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Chief Investment Office GWM
Investment Research

Investing in autocallables

Derivatives Strategy

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- Structured products such as autocallables can enhance portfolio returns across different market scenarios.
- A systematic approach to selecting the underlying stocks for such products can increase returns.
- You should read this report if... you are looking for yield enhancement via autocallables.

Introduction

Structured products can be an interesting tool to generate yields. In particular when markets lack a clear trend, adding structured products to a portfolio can help increasing returns in relative and absolute terms.

In this note we focus on autocallable structured products. In an autocallable an investor takes a short position in a put option and profits from the volatility risk premium through a regular coupon payment. Additionally, the product contains a callable feature and is typically called if the underlying closes above a certain threshold on an observation date. The section product structure gives a detailed overview of the product specification we analyze.

We proceed and build an advanced statistical model using machine learning in order to select a portfolio of stocks best suited for autocallable notes. Our analysis suggests that incorporating fundamental, as well as market data in the decision-making process, can significantly increase returns and decrease losses. While we use a quantitative model to select the stocks, our findings can also help to enhance a bottom-up selection process.

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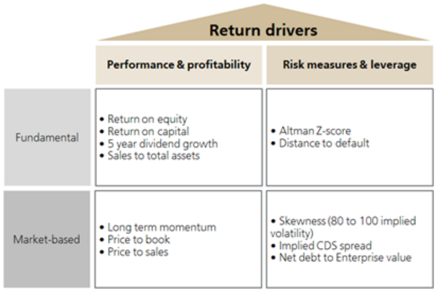
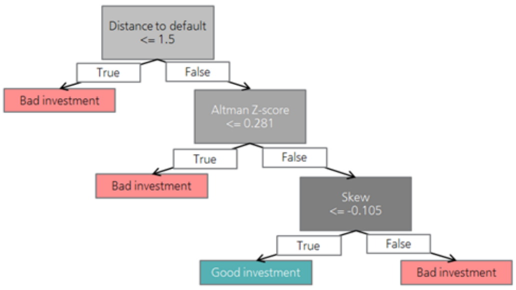
Executive Summary

Q Which stocks are best suited for autocallables ?
In this research note we aim to find a framework to systematically identify suitable stocks

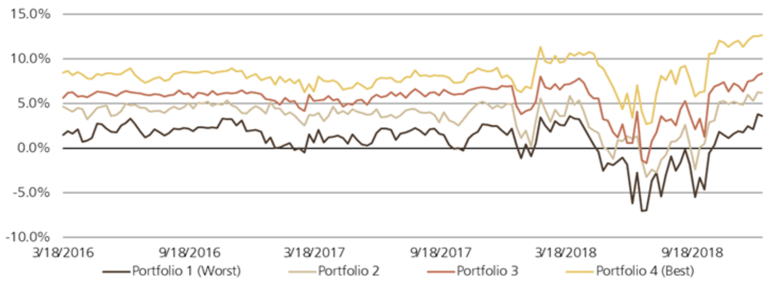
1 Identify return drivers of autocallable returns
We find that 12 fundamental and market-based variables provide explanatory power



2 Build model to systematically select stocks
Using a machine learning model we classify the stocks using the 12 selected variables



3 Analyze performance of autocallables on preferred stocks
Autocallables on preferred stocks achieve higher returns and have lower risk metrics on average



Source: UBS, Bloomberg

Methodology increases autocallable performance
Stocks with high solvency, good profitability and favourable metrics such as skewness are better suited as underlyings for autocallables

How does an autocallable work?

An autocallable is a structured product which pays investors regular coupon payments. The products have a fixed maximum tenor; however, the tenor may be shorter if the product is called. The notes have set observation dates on which the coupon payments are made, but may be called early. The coupon paid by the product is financed by a short position in a put option. The put option has a tenor that matches the life of the product. Our analysis investigates products with a tenor of six months and monthly observation dates. However, there are many different flavors trading in the financial markets.

Figure 1 - Pay-off of short put position at expiry

Illustrative performance of a short put position at expiry. Strike is set to 90% of initial spot.

