Completed 09 Aug 2017 11:51 AM HKT
Disseminated 09 Aug 2017 11:53 AM HKT

J.P.Morgan

Value Strategies based on Machine Learning

Incorporating Profitability Measure and Sentiment Signals to Identify Winners and Losers

Global Quantitative and Derivatives Strategy

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Quantifying equity "fair value" with statistical models

Following the popularity of Big Data and AI Strategies, we demonstrate ideas on implementing Machine Learning algorithms to stock selection processes based on valuation. We attempt to predict the "fair value" of stocks using a large number of equity characteristics, and quantify a "mispricing" signal where we buy undervalued stocks and short overvalued stocks. Machine Learning from Penalized Regressions (LASSO) to Extreme Gradient Boosting (XGBoost) add value on top of simple linear models, as they are capable of extracting information from a large amount of features and/or model the non-linear relationships between variables.

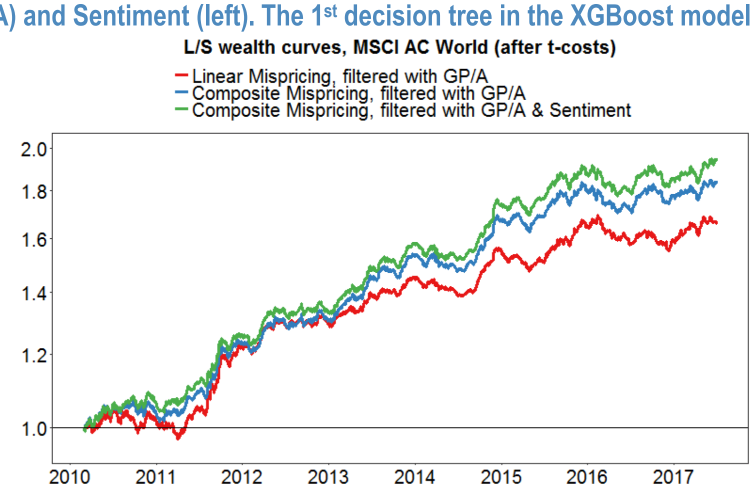
Profitability helps to identify undervalued stocks that will outperform

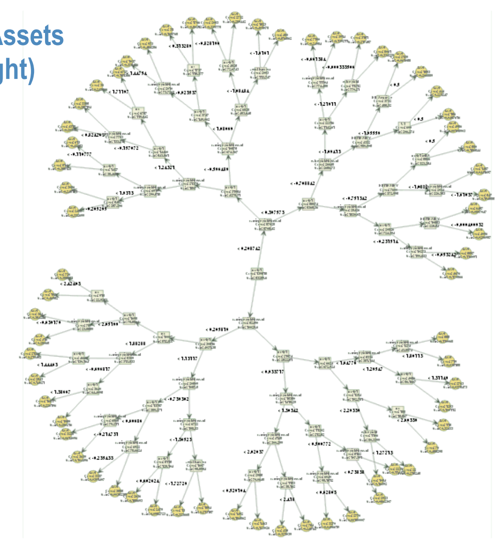
Novy-Marx (2013) highlight the idea that Gross Profits could be a "cleaner" profitability measure compared with the "good old" Return-on-Equity (ROE). Indeed, we find that filtering mispriced stocks based on Gross Profits significantly improves our strategy returns, and results are better than using ROE. We prefer to buy undervalued stocks with high profitability, and short overvalued stocks with poor profitability.

Big Data contains extra information: News sentiment as an overlay

We introduce RavenPack's news sentiment data as a useful overlay to our strategy. Avoiding stocks with poor (good) sentiment in the long (short) portfolio help to improve risk-adjusted returns.

L/S wealth curves of the "mispricing" strategy filtered by Gross-Profit-to-Assets (GP/A) and Sentiment (left). The 1st decision tree in the XGBoost model (right)





Source: J.P. Morgan Quantitative and Derivatives Strategy, RavenPack, Thomson Reuters, FactSet, Bloomberg, IBES, MSCI

See page 53 for analyst certification and important disclosures, including non-US analyst disclosures.

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Key Findings

- For a quick grasp of the idea of this report, please refer to our strategy layout in Figure 4. The final strategy wealth curve is shown in Figure 30
- Readers who want to understand more about Machine Learning algorithms can delve into the details between **P. 14 – P. 24**
- For those who are interested in the news sentiment data offered by RavenPack, please refer to **P. 31 – P. 34**

To help readers navigate through this report, we highlight the key findings below:

Machine Learning

- We look at 3 models for predicting price-to-book as a 'fair value': Penalized regression (LASSO, **P. 14**), Extreme Gradient Boosting (XGBoost, **P. 18**) and simple linear regression using the most important predictors (**P. 22**)
- Dynamically including more features (LASSO) is superior to simple linear regression
- Boosting algorithms (XGBoost) can capture non-linear relationships and "learn" to improve predictions, which is even better than the linear LASSO model
- We briefly discuss the use of ensemble models in Machine Learning on **P. 24**, where we develop a composite signal by combining the 3 models
- Our "mispricing" signal is the difference between the expected price-to-book and the current price-to-book, and we prefer undervalued stocks (positive mispricing) to overvalued stocks (negative mispricing) (Figure 18)

Gross Profits vs ROE

- Inspired by Novy-Marx (2013), we look at the efficacy of using Gross Profits to improve our "mispricing" signal
- We find significant increase in risk-adjusted returns by filtering mispriced stocks with profitability, as measured by Gross-Profit-to-Assets (GP/A) instead of ROE (Figure 20 and Figure 21)

RavenPack's News Sentiment

- We introduce the data set on **P. 31 – P. 34**, showing how to build signals out of the sentiment data
- We analyze the impact of filtering stocks at different sentiment thresholds. We find that avoiding stocks with poor (good) sentiment in the long (short) portfolio help to improve risk-adjusted returns (Figure 30)

Revisiting Value Strategies

Investors use different proxies to estimate equity valuations: One could look at price-to-book from the balance sheet, earnings yield from the income statement, or cash flow yield from the cash flow statement.

Value strategies are looking to buy "cheap" stocks and sell "expensive" stocks. Whilst the logic is simple and intuitive, the actual strategy may not be that straight forward because we cannot observe the true value of a stock directly. Investors can use different proxies to estimate valuation from different perspectives. In equity space, the traditional way is to look at accounting items to infer the valuation of a company. One could look at price-to-book ratios from the balance sheet, earnings yield from the income statement, or cash flow yield from the cash flow statement. As highlighted in "Sorting through the Trash" (Ma and Smith (2014)), combining valuations from different angles can lead to a more holistic measure, and ranking stocks with the "Holistic Value" factor, i.e. a combination of price-to-book (deep value), forward earnings yield (expected value) and price-to-cash-flow (intrinsic value) can drastically improve performance.

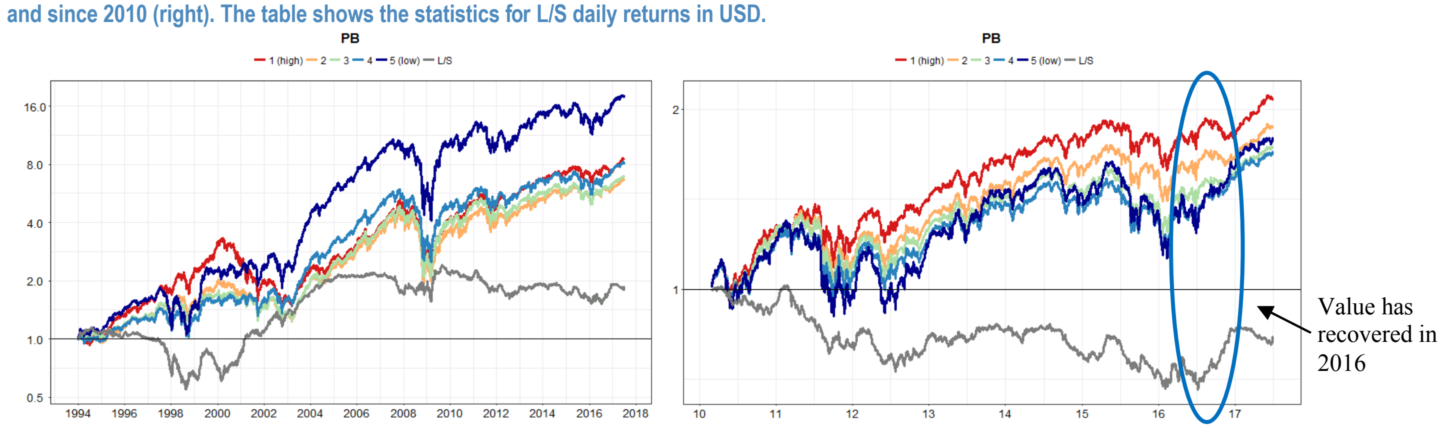
As many of the Value investors would recall, there have been numerous periods when Value has lost favor to other styles, particularly between 2010-2015 where a long/short strategy based on price-to-book in the Global Developed Market has lost 5.5% p.a.. In "Value Everywhere" (Hlavaty et al (2016)), we provide a comprehensive study on different value factors, and analyze their efficacies at the regional and sector levels.

Value strategies have in general suffered since 2010 with "expensive" stocks outperforming "cheap" stocks. In mid-2016, Value has recovered.

Price-to-book: A rough path since 2010

Figure 1 shows the wealth curves of the quintile portfolios based on price-to-book in MSCI AC World. On the left, we show performance since 1994, where we observe an excellent period for value investors between 2000 and 2006. After the Global Financial Crisis in 2008, we have the well-known "junk" rally in 2009, but in general Value investing has been difficult since then. On the right of Figure 1, we zoom into the performance of price-to-book since 2010. Expensive stocks have been outperforming cheap stocks, except in the second half of 2016 where Value came back as a theme under the spotlight.

Figure 1: L/S wealth curves of the quintile portfolios (after transaction costs) based on price-to-book ratios in MSCI AC World since 1994 (left) and since 2010 (right). The table shows the statistics for L/S daily returns in USD.



Signal: P/B	Median # of stocks (Long or Short)	Mean IC	Risk-adj. IC	t-stat	Skew -ness	Excess kurtosis	2-way Turnover	Ann. Returns	Ann. Vol.	IR	Max. Draw-down	Hit Ratio
Since 1994	330	0.3%	0.021	1.40	0.36	6.29	53.5%	2.5%	10.9%	0.23	52.1%	48.6%
Since 2010	335	-1.0%	-0.08	-0.60	0.11	2.27	48.1%	-2.4%	9.3%	-0.26	33.1%	48.2%

Source: J.P. Morgan Quantitative and Derivatives Strategy, Thomson Reuters, FactSet, Bloomberg, IBES, MSCI

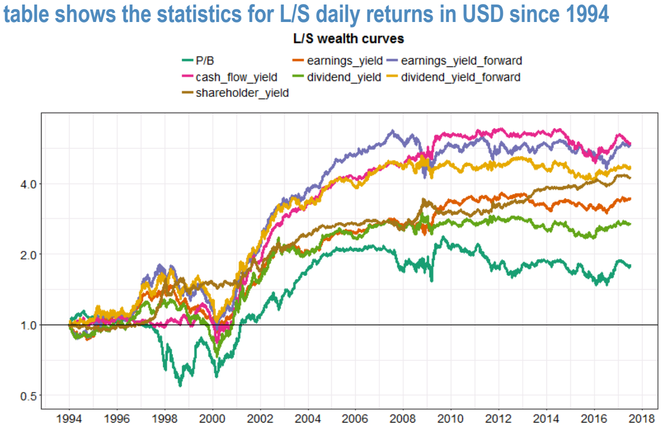
Many other value factors also perform poorly since 2010, with the exception of shareholder yield, which may better capture the reward to shareholders

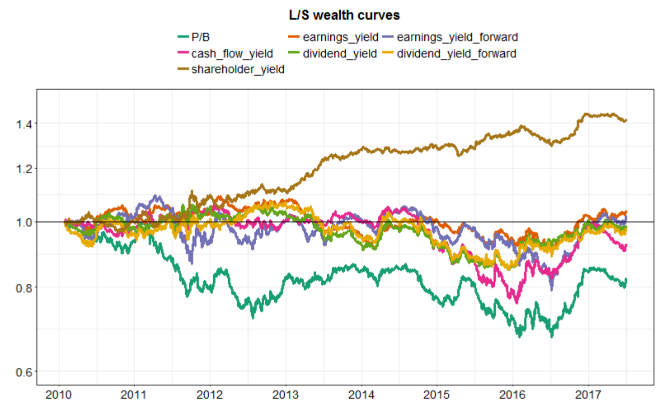
What about other value factors?

Albeit being one of the most popular valuation measures, price-to-book is not the only value factor to look at. In Figure 2, we consider the performance of other value factors including dividend yield (a more defensive value), as well as some forward-looking versions based on analyst forecasts.

As opposed to price-to-book and many other value factors, we find that shareholder yield (combining the effects of dividends, buy-backs and net issuance) performs quite well since 2010, as well as over the whole history from 1994 where it has delivered an Information Ratio of 0.92. As in "Value Everywhere" (Hlavaty et al (2016)), we notice that shareholder yield appears to be one of the best measures of Value. This may due to the fact that shareholder yield better captures the reward to investors compared to dividend yield: Some stocks may prefer not to return cash to shareholders by way of dividends, and instead choose to use the cash for the purpose of M&A activity, share-buybacks or to decrease of the level of total debts (Quant Forensics: Volume 5, Replacing Dividend Yield with Shareholder Yield, Shaikh et al (2013)).

Figure 2: L/S wealth curves (after transaction costs) of various value strategies in MSCI AC World since 1994 (left) and since 2010 (right). The table shows the statistics for L/S daily returns in USD since 1994





Signal	Median # of stocks (Long or Short)	Mean IC	Risk-adjusted IC	t-stat	Skew-ness	Excess kurtosis	2-way Turnover	Ann. Returns	Ann. Vol.	IR	Max. Draw-down	Hit Ratio
Since 1994												
P/B	330	0.3%	0.02	1.36	0.35	6.16	53.5%	2.4%	11.0%	0.22	52.2%	49.1%
earnings yield	392	2.8%	0.28	3.20	0.24	3.96	53.8%	5.2%	8.4%	0.62	36.8%	50.3%
earnings yield forward	384	3.6%	0.26	3.22	0.08	5.26	66.5%	7.5%	12.3%	0.61	47.1%	51.1%
cash flow yield	304	2.3%	0.24	4.54	0.34	4.25	53.6%	7.6%	8.4%	0.91	31.9%	51.4%
dividend yield	391	3.2%	0.27	2.21	0.02	4.11	46.3%	4.1%	10.3%	0.40	43.2%	49.7%
dividend yield forward	373	3.9%	0.29	2.86	-0.08	3.63	53.5%	6.5%	12.2%	0.53	41.1%	50.5%
shareholder yield	380	2.3%	0.33	4.61	-0.06	5.22	48.0%	6.1%	6.6%	0.92	15.8%	52.2%
Since 2010												
P/B	335	-1.0%	-0.08	-0.60	0.12	2.25	48.1%	-2.4%	9.3%	-0.26	33.1%	48.2%
earnings yield	398	0.5%	0.06	0.31	0.27	1.57	53.5%	0.5%	5.7%	0.09	18.3%	49.1%
earnings yield forward	395	0.7%	0.06	0.23	0.25	3.62	59.5%	0.4%	8.3%	0.04	27.7%	49.5%
cash flow yield	311	-0.3%	-0.03	-0.30	0.26	2.36	54.2%	-1.0%	6.9%	-0.14	28.7%	49.1%
dividend yield	398	0.8%	0.09	0.06	0.13	1.82	42.9%	-0.1%	7.3%	-0.02	20.1%	48.1%
dividend yield forward	392	0.8%	0.08	0.13	-0.08	2.24	43.9%	0.0%	8.7%	0.00	20.7%	48.2%
shareholder yield	392	2.6%	0.41	2.60	0.07	2.91	42.7%	4.6%	4.9%	0.94	6.8%	53.0%

Source: J.P. Morgan Quantitative and Derivatives Strategy, Thomson Reuters, FactSet, Bloomberg, IBES, MSCI

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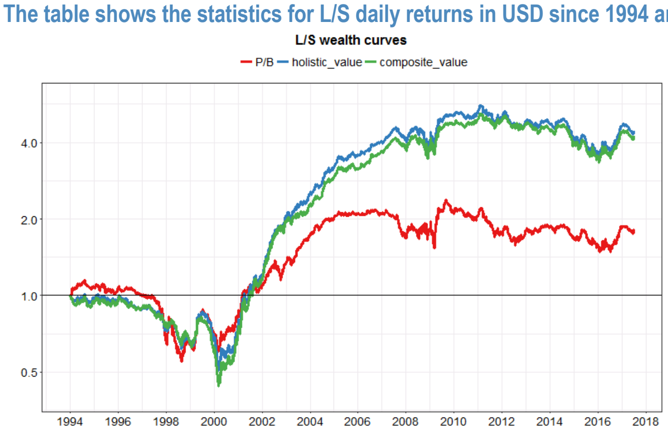
How about composite factors?

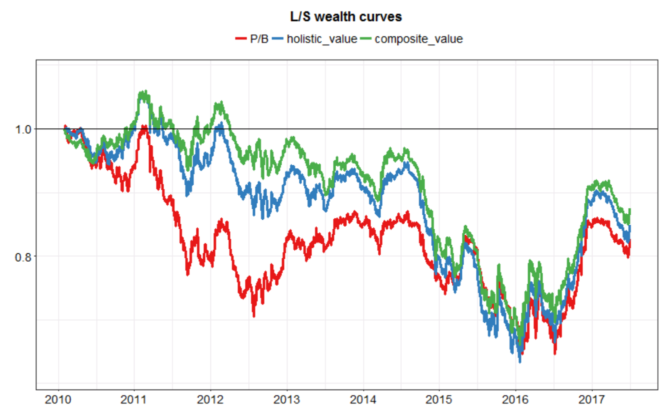
One may wonder if a simple combination of different value factors can help to improve performance, as they can capture different aspects of value (some maybe more forward looking, others maybe more defensive). We look at two examples below:

- **Holistic Value:** A simple average of the z-scores of 3 factors: Price-to-book, forward earnings yield and cash flow yield (Ma and Smith (2014))
- **Composite Value:** A simple average of the z-scores of 4 factors: Price-to-book, forward earnings yield, cash flow yield and dividend yield

We find that merely combining these valuation metrics does not help much in general, probably due to the fact that performances are too correlated. Indeed, Holistic Value has enjoyed some outperformance over the simple price-to-book in 2000-2007. Since 2010, composite value factors have been suffering to a similar extent as the price-to-book strategy.

Figure 3: L/S wealth curves (after transaction costs) of composite value strategies in MSCI AC World since 1994 (left) and since 2010 (right). The table shows the statistics for L/S daily returns in USD since 1994 and since 2010





Signal	Median # of stocks (Long or Short)	Mean IC	Risk-adj. IC	t-stat	Skew-ness	Excess kurtosis	2-way Turnover	Ann. Returns	Ann. Vol.	IR	Max. Draw-down	Hit Ratio
Since 1994												
Holistic Value	244	2.1%	0.17	3.08	0.21	4.67	64.7%	6.3%	10.7%	0.59	49.8%	50.3%
Composite Value	244	2.4%	0.20	2.83	0.13	4.53	62.5%	6.1%	11.5%	0.53	56.2%	50.6%
Since 2010												
Holistic Value	250	-0.7%	-0.05	-0.54	0.26	2.36	60.2%	-2.1%	8.9%	-0.24	37.7%	46.8%
Composite Value	249	-0.4%	-0.03	-0.37	0.28	1.92	61.3%	-1.6%	8.9%	-0.18	35.9%	48.5%

Source: J.P. Morgan Quantitative and Derivatives Strategy, Thomson Reuters, FactSet, Bloomberg, IBES, MSCI

For a more general overview on Equity Risk Premia, one can refer to our primer report on Equity Risk Premia Strategies, which covers Value as well as other styles in equity investing.

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Can We Model "Fair Value"?

As we have seen above, a number of valuation metrics from accounting could be used to capture valuation. Are there other ways to define value, and to discriminate cheap stocks from expensive ones?

We develop a statistical model that considers a large number of stock characteristics to predict an expected value of price-to-book, i.e. a "fair value".

Mispricing is the difference between the fair value and the current price-to-book

In this report, we attempt to look at valuation from another angle. We develop a statistical model that considers a large number of stock characteristics to predict an expected value of price-to-book. In other words, we model the "fair value" of a stock in terms of its expected price-to-book ratio. By comparing our "fair value" to the current price-to-book of the stock, we can estimate a "mispricing" signal to quantify if a stock is likely to be undervalued or overvalued. Our strategy buys undervalued stocks and short overvalued stocks, based on our "fair value" model.

As such, we are essentially taking the view of Value premia arising from "mispricing" rather than "risk". There have long been debates on the source of Value premia, with Piotroski and So (2012) being a recent popular study supporting the mispricing-based arguments.

Following the popularity of the report on Big Data and AI Strategies, we decide to look into a few Machine Learning algorithms that may help us to predict the price-to-book of a stock[1]. We look at stocks in the universe of MSCI AC World, since Machine Learning algorithms typically require a large amount of data for model estimation[2]. The number of stocks and the compositions of the universe in terms of countries and sectors are shown in Figure 5.

Using profitability and sentiment to avoid value traps

Of course, a good strategy seldom relies on a single metric, and this is the same with our "mispricing" signal. We consider filtering our mispricing signal to ensure that we are buying cheap stocks which are indeed profitable, i.e. whilst a stock is undervalued and appear cheap, we expect a positive future returns due to the attractive profitability of the company.

We look at data from a news analytics provider called RavenPack, and use sentiment signals to improve our strategy

As price dynamics are also affected by investor sentiment, whether an undervalued stock (even with good profitability) will go up may, in the short term, depend on recent sentiment towards the company. Another feature of this report is to examine if Big Data can help us to shed light on investors' appetite on a stock. We look at data from a news analytics provider called RavenPack, and investigate if sentiment signals could help us to improve our strategy. Interestingly, we find that stocks with poor sentiment are the ones that we want to avoid, which tend to underperform significantly. Positive sentiment scores, on the other hand, have less clear impact on the future returns of the stocks, but there is still added-value in removing stocks with extremely positive sentiment from the short portfolio.

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[1] Of course, one may directly use Machine Learning models to predict the returns of the stocks. We prefer to focus on valuation ratios here because the model will help us to identify cheap stocks, but if we predict returns directly we cannot quantify "Value". Moreover, returns are much noisier than valuation ratios, and harder to predict.

[2] For instance, bootstrapping and bagging are useful statistical techniques to improve the model via random samplings, and one could not obtain a good number of sub-samples without a large amount of data. More data also enables us to perform cross-validations for tuning the model's hyper-parameters.

Realistic backtests with transaction costs

Sometimes strategy backtests may look nice on paper, but in practice we may find that a notable portion of the profits have been eaten away by transaction costs, especially for strategies that rely on high turnover to capture alpha. To provide a more realistic measure on the performance of our strategies, we impose transaction costs in the backtests, based on the country of the stock (Figure 5):

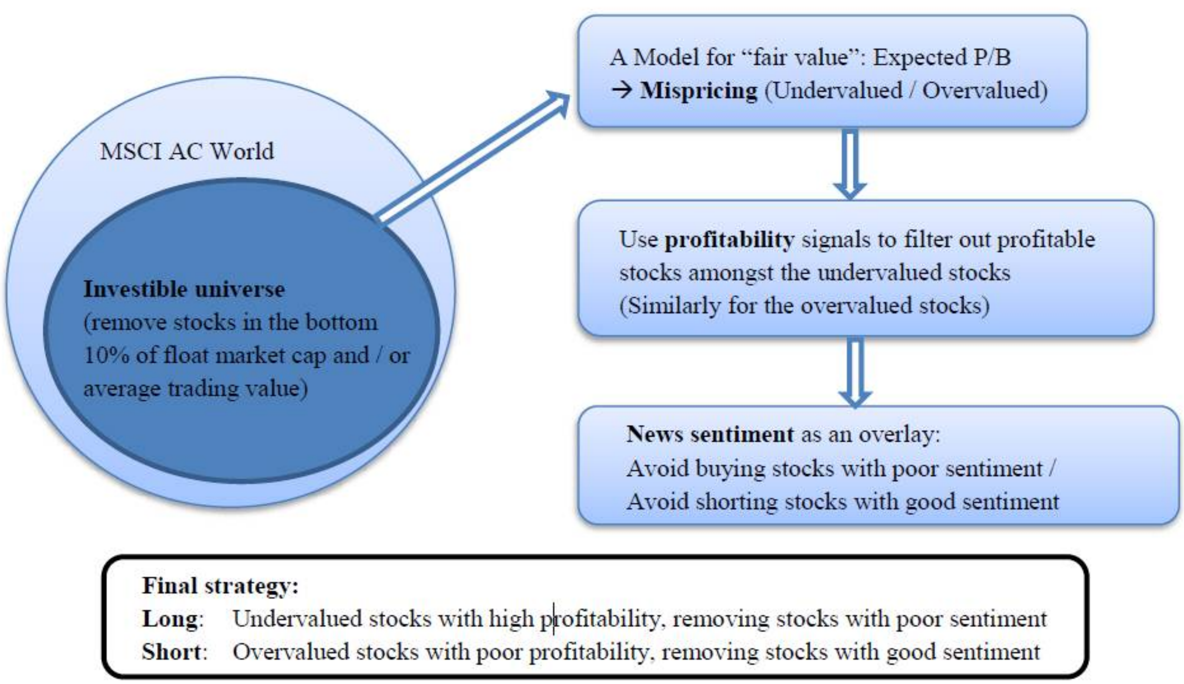
- Developed Markets: 4 bps
- Emerging Markets: buy / sell costs ranging from 10-45 bps

We further impose a few constraints on the universe to ensure our portfolios can in general meet with liquidity and capacity requirements:

- We do not trade stocks that are in the bottom 10th-percentile of the universe, in terms of float market cap
- We remove stocks in the bottom 10th-percentile of average daily trading value over the past 1 month
- We remove stocks from some countries (e.g. Pakistan, Egypt) because of the small number of observations

Our final "investable" universe consists of about 2000 stocks from 39 countries. Figure 4 summarizes our universe and strategy. Figure 5 gives more details on our universe, as well as the transaction costs we impose in our backtests.

