figure 3 through Figure 6 report equal-weighted annualized buy-and-hold returns for each of the different portfolios formed on different price-scaled variables. As we show, for all the different value constructs we consider, the returns are monotonic: the first quintile has the lowest returns, followed by the next quintile and the fifth quintile with the highest fundamental-to-price scores has the highest returns. We also find abysmal returns for non-dividend paying firms and lower returns for firms with negative earnings (not reported).

Consistent with academic literature, we find that high fundamental-to-price firms tend to have higher returns when compared to low fundamental-to-price firms.

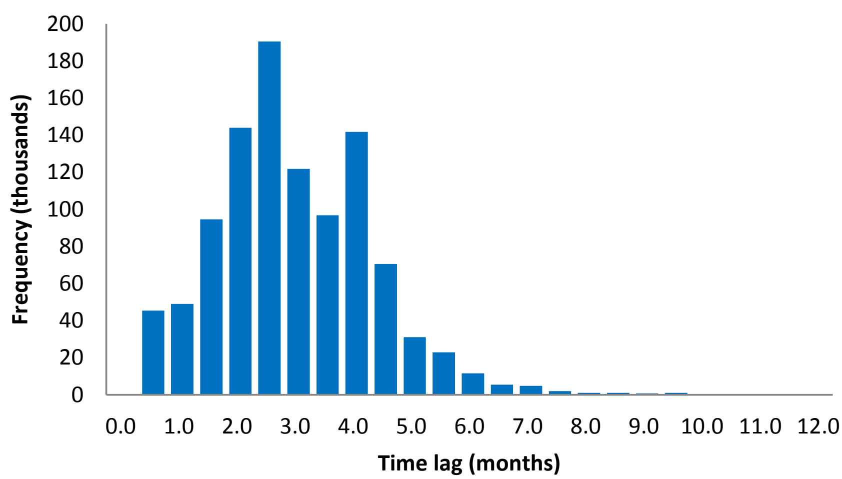
There is variation in each factor's ability to explain cross-sectional return dispersion. For each factor, we form long/short portfolios by taking long positions in those stocks with the highest fundamental-to-price ratios (top 20%, right-most bar on each graph) and short positions in those stocks with the lowest fundamental-to-price ratios (bottom 20%, left-most bar on each graph). Long/ short portfolios formed on backward-looking fundamental information – B/P, E/P, S/P and D/P generate average annualized returns of 5.7%, 7.3%, 8.5% and 3.0% respectively.

Stale Valuations

Evaluating timeliness of fundamental information

Existing empirical work has focused on how to best capture the value premium by evaluating decisions such as the appropriate fundamental for scaling price. This is however not the only problem when deciding how to build a value strategy. In this article, we highlight another challenge associated with the time mismatch between fundamental and price for value strategies. In the United States, firms report financial statement data on a quarterly basis. After the fiscal period ends, company accountants are responsible for calculating different balance statements, income statements, cash flow statements and shareholder's equity information. After the auditors sign off on the accounting analysis, financial statement data is reported on a company's 10-Q which then can be processed by various data providers. This process of creating financial statement information produces a reporting lag.

Figure 7: Histogram of Time Lag (in Months) Between Fiscal Period End Date and First Available Database Reported Date

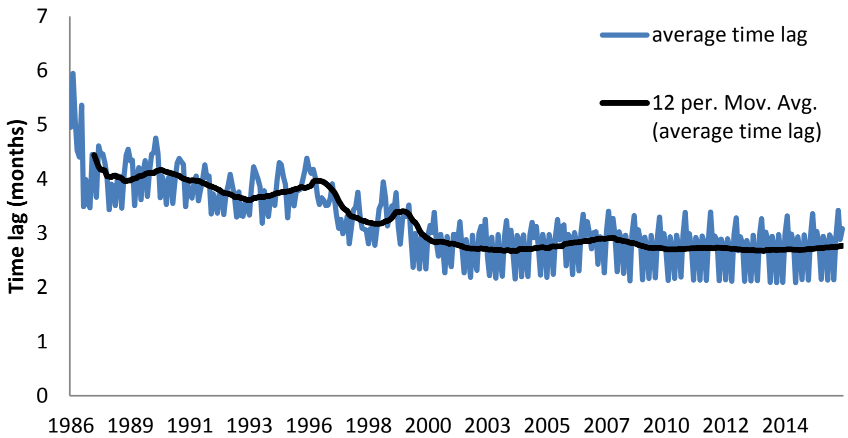


Source: Deutsche Bank Quantitative Strategy, Thomson Reuters, Compustat, IBES, Russell

We estimate an average lag of three months from when a fiscal period ends and financial statement is available in financial databases.

Our analysis uses Compustat point-in-time data, which captures the date that the financial data is first available to the public. There is considerable variation in how quickly a firm reports financial statement information following the end of their fiscal period. Figure 7 illustrates a histogram of this time lag caused by reporting delays using 1,037,132 firm-month observations from the period December 1986 to March 2017. The lag comes from two components: (i) the time difference from when a firm reports and when this information enters into the point-in-time database and (ii) the additional time associated with waiting for the next update (i.e. months two and three following a monthly rebalance using quarterly data). As we show, the median reporting lag is 3 months. For 25% of our sample, the reporting lag exceeds 4 months.

Figure 8: Average Reporting Lag by Year



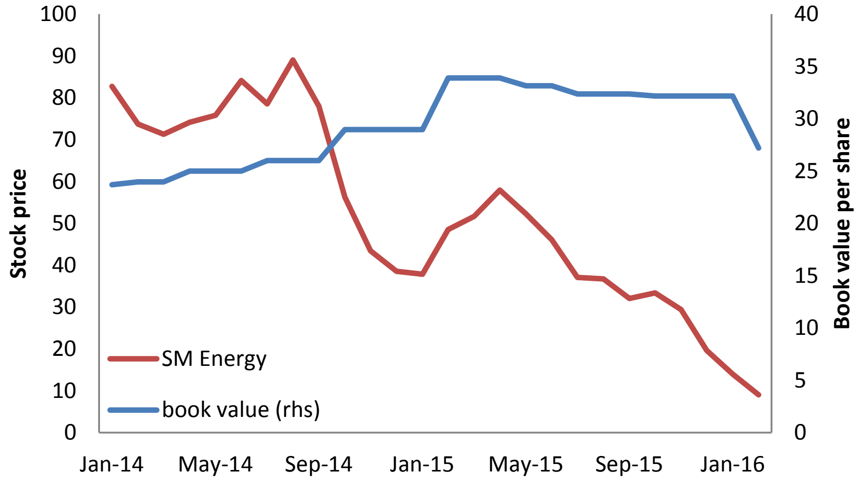
Source: Deutsche Bank Quantitative Strategy, Thomson Reuters, Compustat, IBES, Russell

Figure 8 displays the average reporting lag for Russell 3000 firms from 1986 to 2017. Over time, our analysis shows that the reporting lag has decreased from over 4 months to 2.7 months potentially due to the passage of Sarbanes-Oxley Act in 2002 and more efficient auditing practices. Despite the improvement, the time lag still causes problems when certain corporate actions and market conditions have adverse effects on fundamentals and prices.

SM Energy Case Study

To motivate how reporting lags cause mismatches between stock prices and fundamentals, we examine SM Energy (NYSE Ticker: SM) over the period January 2014 to February 2016. SM Energy is an exploration and production independent energy company whose operations are concentrated in South Texas, Gulf Coast, Rocky Mountain and Permian regions. They also are involved in shale drilling, a particular speculative activity with higher production costs when compared to more traditional means of oil drilling. The nature of their business causes their profits to be highly correlated with changes in oil prices. SM Energy's fiscal year-end date is December 31, and financial statement data is usually available by mid-February of the following year.

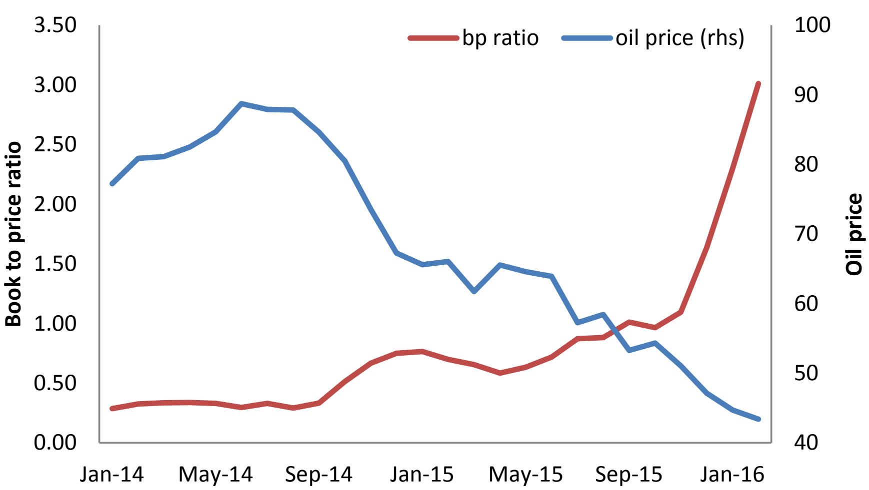
Figure 9: SM Energy and reported Book Equity from January 2014 to February 2016



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

Figure 9 displays for SM energy the stock price (red line) and the book value (blue line) recorded using point-in-time data used to construct book-to-market. Initially, even though the oil price is falling after June 2014, we find increases in book values associated with high retained earnings from earlier in 2014 when oil prices were high. As we show in Figure 10, the large decline in SM Energy's stock price coupled with the increase in book equity between August 2014 and January 2015 causes the book-to-market ratio to rise from 0.29 (January 2014) to 0.77 (January 2015). Despite the rise in book-to-market ratio, the stock declined by 63% in the subsequent period from January 31, 2015 to January 31, 2016. The book value finally starts to reflect the lower profitability associated with lower oil prices in the 2015 10-K.