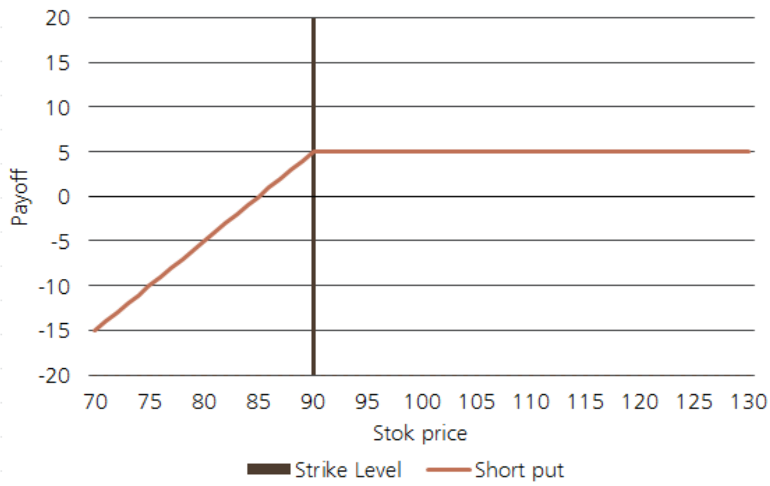


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Figure 1 illustrates a short position in a put with a strike level at 90. The seller of the put will receive the put premium of 5 in any case. However, if the spot lies below the strike level, the seller of the put will have to provide the difference between the strike and the spot level. The short position in the put provides the majority of the coupon payments in an autocallable product. Hence, if the put option has a higher value at inception this will lead to a higher coupon. For example if the underlying stock has a high implied volatility an autocallable on the product will pay a relatively high coupon.

The second main feature of an autocallable product is the callable feature. During the lifetime an autocallable has several observation dates, for example once every month. On these dates the product pays the coupon regardless of the spot price of the underlying. However, if the spot price is above the call barrier the product will be redeemed at notional value. If the spot value is below the call barrier, the product continues to live.

Figure 2 illustrates this feature for four different scenarios. The product has the same characteristics as the one we use in our analysis. It has a tenor of six months and monthly observation / coupon dates. The call barrier is at the 100% of spot, i.e. the value of the spot at issuance. If the spot is above the call barrier on an observation date the product is called and the full initial notional is redeemed. The strike level of all products is set to 85% of spot at inception.

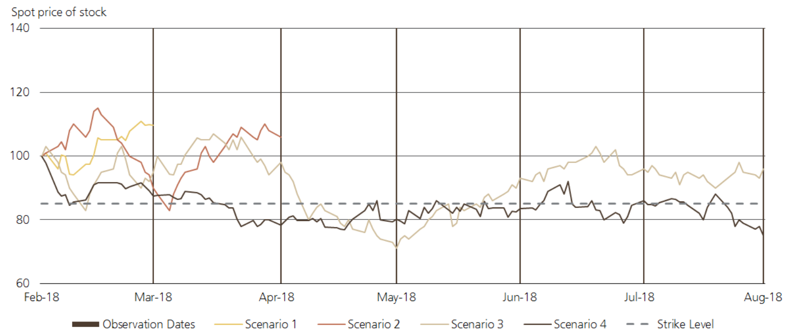
The autocallable in scenario 1 is redeemed early (autocalled) at the first observation date as the spot moved up; therefore the investor receives only the first coupon. In scenario 2 the note does not redeem at the first observation date, but at the second. This product lives for two months and pays the coupon twice.

The third case illustrates a scenario in which the product is not redeemed early. The investor receives the coupon six times and receives the full notional at expiry as the spot at expiry trades above the strike level. Note that even though the stock traded at or above the call barrier multiple times, it is not autocalled, as the days were not observation dates.

In scenario 4 the stock is not redeemed early and trades below the strike level at expiry. Again, the investor receives the six coupons; however the stocks closes at 75% of initial spot, which is below the strike level of 85%. Hence, the investor makes a loss of 10% due to the embedded put option and receives 90% of the initial notional. Nevertheless, this does not necessarily mean that the investor makes a loss on the product. If the sum of the six coupons received exceeds the 10% loss on the notional, the total return of the autocallable is still positive.