Figure 4: Summary of our universe, together with an overview of our stock selection strategy



Source: J.P. Morgan Quantitative and Derivatives Strategy

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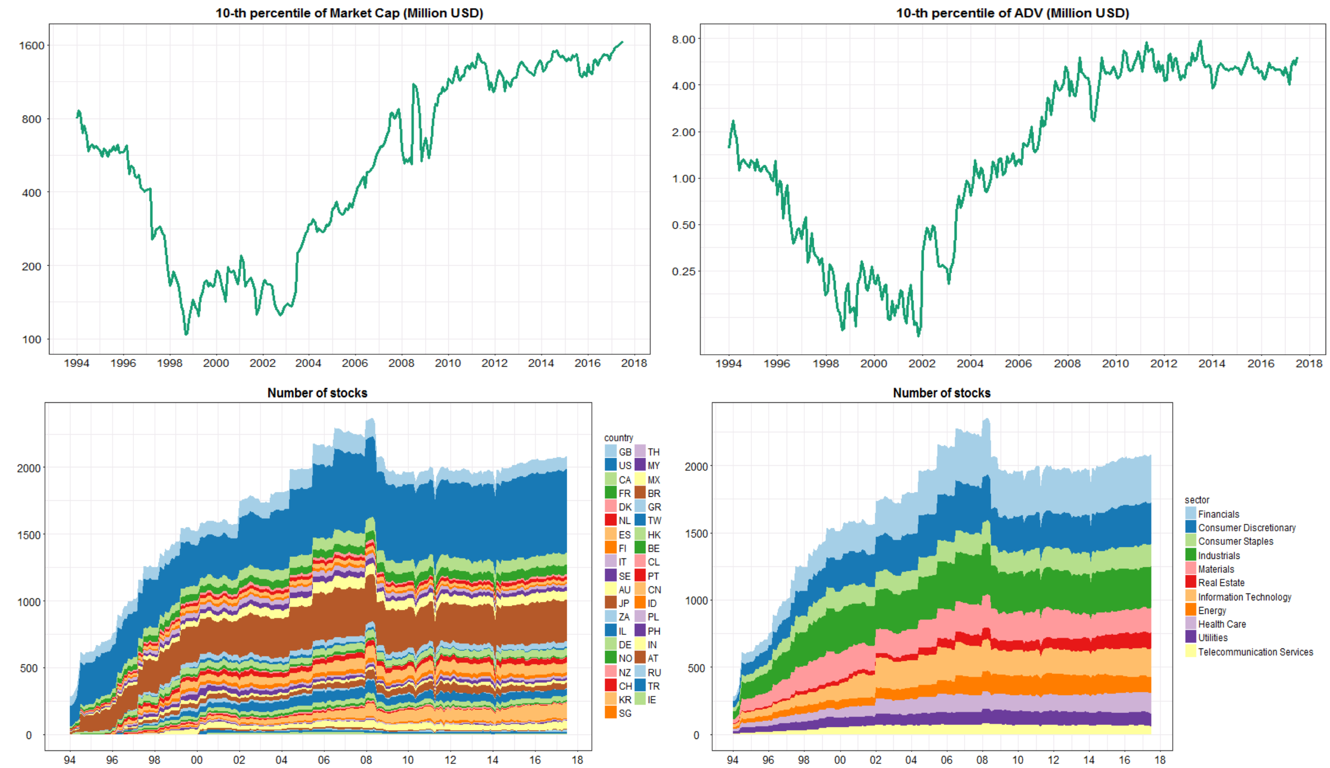
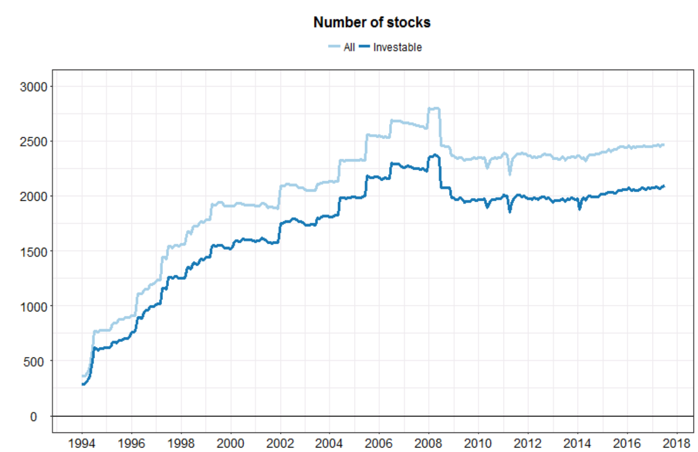
Figure 5: We remove stocks in the bottom 10th percentile of Market Cap and/or Average Daily Trading Value. The table shows the transaction costs that we have included in our backtests.





Countries	Transaction costs Buy (bps)	Sell (bps)
DM countries	4	4
Hungary	10	10
Poland	10	10
Turkey	10	10
Israel	10	10
South Africa	12	12
Czech Republic	15	15
Russia	15	15
China	20	20
India	20	20
Thailand	20	20
Brazil	20	20
Mexico	20	20
UAE	25	25
South Korea	25	25
Taiwan	25	25
Qatar	28	28
Egypt	30	30
Malaysia	30	30
Chile	30	30
Greece	14	34
Indonesia	35	35
Colombia	35	35
Philippines	45	45

Source: J.P. Morgan Quantitative and Derivatives Strategy, Thomson Reuters, FactSet, Bloomberg, IBES, MSCI

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Machine Learning: Uncover Mispricing

Given two stocks, is it true that the one with a lower price to book is cheaper? This is probably a tricky question, as the perception of "cheap" or "expensive" is always relative, and has to depend on some benchmarks. For example, a stock with high growth may have a higher price-to-book ratio than its peers, but for a good reason: investors are pricing in future increase in earnings and payout. As such, is the stock really more expensive?

We think that "cheap" or "expensive" should be defined in a more objective manner based on the notion of "fair value". Of course, we cannot observe the "fair value" of a stock directly. Can we estimate it using a statistical model?

What is the "fair value" of a stock?

Chen et al (2009) consider a dynamic valuation model based on Campbell and Shiller (1988), and estimate "mispricing" as the difference between the observed price-to-dividend ratio and the expected value from the model. They find that it is the mispricing component that predicts future returns, but not the fundamental value component.

Academics have used regression models to estimate fair values in terms of price-to-dividend, price-to-book, or price itself.

Mispricing can be estimated from the residuals of the models.

On the other hand, Nichols et al (2017) run a cross-sectional regression and attempts to explain the share price as a function of book value, earnings, dividends and growth. They find that accounting fundamentals explain a majority of the cross-sectional variation of share prices. From their model, one can obtain the "fair value" of a stock and come up with a valuation residual, defined as

$$residuals = \frac{price - fair\ value}{price}$$

Such residuals play the same role as the "mispricing" signal that we will develop in the following sections. In short, we can estimate if a stock is "cheap" (i.e. undervalued) or "expensive" (i.e. overvalued) based on a model for its fair value.

Following the popularity of our report on Big Data and AI Strategies2F[3], we decide to take this opportunity to further illustrate the use of Machine Learning in the context of the equity valuation. As such, our "fair value" model will not attempt to fit into an accounting or discounted cash flow framework. Instead, we rely on a large number of stock characteristics as inputs into our Machine Learning algorithms, which could help us to uncover mispricing of a stock. Machine Learning algorithms typically require a decently large amount of data for model estimation, and global stock level data would be an ideal playground for these algorithms.

[3] **Kolanovic, M. and Krishnamachari, R. (2017). Big Data and AI Strategies: Machine Learning and Alternative Data Approach to Investing. JPMorgan Global Equity and Quantitative Research, May 2017**

Stock characteristics for predicting price-to-book

Readers familiar with the Discounted Cash Flow (DCF) models from the accounting literature would probably know that the expected return-on-equity (ROE) should be a key determinant of price-to-book[4] (Ohlson, J. (1991), Bernard, V. (1994)). We will see in the next sections (e.g. Figure 9 and Figure 13) that forward ROE is indeed the single most important variable in the prediction of price-to-book. Nevertheless, we do not confine ourselves to traditional accounting models for valuation. Instead, we consider Machine Learning and investigate if other features could help to forecast the "fair value" of a stock.

Machine Learning algorithms are capable of handling hundreds or even thousands of variables without worrying too much about the problem of collinearity among the variables, as in the case with ordinary linear regressions. This is because the algorithms include a regularization term where we penalize for a large number of coefficients and/or large magnitudes of coefficients. This helps to make the model more interpretable, and in many cases also reduce out-of-sample forecast errors[5]. We include 37 stock characteristics that may help to predict the price-to-book of a stock, with measures from valuations, profitability, operational efficiency, quality, growth, sentiment to risk. Table 1 lists the features that we have considered in our models.

Table 1: 37 stock characteristics considered in the model for predicting P/B ratios. For variables related to cash flows (e.g. CFROI), we remove stocks in the Financials.

ROE / Dupont Decomposition / Profitability / Efficiency		**Valuation / Payout**	
	Details		**Details**
ROE	Return on Equity	Earnings yield	Trailing EPS / Price
Net Margin	Net Profit Margin	Forward earnings yield	1 / (12-month forward PE)
Asset turnover	Asset Turnover	Dividend yield	Trailing DPS/ Price
Gearing	Total Assets / Equity	Forward dividend yield	12-month forward dividend yield
ROA	Return on Assets	Sales yield	Trailing Sales / Price
ROC	EBIT / Capital employed	Forward sales yield	12-month forward sales yield
ROE FY1	Return on Equity FY1	Shareholder yield	(Total Dividends + net Repurchases + net changes in Debt) / Market Cap
Gross-Profit-to-Assets	Gross profit / Total Assets	Cash flow yield	Trailing cash flow per share / price
Cash-Flow-to-Assets	Free Cash Flow / Total Assets	Sales to EV	Sales or Operating Revenue / Enterprise Value
CFROI	Cash Flow Return on Investment	EBITDA to EV	EBITDA to Enterprise Value
Positive Earnings	Dummy variable: 1 = positive last reported EPS, 0 otherwise	Payout ratio	Dividend per share / Earnings per share
		Dividend payer	Dummy variable: 1 = positive last reported DPS, 0 otherwise

Growth / Sentiment		**Quality / Risk**	
	Details		**Details**
Forecast EPS growth	Forecast Earnings growth from FY1 to FY2	Earnings Certainty	- [ABS(EPS FY1 Std Dev / EPS FY1) + ABS(EPS FY2 Std Dev / EPS FY2)]
Forecast DPS growth	Forecast 1-year growth in Dividends	ROE volatility	5 year standard deviation in ROE
EPS long-term growth	EPS long-term growth	Accruals	Change in Net Operating Assets / Average Assets
Recommendation change 1M	- (1-month change in Analyst recommendation) (1=Strong Buy, 5=Strong Sell)	Realized Volatility 90D	Historical volatility (past 90 days)
Earnings momentum	Average of 1M and 3M changes in FY1 and FY2 earnings estimates	Beta	MSCI Country Beta
Momentum		Market Cap	Investible Market Cap
	Details	ADV 1M	Average daily value traded (past 20 days)
Momentum 1M	1M price momentum		
Momentum 12M-1M	12M minus 1M price momentum		

Source: J.P. Morgan Quantitative and Derivatives Strategy

[4] **The discounted cash flow model shows that the value of shareholder equity can be written as a function of net book value and discounted expectations of future earnings (Bernard, V. (1994))**

[5] **Many tree-based models are also relatively immune to the inclusion of many irrelevant predictors, and hence are ideal "base learner" for more sophisticated Machine Learning algorithms**

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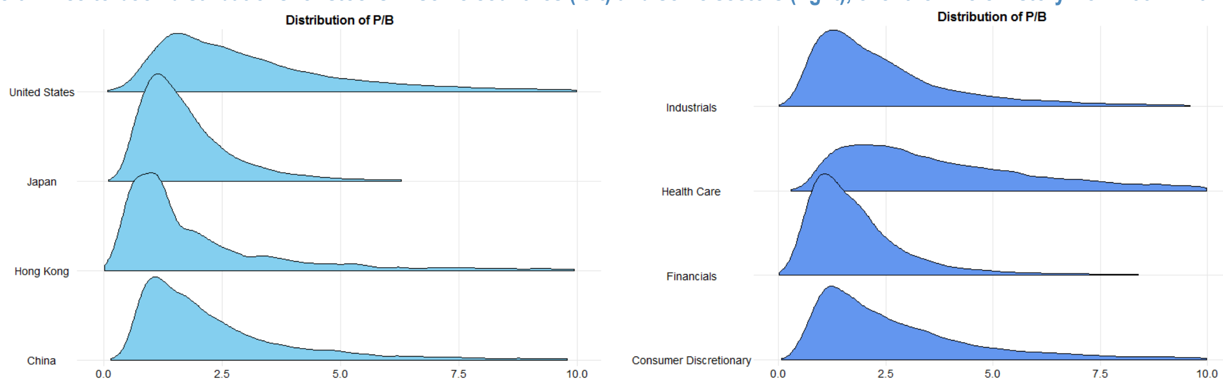
Region, Country and Sector Dummies

Apart from stock characteristics, we also include 6 regions[6], 39 countries and 11 sectors as dummy variables in the models. As the cost of capital can differ significantly across countries and sectors, the valuations on companies depend largely on different discount rates.

Figure 6 shows that stocks in Japan in general have lower price-to-book ratios than stocks in the United States. On the other hand, stocks in the Financials tend to have lower valuations compared to stocks in the Health Care sector. We show the median of price-to-book across different countries in Figure 32 in the Appendix.

Figure 6: Price-to-book distributions for stocks in some countries (left) and some sectors (right), over the whole history from 1994 – 2017

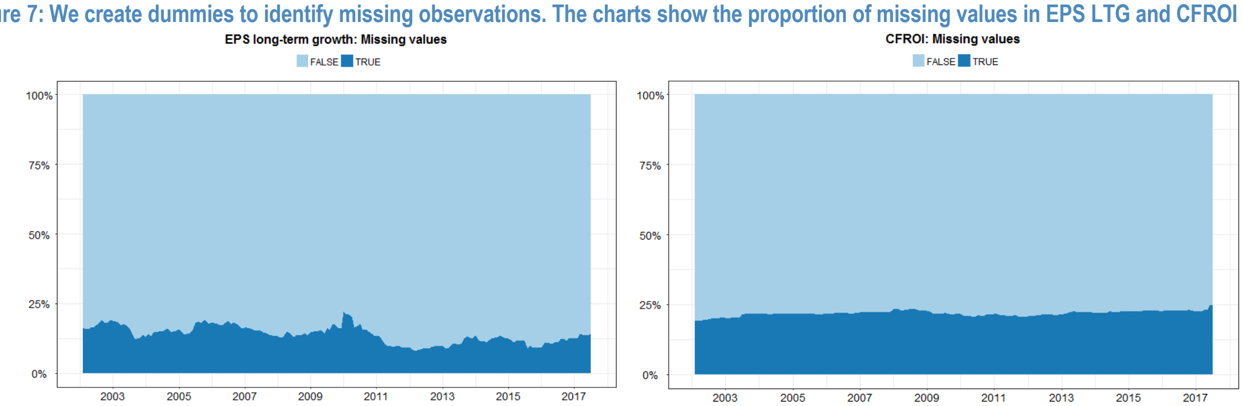


Source: J.P. Morgan Quantitative and Derivatives Strategy, Thomson Reuters, FactSet, Bloomberg, IBES, MSCI

Missing values may also contain information…

We further include derived features from the stock characteristics. We create a dummy variable indicating if the observation is missing or not. Such a dummy variable will have values of either 1 or 0, and may help us to identify certain characteristics of the stock. For example, if a stock is not covered by an analyst, we will not have observations for analyst forecasts such as EPS growth. This may contain useful information on the valuation of a stock. To capture this, we create a derived feature "EPS_LTG_isNA" which has a value of 1 for this stock.

Figure 7: We create dummies to identify missing observations. The charts show the proportion of missing values in EPS LTG and CFROI



Source: J.P. Morgan Quantitative and Derivatives Strategy, Thomson Reuters, FactSet, Bloomberg, IBES, MSCI

[6] DM/EM Americas, DM/EM EMEA, Japan and Asia ex-Japan

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Mispricing signals from our models

We will develop models that predict the price-to-book of a stock in the next month, based on stock characteristics that we observe in the current month:

$$PB_{j,t} = f(X_{j,t-1}) + \varepsilon_{j,t}$$

where $X_{j,t-1}$ is a vector of features for stock j at time $t-1$, $\varepsilon_{j,t}$ is the residuals, and f is our model, which can be linear or non-linear. This model provides an expected value of price-to-book as $E[PB_{j,t+1}] = f(X_{j,t})$, and we quantify the "mispricing" of a stock as the difference between our expected value and the current price-to-book ratio:

$$M_{j,t} = E[PB_{j,t+1}] - PB_{j,t}$$

For instance, a simple linear model based on ROE will have the form:

$$PB_{j,t} = \alpha + \beta \times ROE_{j,t-1} + \varepsilon_{j,t}$$
$$E[PB_{j,t+1}] = \alpha + \beta \times ROE_{j,t}$$

"Mispricing" of a stock is the difference between our expected value from the model and the current price-to-book ratio.

Standardizing the signal with volatility makes it more comparable across stocks.

With this definition, we prefer stocks with a higher value of mispricing $M_{j,t}$, as we expect their price-to-book ratios to expand[7]. We find that a simple approach to account for uncertainties is to scale the mispricing with the standard deviation of the price-to-book over the past 12 months, $\sigma_{j,t}$. Our standardized signal for stock j at time t is then given by

$$S_{j,t} = \frac{E[PB_{j,t+1}] - PB_{j,t}}{\sigma_{j,t}}$$

which is more comparable across stocks with different volatilities.

Before estimating the model, we normalize all variables (including price-to-book) in the cross section because Machine Learning algorithms tend to perform best when different features are of comparable magnitudes. We estimate the model every year at the end of February, using all observations in the past 8 years. Predictions are made using the same model in the next 12 months, until we re-estimate the model in next February[8]. We start estimating the models from February 2010.

[7] This will often be driven by an increase in the stock price because book values tend to change only at a quarterly or annual frequency.

[8] Using a longer lookback window enables us to have more data for model estimation. This can make the models and the predictions more stable.

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Penalized Regression (LASSO)

The first model we look at is one of the simplest linear models amongst Machine Learning algorithms, namely the penalized regression. As detailed in Big Data and AI Strategies, penalized regressions are more robust than ordinary linear regressions, especially when we have a large number of predictors. The idea is to add a regularization term to the objective function to control the coefficients. In ordinary linear regression, we estimate the coefficients β_j by minimizing the sum of squares:

$$\hat{\beta} = \arg\min_{\beta} \left[y - \left(\beta_0 + \sum_{j=1}^{N} \beta_j x_j \right) \right]^2$$

In penalized regression, we avoid having large magnitudes of coefficients β_j by adding regularization terms, which can be written as

$$\hat{\beta} = \arg\min_{\beta} \left(\left[y - \left(\beta_0 + \sum_{j=1}^{N} \beta_j x_j \right) \right]^2 + \lambda \left(\alpha \sum_{j=1}^{N} |\beta_j| + \frac{1}{2}(1-\alpha) \sum_{j=1}^{N} \beta_j^2 \right) \right)$$

where $\lambda > 0$ and $0 \le \alpha \le 1$ are hyper-parameters to be tuned. In essence, this is a Bayesian procedure where we shrink the coefficients towards zero. This can prevent having unstable models with large coefficients when we include a lot of highly correlated variables as inputs. Penalized regressions are usually classified into 3 cases, depending on the regularization terms we adopt:

- **LASSO**: $\alpha = 1$
  Because of the absolute regularization terms, the corresponding solutions tend to be sparse, i.e. many coefficients will be zero (Tibshirani and Friedman (2013))
- **Ridge**: $\alpha = 0$
  Coefficients are shrink to smaller values, but in general will not be zero
- **Elastic Net**: $0 < \alpha < 1$
  It can be viewed as a two-stage procedure where we firstly shrink the coefficients (Ridge) and then threshold the coefficients (LASSO) (Zou and Hastie (2005))

In the following, we fix $\alpha = 1$ and consider the LASSO regression, since we find that LASSO tends to provide better out-of-sample predictions than Ridge or Elastic Net[9]. Moreover, LASSO gives us a sparse model which is easier to interpret, which is another reason that we favor this algorithm over the Ridge regression.

[9] We have tried using the Elastic Net by allowing different values of α, but results are not as good as LASSO.

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Tuning the penalty parameters

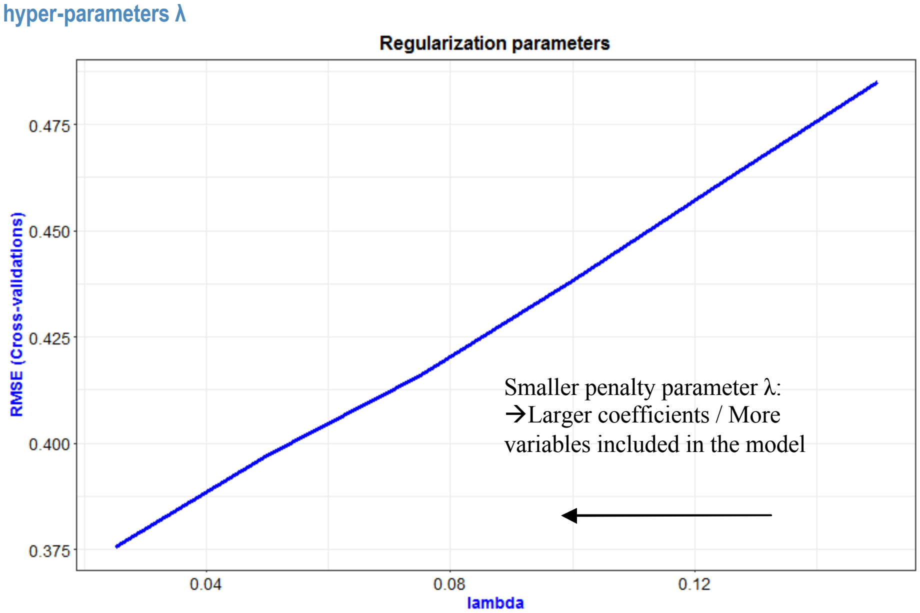
We tune the regularization parameters λ using cross-validations, with the help of the R package "caret". Caret is an excellent package to run Machine Learning algorithms in R, where one can choose from a large set of models, use grid-search and cross-validations to estimate hyper-parameters, and summarize the performance of different models easily.

We use 10-fold cross-validations and a grid search for $\lambda \in [0.025, 0.15]$. It means that we will estimate the model over different values of λ, each time using a subset of the training data. We then evaluate the model based on the prediction accuracies (e.g. RMSE) in the validation sets (i.e. the remaining of the training data where we leave out for cross-validation). Figure 8 shows the RMSE at different hyper-parameters, based on the latest data in 2017.

Cross validations tend to lead to a smaller penalty parameter. To prevent over-fitting, we prefer to stop at some value that correspond to a model with about 25-30 predictors.

We notice that cross-validations tend to point towards smaller penalty parameters, i.e. it favors more complicated models. This may actually not be the best when we want to use the model for out-of-sample predictions. This problem with cross-validation is quite common in time-series data since there are time-dependencies[10]. Our take is to run the algorithm over a large set of hyper-parameters to get an idea of the range of estimation errors as well as prediction errors. There is always some trade-off between the two, and one would probably like to stop at a certain value of λ, in our case we take $\lambda = 0.025$. This corresponds to a model with about 25-30 non-zero variables.

Figure 8: Root-mean squared errors (RMSE) in the cross-validation sets at different values of hyper-parameters λ



Source: J.P. Morgan Quantitative and Derivatives Strategy

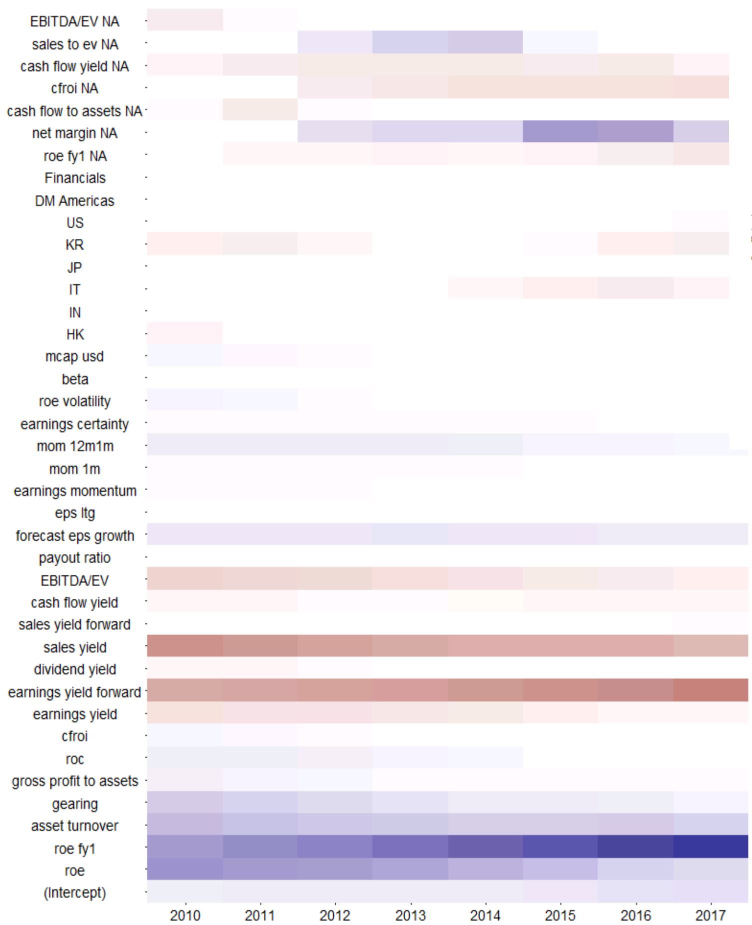
[10] There could be better ways to do cross-validations for time series data by using a "time slice" construction (Cross-validation for time series, Hyndman, R.)

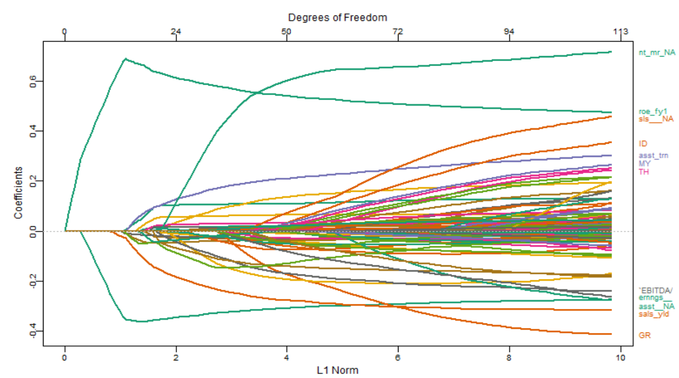
Estimated model and selected variables over time

Figure 9 shows the estimated coefficients for the variables over time, where a white box indicates that the variable is not selected into the LASSO regression. On the right, we show a regularization path from the estimation, which is a family of models at decreasing values of the penalty parameter λ along the horizontal axis, such that our chosen model corresponds to a particular λ.[11]

The table highlights the most important variables in 2017. We see that ROE FY1 is the first variable to enter into the model[12], followed by forward earnings yield and sales yield.

Figure 9: Left: Estimated coefficients in LASSO and selected variables over time (blue: positive, pink: negative, white: not selected). Right: Regularization path (based on data in 2017), showing the estimated coefficients at decreasing values of the penalty parameter, i.e. increasing number of variables.