Figure 10: SM Energy Book/Price ratio and Oil Price from January 2014 to February 2016



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

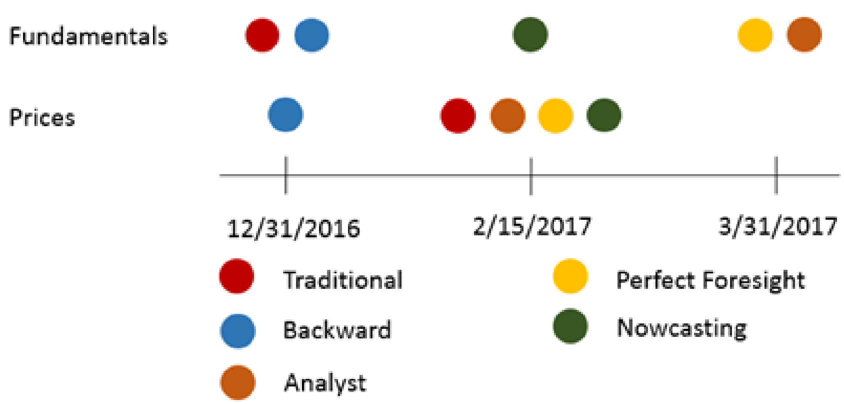
Figure 10 shows that SM Energy's stock return is highly positively correlated with contemporaneous changes in oil prices (Oil Beta = 1.74). In the middle of 2014, oil prices started to decline potentially due to significant increases in oil production in the US and declining demand in emerging countries. The reduction in price had implications for how SM Energy values exploration and production assets on its balance sheet. The value trap we identify involves the fundamental not accurately reflecting current business conditions, even though this information is clearly explained elsewhere in the financial statements. As we show in the Appendix A, the lower energy prices portend declines in earnings and book values through asset impairments that are largely predictable beforehand.

Backward and Analyst Value

We examine various ways to solve the value trap problem associated with mis-matches in information between fundamentals and price.

Our previous analysis suggests that stale and inaccurate fundamentals can lead to value traps, or purchases (sales) of securities whose prices are too low (high) relative to fundamentals due the latter not appropriately reflecting current information. In this section, we examine potential solutions to correct for the time lag between price and fundamental.

Figure 11: Illustration of Different Value Constructs



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

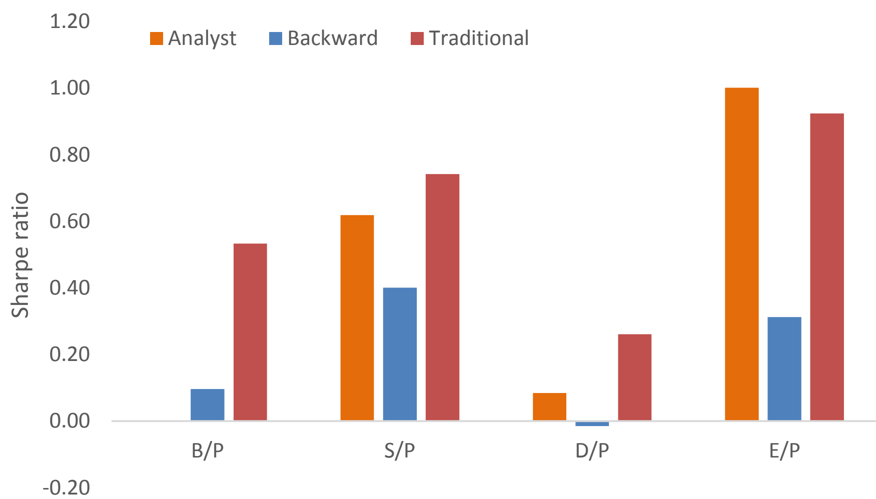
Figure 11 illustrates five different options for constructing value insights. The top five circles reflect the timing of the fundamental (when the fundamental is estimated), while the bottom circles display the timing of the price. In our example, assuming today's date is 2/15/2017, the traditional value signals are formed by dividing the fundamentals dated as of 12/31/2016 by today's prices. For example, traditional (red) value metrics will use current price as of mid-February and historical fundamentals estimated at fiscal period end date as of end of December of the previous year. For each of the different constructs, we evaluate risk-adjusted performance by sorting stocks into five groups within each industry and reporting annualized Sharpe ratios of strategies that go long an equal-weighted portfolio of stocks in the highest quintile of fundamental-to-price ratios and short stocks in the lowest quintile. Our sample period for most tests unless otherwise noted is from November 1990 to March 2017. Our analysis, applies sector neutralization and exclude non-dividend paying stocks for D/P, stocks with negative earnings for E/P and stocks with negative book value for B/P.

One potential solution involves using the historical price at the end of the most recent calendar quarter. The main advantage of this approach involves using prices that reflect all available information when the fundamental is estimated; the disadvantage of this approach is throwing away information in price movements between the fiscal period-end date and today's date.

Another solution involves using consensus sell-side analyst forecasts scaled by price. There are a few challenges with using this approach to avoid value traps.

First, the analyst estimates might incorporate other behavioral biases. Second, analyst estimates might be stale as they are also updated periodically. Third, analyst variables often have much lower universe coverage, particularly among small capitalization securities.

Figure 12: Sharpe Ratios for Backward, Analyst and Traditional Value Metrics



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

Figure 12 reports annualized Sharpe ratios for strategies based on backward (using old price estimated at the end of the fiscal period), analyst (consensus sell-side forecasts) and traditional (using current price) value strategies[1]. Our results for backward value are slightly puzzling and disappointing – backward value metrics have very poor performance when compared to traditional constructs potentially due to disregarding information in current prices. For E/P we find that analyst forecasts are superior to traditional E/P metrics; for S/P and D/P we find better performance using traditional constructs.

1 We drop the B/P ratio by analysts' forecasted book value per share due to poor data coverage.

Perfect Foresight Value

Return to Figure 11, we examine non-investible, perfect foresight value metrics (yellow dots) that use actual future fundamentals scaled by today's price. Specifically, Figure 13 reports Sharpe ratios from long/short quintile portfolios formed on different value metrics that use today's price and future fundamentals (t+0 = current fundamental, t+n = fundamental value estimated n quarter(s) into the future). As we show, there are large gains when scaling current price with future fundamentals which only increases with the forecast horizon. For example, the Sharpe ratio of B/P is four time larger when using the book equity from one year from now.

Figure 13: Sharpe ratios for Perfect Foresight Value Estimated using Different Future Intervals

	t+0	t+1	t+2	t+3	t+4
B/P	0.53	0.87	1.43	1.95	2.24
S/P	0.76	0.96	1.10	1.29	1.43
D/P	0.28	0.44	0.66	0.75	1.04
E/P	0.94	3.75	5.47	6.38	6.60

Time window (quarters)

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

The largest improvement in Sharpe ratios is for E/P which increases from 0.94 to 6.60 when replacing the current trailing twelve month earnings with twelve month earnings estimated 1 year from now. This is not surprising, given the correlation between contemporaneous earnings and stock returns. The perfect foresight results provide us with an "upper bound" of what is possible and provide motivation for constructing predictive models to forecast future fundamentals.

Predicting Future Fundamentals

The main advantage of LASSO involves variable selection, or choosing a parsimonious set of covariates that explains the dependent variable.

In this section, we describe how we use LASSO (least absolute shrinkage and selection operator), a machine learning algorithm to identify relevant parameters for forecasting fundamentals. This procedure was first introduced by Tibshirani (1996). One challenge associated with using ordinary least squares (OLS) regressions to estimate relationships between variables is multi-collinearity, of the inclusion of correlated variables that compete in a regression to explain variation in the dependent variable. A penalized regression creates a prioritization to reduce the set of possible explanatory variables and produce robust, stable and potentially more interpretable forecasts.

In OLS coefficients are estimated using the following equation:

$$\hat{\beta}^{ols} = \arg\min_{\beta}\{\sum_{i=1}^{N}(y_i - \beta_0 - \sum_{j=1}^{p} x_{ij}\beta_j)^2\}$$

Where y is the dependent variable, x_i is the independent variable and Beta$_i$ reflects the coefficient estimate for each independent variable. A LASSO penalized regression imposes a regularization term which shrinks coefficients toward zero:

$$\hat{\beta}^{lasso} = \arg\min_{\beta}\{\sum_{i=1}^{N}(y_i - \beta_0 - \sum_{j=1}^{p} x_{ij}\beta_j)^2 + \lambda\sum_{j=1}^{p}|\beta_j|\}$$

The absolute value term in the above equation effectively forces certain coefficients to be set to zero, and the resulting model is much more parsimonious solution to the problem of multiple covariates than a step-wise regression. Another potential solution is a ridge regression which involves a squared Beta penalty term instead of an absolute value term. Since ridge regression only shrinks the size of the coefficients but does not enforce them to be zero, the trained model may include irrelevant features. In contrast, LASSO regression is more appealing as it performs both variable selection and shrinkage simultaneously. To avoid forward-looking bias, we estimate a rolling LASSO regression using trailing 36 months of cross-sectional data to estimate the future fundamental. The decision to use a rolling regression also allows the possibility for the predictors to vary across time and vary across the fundamental we are trying to predict.