Figure 2 - Comparison of autocallable scenarios

Analysis of the spot development and effect on an autocallable for four different scenarios.



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An investor in an autocallable provides a certain amount of notional to the issuer of the product. Hence, the investor should be compensated for the credit risk to which he is exposed. Bearing this risk will increase the coupon of the product. We incorporate this by taking the average six-month Credit Default Spread of four major banks.

Unlike displayed in figure 2, we do not use the same strike level for all underlying stocks, but adjust the strike level depending on the riskiness of a stock. A volatile stock is more likely to be below the strike level of the embedded put option at expiry and hence is more likely to lose money. This is for example the case when comparing a risky growth stock (for example a tech stock) with a defensive stock (e.g. a utility). Hence, to adjust for the riskiness of the individual stock, we estimate the probability that the underlying will be below the strike price at expiry. We then select the strike level such that the product has a 30% likelihood to be below the strike level at expiry. Note that we do not consider possible early redemptions, and hence the probability of making a loss is therefore below 30% for each product.

Yield enhancement products such as autocallables typically outperform a long position in the underlying stock in sideways or downward trending market environments. Hence, they can be an interesting investment in late-cycle environments where volatility is rising but upside potential is limited. If markets rally strongly a long position in the underlying stock will typically perform better. An autocallable would be called early and investors could switch into the stock.

Setup of the analysis

In this research note we aim to build a model to select suitable stocks for autocallables. We measure the performance of an autocallable as the annualized performance of the product. Thus, we are indifferent of the product lifetime, as different investors have different liquidity needs. Some investors might prefer a product that is called after one month while others prefer a product that does not redeem early and lives for six months.

The analysis considers 972 developed market stocks listed either in the United States or in the Eurozone. Performance is measured in local currency terms, hence we exclude all currency effects. The time period covered spans from January 2008 to June 2019. The time frame from January 2008 to March 2016 is used as a training set to train the model. The second part from March 2016 to June 2019 is used as the test period to evaluate the performance of our model.

Figure 3 - Research process to build a machine learning model

Illustration of the research process to identify stocks suitable for autocallable issuance.