Variable	Coefficients (→	Decreasing Penalty)						
ROE FY1	0.069	0.34	0.6	0.663	0.68	0.689	0.675	0.672
Earnings yield forward		-0.04	-0.276	-0.331	-0.344	-0.355	-0.36	-0.361
Sales yield			-0.004	-0.021	-0.024	-0.028	-0.068	-0.079
Cash flow yield				-0.002	-0.006	-0.01	-0.014	-0.015
EBITDA/EV					-0.003	-0.007	-0.027	-0.032
ROE						0.005	0.027	0.034
CFROI is NA						-0.007	-0.035	-0.043
Asset turnover							0.037	0.048
Forecast EPS growth								0.002

Source: J.P. Morgan Quantitative and Derivatives Strategy, Thomson Reuters, FactSet, Bloomberg, IBES, MSCI

[11] Actually, the horizontal axis shows the magnitudes of the coefficients (L1 Norm) as well as the number of variables in the model (Degrees of Freedom). Our final model takes about 25-30 variables.

[12] This matches with the results in Discounted Cash Flow (DCF) models, where we expect forward ROE to be a key determinant of price-to-book

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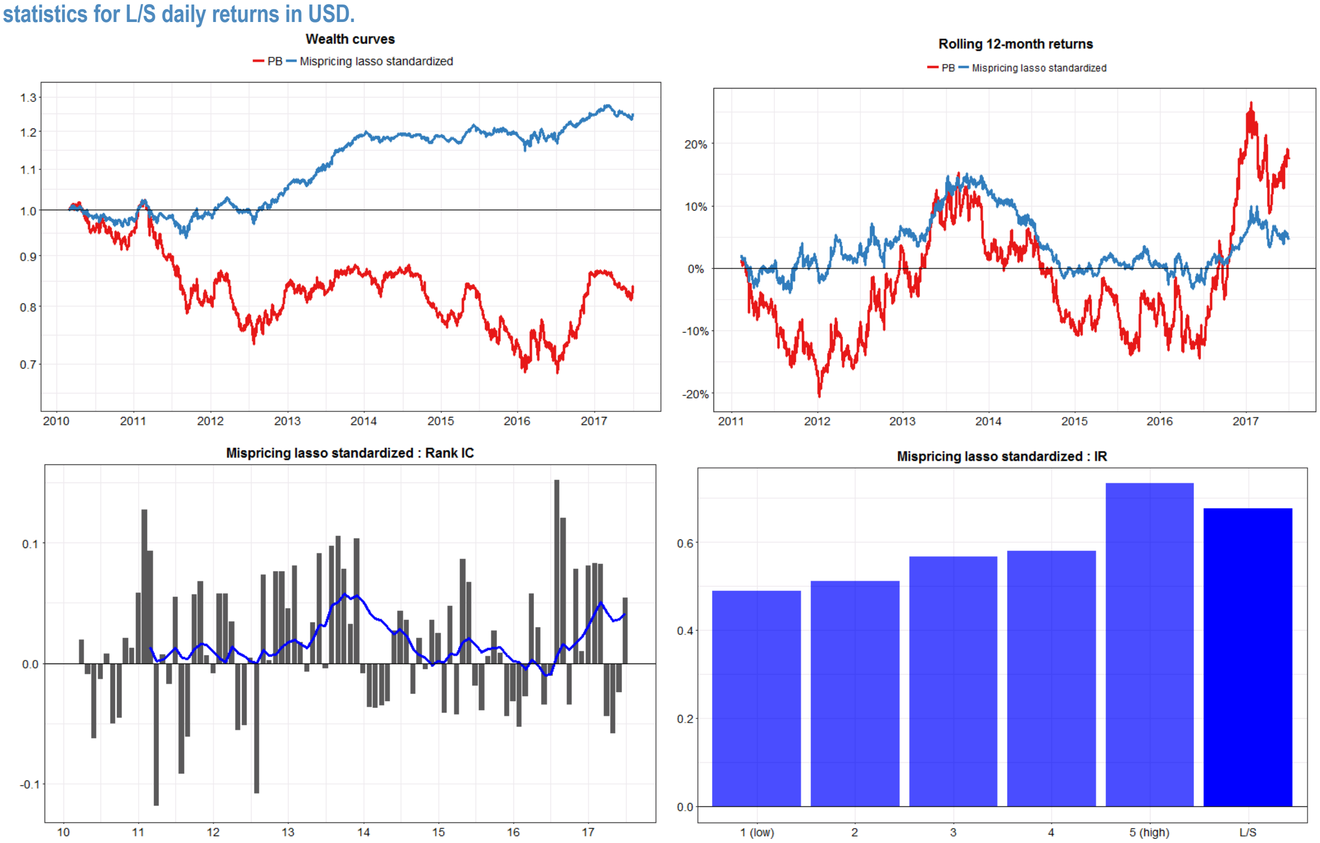
Predictions as a "mispricing" signal

Using the predicted price-to-book from the LASSO regression, we obtain the "mispricing" signal, which is scaled with the volatility of price-to-book:

$$S_{j,t} = \frac{E[PB_{j,t+1}] - PB_{j,t}}{\sigma_{j,t}}$$

We rank stocks into 5 quintile portfolios based on the mispricing signal. Figure 10 shows the long/short wealth curves and the rolling 12-month returns of this strategy, compared with the raw signal of price-to-book. Information Coefficient (IC) (i.e. stock ranking ability) is in general positive, and the Information Ratio (IR) of the quintile portfolios show that the signal is better at identifying undervalued stocks rather than overvalued stocks, i.e. undervalued stocks give significantly higher risk-adjusted returns.

Figure 10: Mispricing (LASSO): L/S quintile wealth curves (after transaction costs) and rolling 12-month returns. The table shows the statistics for L/S daily returns in USD.



Mispricing signals	Median # of stocks (Long or Short)	Mean IC	Risk-adjusted IC	t-stat	Skew-ness	Excess kurtosis	2-way Turnover	Ann. Returns	Ann. Vol.	IR	Max. Draw-down	Hit Ratio
P/B	335	-1.0%	-0.08	-0.60	0.11	2.27	48.1%	-2.4%	9.3%	-0.26	33.1%	48.2%
lasso	331	1.6%	0.28	1.90	-0.12	3.59	87.2%	2.9%	4.2%	0.68	8.3%	51.3%

Source: J.P. Morgan Quantitative and Derivatives Strategy, Thomson Reuters, FactSet, Bloomberg, IBES, MSCI

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Extreme Gradient Boosting (XGBoost)

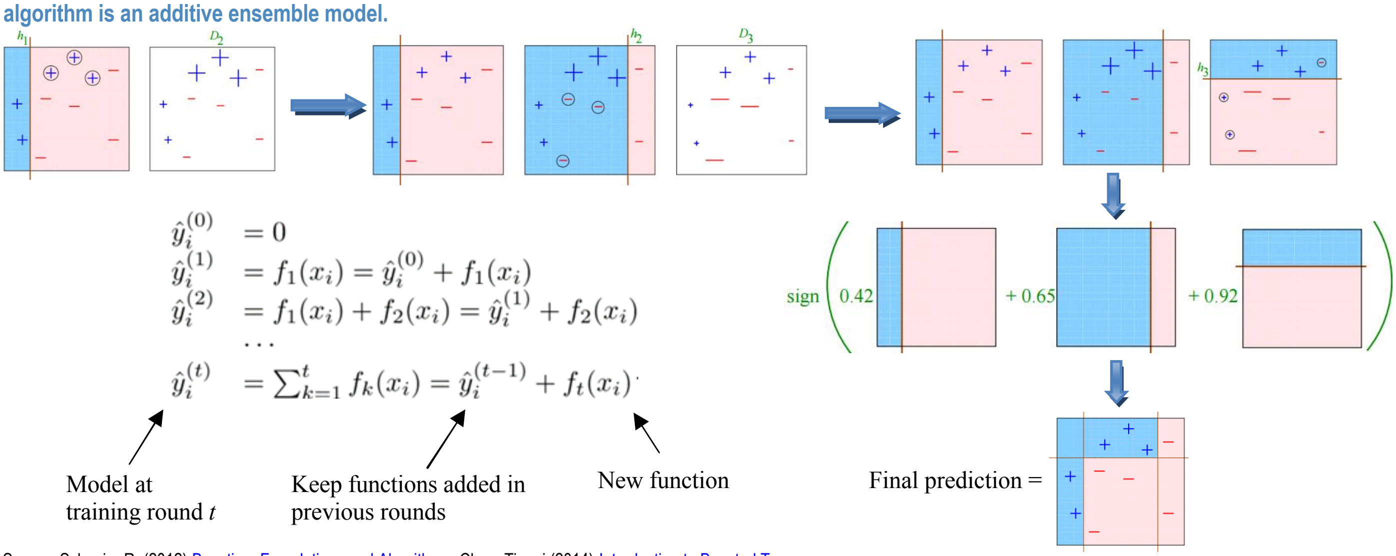
XGBoost is one of the most popular Machine Learning algorithms recently

The second Machine Learning algorithm that we look at is a very popular one due to its prediction accuracies, robustness and speed: Extreme Gradient Boosting (XGBoost). It is one of the variations amongst Gradient Boosting Machines (GBM), which is a type of boosting algorithm that fits a sequence of models so as to improve predictions. XGBoost runs much faster than most of the other GBM libraries since it utilizes OpenMP to perform parallel computations on a multi-threaded CPU. It is one of the most successful winning algorithms on Kaggle[13].

The idea of XGBoost is to build successive models, usually decision trees[14], where each tree is a "weak learner" that attempts to explain the residuals of the prior models. Each weak leaner improves the predictions of the model by putting more focus (i.e. weights) on the data points where predictions made by prior models are poor. For a good overview of the algorithm, one could refer to "Introduction to Boosted Trees" (Chen, 2014).

Figure 11 illustrates a general boosting algorithm with 3 weak learners, where each one focuses on explaining certain parts of the data. The final prediction is obtained as a weighted average of the weak learners. The name of "Extreme Gradient Boosting" refers to the fact that it applies a "gradient descent algorithm" to minimize the loss function during the iterations. We fit the model using the "xgboost" package in R, together with the "caret" package for efficient tuning of model hyper-parameters.

Figure 11: Idea of a boosting algorithm to train successive models that focus more on large residuals (i.e. wrong predictions). Here we have 3 weak learners, and the final predictions are obtained as a weighted average of the weak learners. The equations show that a boosting algorithm is an additive ensemble model.



Source: Schapire R. (2012) Boosting: Foundations and Algorithms, Chen, Tianqi (2014) Introduction to Boosted Trees

[13] Kaggle is a platform for Big Data and Machine Learning advocates to learn, share ideas and run their algorithms on real data sets. XGBoost has become popular since its success in a competition to detect the decay of a Higgs Boson (JMLR conference proceedings (2015))

[14] Unlike Random Forest where we build many independent trees to reduce the out-of-sample forecast variances, XGBoost builds sequences of dependent trees iteratively to reduce bias. We could use any base model (e.g. linear regression) as weak learners, but typically decision trees are preferred

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Tuning hyper-parameters

In XGBoost, there are many more hyper-parameters to be tuned, compared with penalized regressions. Nevertheless, we find that there are 3 particularly important hyper-parameters, which tend to affect model predictions to a greater extent:

- **Learning rate**: the 'step size' in the gradient descent algorithm when we attempt to minimize the loss function
- **Maximum depth** of a decision tree
- **Number of boosting iterations** (i.e. the total number of trees)

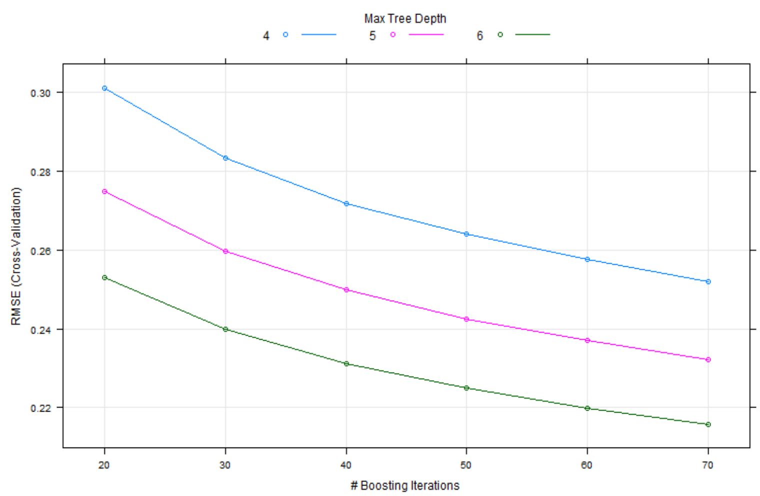
We have also tried to tune other parameters[15], but in general we find the results to be relatively insensitive to them.

We tune the model to firstly decide a learning rate of 0.2. Then we choose a maximum depth of 4-6, and number of trees between 20-70.

One of the approaches in tuning so many parameters is to do it step-by-step. We firstly run the algorithm at different learning rates to estimate a good choice. If the learning rate is too large, the model is learning to quickly and the loss function will not decrease in a consistent manner. If the learning rate is too small, the model is not improving enough over the iterations. We find that a learning rate of 0.2 is good for our data, and we fix this value before tuning the other 2 hyper-parameters.

Similar to our experience with penalized regressions, we find that cross-validations tend to point towards a deeper tree and a larger number of iterations (Figure 12). To prevent overfitting, we decide to stop at a maximum depth of 6, and a maximum of 70 trees[16]. Note that unlike Random Forests where more trees are usually better, for boosting algorithms, too many trees may lead to overfitting since each tree is attempting to 'explain the residuals'. As a rule of thumb, a maximum depth of 4-8 levels tends to give good predictions, and deeper trees tend to overfit.

Figure 12: Tuning the 2 hyper-parameters in XGBoost: Maximum depth and number of iterations.



Source: J.P. Morgan Quantitative and Derivatives Strategy, Thomson Reuters, FactSet, Bloomberg, IBES, MSCI

[15] **For example, we tried to tune the regularization parameters, the proportion of subsamples supplied to a tree, the proportion of features supplied to a tree, the minimum size in a child node etc**

[16] **The trees at the beginning of the sequence have the most influence to the model, whilst trees near the end of the sequence have smaller impacts**

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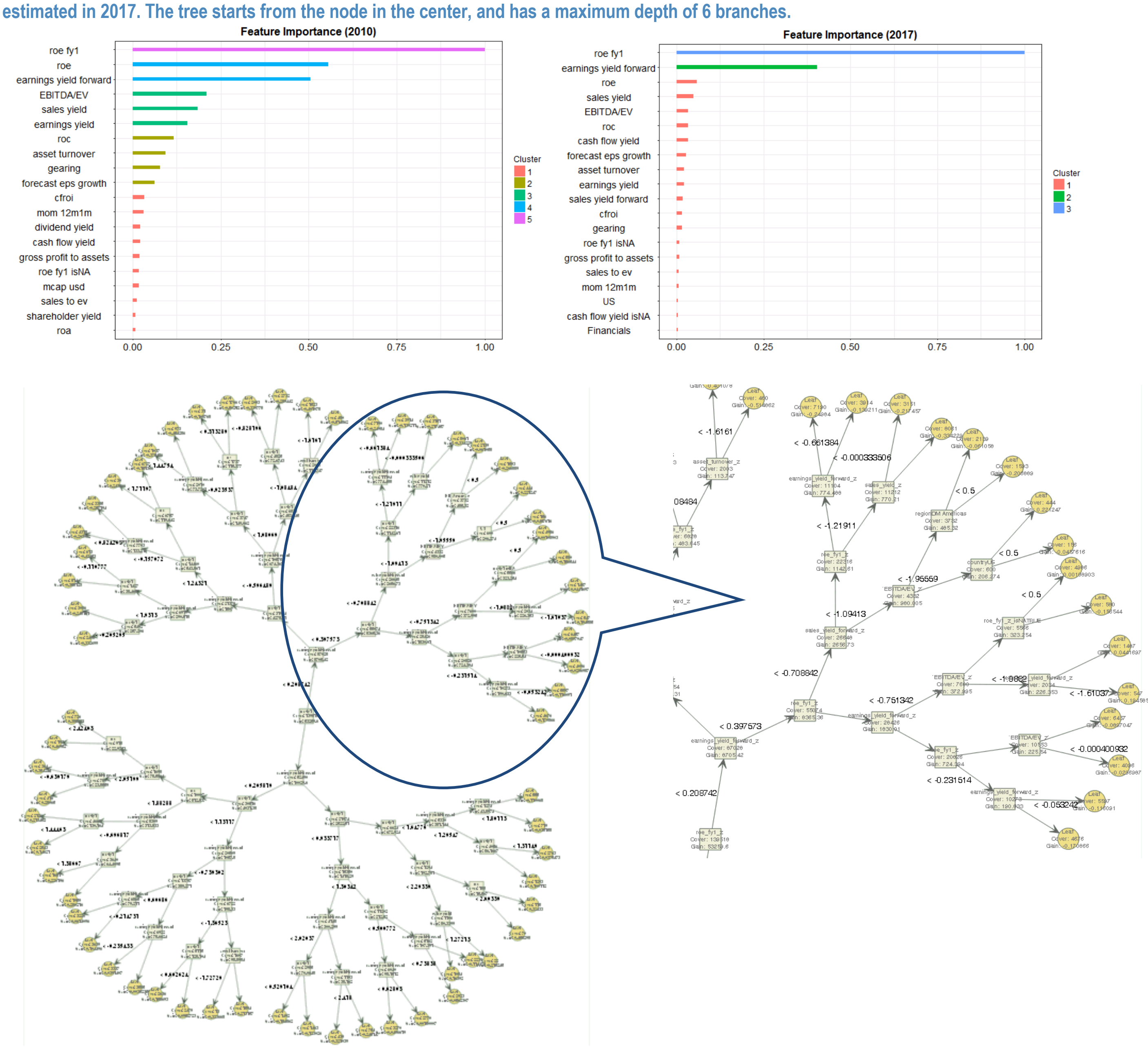
What are the most important variables?

The most important variables in fitting the XGBoost models are shown in Figure 13. They are the variables where we gain the largest improvement in the model fit when we split the nodes using those features. We find that ROE FY1, 12-month forward earnings yield and trailing ROE are the most important in the prediction of price-to-book, followed by EBITDA/EV and sales yield. We also show the first tree in the model in 2017, and zoom into one branch of the tree to see the variables being used. The first split is using the variable ROE FY1, followed by forward earnings yield.

Figure 13: Relative variable importance in the XGBoost model in 2010 (left) and 2017 (right). We also show the first tree in our XGBoost model estimated in 2017. The tree starts from the node in the center, and has a maximum depth of 6 branches.



Source: J.P. Morgan Quantitative and Derivatives Strategy, Thomson Reuters, FactSet, Bloomberg,IBES, MSCI

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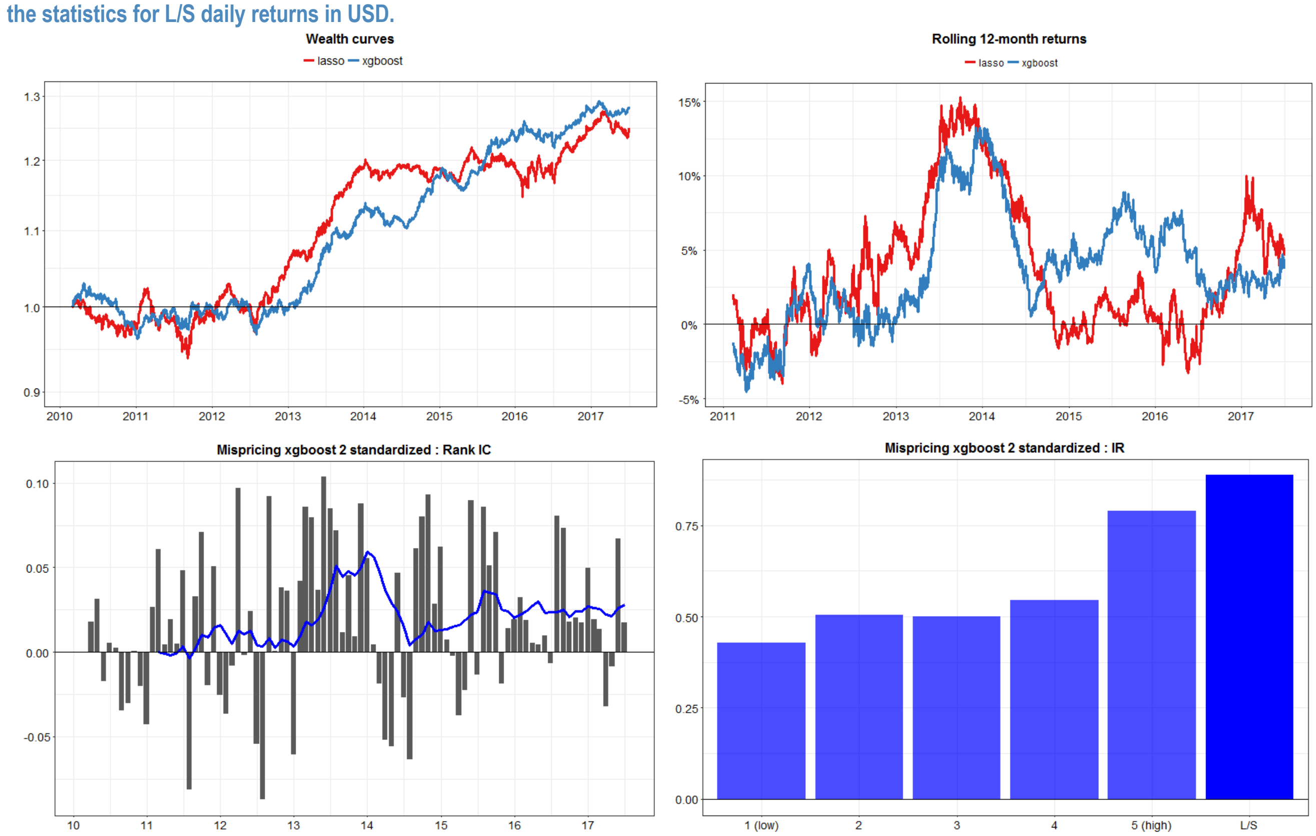
Predictions as a "mispricing" signal

Using the predicted price-to-book values from the XGBoost model, we obtain the "mispricing" signal, which is scaled with the volatility of price-to-book:

$$S_{j,t} = \frac{E[PB_{j,t+1}] - PB_{j,t}}{\sigma_{j,t}}$$

Figure 14 shows the long/short wealth curves and the rolling 12-month returns of the signal, comparing with the results based on penalized regressions. We see some improvements in using the boosting algorithm, where Information Ratio (IR) increases from 0.68 to 0.89. Stock ranking ability of the signal is better with the XGBoost model, giving a mean IC of close to 2%. The Information Ratios of the quintile portfolios shows that the XGBoost model, similar to LASSO, is better at identifying undervalued stocks.

Figure 14: Mispricing (XGBoost vs LASSO): L/S quintile wealth curves (after transaction costs) and rolling 12-month returns. The table shows the statistics for L/S daily returns in USD.



Mispricing signals	Median # of stocks (Long or Short)	Mean IC	Risk-adjusted IC	t-stat	Skew-ness	Excess kurtosis	2-way Turnover	Ann. Returns	Ann. Vol.	IR	Max. Draw-down	Hit Ratio
lasso	331	1.6%	0.28	1.90	-0.12	3.59	87.2%	2.9%	4.2%	0.68	8.3%	51.3%
xgboost	331	1.9%	0.42	2.46	0.01	1.56	139.1%	3.2%	3.6%	0.89	6.7%	51.9%

Source: J.P. Morgan Quantitative and Derivatives Strategy, Thomson Reuters, FactSet, Bloomberg, IBES, MSCI

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Linear Model with the Most Important Features

Although Machine Learning algorithms in general are capable of providing better predictions, one of the drawbacks is the difficulty in model interpretation. It is sometimes regarded as a 'black box' with insufficient transparencies.

Even if we do not want to use complicated Machine Learning algorithms, we can still use them to select the most important features as inputs into our simple linear model

Nevertheless, even though one do not want to apply a Machine Learning algorithm in the end, they are valuable since they often help us to identify the most important features in the model. For instance, the XGBoost algorithm gives us the variable importance as shown in Figure 13. We can utilize this information and estimate a simple linear regression only using a small subset of the most important features. This gives us a simple model which is easy to interpret.