Figure 14: Different Quantitative Factors used to Predict Future Fundamentals

No.	Factor Name	Factor Description	Factor Category
1	SAL_TA	Trailing 12M Sales /Assets	Fundamental
2	BV_TA	Book Value /Assets	Fundamental
3	E_T12MOB_TA	Trailing 12M Earnings /Assets	Fundamental
4	D_T12MOB_TA	Trailing 12M Dividends /Assets	Fundamental
5	CAPEX_TA_12M	Trailing 12M Capex /Assets	Fundamental
6	E_TA_FY0	FY0 Earnings/ Assets	Fundamental
7	E_TA_FY1	Forecast FY1 Earnings /Assets	Analyst Forecast
8	E_TA_FY2	Forecast FY2 Earnings /Assets	Analyst Forecast
9	SAL_TA_FY1	Forecast FY1 Sales /Assets	Analyst Forecast
10	SAL_TA_FY2	Forecast FY2 Sales /Assets	Analyst Forecast
11	D_TA_FY1	FY1 Dividend /Assets	Analyst Forecast
12	D_TA_FY2	FY2 Dividend /Assets	Analyst Forecast
13	IB0_FY1_EPS_UPDN1M	IBES FY1 EPS up/down ratio, 1M	Analyst Forecast
14	IB0_FY1_EPS_UPDN3M	IBES FY1 EPS up/down ratio, 3M	Analyst Forecast
15	IBA0_FY1_EPS_R1AVG	IBES FY1 Mean EPS Revision, 1M	Analyst Forecast
16	IBA0_FY1_EPS_R3AVG	IBES FY1 Mean EPS Revision, 3M	Analyst Forecast
17	IBA0_LTG_REV1M_AVG	IBES LTG Mean EPS Revision, 1M	Analyst Forecast
18	IBA0_LTG_REV3M_AVG	IBES LTG Mean EPS Revision, 3M	Analyst Forecast
19	IBA0_FY1_SAL_R3AVG	IBES FY1 Mean SAL Revision, 3M	Analyst Forecast
20	IBA0_PTG_RTN	Target price implied return	Analyst Forecast
21	IBA0_REC_AVG	Recommendation, mean	Analyst Forecast
22	IBA0_REC_R3AVG	Mean recommendation revision, 3M	Analyst Forecast
23	IBA0_FY1_EPS_DISP	IBES FY1 EPS dispersion	Analyst Forecast
24	IB0_FY1_AVG_EPS_G	IBES FY1 mean EPS growth	Analyst Forecast
25	IBA0_FY2_AVG_DPS_G	IBES FY2 mean DPS growth	Analyst Forecast
26	IB0_SUE	IBES standard unexpected earnings (SUE)	Analyst Forecast
27	IBA0_FY1_EPS_R6MDN	IBES FY1 Median EPS Revision, 6M	Analyst Forecast
28	RTN12_1M	12M-1M total return	Technical
29	RTN1260D	Total return, 1260D (60M)	Technical
30	RTN21D	Total return, 21D (1M)	Technical
31	REAL_VOL_1YD	Realized vol, 1Y daily	Technical
32	ABNORMAL_VOL	Normalized abnormal volume	Technical
33	ALTMAN	Altman's z-score	Other
34	SHORT_COV	# of days to cover short	Other
35	PAYOUT_OEPS	Payout on trailing operating EPS	Other
36	CHG_DEBT	YoY change in debt outstanding	Other
37	SHORT_FLOAT	Short interest/float	Other
38	FLOAT_TO_1M	Float turnover, 1M	Other
39	ACCR	Accruals (Sloan 1996 def)	Other
40	CHG_SHARES	YoY change in # of shares outstanding	Other
41	YOY_EPS_G	Year-over-year quarterly EPS growth	Other
42	CAPEX_DEP_12M	Capex to Dep	Other
43	PERC_LOSS	Percentage of loss quarters	Other
44	SI_TA	Special items/lagged total assets	Other
45	PIOTROSKI	Piotroski's F-score	Other

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

Figure 14 reports the independent variables used in the lasso regression, which are mainly fundamental, analysts' forecasts, and technical factors. For fundamental variables, we scale by total assets instead of prices to avoid confounding our analysis with information from current prices. We do however include momentum and reversal variables – excluding these variables have small effects on our final results.

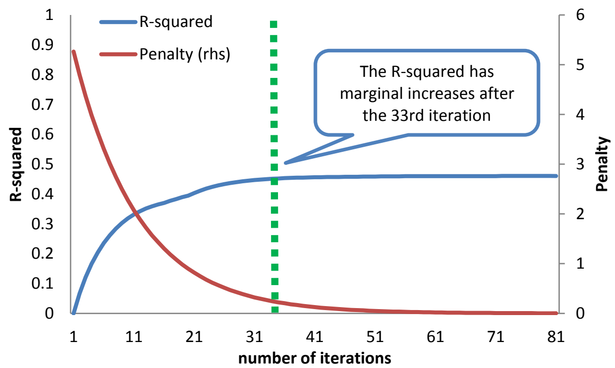
Many academic papers (see for example O'Brien, et al [1988]) find analyst forecasts are influential when predicting future fundamentals. Burgstahler, et al [2006] suggests that firms intentionally manage to just meet or beat analysts' forecasts. For technical factors like momentum and volatility, our colleagues (see Lai, et al [2017]) have shown that these variables are robust predictors of future earnings. The other related factors quantify various key aspects of company's prospects such as earnings quality, earnings growth, short interest and solvency risk.

As we reduce the penalty (Lambda), more variables enter into the model and the explanatory power increases.

The most important element of LASSO regression is the level of penalty, which dictates how many regressors can enter the model. As the penalty goes to zero, the LASSO regression results converge to that of ordinary least squares. The

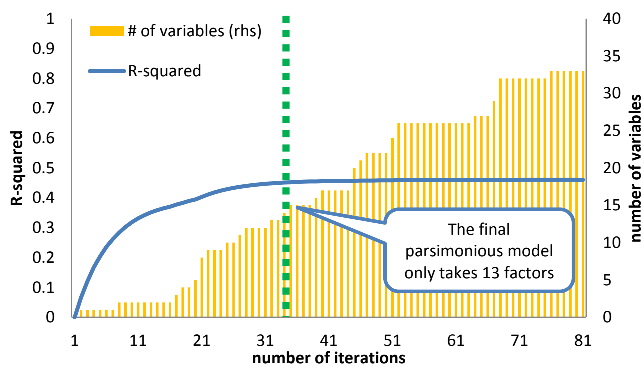
LASSO training process starts initially with an extremely large penalty, which causes the model coefficients and explanatory power to go to zero. At each iteration, we slightly reduce the degree of penalty and improve the model's explanatory power and allow for more variables to enter into the model. This repetitive process stops when we reach an optimal degree of penalty (defined as when the increase in r-squared is lower than a user defined threshold) that yields a relatively parsimonious model with favorable explanatory power.

Figure 15: R-squared and Penalty associated with LASSO regression model iterations predicting 1-year ahead future earnings



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

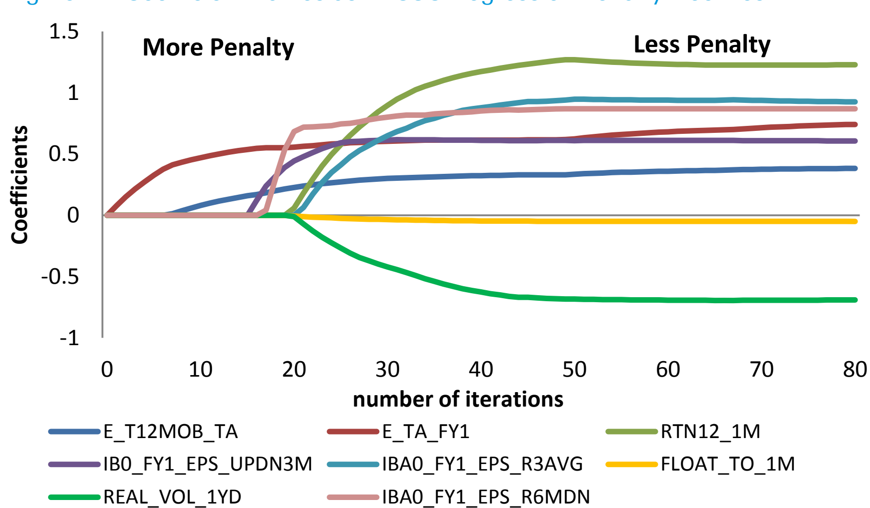
Figure 16: R-squared and Number of Variables associated with LASSO regression model iterations predicting 1-year ahead future earnings



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

Figure 15 and Figure 16 report results from a LASSO regression model that predicts one-year future earnings. For this specific model, the R-squared has only marginal improvements after the 33rd iteration which corresponds to 13 identified factors.

Figure 17: Coefficient Values as LASSO Regression Penalty Declines



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

We look under the hood to examine which variables are favored by the model. Figure 17 reports coefficient values that describe the relationship between the size of the coefficients and the degree of LASSO regression penalty. As the penalty declines (moving from left to right), more variables enter into the regression and the coefficient values increase.

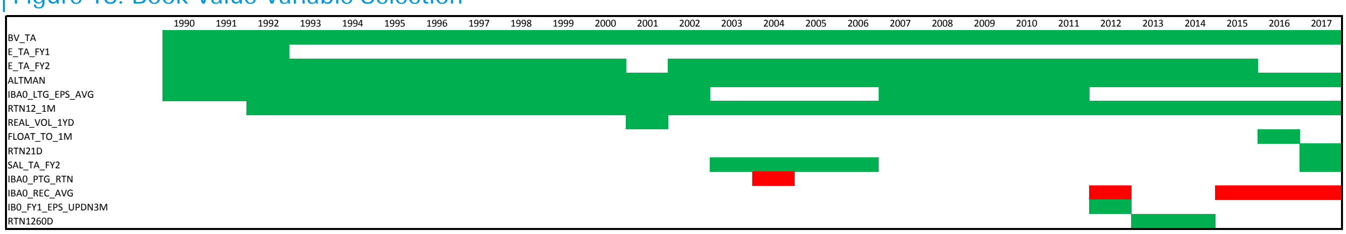
As we show, the first eight factors emerge from the model are primarily earnings-related factors, such as Forecast FY1 Earnings and the Trailing 12M Earnings. The positive signs of earnings-related coefficients advocate assigning higher earnings forecasts to firms that have higher past earnings, analysts' earnings projections and analysts' earnings revisions. Similar to the findings in Javed et al (2011), we also find that stocks with lower volatility, higher momentum and lower turnover are associated with higher earnings.

One advantage of LASSO regression relative to OLS regressions is the ability to select from factors that are highly correlated. The step-wise nature of this model allows for selection of factors that are unique (among those that are correlated), which improves model interpretability. The disadvantage of this approach is greater level of complexity and arbitrary assignment of when to stop adding factors to the model.