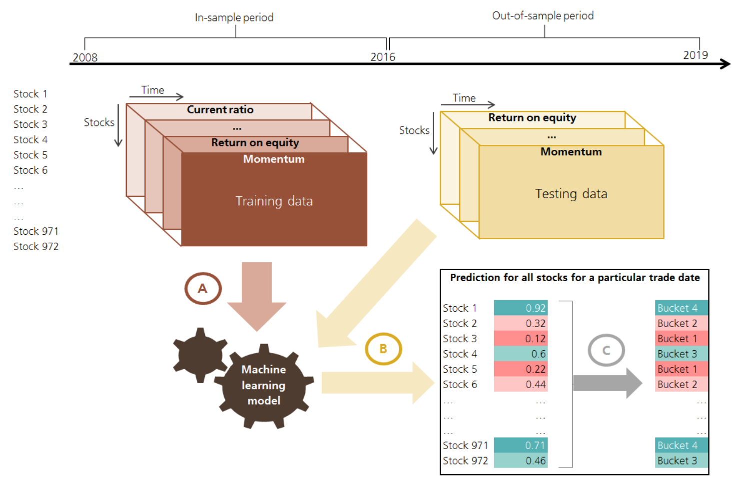

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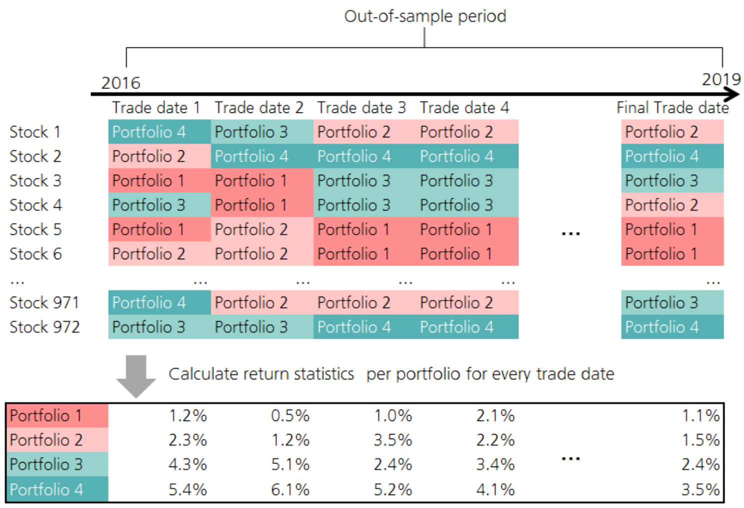
Figure 3 gives a high level overview of our research process across both the in-sample and the out-of-sample period. The process is divided into 3 steps. In step A we look at a large set of explanatory variables and at different machine learning models. The training data is used to calibrate different models and select the relevant explanatory variables.

Next, in step B we use the calibrated machine learning model and apply it to the test data set. For each trade date the model calculates the probability of a stock belonging to the best 25% of stocks for autocallables in terms of annualized performance. A high probability score indicates that the model views the stock as a good candidate for an autocallable structure.

In step C, we build four autocallable portfolios. We rank the stocks according to the probability of being a good underlying for an autocallable product. We then group the stocks into four equal sized portfolios depending on the probability. Portfolio 1 contains the stocks least suited for autocallable issuance and portfolio 4 contains the best suited stocks. These sorting and bucketing algorithms can be repeated for each day in the out-of-sample period as shown in figure 4. For each portfolio we can then calculate the performance of the autocallables in the portfolio. We use the returns of these portfolios to test the strength of our model. In a good model, portfolio 4, containing autocallables on the best-suited stocks, should perform better than the other three portfolios across time.

Figure 4 - Calculation of the strategy for four portfolios

Illustration of bucketing algorithm across out-of-sample period. The analysis uses weekly data and every week has one trade date where we estimate the model and calculate performance.



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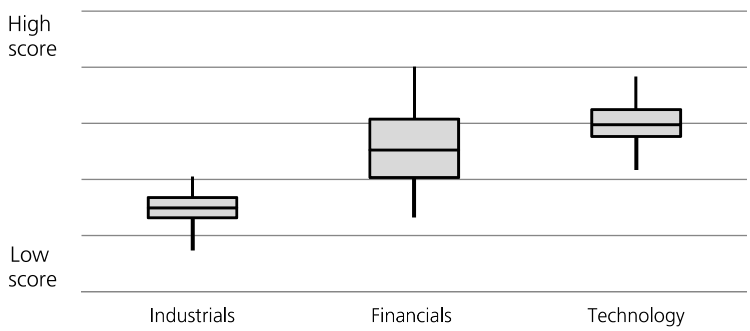
Step B and C are repeated for the different machine learning models trained in step A. This enables us to compare the performance of the various models. The following section 'Selecting features' illustrates the explanatory variables used to train the algorithms. Section 'Building the model' describes our preferred model.

Selecting features

Our analysis started with considering over 40 different features which might be able to partially explain why an autocallable performs better on stock A than on stock B. We look at both market-implied, as well as at fundamental data and technical indicators.

Figure 5 - Variability of feature values across stocks per sector

Illustration of the research process to identify stocks suitable for autocallable issuance.



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To account for different business models and divergent financial metrics, we normalize the explanatory variables by calculating z-scores per sector. Hence all explanatory variables of a company are adjusted for the mean and standard deviation of its sector. We use the sector classification by GICS. This ensures that the riskiest stocks within each sector are highlighted, and that our indicator doesn't continually highlight an entire sector whose business model dictates higher (or lower) scores on a given financial metric. Figure 5 illustrates possible differences for an indicator across three sectors.

As a first step we use four methods to select the features with the best explanatory power. These are the F-Test, the Mutual Information Criterion, Lasso Regression and Random Forests. For the Random Forest model the Gini impurity score is calculated to select the variables with the highest predictive values. We then select the 12 variables which are most popular among the four methods mentioned above and have a relatively high explanatory power in predicting whether an autocallable on a stock performs well.