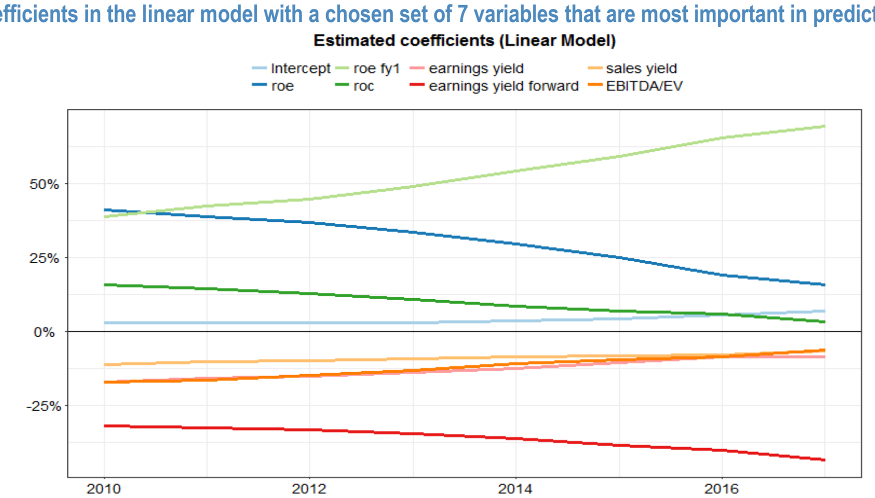
From Figure 13, we see that the most important variables to predict price-to-book are quite stable over time. We select the following 7 variables into our linear model, keeping the same set over time:

- ROE and ROE FY1
- Earnings yield, and 12-month forward earnings yield
- EBITDA/EV
- Sales yield
- Return on Invested Capital (ROC)

The estimated coefficients of this simple linear model are shown in Figure 15:

- Stocks with a higher ROE FY1, ROE and ROC in general commands a higher price-to-book
- Stocks with higher earnings yield, sales yield and EBITDA/EV have lower price-to-book (as yield metrics are inversely related to price-to-book)
- The coefficient of ROE FY1 increases over time, likely because of the decrease of another highly correlated variable: trailing ROE

Figure 15: Estimated coefficients in the linear model with a chosen set of 7 variables that are most important in predicting price-to-book



Source: J.P. Morgan Quantitative and Derivatives Strategy, Thomson Reuters, FactSet, Bloomberg, IBES, MSCI

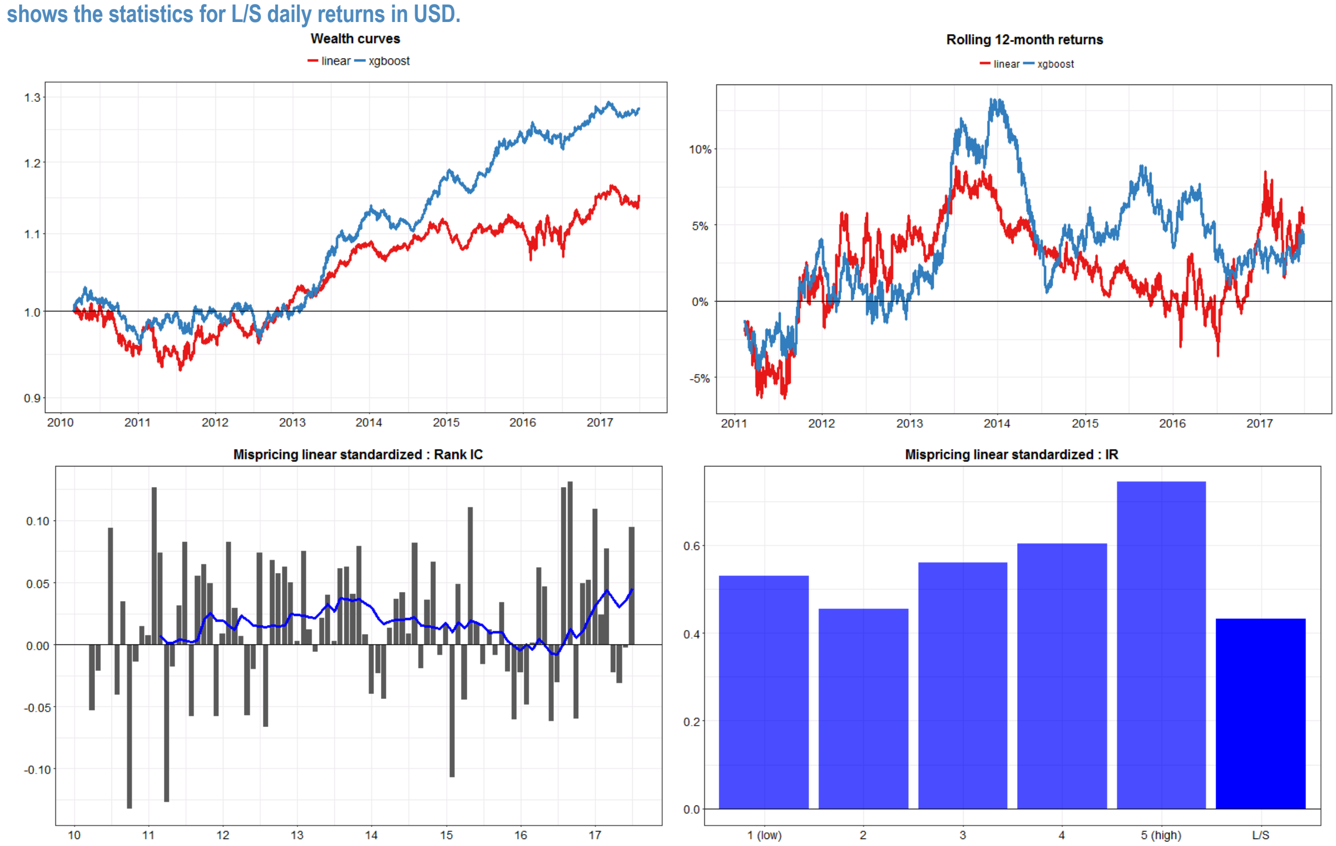
Predictions as a "mispricing" signal

Similarly, we obtain the predicted price-to-book values from the simple linear model, we obtain the mispricing signal for stock *j* at time *t*:

$$S_{j,t} = \frac{E[PB_{j,t+1}] - PB_{j,t}}{\sigma_{j,t}}$$

Figure 16 compares the long/short strategy performance based on the mispricing signals obtained from this simple linear model and the XGBoost model. We do see some advantages of using the non-linear XGBoost model, but it is interesting to see that a much simpler linear model with only 7 variables could still deliver a consistently positive stock ranking ability.

Figure 16: Mispricing (linear model vs XGBoost): L/S quintile wealth curves (after transaction costs) and rolling 12-month returns. The table shows the statistics for L/S daily returns in USD.



Mispricing signals	Median # of stocks (Long or Short)	Mean IC	Risk-adjusted IC	t-stat	Skew-ness	Excess kurtosis	2-way Turnover	Ann. Returns	Ann. Vol.	IR	Max. Draw-down	Hit Ratio
linear	332	1.6%	0.29	1.24	-0.16	4.42	87.2%	1.8%	4.1%	0.43	7.8%	49.9%
xgboost	331	1.9%	0.42	2.46	0.01	1.56	139.1%	3.2%	3.6%	0.89	6.7%	51.9%

Source: J.P. Morgan Quantitative and Derivatives Strategy, Thomson Reuters, FactSet, Bloomberg, IBES, MSCI

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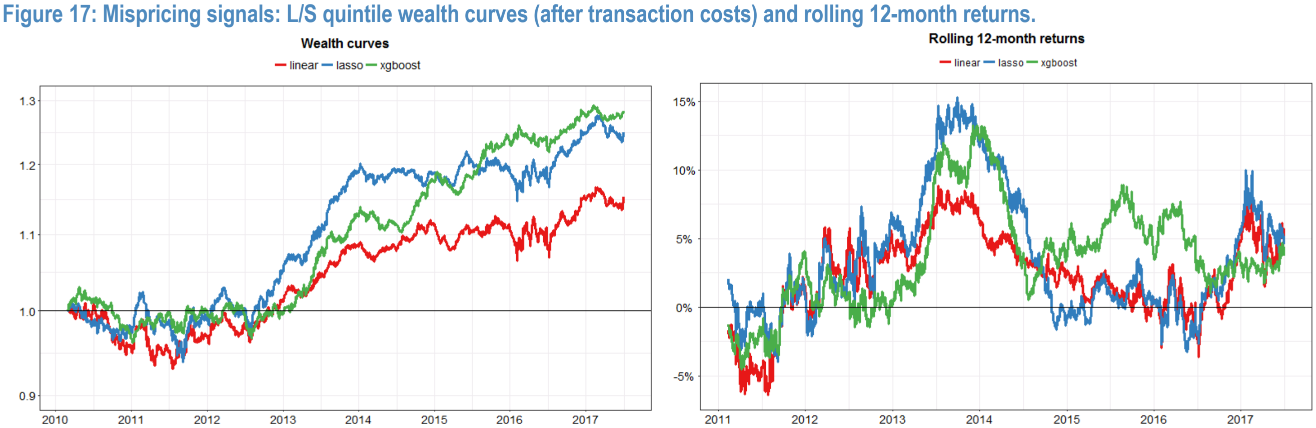
A Composite Model

Combining predictions from different models, even in a heuristic manner, often helps to improve out-of-sample predictions

With the aphorism that “All models are wrong but some are useful” (Box, G), one may want to improve the robustness of the strategy by combining information from different models. In Machine Learning, one of the useful techniques is to consider several “base” models and combine them into a "2nd level model". In many cases, since each model has different features and tends to perform better under particular conditions, the ensemble model usually produces better predictions than any of the single model[17]. This is well demonstrated among the winning solutions on Kaggle competitions: Almost all of the winning algorithms consider a combination of several models, usually a simple linear model (LASSO / Ridge regression) together with a few more complicated non-linear models (Random Forests, XGBoost, etc).

Before trying to combine the models, let us recap their performances in Figure 17. More comparisons of the model prediction accuracies are given in Figure 42 and Figure 43 in the Appendix.

Figure 17: Mispricing signals: L/S quintile wealth curves (after transaction costs) and rolling 12-month returns.



Source: J.P. Morgan Quantitative and Derivatives Strategy, Thomson Reuters, FactSet, Bloomberg, IBES, MSCI

From Figure 17, we see that over time different models may perform better, e.g. in 2013 – 2014, LASSO performs very well, whilst in 2015 – 2016, XGBoost is much better. As such, let us consider a combination of the normalized mispricing signals, M_z, from the 3 models:

$$M_{z,Composite} = w_{linear} M_{z,linear} + w_{LASSO} M_{z,LASSO} + w_{XGBoost} M_{z,XGBoost}$$

We simply use the Information Ratio (IR, no t-costs)[18] as the model weights, and keep it constant over time. Again, we compute the standardized signal by scaling it with the volatility of the z-score of price-to-book in the past 12 months:

$$S_{Composite} = \frac{M_{z,Composite}}{\sigma(PB_z)}$$

17 One can either use a heuristic approach to combine the models, or do that via a more systematic way. When the models are combined based on cross-validations, this is often called Stacking. When the models are aggregated based on their posterior probabilities, this is the Bayesian Model Averaging

18 We admit that this exercise has look-ahead bias, and there are better ways to combine models

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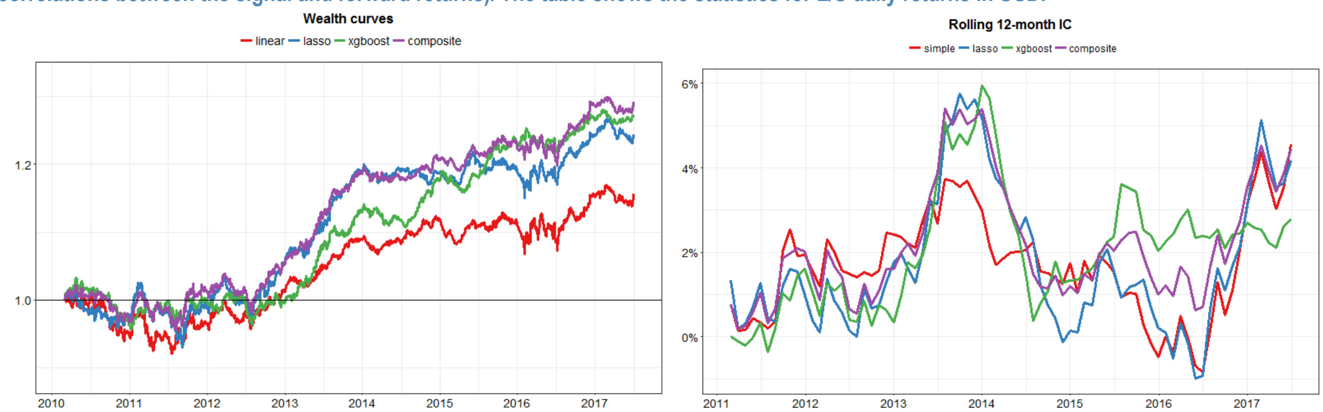
In Figure 18, we compare the long/short wealth curves of the composite mispricing signal, together with each of the individual mispricing signal based on the simple linear model, LASSO and XGBoost. We see that a combination of models could help to improve returns, as well as reduce drawdowns.

In terms of Information Coefficient (IC) (i.e. rank correlations between the signal and forward returns), we also find that a composite mispricing signal is better than any of the individual signals.

In Figure 37 of the Appendix, we further compare our final strategy based on the composite model together with each of the individual model, where we see a clear improvement from a single model to an ensemble model.

Figure 18: Comparing mispricing signals: L/S quintile wealth curves (after transaction costs) and rolling Information Coefficient (IC) (i.e. rank correlations between the signal and forward returns). The table shows the statistics for L/S daily returns in USD.



Mispricing signals	Median # of stocks (Long or Short)	Mean IC	Risk-adj. IC	t-stat	Skew-ness	Excess kurtosis	2-way Turnover	Ann. Returns	Ann. Vol.	IR	Max. Drawdown	Hit Ratio
linear	332	1.6%	0.29	1.24	-0.16	4.42	87.2%	1.8%	4.1%	0.43	7.8%	49.9%
lasso	331	1.6%	0.28	1.90	-0.12	3.59	87.2%	2.9%	4.2%	0.68	8.3%	51.3%
xgboost	331	1.9%	0.42	2.46	0.01	1.56	139.1%	3.2%	3.6%	0.89	6.7%	51.9%
composite	331	2.0%	0.44	2.45	0.01	3.04	112.2%	3.4%	3.9%	0.88	5.8%	51.0%

Source: J.P. Morgan Quantitative and Derivatives Strategy, Thomson Reuters, FactSet, Bloomberg, IBES, MSCI

Of course, the composite signal is not too satisfying yet: the performance during 2010 – 2012 has been flat, although it's still better than the raw price-to-book which has made a large loss (Figure 3). In the next section, we delve into another dimension that helps to complement our mispricing signals and avoid value traps: Profitability.

Profitability Matters

Whilst we have put some efforts in estimating a signal to spot out mispriced stocks, we would not use it as a standalone signal. There is one important aspect that we have to improve: Can we identify which undervalued / overvalued stocks will indeed revert to their "fair value"?

In the followings, we attempt to understand how profitability can be used to enhance the mispricing strategies. Intuitively, we would like to invest in stocks at a reasonable price (i.e. value stocks) which also demonstrate their abilities to make profits. This coincides with the idea in "Sorting Through the Trash: Quality at a Reasonable Price", where Value with Quality is a good combination for stock selection, especially in Asia. In that report, we look at return-on-equity (ROE) and its DuPont decompositions as Quality measures, together with earnings certainty. Is ROE the factor that we should look at? Are there other better candidates?

The "Magic Formula"

In "The little book that beats the market", Greenblatt (2006) discuss a simple stock selection methodology where he deems the "Magic Formula". The formula simply ranks stocks based on a combination of Value and Profitability measures: Earnings yield and Return-on-Capital (i.e. EBIT / Tangible capital).

Novy-Marx (2013) suggests that Gross Profit is the cleanest accounting measure of true economic profitability, since it is at the highest level of an income statement.

Gross Profit is a better predictor of returns than EBIT (or Net Income)

Whilst this simple "Magic Formula" sounds appealing, there are studies showing evidence that the use of Gross Profit could be a better measure for profitability than EBIT. For instance, in "The other side of value: The gross profitability premium", Novy-Marx (2013)[19] argues that Gross Profit is the cleanest accounting measure of true economic profitability, because items further down the income statement (e.g. EBIT) are more polluted measures. For example, a firm that invests heavily in R&D or sales could have lower earnings than its competitors, but one may expect the firm to deliver higher future returns due to the growth potential.

In a recent paper "The Magic Formula: Value, Profitability, and the Cross Section of Global Stock Returns", Blackburn and Cakici (2017) also find similar conclusions supporting the arguments in Novy-Marx (2013). The authors find that the "Magic Formula" fails to generate significant abnormal returns, but a version that uses Gross Profits instead of EBIT yields statistically significant risk-adjusted returns over North America, Europe, Japan as well as Asia, and is a more powerful predictor of cross-sectional returns than EBIT.

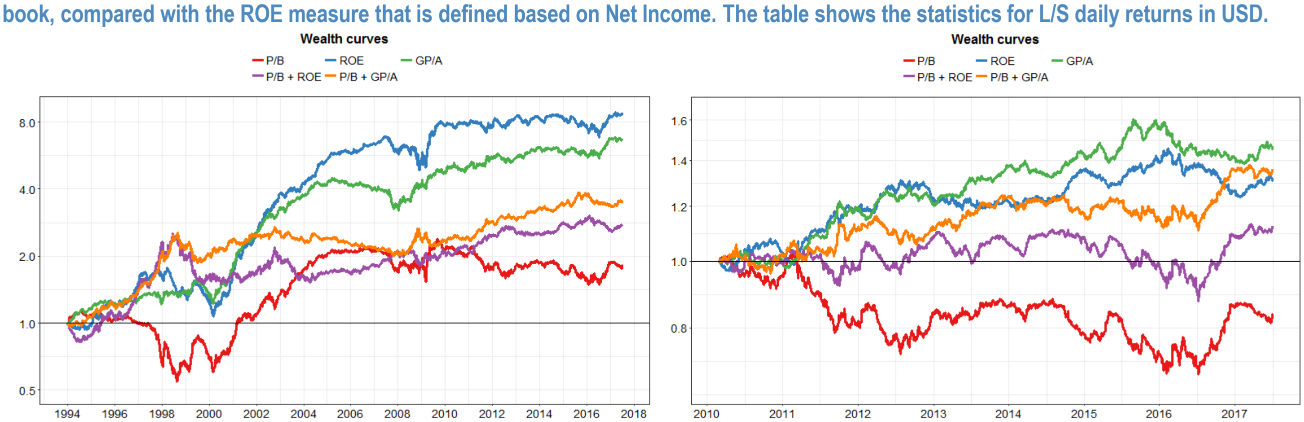
[19] The author finds that firms with higher profitability, measured by gross profits to assets, have higher returns than unprofitable firms, despite significantly higher valuation ratios (in terms of book-to-market) and higher market capitalization. As a result, controlling for profitability improves the performance of value strategies. The author analyzes the performance of 5x5 double-sorted portfolios on gross profits to assets and book-to-market, and observes that among "cheap" stocks, those with higher profitability generate significantly higher returns

Gross Profits: A Cleaner Measure of Profitability?

To kick start with some ideas, let us first make a slight detour from our mispricing signals, and look at how a "good old" (P/B + ROE) strategy performs, as compare with an alternative strategy of P/B + Gross-Profits-to-Assets (GP/A). The (P/B + ROE) factor is a classic "Quality at a Reasonable Price" (QARP) strategy, which has delivered nice returns profile in Asia (Sorting Through the Trash: Quality at a Reasonable Price in Asia) and Global Emerging Markets (Return on Equity: Is it useful for stock picking?).

Figure 19 shows the wealth curves of the strategies, where the Information Ratio (IR) increases significantly when one combines price-to-book with Gross-Profit-to-Assets (GP/A). This may not be too surprising, given that as a standalone signal, GP/A also provides higher returns and Information Ratio than ROE.

Figure 19: Backtests of P/B, ROE and Gross-Profit-to-Assets since 1994 (left) and since 2010 (right). Wealth curves are based on the L/S quintile portfolios after transaction costs. Profitability measure, as defined by Gross Profits, seems to be a better companion with price-to-book, compared with the ROE measure that is defined based on Net Income. The table shows the statistics for L/S daily returns in USD.



Signal	Start	End	Annualized Returns	Annualized Volatility	IR	Maximum Drawdown	Hit Ratio
Since 1994							
P/B	1994-01-04	2017-06-30	2.4%	11.0%	0.22	52.2%	49.3%
ROE	1994-01-04	2017-06-30	9.3%	10.4%	0.89	39.7%	51.5%
GP/A	1994-01-04	2017-06-30	8.1%	8.4%	0.97	28.5%	51.2%
P/B + ROE	1994-01-04	2017-06-30	4.2%	10.5%	0.40	40.8%	51.4%
P/B + GP/A	1994-01-04	2017-06-30	5.2%	7.7%	0.68	27.0%	51.3%
Since 2010							
P/B	2010-03-02	2017-06-30	-2.3%	9.3%	-0.25	33.1%	48.2%
ROE	2010-03-02	2017-06-30	3.6%	6.7%	0.54	15.2%	51.6%
GP/A	2010-03-02	2017-06-30	5.1%	5.9%	0.86	13.9%	52.1%
P/B + ROE	2010-03-02	2017-06-30	1.5%	7.5%	0.20	21.2%	49.7%
P/B + GP/A	2010-03-02	2017-06-30	4.1%	7.8%	0.53	11.2%	50.5%

Source: J.P. Morgan Quantitative and Derivatives Strategy, Thomson Reuters, FactSet, Bloomberg, IBES, MSCI

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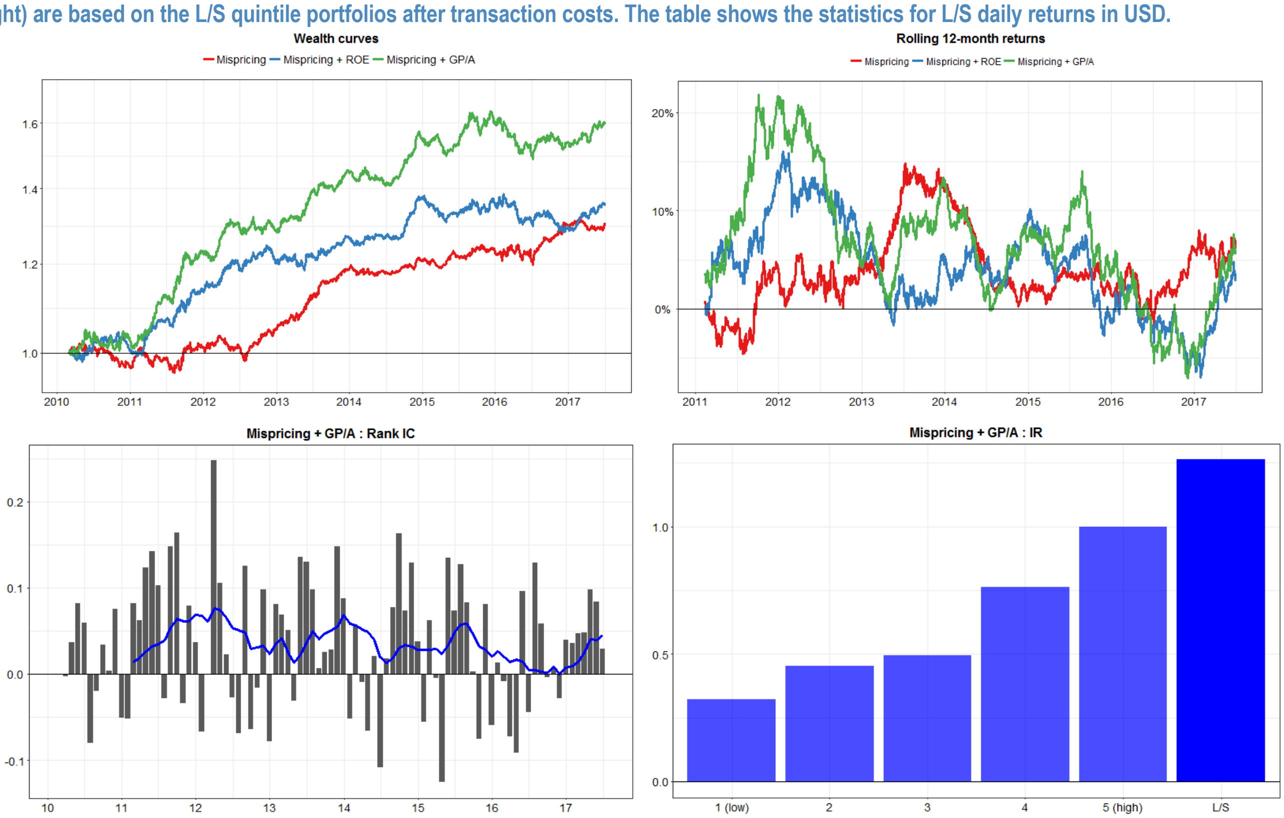
Filtering Mispriced Stocks with Profitability

A simple way of combining the mispricing signals and profitability is to firstly normalize each signal to a z-score, and then take the simple average. In the followings, we focus on the mispricing signals obtained from the composite model, unless otherwise stated. We combine this mispricing signal with the traditional ROE and Gross-Profit-to-Assets (GP/A) respectively.

We first look at a simple z-score average of the composite mispricing and Gross-Profit-to-Assets

Figure 20 shows the wealth curves and the rolling 12-month returns of the strategies. We see that combining the mispricing signal with Gross-Profit-to-Assets provides significant improvements in the strategy returns, especially during 2011-2012 and 2015-2016. As such, Information Ratio (IR) increases from 0.88 (with the mispricing signal only) to 1.26 (with the combination of GP/A). On the other hand, combining with ROE increases the returns to a lesser extent, and with the higher volatility, risk-adjusted returns (i.e. Information Ratio) actually decreases.

Figure 20: Mispricing signal (Composite) combined with ROE or Gross-Profit-to-Assets. Wealth curves (left) and rolling 12-month returns (right) are based on the L/S quintile portfolios after transaction costs. The table shows the statistics for L/S daily returns in USD.



Signal	Median # of stocks (Long or Short)	Mean IC	Risk-adj. IC	t-stat	Skew-ness	Excess kurtosis	2-way Turnover	Ann. Returns	Ann. Vol.	IR	Max. Draw-down	Hit Ratio
Mispricing	331	2.0%	0.44	2.45	0.01	3.04	112.2%	3.4%	3.9%	0.88	5.8%	51.0%
Mispricing + ROE	331	2.6%	0.42	2.24	0.30	2.38	90.1%	4.0%	5.0%	0.80	7.5%	51.5%
Mispricing + GP/A	272	3.5%	0.47	3.45	0.04	0.79	85.1%	6.3%	5.0%	1.26	9.4%	53.6%

Source: J.P. Morgan Quantitative and Derivatives Strategy, Thomson Reuters, FactSet, Bloomberg, IBES, MSCI

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Filtering: A more effective way to identify "value traps"

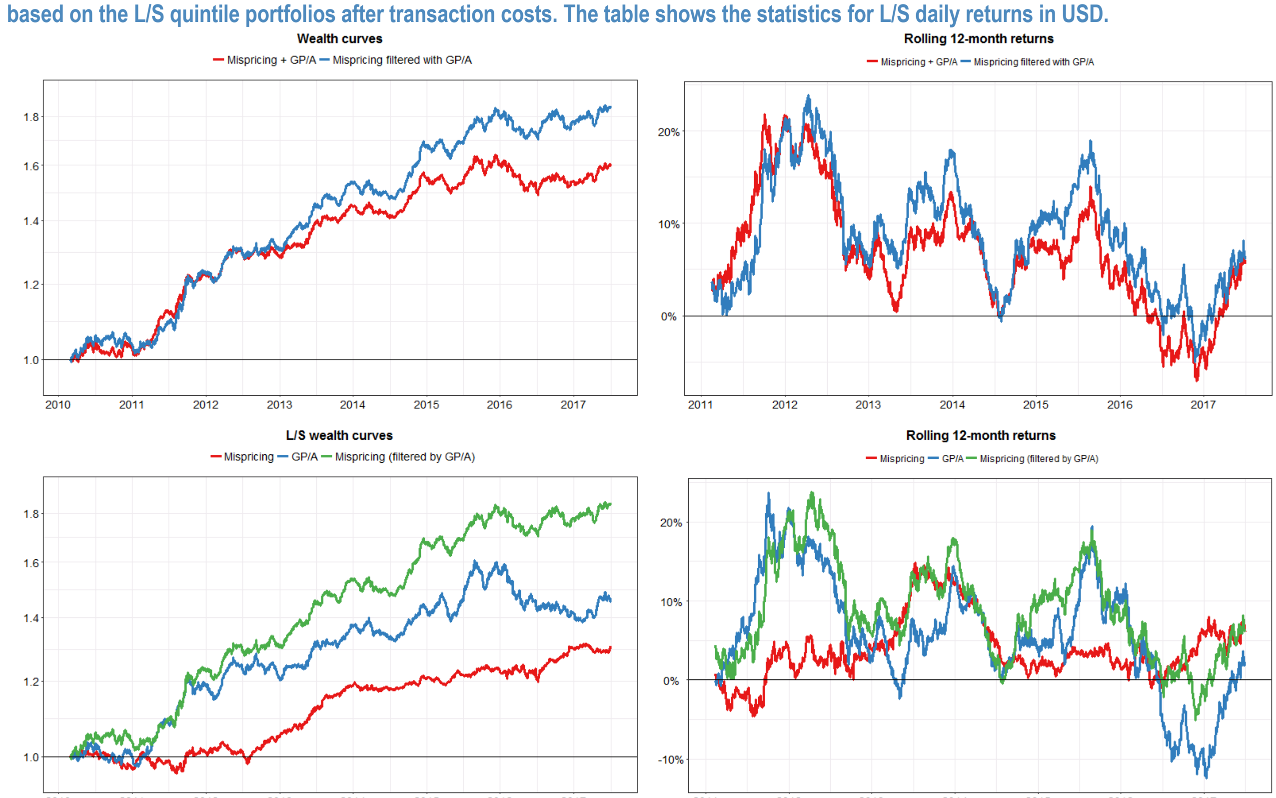
However, in the above "combinative" approach, we may like stocks that are either largely undervalued (but not really profitable), or with a very high profitability (but not necessarily undervalued). A better way to play the mispricing signal is to firstly look at stocks that are highly undervalued or overvalued, and then use the Gross-Profit-to-Assets (GP/A) as a filter[20]:

In contrast to z-score averages, we find that filtering mispriced stocks based on Gross-Profit-to-Assets is a more effective way to identify "value traps", i.e. cheap stocks with poor profitability

- In the *long* portfolio with undervalued stocks, we only keep those with the *top 40%* of Gross-Profit-to-Assets
- In the *short* portfolio with overvalued stocks, we only keep stocks with the *bottom 40%* of Gross-Profit-to-Assets

Figure 21 shows the wealth curves and rolling 12-month returns. We find that filtering mispriced stocks is a better strategy compared to a simple "z-score average" of the signals, especially since 2014.