Figure 18 to Figure 21 display the first five factors selected by LASSO regression model trained on 1-year forward book values, sales, earnings and dividends scaled by assets. Green shaded regions represent positive coefficients, red shaded regions signify negative coefficients and white shaded regions reflect zero coefficients. The main advantage of our approach is that we allow variables to enter and exit the regression depending on which predictor explains the variation in future fundamentals scaled by assets for each point-in-time. Thus, we account for the dynamic nature of financial markets by changing our model over time. As we show, there are often 13-15 variables who enter and exit the top five regressors over time.

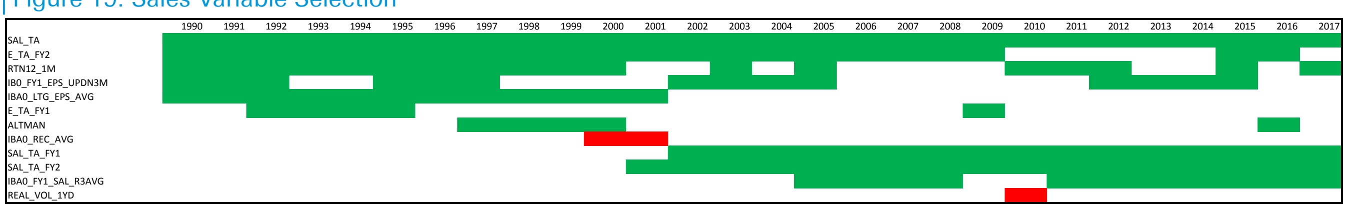
One of the main advantages of our approach involves the dynamic nature of how we select variables for forecasting fundamentals – different variables are used to predict fundamentals at different points-in-time.

Figure 18: Book Value Variable Selection



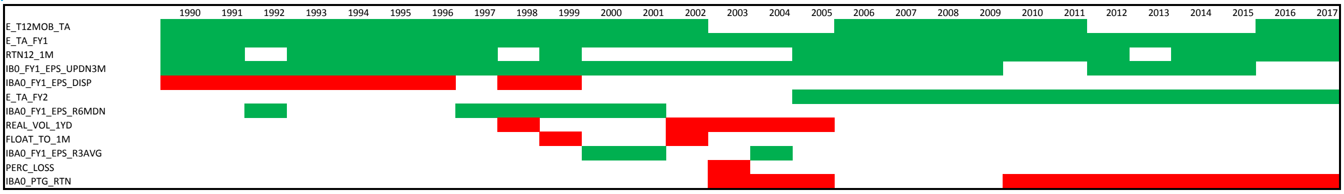
Source: Deutsche Bank Quantitative Strategy, Thomson Reuters, Compustat, IBES, Russell

Figure 19: Sales Variable Selection



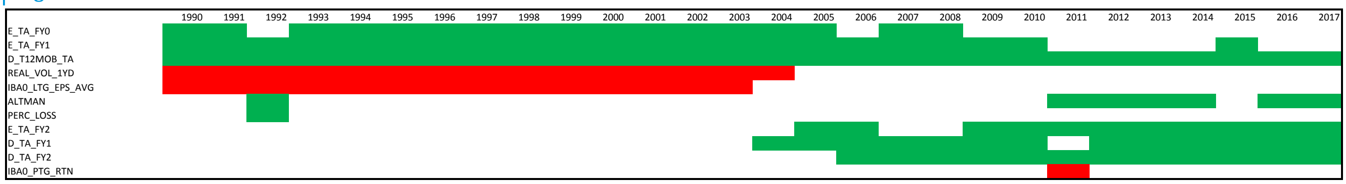
Source: Deutsche Bank Quantitative Strategy, Thomson Reuters, Compustat, IBES, Russell

Figure 20: Earnings Variable Selection



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

Figure 21: Dividends Variable Selection



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

For regressions that predict future book value; book value, earnings forecasts, momentum and Altman Z-score are often present. Interestingly, Altman Z-score, which measures default risk, explains the cross-section of future book value in all periods. For regressions that explain future sales, old sales, earnings forecasts and momentum are prominent factors, especially in earlier years.

Figure 20 shows that earnings and analysts' earnings forecasts predict variation in future earnings. Kerl, A et al [2011] and Bonini, S et al [2010] suggest that target prices have systematic upward bias and decreased accuracy due to over-optimism. We find similar evidence in our analysis and show that in recent years higher target price implied returns predicts lower future earnings.

Value Nowcasting

Another value implementation explored in Figure 11 (green dots) involves using a technique we coin as "Nowcasting" or using current price and current information to forecast future fundamentals. Previously, we examine perfect foresight value signals [Figure 11 (yellow dots)] and show large improvements in performance associated with scaling price with future fundamentals. In this section, we evaluate the performance of fitted values of the LASSO regression model on future fundamentals scaled by current price.

Nowcasting value strategies reflect substantial improvements in risk-adjusted performance over traditional value metrics.

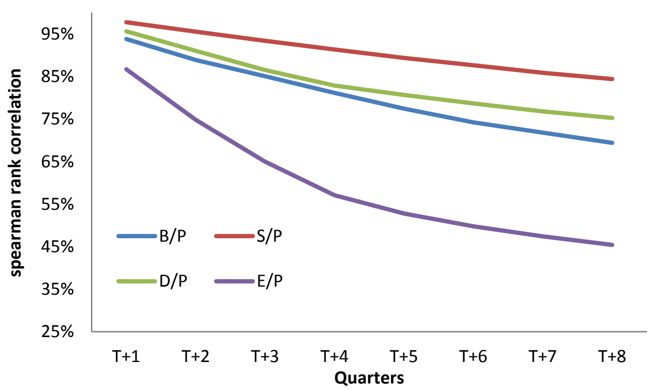
Figure 22: Nowcasting Value Strategy Sharpe Ratio Estimated Using Different Horizons

	t+0	t+1	t+2	t+3	t+4
B/P	0.53	0.58	0.62	0.66	0.67
S/P	0.74	0.80	0.83	0.86	0.85
D/P	0.26	0.49	0.56	0.69	0.52
E/P	0.92	1.28	1.28	1.05	0.88
	Time window (quarters)				

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

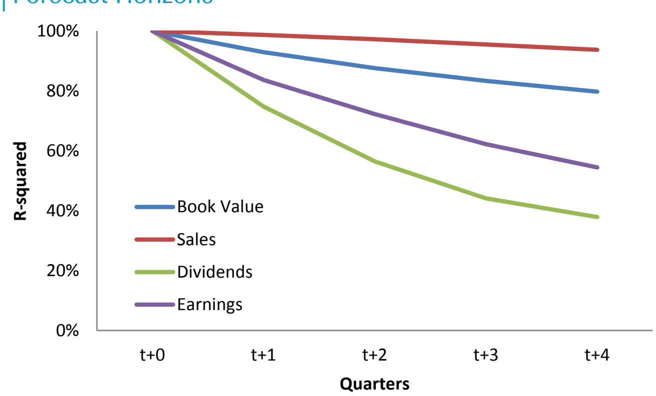
Figure 22 examines the Sharpe ratios of different nowcasting value strategies which use future fundamentals which are estimated over different forecast horizons (1 quarter to 1 year). As we show, B/P and S/P have higher risk-adjusted performance as the forecast horizon increases. Specifically the Sharpe ratios are as much as 16% higher for B/P and 26% for S/P. D/P has highest performance when estimating dividends 3 quarters from today there, while E/P has the best performance over the short-term (1 or 2 quarters). The value-add associated with nowcasting involves using current information to "update" the fundamental and avoid mis-matches between the price and fundamentals.

Figure 23: Variable Persistence for Different Fundamental-to-Price Variables



Deutsche Bank Quantitative Strategy, Thomson Reuters, Compustat, IBES, Russell

Figure 24: Average R^2 for Different Fundamentals and Forecast Horizons



Deutsche Bank Quantitative Strategy, Thomson Reuters, Compustat, IBES, Russell

Figure 23 displays that most price-scaled variables are highly persistent – which helps explain why one of the consistent predictors of future fundamentals are current fundamental values. Specifically, we estimate the correlation in factor

Sales and dividends are highly persistent over time. Our LASSO model works particularly well for forecasting sales and book equity.

scores from time T and time T+N, where N is for one to eight quarters into the future. We then report the time-series average rank correlation. As we show S/P signals decay slowly with greater than 85% correlations after 2 years. In contrast, earnings variables are much less stable, as E/P have much faster decay and correlations of 45% after two years.

Figure 24 reports the average R^2 (estimated over the entire sample period) for LASSO regressions predicting different future fundamentals scaled by assets. We find that our models have the highest predictive power for sales, followed by book equity, earnings and then dividends. Each of our predictive models includes the current fundamental scaled by assets. Thus, one interpretation of how our R^2 results displayed in Figure 24 differs from those reported in Figure 23 is that other explanatory variables (other fundamental, analyst or technical) can explain future changes in sales, book equity and earnings but are poor at explaining changes in dividends. Thus, even though dividends is highly persistent, our LASSO model has relatively poor explanatory power indicating that either selected variables are weak predictors for future changes in dividends or more generally that changes in dividends are unpredictable relative to forecasting changes in other fundamentals. This is not surprising, as dividends change infrequently while our model is likely to capture implied dividends.