Figure 21: Mispricing signal (Composite) filtered with Gross-Profit-to-Assets. Wealth Curves (left) and rolling 12-month returns (right) are based on the L/S quintile portfolios after transaction costs. The table shows the statistics for L/S daily returns in USD.



Signal	Median # of stocks (L/S)	t-stat	Skewness	Excess kurtosis	Annualized Returns	Annualized Volatility	IR	Maximum Drawdown	Hit Ratio
Mispricing	331	2.45	0.01	3.04	3.4%	3.9%	0.88	5.8%	51.0%
GP/A	339	2.37	0.00	0.97	5.1%	5.9%	0.86	13.9%	52.1%
Mispricing + GP/A	272	3.45	0.04	0.79	6.3%	5.0%	1.26	9.4%	53.6%
Mispricing filtered with GP/A	262	3.9	0.2	0.7	8.3%	5.7%	1.46	7.5%	52.1%

Source: J.P. Morgan Quantitative and Derivatives Strategy, Thomson Reuters, FactSet, Bloomberg, IBES, MSCI

[20] **We decide to use 40% as a threshold after taking into account the number of stocks remained in the portfolios after filtering**

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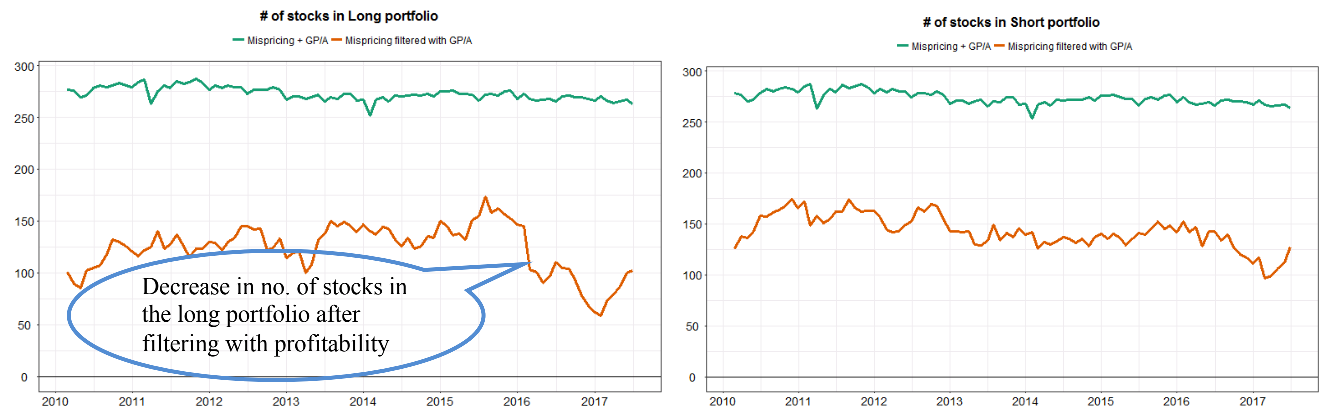
Significant improvements by removing stocks with poor profitability

As we see in Figure 21, filtering stocks based on Gross-Profit-to-Assets significantly improves returns of the mispricing signal. Why is this approach better than a simple z-score combination of the two signals?

In Figure 22, we observe that there is a significant drop in the number of stocks in the long portfolio after we filter by Gross-Profit-to-Assets. Apparently, since the end of 2015, there are more stocks in the long portfolio that are undervalued but with a poor profitability.

Figure 22: Number of stocks in the Long basket (left) and in the Short basket (right). "Combine with GP/A" means simple z-score combination of Mispricing and Gross-Profit-to-Assets. "Filtered with GP/A" means filtering the Mispricing signal based on percentiles of Gross-Profit-to-Assets.

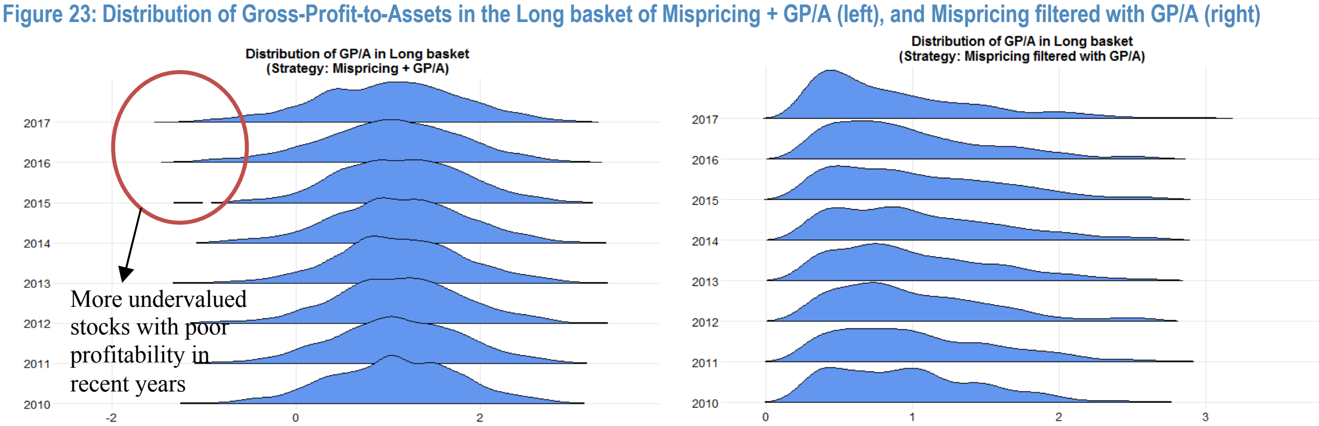


Source: J.P. Morgan Quantitative and Derivatives Strategy, Thomson Reuters, FactSet, Bloomberg, IBES, MSCI

Figure 23 confirms that there are indeed more unprofitable stocks in the long portfolio since 2015. The chart shows the distributions of Gross-Profit-to-Assets (normalized to z-scores) in the long portfolio each year. Since 2015, we see a longer tail on the left, corresponding to stocks with extremely poor profitability which we would like to avoid.

This filtering mechanism in general improves our strategy returns (see Figure 21), especially during periods when unprofitable stocks are cheap (value traps).

Figure 23: Distribution of Gross-Profit-to-Assets in the Long basket of Mispricing + GP/A (left), and Mispricing filtered with GP/A (right)



Source: J.P. Morgan Quantitative and Derivatives Strategy, Thomson Reuters, FactSet, Bloomberg, IBES, MSCI

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News Sentiment: Enhancing the Strategy

Now, with our mispricing signal and the help of Gross-Profit-to-Assets to identify "good value" from "bad value", are there ways to further enhance the strategy? We think that another element we may want to include is investor sentiment. Imagine you spot a deeply undervalued stock with high profitability. Does it mean that its price will likely go up? Normally there is a good chance, but if a newspaper suddenly discloses an accounting scandal about the company, what will you think?

As such, being able to obtain and react quickly to news about the market and economic / political events is important for asset managers. In this era of information explosion, collecting articles from the web in real time and converting unstructured textual data into an organized database is a valuable business. Many vendors have come into the field in recent years. In this report, we take a look at the news sentiment data provided by a company called RavenPack.

Introducing RavenPack's News Analytics

RavenPack is a sentiment data provider that analyzes and extracts sentiment out of news articles and blogs on the internet, using proprietary Natural Language Processing (NLP) algorithms[21]. It tracks over 192,000 entities including companies[22], currencies, commodities, organizations etc. Historical intraday data starts from January 2000, leading to over 650 GB of raw data. Since March 2017, RavenPack has introduced a new product which provides real-time analytics to clients (Hafez 2017). Table 2 shows a snapshot of the RavenPack data for the Apple Inc, highlighting some of the major items in the dataset.

Table 2: Snapshot of RavenPack data for Apple Inc

Timestamp	Entity Name	Relevance	Event Sentiment Score	Event Relevance	Event Similarity Days	Topic	Group	Fact Level	Event Text	Source Name
2017-06-02 19:50	Apple Inc.	99	0.52	30	120.1	business	products-services	opinion	Apple would unveil a MacBook Pro	Dow Jones Newswires
2017-06-05 8:53	Apple Inc.	100	0.55	100	51.1	business	acquisitions-mergers	fact	Apple, Amazon to join its bid for Toshiba	MSN
2017-06-05 17:05	Apple Inc.	100	0.52	100	0.1	business	products-services	fact	Apple unveils iOS 11	Yahoo! News
2017-06-05 22:10	Apple Inc.	99	0.72	80	26.6	business	revenues	forecast	Ipad outlook presents a fair amount of sales growth	Seeking Alpha
2017-06-12 6:33	Apple Inc.	41	0.52	50	0.0	business	products-services	fact	Iphones to be launched this year	Reuters
2017-06-20 12:45	Apple Inc.	99	-0.48	60	13.8	society	legal	fact	Apple files $1 billion lawsuit against chip supplier Qualcomm	The Express Tribune
2017-06-26 19:44	Apple Inc.	92	0	80	365.0	economy	domestic-product	fact	Iphone's estimated 15 percent unit growth in China	CNBC

Source: RavenPack, J.P. Morgan Quantitative and Derivatives Strategy

[21] A popular NLP model is the "Bags of Words", which represents the words in articles using matrices

[22] Out of the 192,000 entities, over 43,000 are companies

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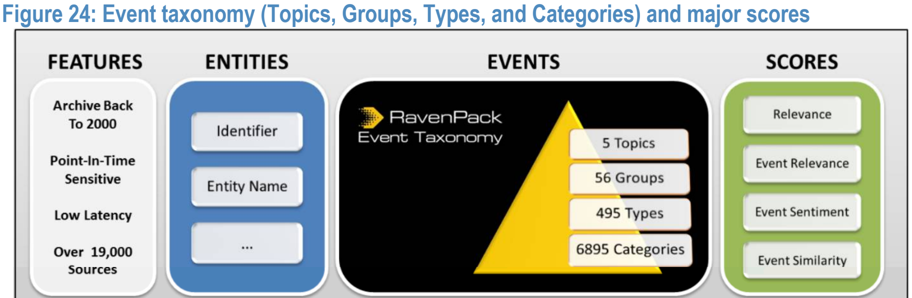
There are 4 major scores provided by RavenPack:

- **Relevance:** An integer score between 0-100 that indicates how strongly related the mention of an entity is to the underlying news story, with higher values indicating greater relevance
- **Event Sentiment Score (ESS):** A granular score between -1.00 and +1.00 that represents the news sentiment for a given entity, where 0 indicates neutral sentiment. ESS leverages RavenPack's event detection technology and produces a sentiment score every time an event is matched
- **Event Relevance:** An integer between 0-100 that reflects the relevance of the event in the story.
- **Event Similarity Days:** A number between 0-365 indicating the number of days since a similar event was detected over the last 365 days

RavenPack's Events Taxonomy

RavenPack defines over 6000 business, geopolitical and macroeconomic events that could be identified in a story. Examples include merger and acquisition, resignation of the CEO, announcement of a new product, analyst forecasts on earnings, or an opinion expressed on legal matters.

Figure 24: Event taxonomy (Topics, Groups, Types, and Categories) and major scores



Timestamp	RavenPack ID	Entity Name	Topic	Group	Type	Category	Event Relevance	Event Sentiment	Similarity Days
7/22/2010 10:06	B72D17	Continental Airlines Inc.	business	earnings	earnings	earnings-up	100	0.84	0
4/23/2013 19:26	A0173B	Egypt	politics	government	presidency	presidential-resignation	100	-0.65	1.29
8/15/2016 21:38	12E454	Facebook Inc.	business	Insider-trading	Insider-buy	Insider-buy	75	0.52	365

Source: RavenPack

Figure 25 displays the increasing granularity of the event taxonomy adopted by RavenPack via a flow chart. The thicknesses of the pipelines indicate the number of events in the database. Clearly, the majority of the events are under the topic of "Business", whilst there are relatively fewer events on politics. Among business-related events, most of them are on "Earnings", and one could dig deeper into different types of earnings events (e.g. earnings guidance or earnings above expectations).

With such granularity, one could build customized sentiment signals that are targeted towards particular strategies. For instance, by filtering "Topic = Business" and "Group = Earnings", we may use the resulting signal to enhance a trading strategy around earnings announcements. (Hafez et al (2017)) shows that sentiment signals have asymmetric price impacts on different groups.

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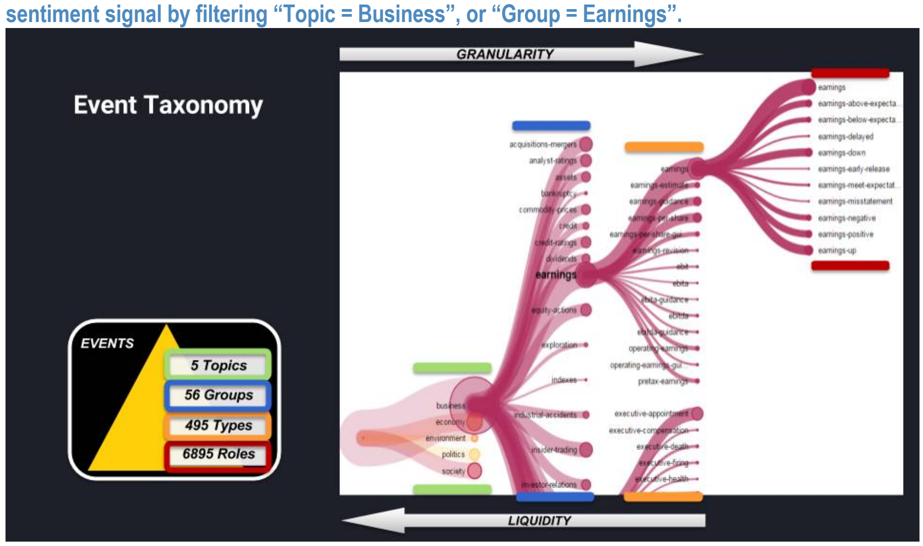
Figure 25: Increasing granularity of Event Taxonomy from Topics, Groups, Types, to Categories. The thicknesses of the pipelines indicate the number of events. One could build a customized sentiment signal by filtering "Topic = Business", or "Group = Earnings".



Source: RavenPack

Building Sentiment Signals for Stocks

Aggregating intraday sentiment

To extract sentiment scores at stock levels, we filter out all companies based on entity type. We only consider stories that are indeed relevant to the mentioned company by only retaining data with relevance score above 70. For each stock, we calculate the daily sentiment score by averaging over the N stories on the company, weighted by the relevance score of each story:

$$daily\ sentiment\,(t) = \frac{\sum_{j=1}^{N} relevance_j \times sentiment_j}{\sum_{j=1}^{N} relevance_j}$$

Do novel stories matter more? We do not find much evidence in our case

One may further weight by the novelty of the story (from the event similarity days), e.g. only consider stories that have not appeared in other sources at least in the past 1 day. We think that there are pros and cons for filtering by novelty. Indeed, the first story on a certain piece of news should have a greater impact than an article that merely repeats the information published in another source yesterday. However, if there are many stories mentioning a similar headline event, it may indicate that the event is important and hence deserves a large weight, in this case reflected by the volume of the news. Novelty should be more relevant to high frequency trading and less so in our monthly-rebalancing strategy. Indeed, we have tried to aggregate sentiment by removing stories that have already appeared within a day. We do not find significant differences in the scores, as well as the returns in the L/S strategy. One may try to filter "old" stories based on different values of event similarity days. Some reports show that infrequent news may have larger price impacts (Hafez and Xie (2014)).

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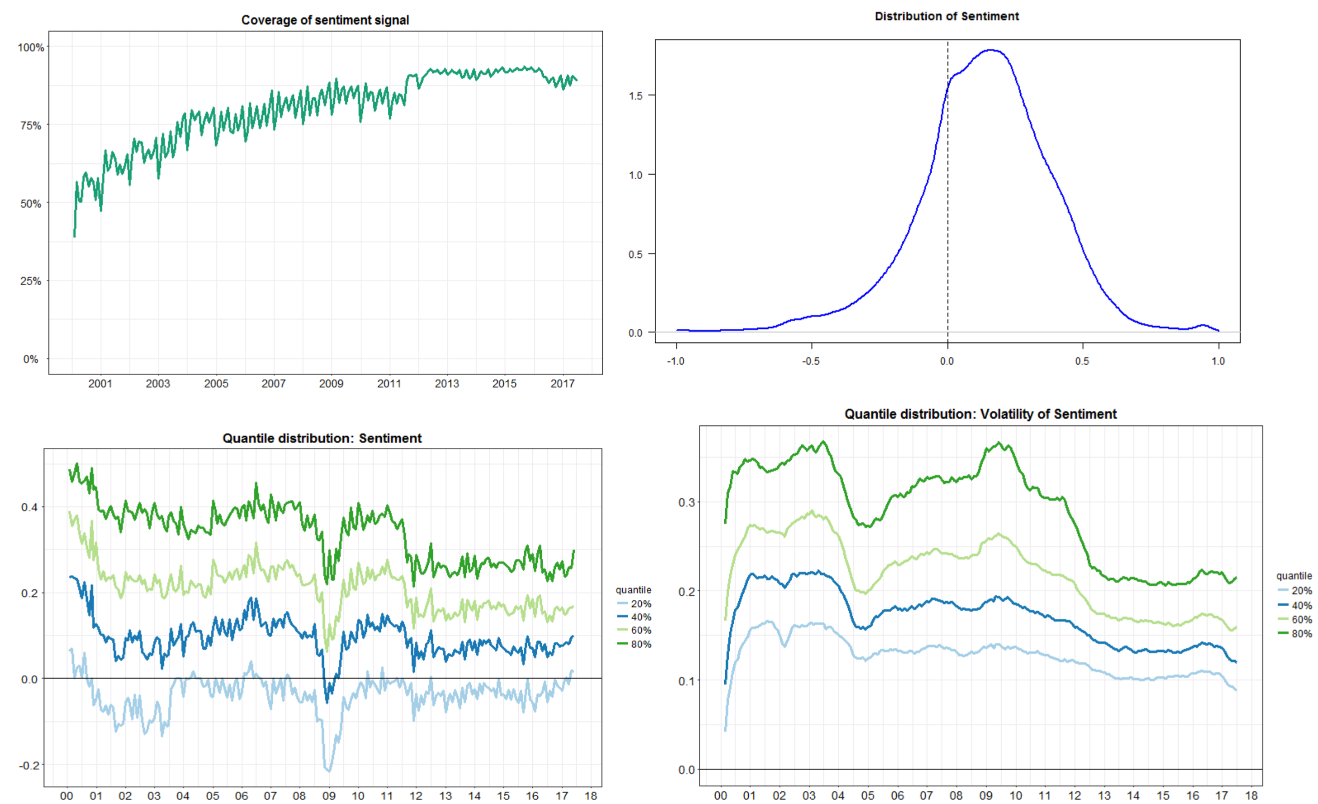
Weighting daily sentiment into a monthly measure

Since our rebalancing is on every month end, we further aggregate the daily sentiment into a monthly measure. We hope the signal can be more reactive to recent events, hence we put a larger weight on sentiment scores closer to month end T. For instance, if there are 20 days in the month, we average the $T = 20$ sentiment scores:

$$monthly\ sentiment\ (T) = \frac{\sum_{t=1}^{T} w_t \times (daily\ sentiment_t)}{\sum_{t=1}^{T} w_t}$$

Figure 26 shows that over 70% of stocks in our MSCI AC World universe have sentiment scores from RavenPack, and over time the distribution of scores seem to become less disperse. This could due to the increase in news volume which may dilute the effect from a small number of stories with more extreme sentiment scores.

Figure 26: Coverage of RavenPack's sentiment scores for our universe in MSCI AC World (top left), the overall distribution of sentiment scores (top right), the distribution of sentiment scores over time (bottom left), and the distribution of the volatility of the sentiment (bottom right)



Source: J.P. Morgan Quantitative and Derivatives Strategy, RavenPack

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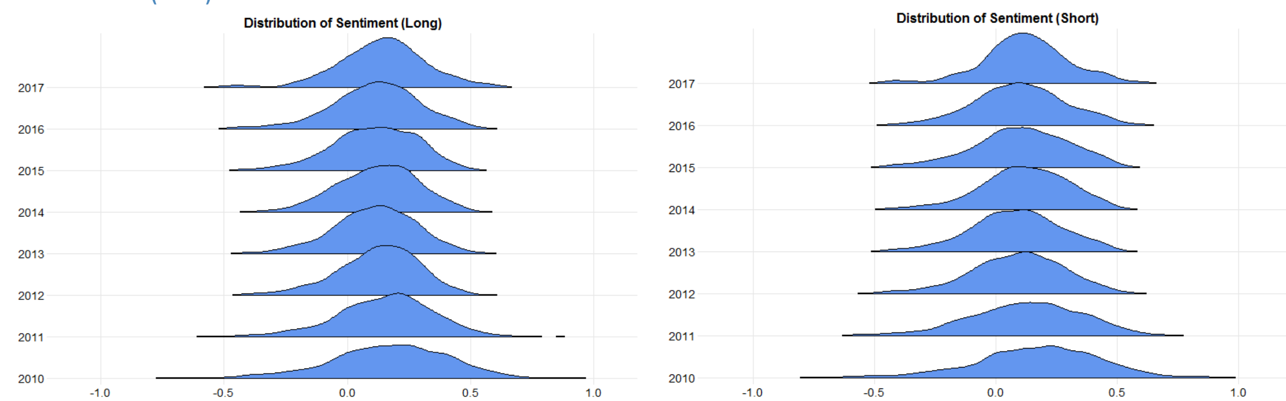
Sentiment Signals as a Useful Overlay

It is perhaps not too surprising to see that simply using the sentiment signal to rank stocks does not work well (see Figure 34 in the Appendix), especially when we are looking at a longer horizon because sentiment is a high frequency signal. Nevertheless, can we overlay sentiment with our signal to enhance returns, e.g. identify stocks with poor sentiment that we should avoid even they look cheap and profitable?

First, we look at the distribution of sentiment scores within the long and short portfolios of the strategy based on the mispricing signal filtered by Gross-Profit-to-Assets. We find that most of the scores are positive, and the sentiment in the short portfolio is not significantly worse than those in the long portfolio

Figure 27: Distribution of sentiment scores in the long and short portfolios, based on the composite mispricing signal and filtered with Gross-Profit-to-Assets (GP/A)



Source: J.P. Morgan Quantitative and Derivatives Strategy, RavenPack, Thomson Reuters, FactSet, Bloomberg, IBES, MSCI

Filtering stocks based on sentiment levels

Next, we try to understand the impact on the long and the short portfolios when we filter out stocks based on their sentiment scores. We look at a range of sentiment thresholds k, and we filter the portfolios as follows:

- *Long* portfolio: If sentiment of the stock is *below* k, we remove the stock
- *Short* portfolio: If sentiment of the stock is *above* k, we remove the stock

Interestingly, we find that the price impacts on stocks with negative sentiments are much stronger than those with positive sentiments. This information asymmetry in sentiment signals coincides with the findings in other studies such as Hafez (2015).

In Figure 28, if we only include stocks with negative sentiment scores in our short portfolio, the number of stocks drops from an average of 136 to around 46, but this concentrated portfolio delivers 0.9% returns p.a. compared with 3% p.a for the original short portfolio.

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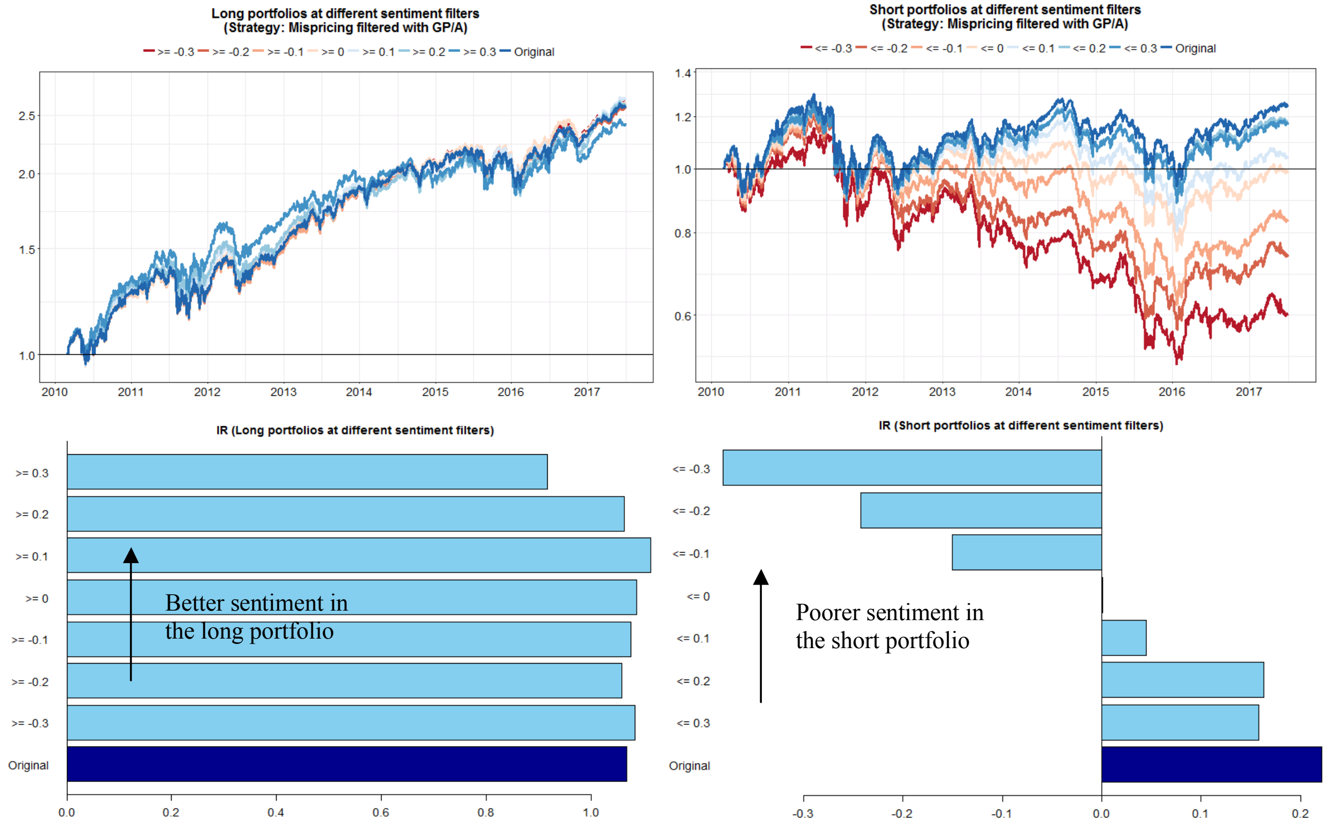
Figure 28: Applying filters on sentiment level to the long portfolio (left) and the short portfolio (right), based on the mispricing signal filtered by Gross-Profit-to-Assets. All backtests have included transaction costs.



Mispricing, filtered by GP/A	Median # of stocks	t-stat	Skewness	Excess kurtosis	Annualized Returns	Annualized Volatility	IR	Maximum Drawdown	Hit Ratio
Original Long Portfolio	**121**	**2.9**	**-0.4**	**4.2**	**13.3%**	**12.5%**	**1.07**	**18.0%**	**56.0%**
Sentiment >= -0.3	120	3.0	-0.4	4.2	13.6%	12.5%	1.08	17.9%	55.9%
>= -0.2	117	2.9	-0.4	4.2	13.2%	12.5%	1.06	17.9%	55.7%
>= -0.1	108	3.0	-0.4	4.2	13.4%	12.4%	1.08	17.6%	56.3%
>= 0	92	3.0	-0.4	4.1	13.5%	12.4%	1.09	16.5%	55.7%
>= 0.1	71	3.1	-0.4	3.9	13.7%	12.3%	1.11	15.2%	56.3%
>= 0.2	47	2.9	-0.4	3.6	13.3%	12.5%	1.06	14.1%	56.1%
>= 0.3	22	2.6	-0.3	2.8	12.3%	13.4%	0.92	15.6%	53.8%
Original Short Portfolio	**136**	**0.8**	**-0.5**	**4.7**	**3.0%**	**13.5%**	**0.22**	**29.2%**	**52.2%**
Sentiment <= 0.3	116	0.6	-0.4	4.7	2.2%	13.7%	0.16	29.1%	52.2%
<= 0.2	97	0.6	-0.4	4.5	2.2%	13.6%	0.16	30.3%	52.1%
<= 0.1	70	0.3	-0.4	4.1	0.6%	13.7%	0.05	35.8%	51.4%
<= 0	46	0.2	-0.3	3.4	0.0%	13.8%	0.00	40.0%	51.9%
<= -0.1	28	-0.2	-0.2	2.9	-2.1%	14.2%	-0.15	49.8%	50.6%
<= -0.2	17	-0.5	-0.2	2.6	-3.7%	15.2%	-0.24	53.1%	50.4%
<= -0.3	13	-0.9	-0.2	3.2	-6.2%	16.3%	-0.38	56.6%	49.4%

Source: J.P. Morgan Quantitative and Derivatives Strategy, RavenPack, Thomson Reuters, FactSet, Bloomberg, IBES, MSCI

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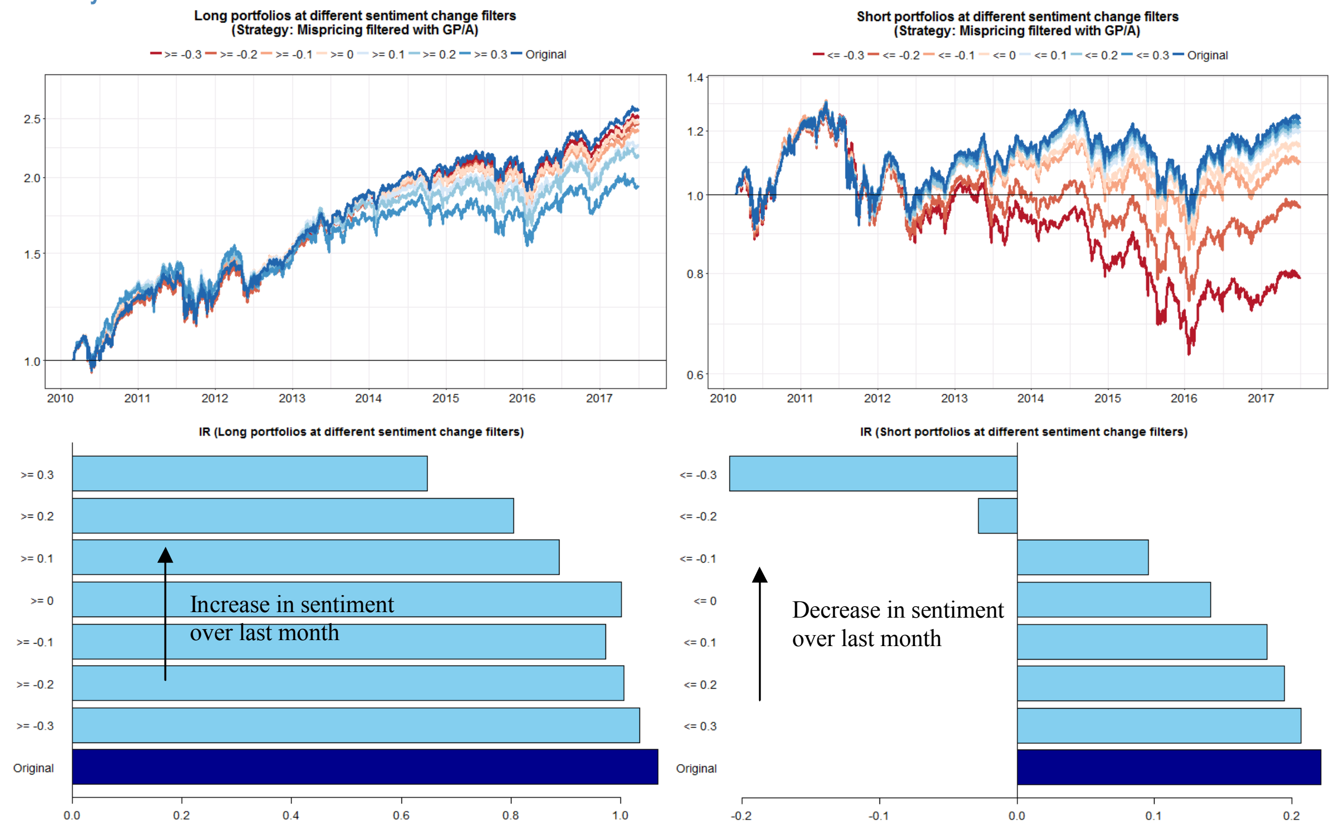
How about changes in sentiment?

There is another interesting observation regarding the change in sentiment: We should be wary about stocks that have a very positive increase in sentiment. Investors maybe over-reacting to such news and stock prices tend to revert the next month. This is similar to the "lottery factor", where in general stocks with the largest daily returns in the past month underperform in the next month. On the other hand, we find that stocks with a large decrease in sentiment also perform worse.

Figure 29: Applying filters on sentiment changes to the long portfolio (left) and the short portfolio (right), based on the mispricing signal filtered by Gross-Profit-to-Assets. All backtests have included transaction costs.



Mispricing, filtered by GP/A	Median # of stocks	t-stat	Skewness	Excess kurtosis	Annualized Returns	Annualized Volatility	IR	Maximum Drawdown	Hit Ratio
Original Long Portfolio	**121**	**2.9**	**-0.4**	**4.2**	**13.3%**	**12.5%**	**1.07**	**18.0%**	**56.0%**
Sentiment change >= -0.3	112	2.9	-0.4	4.2	12.9%	12.5%	1.03	17.7%	55.9%
>= -0.2	103	2.8	-0.4	4.2	12.6%	12.5%	1.01	17.3%	55.9%
>= -0.1	86	2.7	-0.4	4.2	12.2%	12.5%	0.97	17.2%	56.0%
>= 0	62	2.8	-0.4	4.1	12.6%	12.6%	1.00	17.3%	55.9%
>= 0.1	42	2.5	-0.4	3.6	11.4%	12.8%	0.89	17.1%	55.5%
>= 0.2	26	2.3	-0.4	3.7	10.8%	13.4%	0.80	19.0%	55.6%
>= 0.3	18	1.9	-0.4	2.8	9.0%	14.0%	0.65	19.7%	54.2%
Original Short Portfolio	**136**	**0.8**	**-0.5**	**4.7**	**3.0%**	**13.5%**	**0.22**	**29.2%**	**52.2%**
Sentiment change <= 0.3	124	0.8	-0.4	4.8	2.8%	13.5%	0.21	28.9%	52.0%
<= 0.2	114	0.7	-0.5	4.8	2.6%	13.6%	0.19	29.3%	52.2%
<= 0.1	98	0.7	-0.4	4.2	2.5%	13.5%	0.18	28.4%	52.6%
<= 0	7	0.6	-0.4	4.1	1.9%	13.5%	0.14	31.2%	51.9%
<= -0.1	53	0.5	-0.4	3.7	1.3%	13.6%	0.10	34.8%	51.8%
<= -0.2	37	0.1	-0.3	3.4	-0.4%	13.9%	-0.03	42.1%	51.6%
<= -0.3	25	-0.4	-0.3	2.9	-3.0%	14.2%	-0.21	51.2%	51.4%

Source: J.P. Morgan Quantitative and Derivatives Strategy, RavenPack, Thomson Reuters, FactSet, Bloomberg, IBES, MSCI

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Here we take a heuristic approach to decide on thresholds of filtering sentiment in our final strategy.

It seems to be better to filter only stocks with more extreme sentiment (+/- 0.3).

Sentiment signal overlay: Do not go against the crowd

With a little hindsight, what would be the ideal thresholds for the sentiment filters? From the analysis in Figure 28 and Figure 29, we summarize as follows:

Sentiment levels:

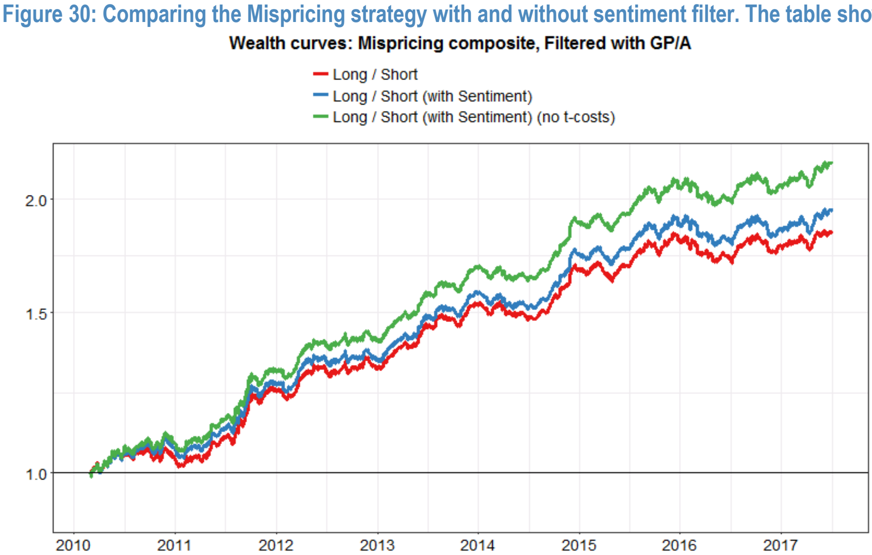
- Removing stocks with very poor sentiment (< -0.3) helps to improve the returns of the long portfolio without sacrificing much on volatility
- Whilst we see a clear decrease in returns by including only stocks with poor sentiments in the short portfolio, volatility also increases significantly. We prefer to take a more conservative threshold at 0.3, i.e. only removing stocks in the short portfolio which have relatively positive sentiment over 0.3.

Monthly changes in sentiment:

- Stocks with an extremely positive increase in sentiment over the last month tend to perform worse. However, filtering these stocks from the long portfolio increases volatility and hence is not preferred.
- Removing stocks with large increase in sentiment (> 0.3) helps to improve the short portfolio (i.e. lower the returns)

Figure 30 shows the results of our final strategy which filters the long and short portfolios based on sentiment levels and changes in sentiment, together with the thresholds that we choose. The Information Ratio (after transaction costs) improves from 1.46 to 1.55. This is mainly due to an increase in returns, while volatility is almost the same.

Figure 30: Comparing the Mispricing strategy with and without sentiment filter. The table shows the statistics for L/S daily returns in USD.



	Sentiment level		Sentiment change
	< -0.3	> 0.3	> 0.3
Long	Avoid		
Short		Avoid	Avoid

Mispricing Strategy	Median # of stocks (Long)	Median # of stocks (Short)	t-stat	Skewness	Excess kurtosis	Annualized Returns	Annualized Volatility	IR	Maximum Drawdown	Hit Ratio
Long / Short	121	136	3.9	0.2	0.7	8.3%	5.7%	1.46	7.5%	52.1%
Long / Short (sentiment filter)	120	111	4.2	0.1	0.7	9.1%	5.8%	1.55	7.5%	52.4%
Long / Short (sentiment filter) (no transaction costs)	120	111	4.9	0.1	0.7	10.8%	5.8%	1.85	6.9%	53.5%

Source: J.P. Morgan Quantitative and Derivatives Strategy, RavenPack, Thomson Reuters, FactSet, Bloomberg, IBES, MSCI

Strategy Performance in Developed Markets

We repeat the strategy within 2 subsets of our MSCI AC World universe, namely the Global Developed Markets (with 23 countries) and the Developed Markets in Europe (with 15 countries), based on our mispricing signals obtained from the same composite model as described in the above sections. The reasons that we focus on Developed Markets here are two-fold:

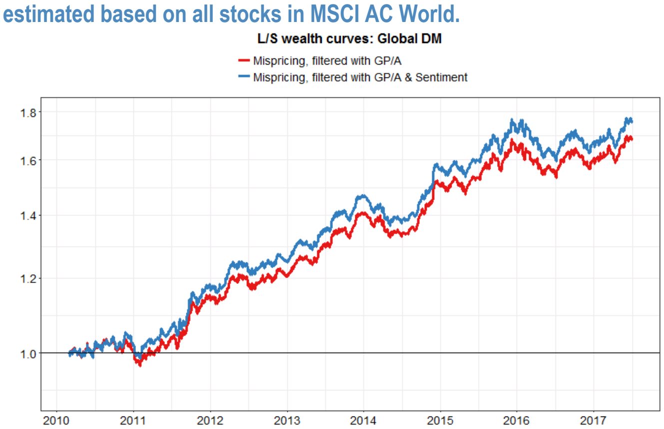
We repeat the same strategy confined to 2 universes of Developed Markets.

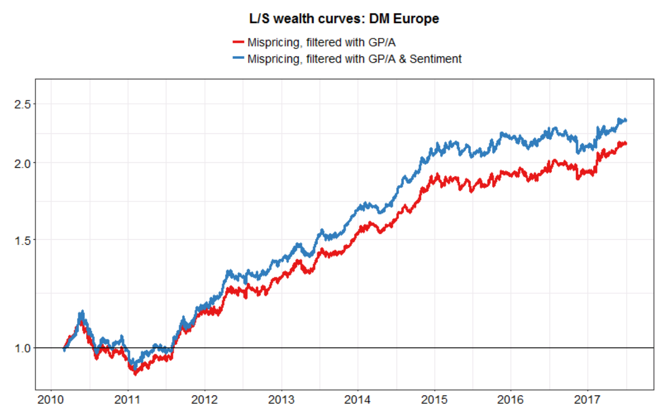
Clients interested in a customized analysis, say for an Emerging Markets universe, can contact us for details

- Our composite mispricing model is estimated based on stocks within the MSCI AC World. As in Figure 5, most of the stocks are from Developed Markets, with the United States and Japan being the majorities. As such, if we are interested in a universe for the Emerging Markets, we should estimate another "fair value" model separately. Clients interested in a customized analysis with a similar framework can contact us for details.
- The sentiment signals have better coverage within the Developed Markets, as English is usually one of the most popular languages among those countries. In Asia, for example, we may have missed a large number of articles in local languages (e.g. Chinese), leading to a less reliable sentiment score.

Figure 31 shows the performance of our final strategy applied to the Global DM as well as the sub-universe of DM Europe. We do find that sentiment signals add value on top of our strategy based on mispricing and Gross-Profit-to-Assets.

Figure 31: Mispricing strategy L/S wealth curves in different developed markets, based on the same composite model for mispricing that is estimated based on all stocks in MSCI AC World.





L/S Mispricing Strategy, filtered with GP/A	Median # of stocks	t-stat	Skewness	Excess kurtosis	Annualized Returns	Annualized Volatility	IR	Maximum Drawdown	Hit Ratio
Global DM	191	3.2	0.2	0.8	7.1%	6.2%	1.16	9.0%	51.2%
Global DM (sentiment filter)	172	3.3	0.2	1.2	7.7%	6.4%	1.21	9.8%	52.0%
DM Europe	35	3.1	0.0	1.6	10.6%	9.5%	1.11	19.7%	52.5%
DM Europe (sentiment filter)	28	3.2	0.1	2.3	11.8%	10.1%	1.17	19.8%	53.3%

Source: J.P. Morgan Quantitative and Derivatives Strategy, RavenPack, Thomson Reuters, FactSet, Bloomberg, IBES, MSCI

References

Bernard, V. (1994) Accounting-Based Valuation Methods, Determinants of Market-to-Book Ratios, and Implications for Financial Statement Analysis. Working Paper, University of Michigan

Blackburn, Douglas W. and Cakici, Nusret (2017) The Magic Formula: Value, Profitability, and the Cross Section of Global Stock Returns

Breiman (1996), Bagging predictors, Machine Learning 26: 123–140

Campbell, John Y. and Shiller, Robert J. (1988) The Dividend-Price Ratio and Expectations of Future Dividends and Discount Factors. NBER Working Paper No. w2100.

Chen, Carl R., Lung, Peter P. and Wang, F. Albert (2009), Mispricing and the Cross-Section of Stock Returns. Rev Quant Finan Acc, 32(4), 317-349.

Chen, Tianqi (2014) Introduction to Boosted Trees

Freund, Y. and Schapire, R. (1999) A Short Introduction to Boosting, Journal of Japanese Society for A.I. 14(5) 771-780

Friedman, J.H. (2001) Greedy function approximation: a gradient boosting machine. Annals of Statistics, P. 1189–1232

Greenblatt, Joel (2006) The little book that beats the market. John Wiley & Sons.

Hafez, P. and Xie, J. (2014). Improved Stock Market Returns From Systematically Trading Infrequent News, RavenPack Quantitative Research

Hafez P., J. A. Guerrero-Colon and S. Duprey (2015). Thematic Alpha Streams Improve Performance of Equity Portfolios. RavenPack Research Paper

Hafez, P. et al (2017). Introducing RavenPack Analytics For Equities. RavenPack Quantitative Research

Hafez P, Koefoed, M., Guerrero-Colon and Lautizi, F. (2017). A Multi-Topic Approach To Building Quant Models. RavenPack Quantitative Research

Hastie, T; Tibshirani, R and Friedman, J (2013) The Elements of Statistical Learning, 2nd edition, Springer

Heston, Steven L. and Sinha, Nitish Ranjan (2016). News Versus Sentiment: Predicting Stock Returns from News Stories. FEDS Working Paper No. 2016-048

Hlavaty et al (2016) Value Everywhere: Global Comparison of the Value Equity Risk Premium. JPMorgan Global Equity and Quantitative Research, 26 August 2016

James, G., Witten, D., Hastie, T. and Tibshirani, R. (2013). An Introduction to Statistical Learning. Springer Texts in Statistics

Kolanovic, M. and Wei, Z. (2014) Equity Risk Premia Strategies: Risk Factor Approach to Portfolio Management. JPMorgan Global Quantitative and Derivatives Research, September 2014

Kolanovic, M. and Krishnamachari, R. (2017). Big Data and AI Strategies: Machine Learning and Alternative Data Approach to Investing. JPMorgan Global Equity and Quantitative Research, May 2017

Kuhn, M. (2008). Building Predictive Models in R Using the caret Package, Journal of Statistical Software, 28(5) 1-26

Kuhn, M. (2013). Predictive Modeling with R and the caret Package, Presentation slides, useR! 2013

Ma, C. and Smith, R. (2014) Sorting through the Trash: Quality at a Reasonable Price in Asia. JPMorgan Global Equity and Quantitative Research, 21 November 2014

Ma et al (2015) What is Quality? Harvesting Quality Risk Premia in Developed and Emerging Markets. JPMorgan Global Equity and Quantitative Research, 13 July 2015

Nichols, D. C., Wahlen, J. M. and Wieland, M. M. (2017) Pricing and Mispricing of Accounting Fundamentals in the Time-Series and in the Cross Section. Contemp Account Res.

Novy-Marx, Robert (2013). The other side of value: The gross profitability premium. Journal of Financial Economics, 108(1), 1-28

Ohlson, J. A. (1995). Earnings, Book Values, and Dividends in Equity Valuation. Contemporary Accounting Research, 11: 661–687

Piotroski, J. (2000) Value Investing: The Use of Historical Financial Statements to Separate Winners from Losers. Journal of Accounting Research (38)

Piotroski, Joseph D. and So, Eric C. (2012) Identifying Expectation Errors in Value/Glamour Strategies: A Fundamental Analysis Approach. Review of Financial Studies (RFS), 25(9): 2841-2875

Schapire, R. (2012) Boosting: Foundations and Algorithms

Smith, R. et al (2010). Return on Equity: Is it useful for stock picking? JPMorgan Global Quantitative and Derivative Research, 16 September 2010

Smith, R. et al (2016). Trade Timing in Global Equities, Fast-burn signals to enhance slower strategies. JPMorgan Global Quantitative and Derivative Research, 10 May 2016

Shaikh et al (2013). Quant Forensics: Volume 5, Replacing Dividend Yield with Shareholder Yield, JPMorgan Equity Quantitative Research, 23 April 2013

Zou, H. and Hastie, Trevor (2005). Regularization and variable selection via the elastic net. J. R. Statist. Soc. B, 67 (2) 301-320

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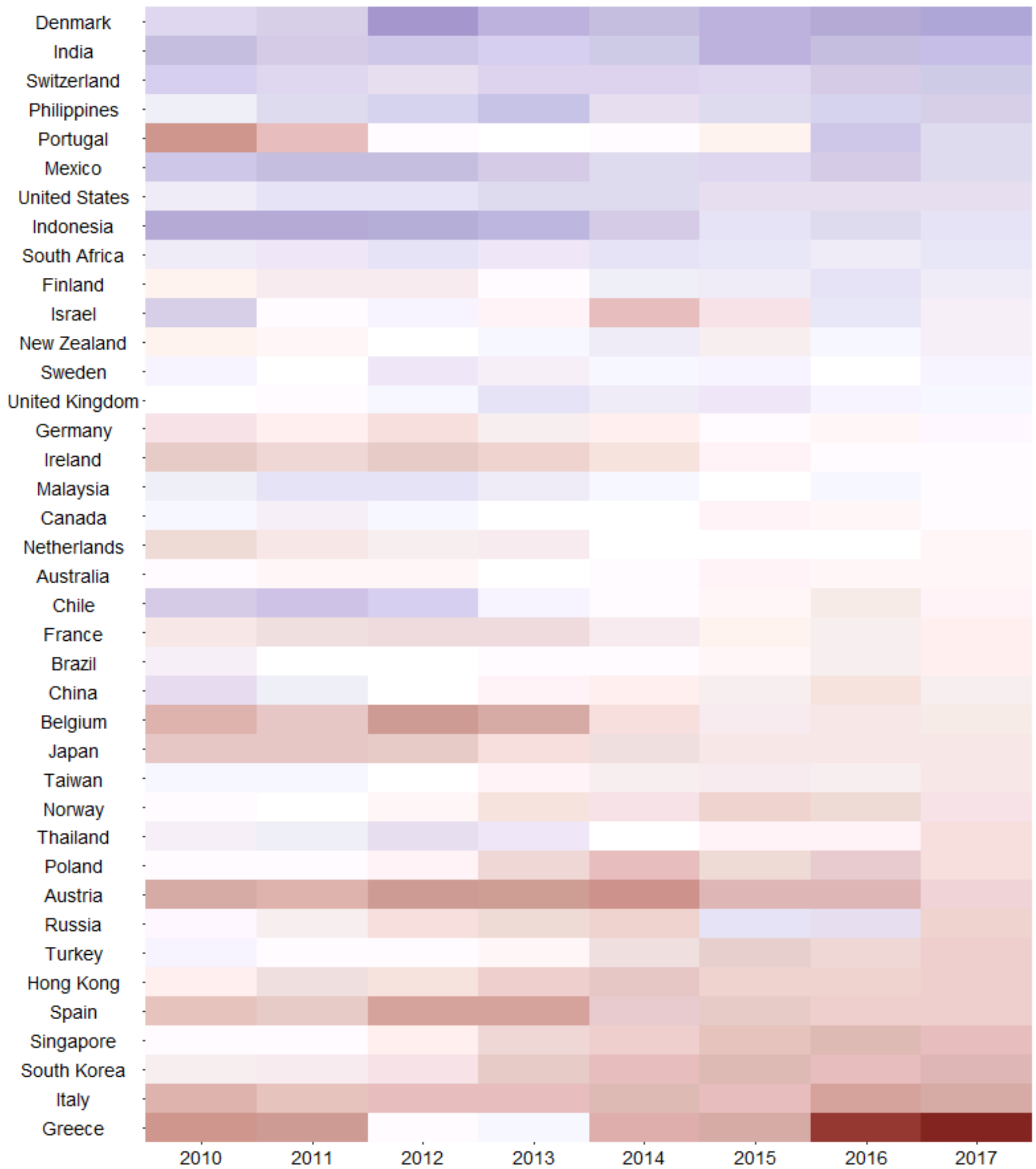
Appendix

Distributions across Countries

Price-to-book

Figure 32 shows the median price-to-book (normalized to z-scores) for stocks in different countries. We see that in 2017, stocks in Greece and Italy tend to trade at a discount, whilst stocks in Denmark and India command the highest premia.

Figure 32: Median price-to-book (z-scores) for stocks in different countries. (Blue: positive, Pink: negative). The countries are ranked according to their median price-to-book in 2017. Note that the number of stocks in different countries varies a lot.