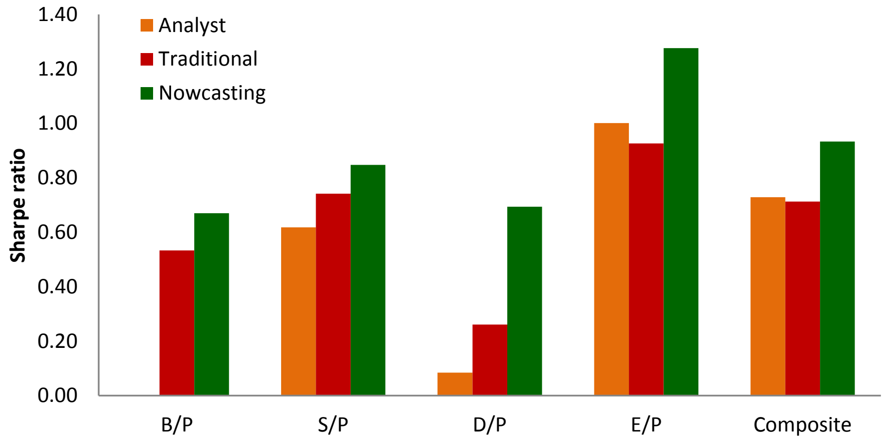
To analyze the performance of value strategies, we aggregate (equal-weight) the four value signal cross-sectional z-scores to form a value composite. We choose to equal-weight for simplicity purposes – for more research on methods for weighing value signals to form a value composite please see Mesomeris et al (2017). We then compare the nowcasting value composite (using estimated future fundamental scaled by current price) to the traditional value composite (using lagged fundamental scaled by current price) and the traditional/analyst value composite formed by first taking the average factor z-score by metric, and then averaging the four metrics[2]. When a traditional (B/P, D/P, E/P, S/P) or analyst value (D*/P, E*/P, S*/P) metric is missing, we simply take the average over all the other variables.

$$Z_{Traditional/Analyst} = \text{Average}\,[Z_{B/P},\ \text{Average}\,(Z_{D^*/P}, Z_{D/P}),\ \text{Average}\,(Z_{E^*/P}, Z_{E/P}),\ \text{Average}\,(Z_{S^*/P}, Z_{S/P})]$$

The decision on the how far in the future to forecast is somewhat arbitrary. On one hand, the results in Figure 22 suggest the high level of persistence in price-scaled value factors dictates forecasting farther out as near-term variables are very well explained by current fundamentals and thus no forecasting technique is necessary. On the other hand, Figure 23 suggests that our machine learning LASSO nowcasting model is better at predicting over closer horizons. For book equity and sales, we use the maximum forecast window (12 months), as forecasting model continues to have high explanatory power (R^2>85%). For dividends, we use the 9-month version as our model R^2 declines as we increase the forecasting horizon, but the fundamental is very persistent which dictates increasing the horizon. For earnings, we use a 3-month forecasting window to reflect the poor persistence in the variable and low explanatory power of our earnings forecasting model relative to other fundamentals.

2 For Book value scaled by price, we do not use analyst estimates due to low coverage among Russell 3000 firms.

Figure 25: Sharpe ratios for Nowcasting, Analyst and Traditional Value Strategies

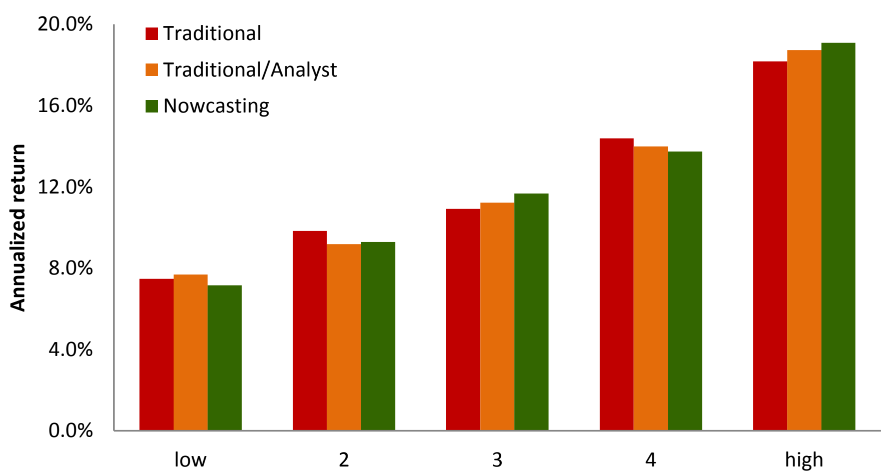


Source: Deutsche Bank Quantitative Strategy, Thomson Reuters, Compustat, IBES, Russell

Nowcasting value composite has higher risk-adjusted returns when compared to more traditional value constructs that use past fundamentals or analyst estimates by 28% - 31%.

Figure 25 displays Sharpe ratios for the Nowcasting, Traditional and Analyst fundamental-to-price variables and composite value strategy. For each of the four value insights, we show that the Nowcasting version improves over both traditional and analyst constructs. The composite score for Analyst is the Traditional/Analyst z-score calculated in the equation above. As we show, the Sharpe ratio of the Nowcasting value strategy (0.93) is 31% higher than that of the Traditional composite (0.71) and 28% higher than the Sharpe ratio of the Analyst/ Traditional (0.73) composite.

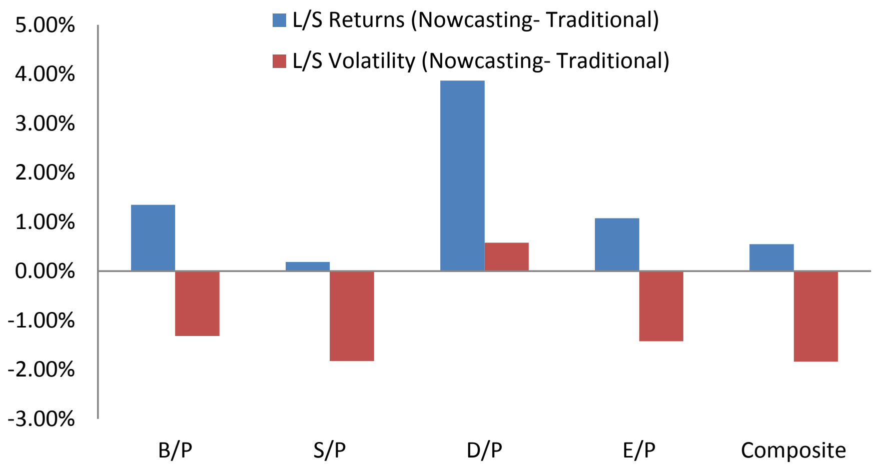
Figure 26: Returns for Portfolios Formed on Nowcasting, Traditional/Analyst, and Traditional Value Composite Strategies



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

Figure 26 shows that the Nowcasting has the lowest return among the three composite strategies in the lowest fundamental-to-price quintile. Our results suggest that by forecasting fundamentals, we mitigate the value trap problem by avoiding stocks with high fundamentals-to-price whose fundamentals are temporarily inflated and are likely to decline in the near future. We also find evidence of a growth trap, or securities whose fundamentals are low and likely to increase in the future as the nowcasting strategy has the highest return when compared to the other two composite strategy for the highest fundamental-to-price quintile.

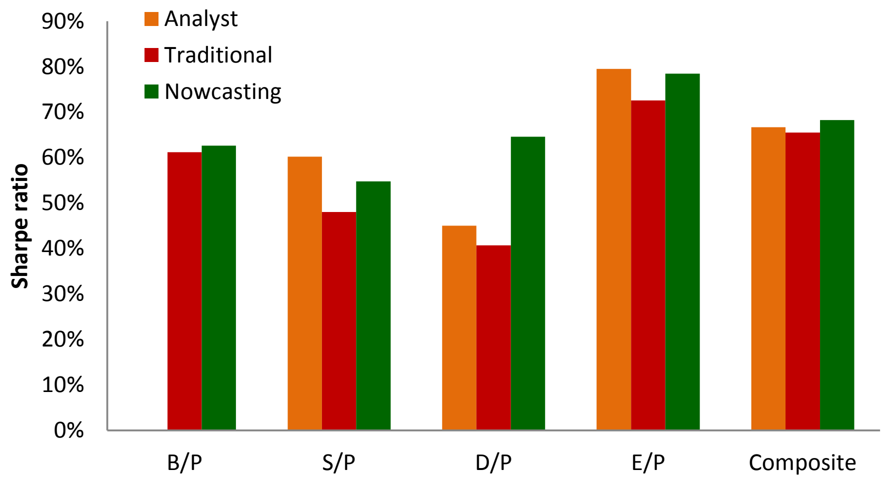
Figure 27: Long/short return and volatility for Traditional and Nowcasting Value Composite Strategies



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

Figure 27 compares the monthly return for long/short hedged portfolios formed on nowcasting and traditional value metrics. As we show, in each of the cases the returns increase (blue bars), and volatility decreases (red bars) for all signals, except for D/P. For the composite, bucket-level strategy, even though the expected return increase is meaningful (0.55%), much of the value-add is from the reduction in volatility (1.84%). Consider the case of SM Energy – the future decrease in book-to-market ratio (due to deterioration in fundamental) is largely predictable from the current environment for energy prices that existed in January 2015. Thus, incorporating forward-looking information when estimating book-to-market ratio may avoid buying this stock that declined 63% over the next year. Even though SM Energy's stock price recovered in 2016, including this stock in our value portfolio would have likely led to negative returns and increases in volatility.

Figure 28: Turnover rate for Nowcasting, Traditional/Analyst, and Traditional Value Signals and Composite Strategies

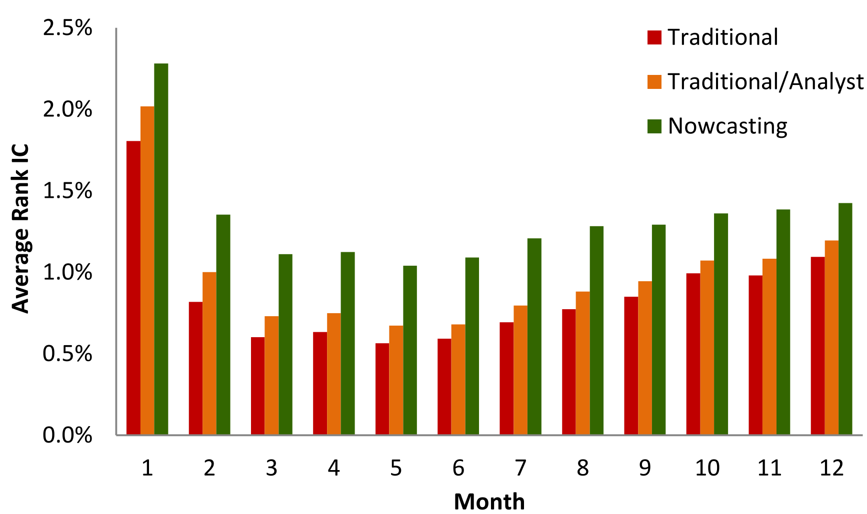


Source: Deutsche Bank Quantitative Strategy, Thomson Reuters, Compustat, IBES, Russell

Figure 28 displays turnover for the four individual value signals and the composite. Turnover is calculated out of 400% (Buys, Sells, Shorts and Covers); value strategies tend to be persistent and generates low turnover relative to other quantitative factors. Dividend-to-Price has the largest increase in turnover – 41% for traditional and 65% for Nowcasting versions. As we show, the composite formed from four signals has a marginal increase in turnover (66% for Traditional, 68% for Nowcasting).