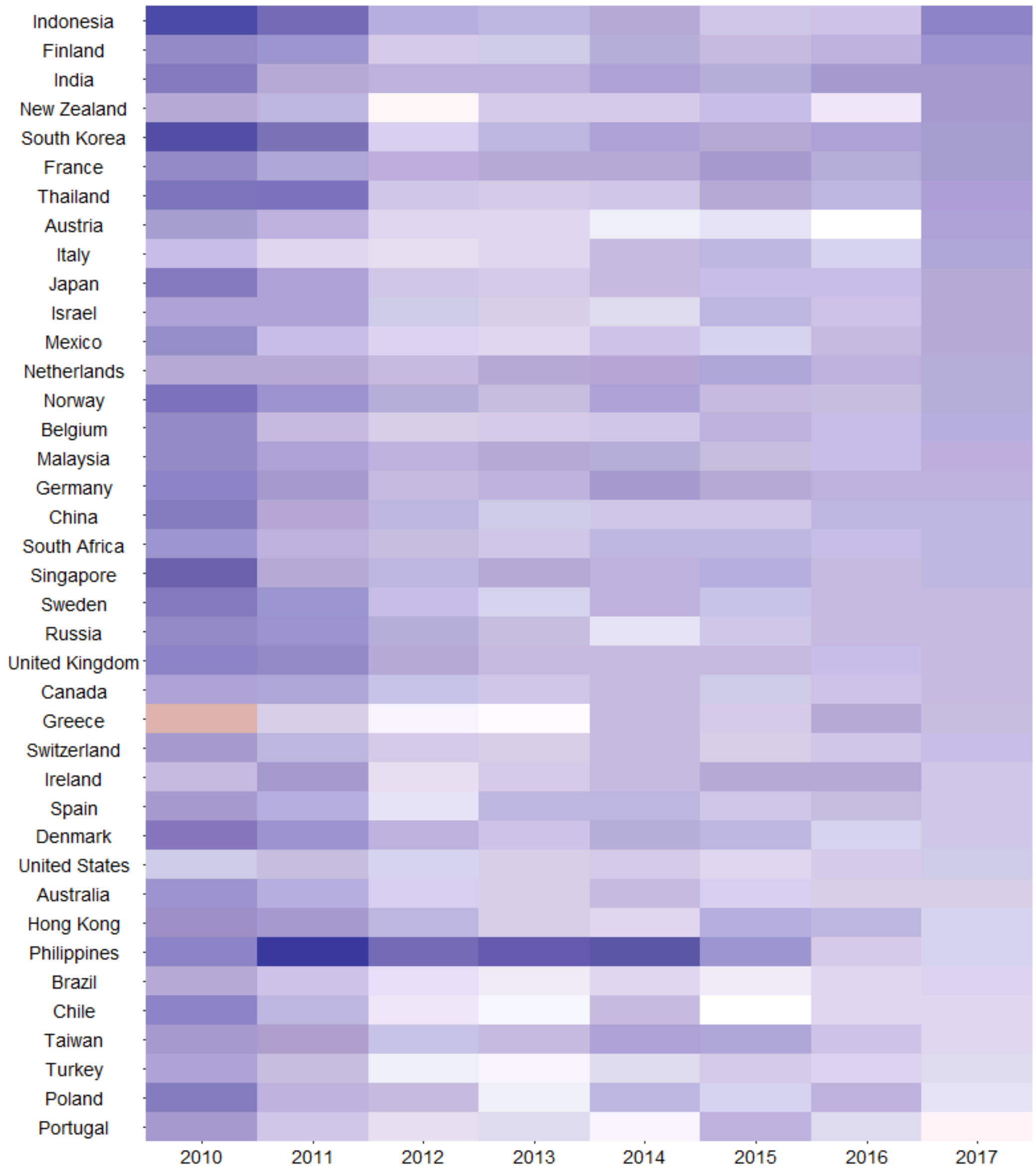


Source: J.P. Morgan Quantitative and Derivatives Strategy, Thomson Reuters, FactSet, Bloomberg, IBES, MSCI

Stock Sentiment

Figure 33 shows the median scores of sentiment for stocks in different countries. One may use this information for country rotation, e.g. overweighting countries with more positive sentiment at the stock level. Note that RavenPack does provide country level sentiment scores, but the below is obtained from stock level sentiment scores.

Figure 33: Median sentiment scores for stocks in different countries. (Blue: positive, Pink: negative). The countries are ranked according to their median sentiment in 2017. Note that the number of stocks in different countries varies a lot.



Source: J.P. Morgan Quantitative and Derivatives Strategy, RavenPack

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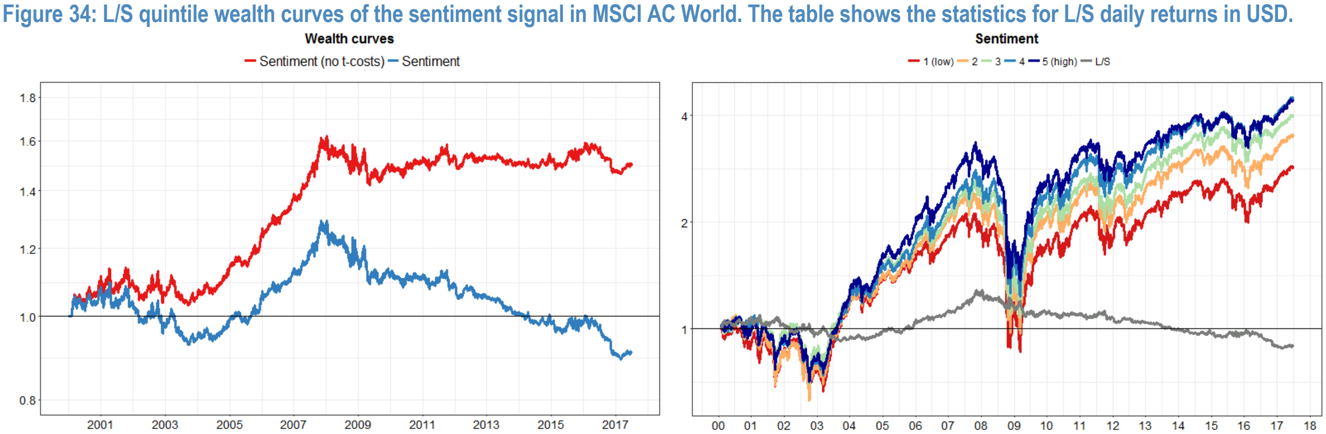
Strategies based on Sentiment: Additional Analysis

Does sentiment work as a standalone signal?

Using the sentiment signal we built from RavenPack's sentiment scores, we consider a quintile long-short portfolio in MSCI AC World, buying stocks with high scores and shorting those with low scores. Interestingly, the signal works pretty well before the Global Financial Crisis in 2008, but since then the efficacy has gone. The returns after accounting for transaction costs are even negative, partly due to the high 2-way monthly turnover of over 290%. We find similar results for other regions.

Figure 34: L/S quintile wealth curves of the sentiment signal in MSCI AC World. The table shows the statistics for L/S daily returns in USD.

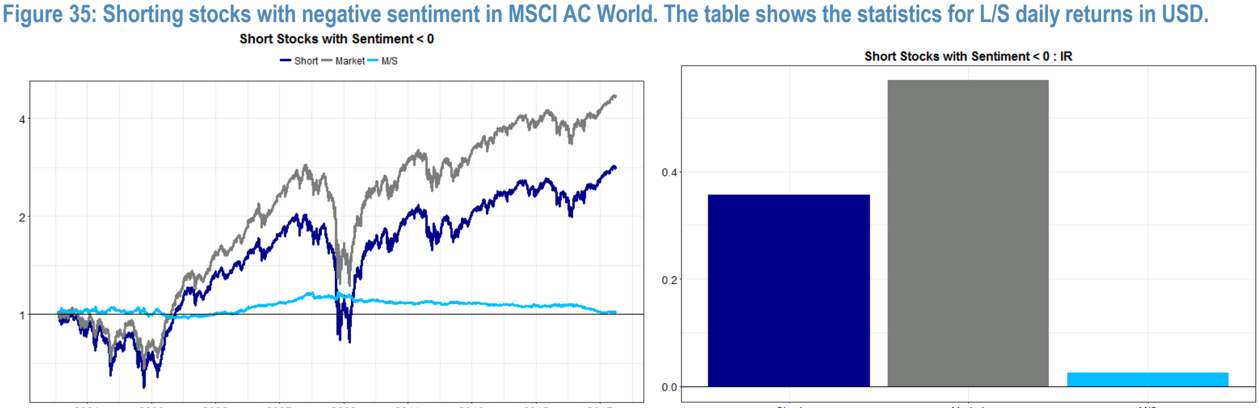


Median # of stocks (Long or Short)	Mean IC	Risk-adjusted IC	t-stat	Skewness	Excess kurtosis	2-way Turnover	Annualized returns (%)	Annualized Volatility (%)	IR	Max. Drawdown	Hit Ratio
357.5	1.1%	0.20	-0.25	-0.30	6.10	291.9%	-0.6%	6.6%	-0.09	31.5%	51.5%

Source: J.P. Morgan Quantitative and Derivatives Strategy, RavenPack

Whilst most of the stocks have a positive sentiment (see Figure 26), we find that simply buying stocks with a positive (or high) sentiment does not beat the market. However, we do observe some evidence that stocks with negative sentiment tend to underperform, as shown in Figure 35.

Figure 35: Shorting stocks with negative sentiment in MSCI AC World. The table shows the statistics for L/S daily returns in USD.



Portfolio	Median # of stocks	t-stat	Skewness	Excess kurtosis	Annualized Returns	Annualized Volatility	IR	Maximum Drawdown	Hit Ratio
Short	397.5	1.8	-0.3	8.0	6%	17%	0.36	59.7%	53.2%
Market	1983	2.7	-0.3	8.5	9%	16%	0.57	57.7%	54.2%

Source: J.P. Morgan Quantitative and Derivatives Strategy, RavenPack

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Enhancing the (P/B + ROE) strategy with sentiment signals

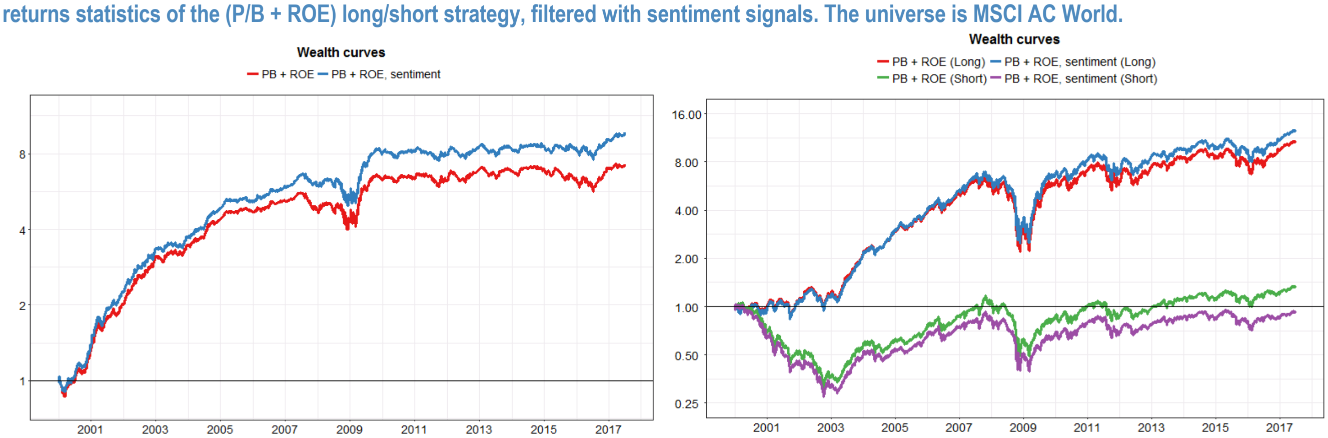
Here we show some results using the sentiment signal to filter the long and short baskets selected based on the good old (P/B + ROE) strategy. In Figure 26, we have seen that most of the sentiment scores are positive. For illustration purpose, we choose the filters below:

- We only retain stocks in the *long basket* with a *sentiment score above 0.1*
- We only retain stocks in the *short basket* with a *negative sentiment score*

For stocks without a sentiment score, we keep them in the baskets.

Figure 36 compares the wealth curves of the original (P/B + ROE) strategy in MSCI AC World, and the one enhanced with sentiment signals based on the above filtering mechanism. We see that sentiment signals help to improve both the long and the short leg of the portfolio.

Figure 36: Filtering long/short legs of the (P/B + ROE) strategy with sentiment signal, after transaction costs. The table shows the daily USD returns statistics of the (P/B + ROE) long/short strategy, filtered with sentiment signals. The universe is MSCI AC World.



Signal	Start	End	Annualized Returns	Annualized Volatility	IR	Maximum Drawdown	Hit Ratio
Past 3 years, Long/Short							
PB + ROE	2014-07-01	2017-06-30	1.1%	8.0%	0.14	21.1%	49.6%
PB + ROE, sentiment	2014-07-01	2017-06-30	3.9%	8.5%	0.47	13.5%	51.1%
Long/Short							
PB + ROE	2000-01-03	2017-06-30	11.4%	10.1%	1.12	28.5%	51.6%
PB + ROE, sentiment	2000-01-03	2017-06-30	13.1%	10.0%	1.31	25.1%	52.5%
Long							
PB + ROE	2000-01-03	2017-06-30	13.8%	19.3%	0.71	66.0%	54.6%
PB + ROE, sentiment	2000-01-03	2017-06-30	14.8%	18.6%	0.79	64.2%	54.4%
Short							
PB + ROE	2000-01-03	2017-06-30	1.5%	16.4%	0.09	70.3%	52.0%
PB + ROE, sentiment	2000-01-03	2017-06-30	-0.5%	16.6%	-0.03	73.4%	51.6%

Source: J.P. Morgan Quantitative and Derivatives Strategy, RavenPack, Thomson Reuters, FactSet, Bloomberg, IBES, MSCI

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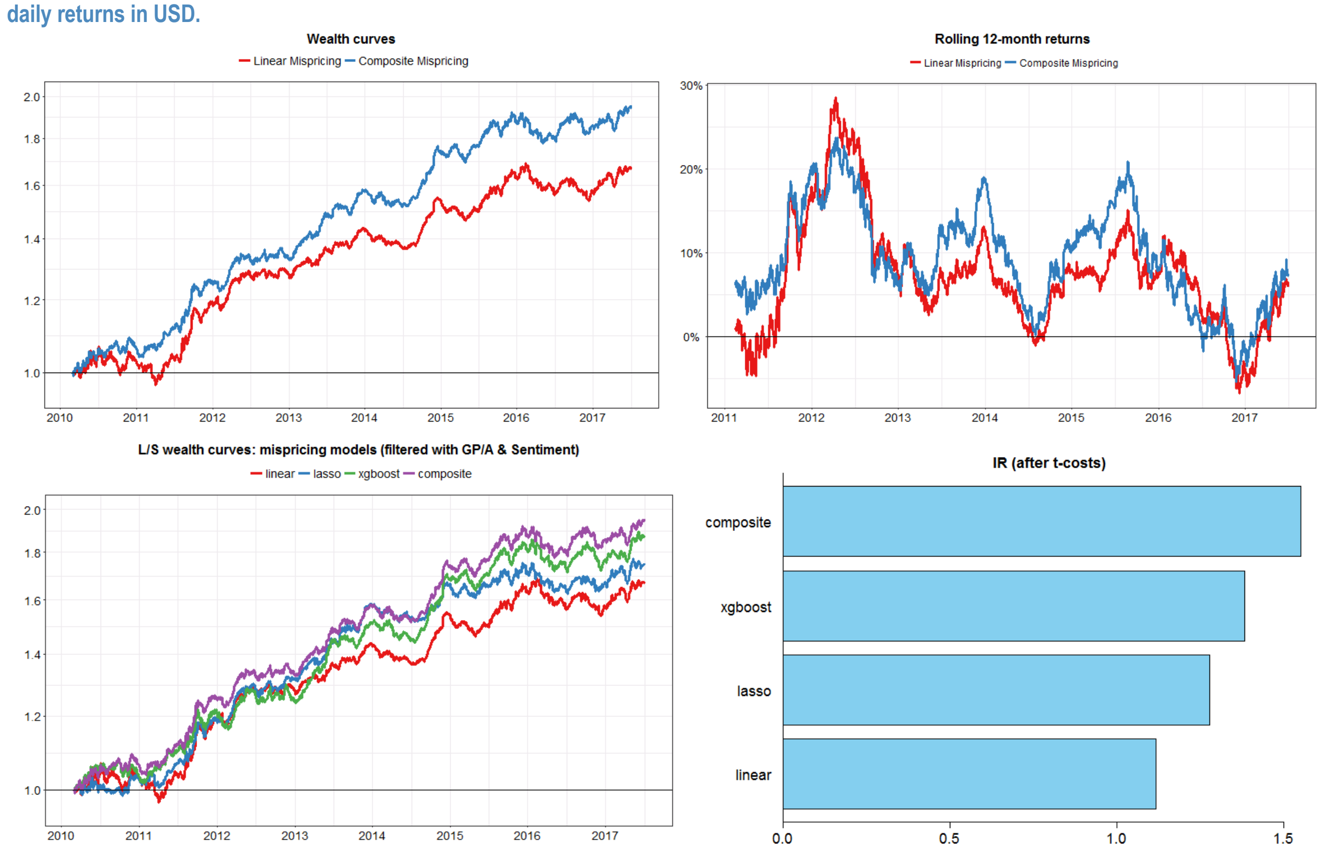
Strategies based on Individual Models

For investors who feel that Machine Learning algorithms are not transparent enough and a bit "black-boxish", we can still consider the simple linear model on mispricing that only include the 7 most important variables (e.g. ROE FY1) into the model.

Figure 37 shows that a strategy based on the simple linear model (together with the filters on Gross-Profit-to-Assets and Sentiment) still provides a decent risk-adjusted returns of 1.12. Nevertheless, the composite mispricing model (that combines the linear model, the LASSO and XGBoost) do provide a significantly higher Information Ratio (IR) of 1.55, especially since 2014.

For completeness, we also show the performance of the final strategies based on the LASSO model and the XGBoost model respectively.

Figure 37: Mispricing strategies (composite model versus individual models) filtered with Gross-Profit-to-Assets and Sentiment. Wealth Curves and rolling 12-month returns are based on the L/S quintile portfolios after transaction costs. The table shows the statistics for L/S daily returns in USD.



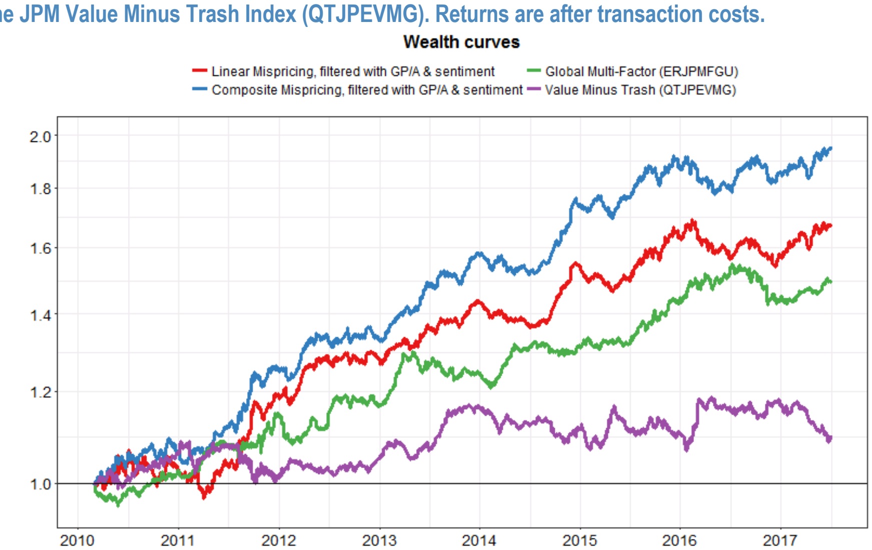
L/S signal (Mispricing, filtered by GP/A & Sentiment)	Median # of stocks (Long + Short)	t-stat	Skewness	Excess kurtosis	Annualized Returns	Annualized Volatility	IR	Maximum Drawdown	Hit Ratio
Mispricing model									
linear	213	3.1	0.1	2.6	6.8%	6.1%	1.12	9.2%	51.9%
lasso	207	3.5	-0.1	1.0	7.5%	5.9%	1.28	7.3%	53.4%
xgboost	240	3.8	0.1	0.9	8.5%	6.2%	1.38	7.6%	53.6%
composite	230	4.2	0.1	0.7	9.1%	5.8%	1.55	7.5%	52.4%

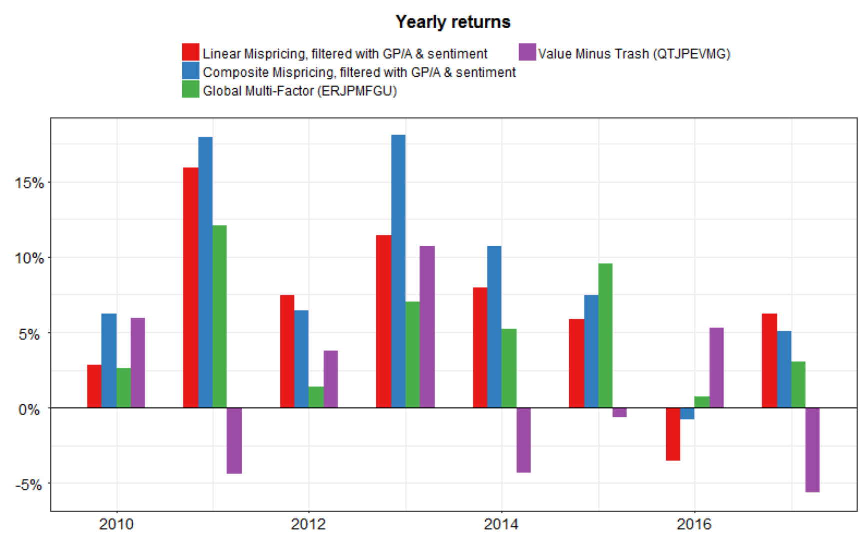
Source: J.P. Morgan Quantitative and Derivatives Strategy, RavenPack, Thomson Reuters, FactSet, Bloomberg, IBES, MSCI

Comparison with Equity Risk Premia

Currently, there are many tradable Risk Premia Indices that are offered by JPMorgan. Among the Equity Risk Premia Indices, let us look at the "Global Multi-Factor" (ERJPMFGU), and "Value Minus Trash", which is developed for Global Emerging Markets based on the report "Sorting Through the Trash" (QTJPEVMG)[23]. Figure 40 compares the performances of our models with these existing JPMorgan indices.

Figure 38: Comparing our "mispricing" strategies (either with the Linear model, or the Composite model), with the JPM Global Multi-Factor Index (ERJPMFGU) or the JPM Value Minus Trash Index (QTJPEVMG). Returns are after transaction costs.





L/S Strategy	Ann. Returns	Ann. Vol.	IR	Max DD	Hit Ratio	Past 3Y returns	Past 3Y Vol.	Past 3Y IR	YTD Returns	YTD Vol.	YTD IR
Linear, filtered with GP/A & sentiment	7.0%	6.1%	1.14	9.2%	52.1%	6.8%	5.6%	1.20	6.2%	5.8%	1.07
Composite, filtered with GP/A & sentiment	9.1%	5.8%	1.55	7.5%	52.4%	8.4%	6.0%	1.41	5.0%	5.9%	0.85
Global Multi-Factor (ERJPMFGU)	5.4%	5.2%	1.05	7.8%	52.8%	4.2%	5.1%	0.83	3.0%	3.8%	0.81
Value Minus Trash (QTJPEVMG)	1.3%	5.8%	0.22	8.8%	50.9%	-0.7%	5.7%	-0.12	-5.6%	5.0%	-1.13

Source: J.P. Morgan Quantitative and Derivatives Strategy, RavenPack, Thomson Reuters, FactSet, Bloomberg, IBES, MSCI

[23] For more details on the indices, please contact our structuring desks

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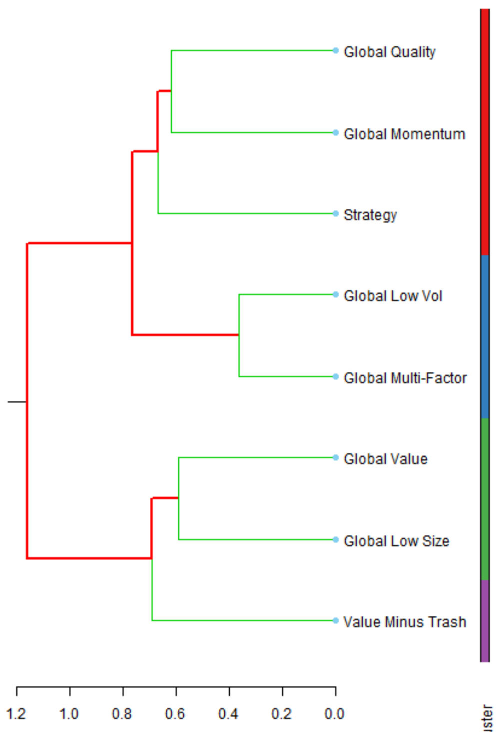
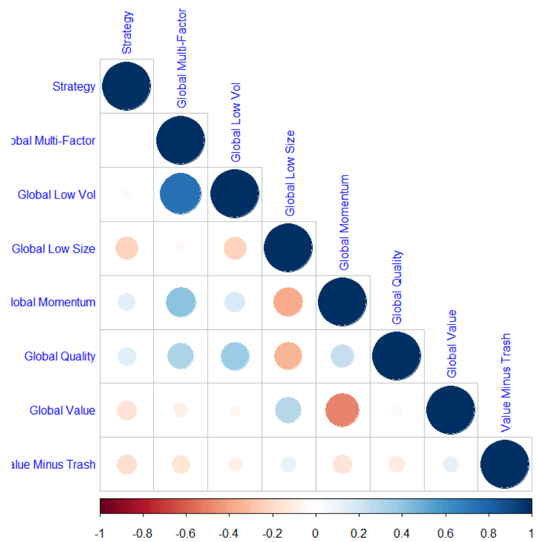
Correlations with Equity Risk Premia

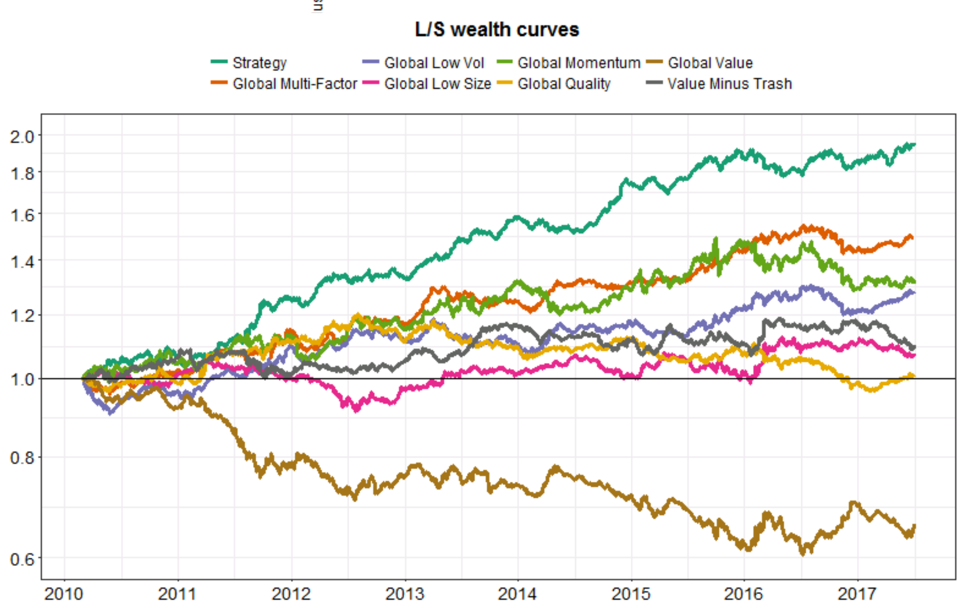
In Figure 39, we show the correlations between our long/short strategy (mispricing signal filtered with Gross-Profit-to-Assets and Sentiment) and some of the JPMorgan L/S Global Equity Risk Premia Indices.