Nowcasting strategies despite the added level of complexity associated with forecasting fundamentals do not appear to have significantly more turnover when compared to other traditional ways of constructing value strategies.

Figure 29: Monthly Rank IC at Different Lags for Long/Short Portfolios Formed on Nowcasting, Traditional, and Traditional /Analyst Value Composite Strategies

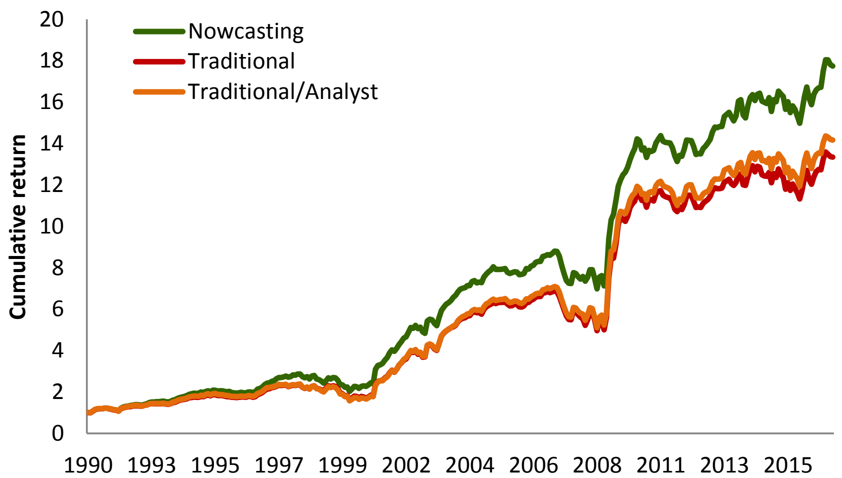


Source: Deutsche Bank Quantitative Strategy, Thomson Reuters, Compustat, IBES, Russell

Figure 29 illustrates the average Spearman rank IC at different lags. For the first month, the average Spearman rank IC increases from 1.81% to 2.25% and the risk-adjusted rank IC increases from 0.22 to 0.30. The performance improvement persists even at different lags, and the information decay is a bit slower for the

Nowcasting relative to the Traditional composite value strategy. For example, at month two, the Nowcasting strategy generates a rank IC of 1.4% (compared to the first month rank IC of 2.3%), whereas the Traditional strategy retains a rank IC of 0.8% out of its initial first month rank IC of 1.8%.

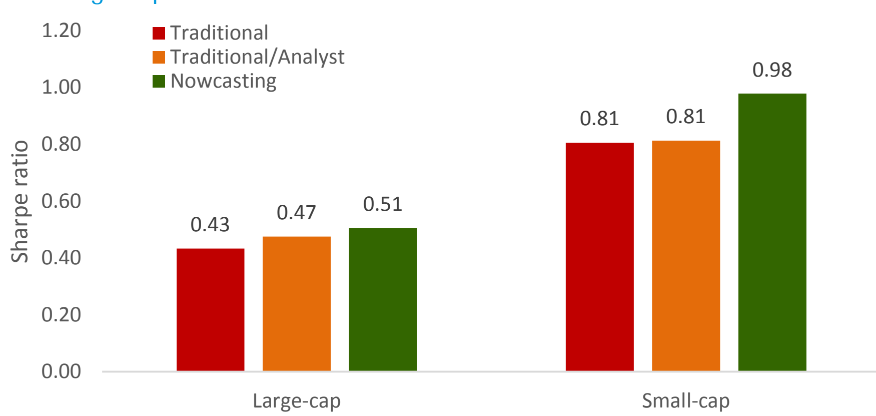
Figure 30: Growth in Wealth for $1 Invested in the Nowcasting Traditional/Analyst, and Traditional Value Composite Strategies



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

Figure 30 shows that investing $1 in the Nowcasting value strategy beginning of November 1990 generates $17.75 at the end of March 2017, compared to $13.34 Traditional value strategy.

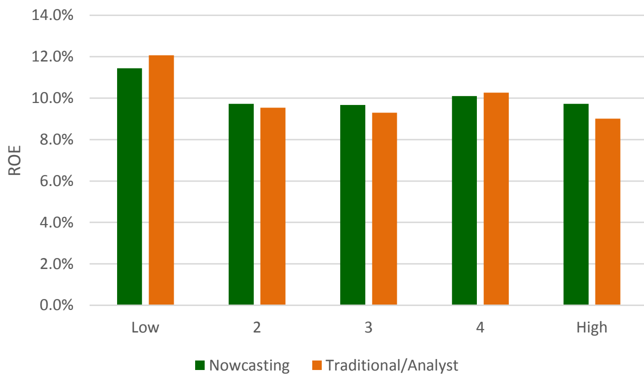
Figure 31: Sharpe Ratios for Long/Short portfolios formed on Nowcasting, Traditional/Analyst, and Traditional Value Composite Strategies for Small-cap and Large-cap Stocks



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

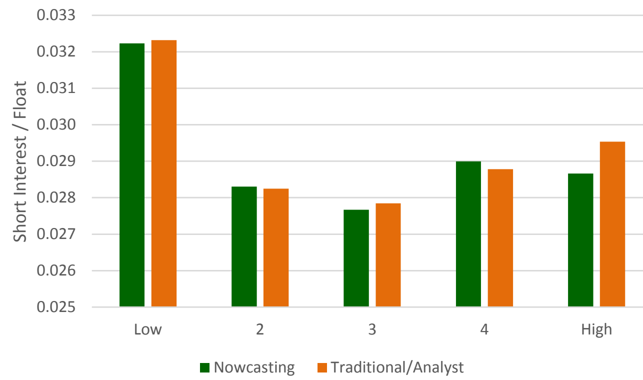
Figure 31 reports the Sharpe ratios for each composite strategy for large capitalization stocks (Russell 1000) and small capitalization stocks (Russell 2000). As we show, the Nowcasting value strategy has 7% and 17% higher risk-adjusted returns when compared to Traditional/Analyst and Traditional composite strategies, respectively. The gains in Small Cap are larger: Nowcasting increases risk-adjusted returns by 20% for both the Traditional/Analyst and Traditional value composite strategies.

Figure 32: Average Return-to-Equity Ratio for Quintile Portfolios formed on Nowcasting and Tradition/Analyst Value Composite Signals



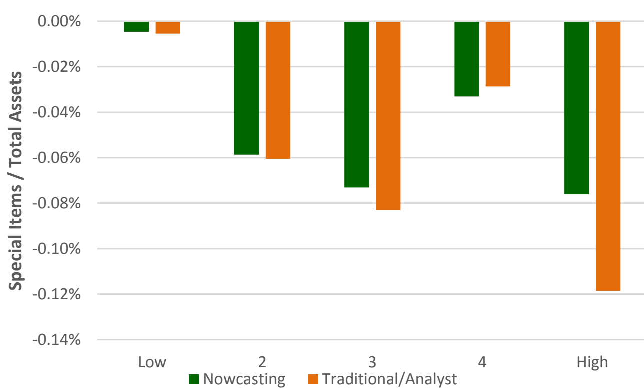
Source: Deutsche Bank Quantitative Strategy, Thomson Reuters, Compustat, IBES, Russell

Figure 33: Average Short Interest Scaled by Float for Quintile Portfolios formed on Nowcasting and Tradition/ Analyst Value Composite Signals



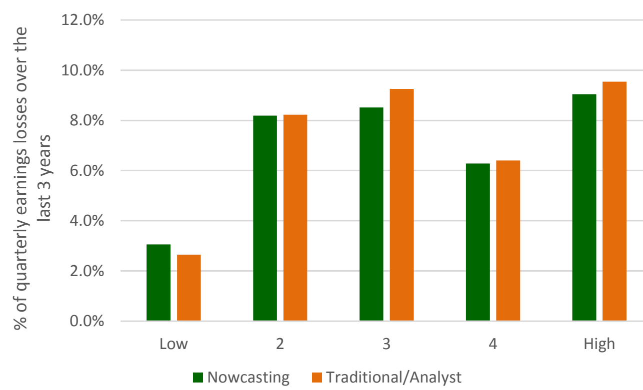
Source: Deutsche Bank Quantitative Strategy, Thomson Reuters, Compustat, IBES, Russell

Figure 34: Average Special Items Scaled by Total Assets for Quintile Portfolios formed on Nowcasting and Tradition/Analyst Value Composite Signals



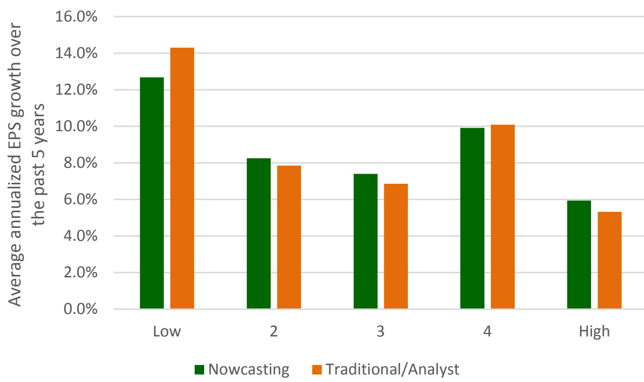
Source: Deutsche Bank Quantitative Strategy, Thomson Reuters, Compustat, IBES, Russell

Figure 35: Average Percentage of Quarterly Earnings Losses over the Last Three Years for Quintile Portfolios formed on Nowcasting and Tradition/Analyst Value Composite Signals



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

Figure 36: Average annualized EPS growth over the past 5 years for Quintile Portfolios formed on Nowcasting and Tradition/Analyst Value Composite Signals



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

To understand how well the nowcasting strategy avoids value traps, we look into various value trap indicators including ROE, long-term growth, special items, earnings losses, and short interest. In particular, value trap stocks are inclined to have low quality and deteriorating growth prospect, which leads to lower ROE and weaker EPS growth.

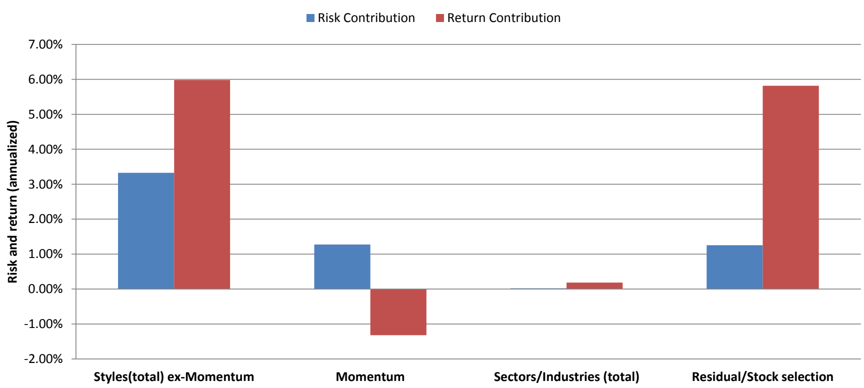
Special items are defined as large expenses or sources of income that companies do not anticipate to recur. Companies that suffer from significant negative special items are possible value traps. Similarly, companies with continuous earnings losses are likely to be value traps. Lastly, as short sellers tend to be more sophisticated professional investors, stocks with large short interest are potential value traps.

Figures 32 to 36 report time-series average firm characteristics for stocks sorted by traditional or nowcasting value composite. As we show, the stocks in the highest nowcasting fundamental-to-price quintile tend to be more profitable as measured by return-on-equity (Figure 32), have less short interest relative to free-float market capitalization (Figure 33), have less special items scaled by total assets (Figure 34), have lower percentage of quarterly earnings losses over the last three years (Figure 35), and have higher average annualized EPS growth over the past 5 years (Figure 36) when compared to stocks in the highest traditional fundamental-to-price quintile.

Nowcasting Risk Attribution

Our Nowcasting value strategy improves on a traditional value strategy by incorporating recent information into fundamentals. Many of the different attributes are standard quantitative factors (for example forward earnings yield estimated from sell-side analysts) that explain the cross-sectional variation in expected returns. In this section we decompose the return and risk of the strategy to understand the value contribution after accounting for industry and systematic style factor exposure.

Figure 37: Overall Risk and Return Contribution for the Nowcasting Value Composite from Nov 1990 – Mar 2017

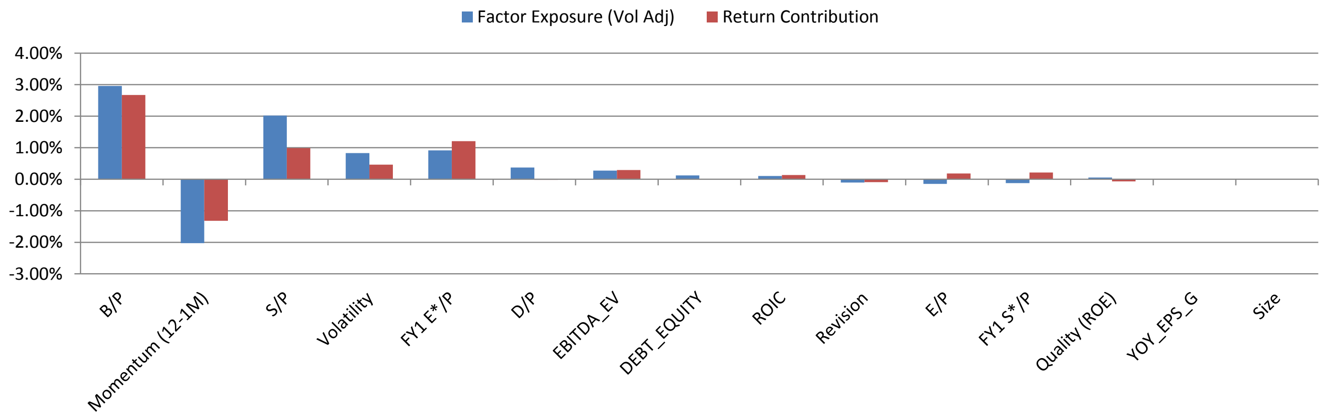


Source: Deutsche Bank Quantitative Strategy, Thomson Reuters, Compustat, IBES, Russell

Figure 37 summarizes our main findings when attributing variation in Nowcasting strategy returns. First, we find that styles excluding momentum (mostly generic value exposures) has almost the same return contribution as the residual, but the residual contributes much less risk when compared to the risk coming from various style exposures. Momentum is still a drag on performance, due to the negative correlation with value. Our results support the idea that having a dynamic model that allows for covariates that explains future fundamentals to change over time can improve risk-adjusted performance for a relative price, value strategy.

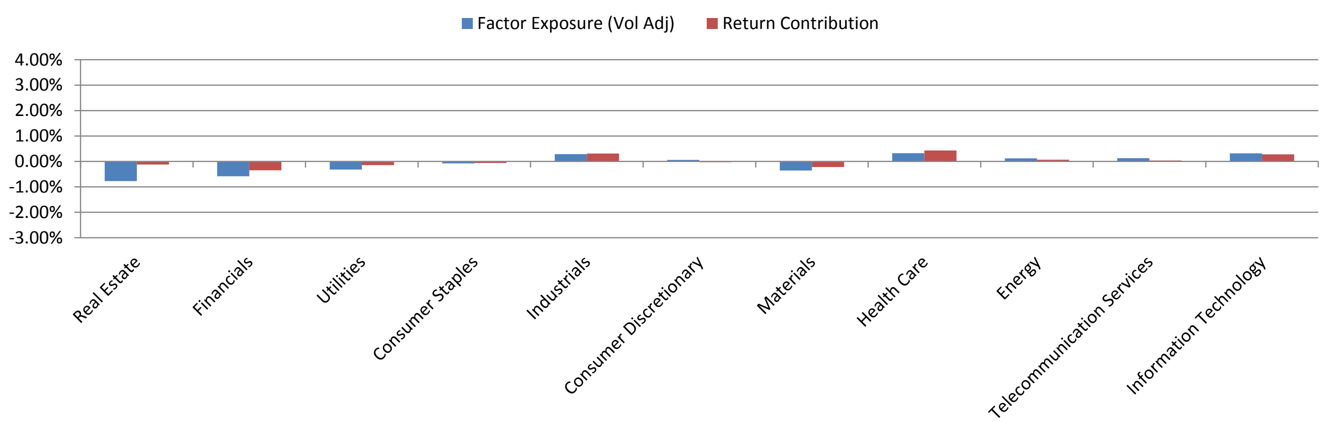
Residual/Stock selection component for the Nowcasting strategy generates close to 6% in returns (similar to the styles ex-Momentum contribution to return) with only a 1% contribution to risk.

Figure 38: Average Style Factor Exposure (vol. adj.) and Return Contribution for the Nowcasting Value Composite Strategy from Nov 1990 – Mar 2017



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

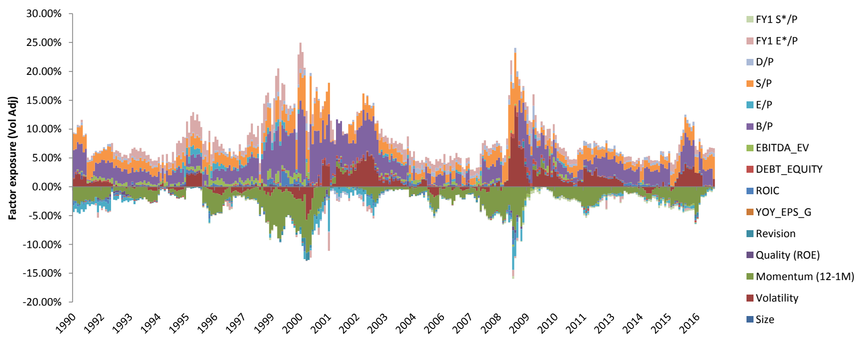
Figure 39: Average Sector Exposure (vol. adj.) and Return Contribution for the Nowcasting Value Composite Strategy from Nov 1990 – Mar 2017



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

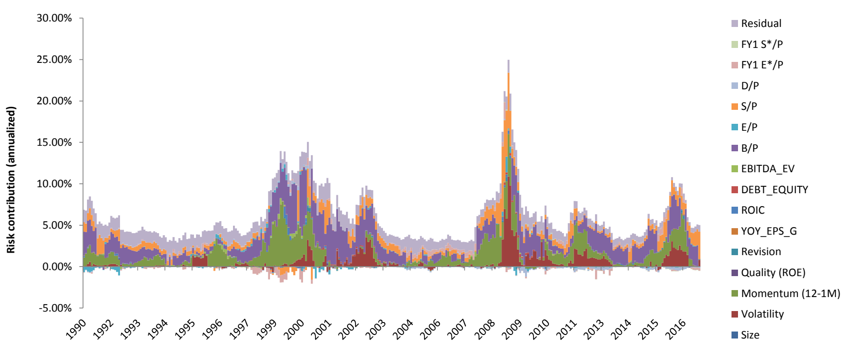
Figure 38 and Figure 39 illustrate results from a standard cross-sectional attribution analysis that measures exposures to systematic factors and industries, respectively. As we show in Figure 38, the majority of the positive return contribution comes from B/P, S/P and forward earnings yield, FY1 E*/P. We find negative return contribution to Momentum, consistent with prior research. Due to the sector neutralization when forming long/short portfolios, Figure 39 shows very small sector exposures.