Figure 39: Correlations between our long/short strategy (based on mispricing signal filtered with Gross-Profit-to-Assets and Sentiment) (2010-2017)





	Mispricing Strategy	Global Multi-Factor (ERJPMFGU)	Global Low Vol (ERJPLVGU)	Global Low Size (ERJPLSGU)	Global Momentum (ERJPMOGU)	Global Quality (ERJPMOGU)	Global Value (ERJPMOGU)
Strategy	100%						
Global Multi-Factor	2%	100%					
Global Low Vol	3%	73%	100%				
Global Low Size	-23%	-4%	-23%	100%			
Global Momentum	14%	40%	18%	-38%	100%		
Global Quality	15%	30%	35%	-34%	23%	100%	
Global Value	-17%	-10%	-5%	30%	-49%	5%	100%
Value Minus Trash	-17%	-14%	-8%	10%	-15%	-12%	12%



Source: J.P. Morgan Quantitative and Derivatives Strategy, RavenPack, Thomson Reuters, FactSet, Bloomberg, IBES, MSCI

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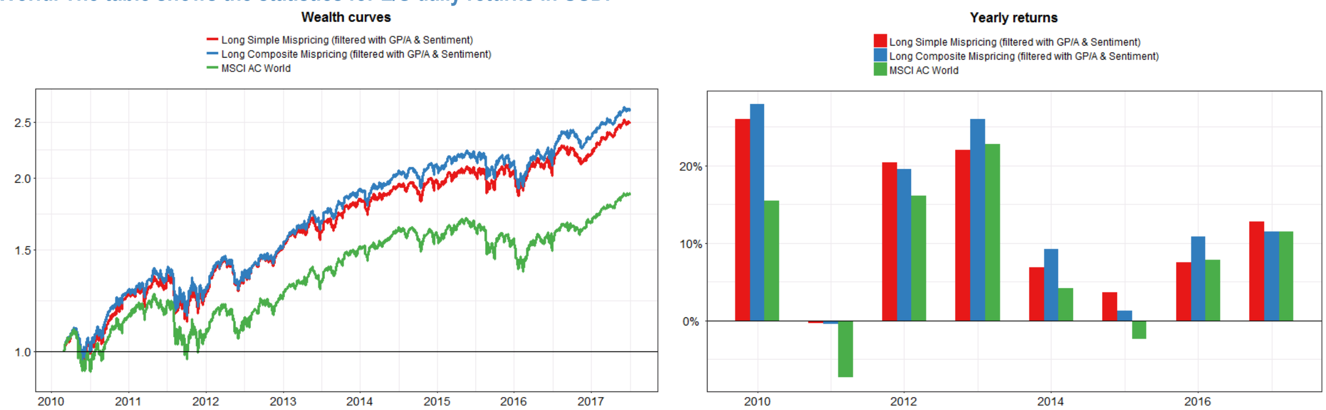
Performances of Long-Only Strategies

For long-only investors, we show that our long-only mispricing strategy adds value on top of the MSCI benchmark consistently over the year.

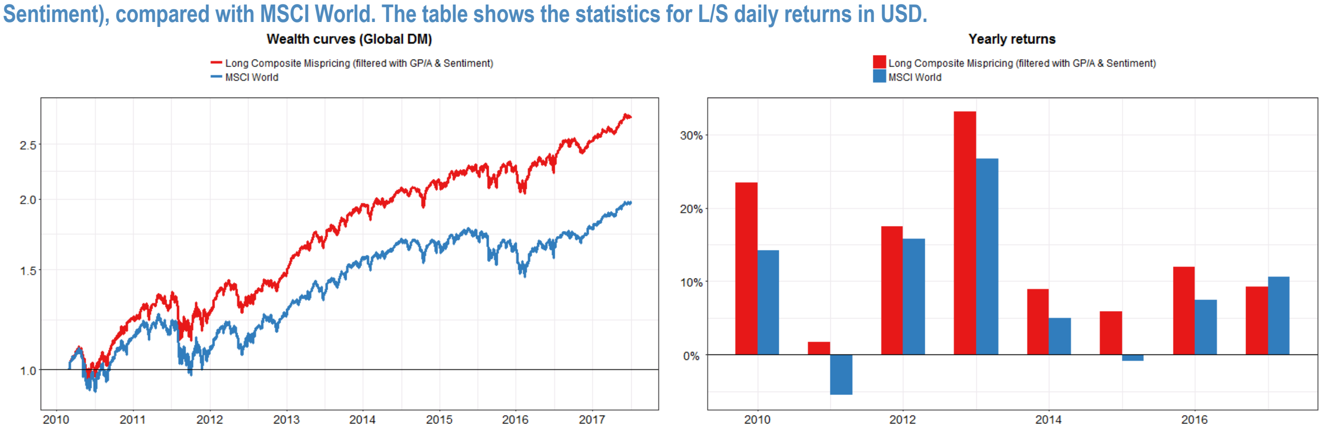
Figure 40: Long-only wealth curves of the mispricing strategy (filtered with Gross-Profit-to-Assets and Sentiment), compared with MSCI AC World. The table shows the statistics for L/S daily returns in USD.



Long-Only Strategy	Ann. Returns	Ann. Vol.	IR	Max DD	Hit Ratio	Past 3Y returns	Past 3Y Vol.	Past 3Y IR	YTD Returns	YTD Vol.	YTD IR
Simple Mispricing (filtered with GP/A & Sentiment)	12.7%	12.0%	1.06	17.1%	56.2%	8.2%	10.7%	0.77	12.8%	6.5%	1.97
Composite Mispricing (filtered with GP/A & Sentiment)	13.5%	12.5%	1.08	17.9%	56.1%	8.4%	10.9%	0.77	11.5%	6.6%	1.73
MSCI AC World (NDUEACWF)	8.6%	13.4%	0.64	23.1%	54.2%	4.5%	11.3%	0.39	11.5%	6.1%	1.87

Source: J.P. Morgan Quantitative and Derivatives Strategy, RavenPack, Thomson Reuters, FactSet, Bloomberg, IBES, MSCI

Figure 41: Long-only wealth curves of the mispricing strategy in Global Developed Markets (filtered with Gross-Profit-to-Assets and Sentiment), compared with MSCI World. The table shows the statistics for L/S daily returns in USD.



Long-Only Strategy	Ann. Returns	Ann. Vol.	IR	Max DD	Hit Ratio	Past 3Y returns	Past 3Y Vol.	Past 3Y IR	YTD Returns	YTD Vol.	YTD IR
Composite Mispricing (filtered with GP/A & Sentiment)	14.4%	13.0%	1.10	18.0%	55.5%	9.7%	11.2%	0.87	9.3%	6.9%	1.34
MSCI World (NDDUWI)	9.3%	13.6%	0.68	22.0%	54.0%	4.8%	11.5%	0.42	10.7%	6.3%	1.69

Source: J.P. Morgan Quantitative and Derivatives Strategy, RavenPack, Thomson Reuters, FactSet, Bloomberg, IBES, MSCI

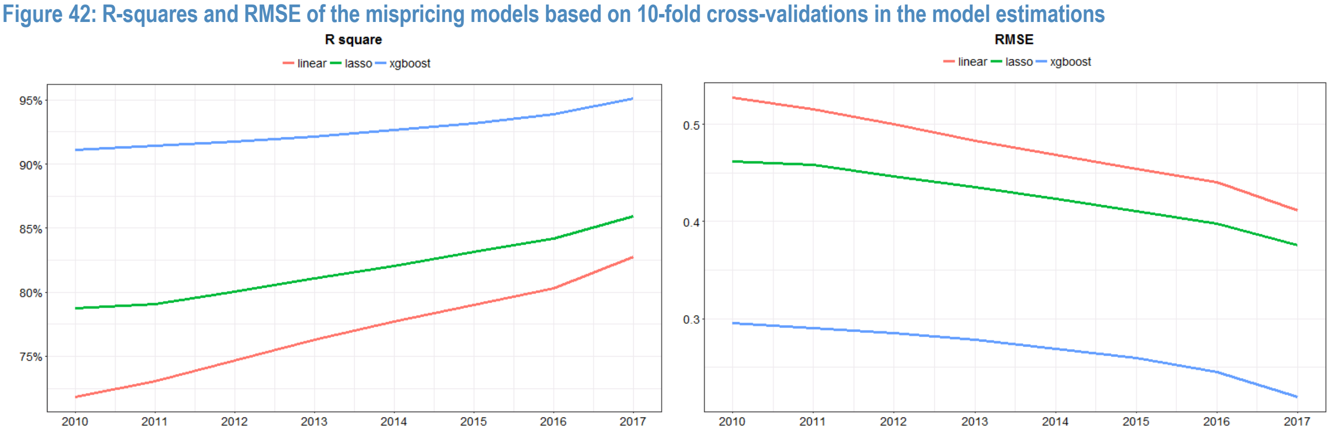
Comparison of the Models

Goodness of fit and prediction accuracies

Figure 42 compares the R-squares and the root-mean-squared error (RMSE) of the models, based on the predictions within the cross-validation sets.

- LASSO, which is still itself a linear model, gives higher R-squares than the simple linear model with only 7 "most important" predictors fixed over time. This shows the advantages of dynamically including more variables.
- Non-linear models like the XGBoost help to improve the in-sample predictions significantly, with R-squares jumping from 80% to above 90%.
- Our model fits are improving over time, which is in line with the better strategy performance since 2012. More research could be done on designing other features to predict price-to-book, with the hope of improving the predictions (and hence strategy performance) between 2010 and 2012.

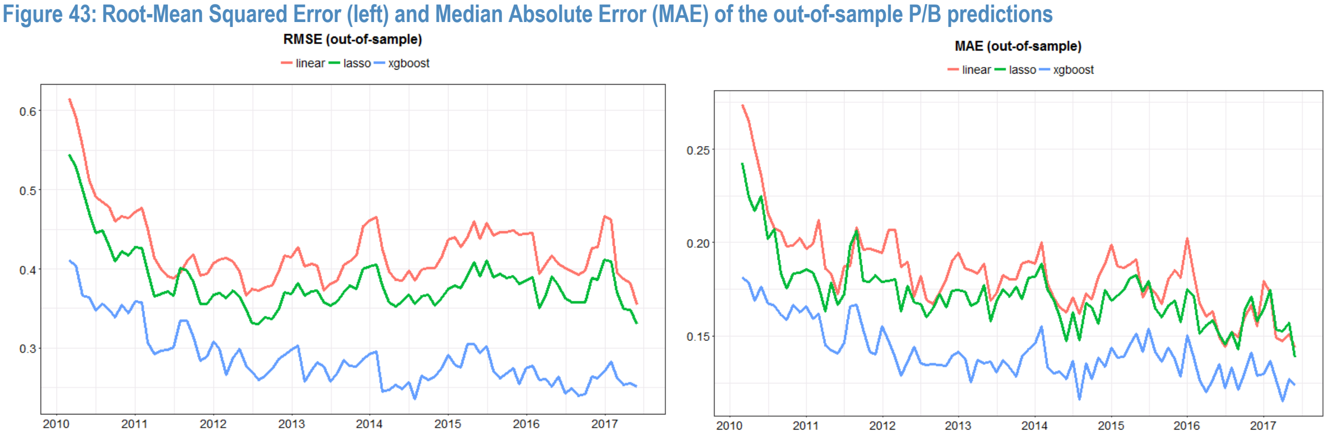
Figure 42: R-squares and RMSE of the mispricing models based on 10-fold cross-validations in the model estimations



Source: J.P. Morgan Quantitative and Derivatives Strategy, Thomson Reuters, FactSet, Bloomberg, IBES, MSCI

Figure 43 shows the out-of-sample prediction accuracies of the models. Again, XGBoost provides much better forecasts than the linear models including LASSO.

Figure 43: Root-Mean Squared Error (left) and Median Absolute Error (MAE) of the out-of-sample P/B predictions



Source: J.P. Morgan Quantitative and Derivatives Strategy, Thomson Reuters, FactSet, Bloomberg, IBES, MSCI

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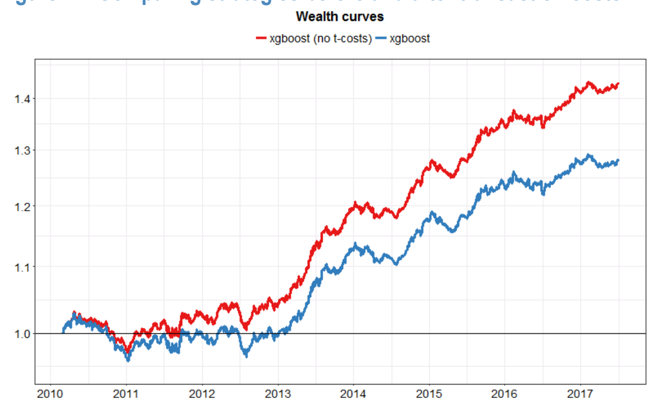
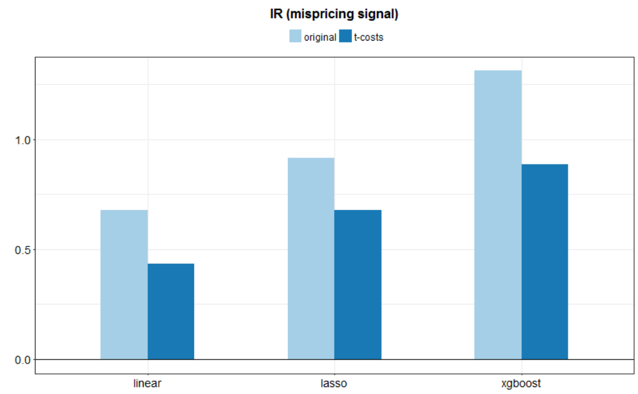
The effect of transaction costs

The signal based on XGBoost has the highest turnover, which is typical for a more dynamic, non-linear model. As such, when we evaluate strategies based on these algorithms, we should take into account transaction costs. We compare the strategies before and after costs in Figure 44.

Figure 44: Comparing strategies before and after transaction costs. The table shows the statistics for L/S daily returns in USD.





Mispricing signals	Median # of stocks (Long or Short)	Mea n IC	Risk-adj. IC	t-stat	Skew-ness	Excess kurtosis	2-way Turnover	Ann. Returns	Ann. Vol.	IR	Max. Drawdown	Hit Ratio
linear	332	1.6%	0.29	1.24	-0.16	4.42	87.2%	1.8%	4.1%	0.43	7.8%	49.9%
linear (no t-costs)	332	1.6%	0.29	1.91	-0.15	4.47	87.2%	2.8%	4.1%	0.68	6.8%	50.9%
lasso	331	1.6%	0.28	1.90	-0.12	3.59	87.2%	2.9%	4.2%	0.68	8.3%	51.3%
lasso (no t-costs)	331	1.6%	0.28	2.54	-0.12	3.65	87.2%	3.9%	4.2%	0.91	7.7%	51.8%
xgboost	331	1.9%	0.42	2.46	0.01	1.56	139.1%	3.2%	3.6%	0.89	6.7%	51.9%
xgboost (no t-costs)	331	1.9%	0.42	3.59	0.01	1.56	139.1%	4.8%	3.6%	1.31	5.7%	53.0%

Source: J.P. Morgan Quantitative and Derivatives Strategy, Thomson Reuters, FactSet, Bloomberg, IBES, MSCI

Stock Screens

Here we show a snapshot of the stocks in our long and short portfolio respectively, based on the strategy that looks for mispriced stocks (composite model), and applies filters of profitability and sentiment. Details are provided in the report.

Figure 45: Undervalued stocks with positive mispricing (i.e. expect P/B to expand) and high profitability, filtered with RavenPack's sentiment score (1: positive, -1: negative). The screen shows the top 30 stocks ranked by mispricing (as of 2017-07-31)

Ticker	Name	Country	Sector	Mcap (USD bn)	ADV1M (USD mn)	Mispricing (z-score)	Gross-Profit / Assets	Sentiment	Sentiment change	P/B	ROE (%)	ROE FY1 (%)
ANET US	ARISTA NETWORKS	US	I.T.	6.9	135.5	3.24	42%	-0.15	-0.16	8.7	19.3	26.2
REC IM	RECORDATI SPA	IT	Health Care	4.5	37.0	2.82	51%	0.20	0.29	7.5	25.1	28.0
CBOE US	CBOE HOLDINGS	US	Financials	9.5	105.2	2.74	112%	0.23	0.10	4.4	11.9	19.2
GOOG US	ALPHABET	US	I.T.	290.5	1767.0	2.23	33%	0.24	0.13	4.4	14.3	16.3
ORK NO	ORKLA ASA	NO	Consumer Staples	8.4	17.9	2.18	32%	0.03	-0.11	2.5	12.4	15.1
EL US	ESTEE LAUDER COMPANIES	US	Consumer Staples	22.0	129.6	2.09	98%	0.21	0.13	8.9	30.6	33.6
2579 JP	COCA-COLA BOTTLERS JAPAN	JP	Consumer Staples	3.7	24.8	2.07	61%	NA	NA	1.4	2.0	8.3
NKE US	NIKE	US	Consumer Discretionary	78.3	627.6	2.04	70%	0.15	0.07	7.7	31.8	31.3
NLMK RM	NOVOLIPETSK STEEL PJSC	RU	Materials	2.5	17.3	1.99	25%	0.03	0.18	1.8	19.7	20.6
GRMN US	GARMIN	US	Consumer Discretionary	6.4	43.4	1.96	37%	0.26	0.12	2.6	17.8	15.1
CDH IN	CADILA HEALTHCARE	IN	Health Care	1.7	13.1	1.92	58%	0.39	0.15	8.0	21.4	26.4
7752 JP	RICOH CO	JP	I.T.	6.6	32.9	1.87	27%	0.05	-0.03	0.7	0.3	0.8
EMR US	EMERSON ELECTRIC CO	US	Industrials	38.5	225.0	1.82	28%	0.09	-0.14	4.8	20.8	21.4
IOCL IN	INDIAN OIL	IN	Energy	3.3	43.7	1.79	63%	0.02	-0.03	1.7	20.0	19.7
KNIN VX	KUEHNE + NAGEL INTL	CH	Industrials	9.4	39.4	1.75	100%	0.23	0.07	8.8	31.2	34.7
SPK NZ	SPARK NEW ZEALAND	NZ	Telecom	5.2	8.2	1.74	46%	0.09	-0.19	4.1	23.6	23.8
EXPD US	EXPEDITORS INTL WASH	US	Industrials	10.6	65.7	1.69	76%	0.12	0.04	5.4	21.8	22.6
FB US	FACEBOOK	US	I.T.	398.6	2738.8	1.66	37%	0.25	-0.02	7.9	19.1	23.8
386 HK	CHINA PETROLEUM and CHEMICAL	CN	Energy	19.4	62.6	1.64	29%	0.19	0.25	0.8	7.8	7.5
151 HK	WANT WANT CHINA HOLDINGS	CN	Consumer Staples	3.4	9.5	1.61	35%	NA	NA	4.6	28.7	26.8
PAYX US	PAYCHEX	US	I.T.	18.7	130.6	1.56	33%	0.04	-0.07	11.0	42.2	45.1
HCLT IN	HCL TECHNOLOGIES	IN	I.T.	7.9	23.9	1.54	32%	0.28	-0.02	3.9	26.1	24.6
3045 TT	TAIWAN MOBILE	TW	Telecom	5.8	11.8	1.53	25%	0.30	-0.15	4.6	24.0	24.9
XLNX US	XILINX	US	I.T.	15.7	235.3	1.49	35%	0.15	0.15	6.3	24.4	27.1
ITC IN	ITC	IN	Consumer Staples	15.1	58.4	1.47	71%	0.20	0.10	7.5	22.2	26.6
TLS AU	TELSTRA	AU	Telecom	13.6	106.8	1.42	34%	-0.01	-0.09	3.4	37.7	26.2
005935 KS	SAMSUNG ELECTRONICS	KR	I.T.	30.6	54.5	1.41	31%	0.39	0.04	1.5	13.5	19.6
TATN RM	TATNEFT PJSC	RU	Energy	9.9	11.6	1.37	44%	0.30	0.15	1.2	16.8	16.8
DD US	DU PONT (E.I.) DE NEMOURS	US	Materials	71.1	188.1	1.33	25%	0.15	-0.15	6.4	23.6	37.8
ITX SM	INDUSTRIA DE DISENO TEXTIL	ES	Consumer Discretionary	43.2	144.4	1.31	63%	0.24	-0.08	8.2	24.8	27.3

Source: J.P. Morgan Quantitative and Derivatives Strategy, RavenPack, Thomson Reuters, FactSet, Bloomberg, IBES, MSCI

Figure 46: Overvalued stocks with negative mispricing (i.e. expect P/B to contract) and low profitability, filtered with RavenPack's sentiment score (1: positive, -1: negative). The screen shows the top 30 stocks ranked by mispricing (as of 2017-07-31)

Ticker	Name	Country	Sector	Mcap (USD bn)	ADV1M (USD mn)	Mispricing (z-score)	Gross-Profit / Assets	Sentiment	Sentiment change	P/B	ROE (%)	ROE FY1 (%)	Indicative Lending Fee (bps)
TSRO US	TESARO	US	Health Care	4.8	213.4	-3.24	5%	0.01	-0.10	13.4	-88.9	-86.7	62.5
JS SP	JARDINE STRATEGIC HLDGS	SG	Industrials	9.0	14.3	-2.82	11%	NA	NA	1.7	10.5	6.0	62.5
MGM US	MGM RESORTS INTERNATIONAL	US	Consumer Discretionary	15.1	217.3	-2.74	11%	0.15	0.06	3.0	19.6	9.0	37.5
UDR US	UDR	US	Real Estate	10.5	50.6	-2.68	3%	0.05	0.05	3.5	3.1	3.0	37.5
MMFS IN	MAHINDRA and MAHINDRA FIN	IN	Financials	1.7	13.9	-2.63	8%	-0.09	NA	3.3	7.4	13.7	NA
MAN GR	MAN SE	DE	Industrials	3.9	8.4	-2.55	13%	0.21	-0.20	2.4	2.3	5.4	50
PPL CN	PEMBINA PIPELINE	CA	Energy	13.6	38.5	-2.51	7%	0.18	0.16	2.5	7.4	9.0	37.5
MIC US	MACQUARIE INFRASTRUCTURE	US	Industrials	5.9	32.9	-2.44	9%	-0.11	-0.30	2.2	5.9	-2.0	37.5
BXP US	BOSTON PROPERTIES	US	Real Estate	18.6	78.2	-2.36	5%	-0.04	-0.07	3.3	7.5	1.1	37.5
BAM/A CN	BROOKFIELD ASSET MANAGE	CA	Financials	34.4	38.9	-2.31	6%	0.17	0.00	1.7	5.4	1.7	37.5
DLR US	DIGITAL REALTY TRUST	US	Real Estate	18.3	177.3	-2.29	6%	0.08	-0.14	4.6	6.7	6.2	37.5
EQIX US	EQUINIX	US	Real Estate	34.7	236.6	-2.25	14%	0.21	0.06	5.4	3.1	7.4	62.5
EQR US	EQUITY RESIDENTIAL	US	Real Estate	25.0	104.4	-2.23	4%	0.22	0.19	2.4	3.1	4.9	37.5
LNT US	ALLIANT ENERGY	US	Utilities	9.2	50.6	-2.22	5%	0.05	-0.16	2.4	9.7	10.9	37.5
PXD US	PIONEER NATURAL RESOURCES	US	Energy	27.7	283.8	-2.17	1%	-0.10	-0.13	2.7	-1.2	1.8	37.5
AWK US	AMERICAN WATER WORKS CO	US	Utilities	14.5	63.5	-2.12	7%	-0.09	-0.06	2.7	9.0	10.1	37.5
TSLA US	TESLA	US	Consumer Discretionary	41.6	2840.1	-2.11	7%	0.15	-0.09	10.6	-16.3	-23.3	112.5
OXY US	OCCIDENTAL PETROLEUM	US	Energy	47.3	323.6	-2.08	2%	0.03	-0.06	2.2	1.1	2.0	37.5
CPT US	CAMDEN PROPERTY TRUST	US	Real Estate	7.9	40.4	-2.02	5%	0.16	-0.02	2.9	15.8	4.7	37.5
TLEVICPO MM	GRUPO TELEVISA SAB-SER	MX	Consumer Discretionary	13.0	10.8	-2.01	12%	0.12	-0.04	3.3	5.3	7.0	62.5
EXR US	EXTRA SPACE STORAGE	US	Real Estate	10.0	74.1	-1.99	8%	0.10	0.01	4.5	16.4	12.4	37.5
FNV CN	FRANCO-NEVADA	CA	Materials	12.9	31.4	-1.98	5%	0.17	0.08	3.1	4.1	4.1	37.5
9007 JP	ODAKYU ELECTRIC RAILWAY	JP	Industrials	5.8	11.3	-1.97	10%	0.12	0.12	2.4	7.8	8.5	50
VMC US	VULCAN MATERIALS CO	US	Materials	16.3	129.7	-1.95	12%	0.09	-0.12	3.6	9.8	11.5	37.5
ICAD FP	ICADE	FR	Real Estate	2.9	8.0	-1.91	3%	0.29	0.19	1.6	0.3	8.9	50
MRW LN	WM MORRISON SUPERMARKETS	GB	Consumer Staples	7.0	28.9	-1.90	7%	-0.07	0.08	1.4	4.4	6.9	NA
WYNN US	WYNN RESORTS	US	Consumer Discretionary	10.5	229.9	-1.89	11%	0.11	0.01	60.1	122.7	148.4	37.5
FFB SJ	FORTRESSOME FUND	ZA	Real Estate	2.3	6.6	-1.87	3%	0.22	NA	2.0	8.1	4.3	50
ESS US	ESSEX PROPERTY TRUST	US	Real Estate	17.2	89.1	-1.86	4%	0.06	0.05	2.7	8.2	5.5	37.5
D US	DOMINION ENERGY	US	Utilities	48.5	220.3	-1.84	5%	0.10	0.07	3.3	15.1	14.1	37.5

Source: J.P. Morgan Quantitative and Derivatives Strategy, RavenPack, Thomson Reuters, FactSet, Bloomberg, IBES, MSCI

Disclosures

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