Figure 40: Style factor exposures (Vol. Adj.) of the Nowcasting Value Composite Strategy from Nov 1990 – Mar 2017



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

Figure 41: Risk contribution from style factors of the Nowcasting Value Composite Strategy from Nov 1990 – Mar 2017



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

Figures 40 and 41 display the style exposures and risk contributions from style factors over time. Figure 40 shows that momentum exposure tends to be very large and negative in 1996-2000 and again from 2007-2009. B/P exposure tends to be large during the dot-com period between 1998 and 2003. Figure 41 finds that the residual component does not contribute meaningfully towards total strategy risk.

Conclusion

As we show, using a LASSO regression model to estimate future fundamentals improves forecasting of traditional, price-scaled value strategies. Our findings suggest that “value traps” or differences in incorporated information between stale fundamentals and today’s price can be mitigated using techniques discussed in this paper. The increases in risk-adjusted performance does not come at the expense of larger transactions costs and our risk attribution shows that our model explains returns even after controlling for other systematic exposures such as book-to-market or forward earnings yield factors. One interpretation of our results is that by using a structural approach that selects only those variables that explain future fundamentals, we are able to generate improved capital allocation across existing quantitative signals. In the future, we hope to extend our analysis into foreign (non-US) markets and use our approach to estimate fundamentals for a variety of traditional quantitative factors.

Appendix A: SM Energy's Asset Impairment Impacting Fundamentals

Figure 42: SM Energy Present Value of Future Cash Flow Analysis

	As of December 31		
	2016	2015	2014
		(in millions)	
Standardized measure of discounted future net cash flows (GAAP)	$ 1,152.1	$ 1,790.5	$ 5,698.8
Add: 10 percent annual discount, net of income taxes	937.1	1,307.1	3,407.2
Add: future undiscounted income taxes	-	-	3,511.4
Undiscounted future net cash flows	2,089.2	3,097.6	12,617.4
Less: 10 percent annual discount without tax effect	(937.1)	(1,307.1)	(5,000.5)
PV-10 (non-GAAP)	$ 1,152.1	$ 1,790.5	$ 7,616.9

Source: SM Energy 2016 Annual Report

Figure 42 is taken from SM Energy's annual report and provides an NPV cash flow standard analysis for exploration and production firms to estimate the value of oil and gas assets. Net cash flows are estimated at the discretion of the company. The large declines in oil prices generated decreases in the value of their reserves, while the actual quantity of reserves did not decline as much (Total Proved MMBOE: 395.8 (2016), 471.3 (2015) and 547.7 (2014)).

Figure 43: SM Energy Impairment Analysis

	For the Years Ended December 31,		
	2016	2015	2014
		(in millions)	
Impairment of proved properties	$ 354.6	$ 468.7	$ 84.5
Abandonment and impaiment of unproved properties	$ 80.4	$ 78.6	$ 75.6

Source: SM Energy 2016 Annual Report

The declines in the commodity price causes SM Energy to record material impairments, which result in negative net income (earnings) and translate to declines in book values. The decline in commodity prices also reduces sales expectations going forward. Figure 43 shows that impairment of unproved properties is largely unchanged in different calendar years, impairments of proved properties is 270 MM (2016) and 384 MM (2015) higher than those numbers reported for 2014.

Figure 44: Excerpt on Impairments from SM Energy 2015 Annual Report

Proved and unproved property impairments recorded in 2015 were due to continued commodity price declines, largely impacting our Powder River Basin program and certain legacy and non-core assets, as well as our decision to reduce capital invested in the development of our east Texas exploration program in light of the sustained, low commodity price environment. Commodity prices significantly declined subsequent to the filing date of our September 30, 2015 Quarterly Report on Form 10-Q resulting in additional impairments of proved and unproved properties in the fourth quarter of 2015 totaling $398.8 million. Any amount of future impairments is difficult to predict. If commodity prices remain at levels near those as of January 31, 2016, we would expect to incur impairments in the first quarter of 2016 of up to approximately $250 million. If commodity prices deteriorate further, additional impairments in future periods could occur. In addition to future commodity price declines, changes in drilling plans, downward engineering revisions, or unsuccessful exploration efforts may result in additional proved and unproved property impairments.

Source: SM Energy 2015 Annual Report

Figure 44 is an excerpt from the SM Energy report that reveals the dire situation surrounding the business at the end of 2015 where they forecast additional impairments due to potential future declining commodity prices.

Figure 45: SM Energy Consolidated Statement of Operations

(in thousands, except per share amounts)

	For the Years Ended December 31, 2016	2015	2014
Operating revenues and other income:			
Oil, gas, and NGL production revenue	$ 1,178,426	$ 1,499,905	$ 2,481,544
Net gain on divestiture activity	37,074	43,031	646
Marketed gas system revenue	-	9,485	24,897
Other operating revenues	1,950	4,544	15,220
Total operating revenues and other income	1,217,450	1,556,965	2,522,307
Operating expenses:			
Oil, gas, and NGL production expense	597,565	723,633	715,878
Depletion, depreciation, amortization, and asset retirement obligation liability accretion	790,745	921,009	767,532
Exploration	65,641	120,569	129,857
Impairment of proved properties	354,614	468,679	84,480
Abandonment and impairment of unproved properties	80,367	78,643	75,638
Impairment of other property and equipment	-	49,369	-
General and administrative	126,428	157,668	167,103
Change in Net Profits Plan liability	(7,200)	(19,525)	(29,849)
Net derivative (gain) loss	250,633	(408,831)	(583,264)
Marketed gas system expense	-	13,922	24,460
Other operating expenses	17,972	30,612	4,658
Total operating expenses	2,276,765	2,135,748	1,356,493
Income (loss) from operations	(1,059,315)	(578,783)	1,165,814
Non-operating income (expense):			
Interest expense	(158,685)	(128,149)	(98,554)
Gain (loss) on extinguishment of debt	15,722	(16,578)	-
Other, net	362	649	(2,561)
Income (loss) before income taxes	(1,201,916)	(722,861)	1,064,699
Income tax (expense) benefit	444,172	275,151	(398,648)
Net income (loss)	**$ (757,744)**	**$ (447,710)**	**$ 666,051**
Basic weighted-average common shares outstanding	76,568	67,723	67,230
Diluted weighted-average common shares outstanding	76,568	67,723	68,044
Basic net income (loss) per common share	$ (9.90)	$ (6.61)	$ 9.91
Diluted net income (loss) per common share	$ (9.90)	$ (6.61)	$ 9.79

Source: SM Energy 2016 Annual Report

Figure 45 displays the 2014, 2015 and 2016 income statement for SM Energy. Without the impairment charges, the net income in 2015 should have been positive, instead of a loss of $448MM. The decline in fundamentals (sales, earnings, dividends and book equity) is largely predictable – sharp declines in the oil price led to a reduction in future profitability and impairments.

Appendix B: Custom Factor Attribution Summary for the Nowcasting Value Composite Signal

Figure 46: Custom factor attribution summary, Nowcasting value composite signal, Nov 1990 – Mar 2017

	Factor Exposure	Factor Percentile	Factor Exposure (Vol Adj)	Risk Contribution	Risk Contribution (%)	Return Contribution
B/P	1.06	85.45%	2.96%	1.82%	30.75%	2.67%
Momentum (12-1M)	(28.90)	0.00%	-2.03%	1.27%	19.73%	-1.32%
S/P	4.40	100.00%	2.02%	0.76%	13.00%	0.99%
Volatility	0.31	62.29%	0.83%	0.62%	8.16%	0.46%
FY1 E*/P	3.61	99.98%	0.92%	0.05%	1.78%	1.21%
D/P	5.44	100.00%	0.37%	-0.04%	-0.89%	-0.02%
EBITDA_EV	8.32	100.00%	0.28%	0.04%	0.65%	0.29%
DEBT_EQUITY	0.80	78.81%	0.12%	0.03%	0.46%	0.01%
ROIC	6.30	100.00%	0.11%	0.03%	0.36%	0.14%
Revision	(9.28)	0.00%	-0.11%	0.02%	0.29%	-0.09%
E/P	(9.09)	0.00%	-0.14%	-0.01%	-0.20%	0.18%
FY1 S*/P	(4.15)	0.00%	-0.13%	0.00%	0.11%	0.22%
Quality (ROE)	5.97	100.00%	0.06%	0.00%	0.04%	-0.07%
YOY_EPS_G	(0.27)	39.38%	0.00%	0.00%	0.00%	0.00%
Size	(0.01)	49.77%	0.00%	0.00%	0.00%	0.00%
Styles (total)	-	**50.00%**	**0.00%**	**4.60%**	**74.24%**	**4.66%**
Real Estate	(0.05)	47.86%	-0.77%	-0.15%	-3.16%	-0.12%
Financials	(0.05)	48.17%	-0.58%	0.06%	1.54%	-0.35%
Utilities	(0.03)	48.99%	-0.32%	0.07%	1.40%	-0.15%
Consumer Staples	(0.01)	49.60%	-0.08%	0.02%	0.59%	-0.06%
Industrials	0.03	51.11%	0.29%	-0.01%	-0.37%	0.31%
Consumer Discretionary	0.00	50.08%	0.06%	0.02%	0.29%	-0.03%
Materials	(0.02)	49.04%	-0.35%	-0.02%	-0.19%	-0.22%
Health Care	0.03	51.01%	0.32%	0.02%	0.17%	0.43%
Energy	0.01	50.26%	0.12%	0.02%	0.13%	0.07%
Telecommunication Services	0.01	50.32%	0.13%	0.01%	0.11%	0.03%
Information Technology	0.02	50.85%	0.32%	-0.01%	-0.09%	0.28%
Sectors/Industries (total)	-	**50.00%**	**0.00%**	**0.02%**	**0.41%**	**0.18%**
Residual/Stock selection				**1.25%**	**25.34%**	**5.82%**
Total				**5.87%**	**100.00%**	**10.66%**

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

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