Figure 6 displays the 12 selected variables with highest explanatory power. We split these into two categories according to their drivers of return. The first is a measure of performance or profitability and the second is a measure of risk. Additionally these categories can each be separated into fundamental or market-based predictors.

Figure 6 - Selected variables

Selected variables can be separated by return driver (return or risk) and by data type (fundamental or market-based).

	Return drivers	
	Performance & profitability	**Risk measures & leverage**
Fundamental	• Return on equity • Return on capital • 5 year dividend growth • Sales to total assets	• Altman Z-score • Distance to default
Market-based	• Long term momentum • Price to book • Price to sales	• Skewness (80 to 100 implied volatility) • Implied CDS spread • Net debt to Enterprise value

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Building the model

We now use the 12 variables to build a model to predict if a stock is suited for an autocallable investment. We compare different statistical models, among them logistic regression, random forest, gradient boosting and support vector machines. As displayed in figure 3 we use the in-sample period to train the model and the out-of-sample period to test the performance. We measure the performance of a model in the ability to build portfolios where portfolio 4 (containing autocallables on the most favored stocks) performs the best, as illustrated in figure 4.

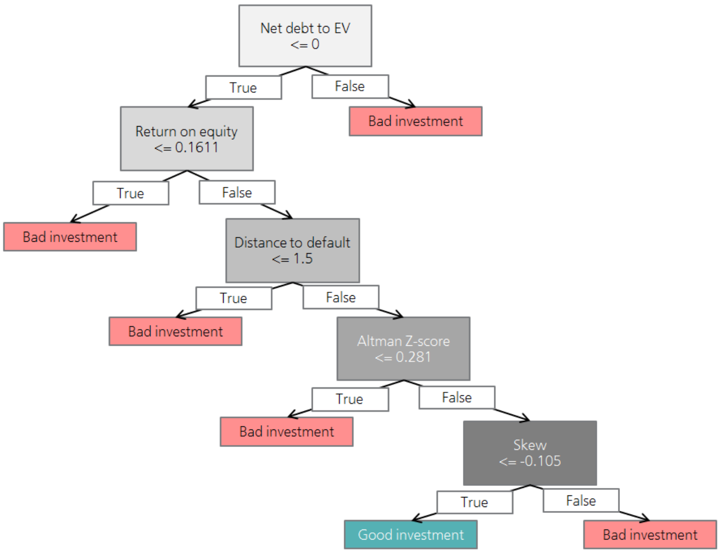
In general we find that all models manage to distinguish between stocks which make good and bad picks for autocallable notes. The logistic regression is the simplest model we test, as it only considers linear relationships between the explanatory variables. It already performs relatively well.

Advanced machine learning models can incorporate non-linear relationships. Using such a model typically increases the performance, meaning that the average performance of the preferred portfolio has a higher return on average. We favor a random forest model, as it performs well in both the in-sample as well as in the out-of-sample period. Random forests are a popular machine learning method and have been discussed by Breimann (2001) or Denil et al.(2014).

In a random forest the algorithm builds a large set of decision trees. An example of a decision tree is shown in figure 7. A random forest consists of many different decision trees, which each classify the observation as good or bad trade. Single decision trees are prone to overfitting, using many different decision trees, a forest, can counteract this. Furthermore, we restrict the depth of the decision trees in the random forest to six. This means a single decision tree can use at maximum six variables within the tree. This should again help avoid overfitting.

Figure 7 - Illustration of a simplified decision tree in a random forest

For every stock the decision tree will determine if the stock is suitable for an autocallable or not. In the example below there is only one leaf for which trades are classified as a good investment. Note that this does not have to hold for every tree.



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One can use the single decision trees and subsequently the forest as a whole to calculate the probability of an observation to be a good trade. We use this probability to group observations and build portfolios.

Performance of our model

The random forest is now put to the test and used to select the most favored stocks. It performs well both on the in-sample period and the out-of-sample periods and manages to separate good from bad trades. We focus on the out-of-sample period as it considers data, which the model has not previously seen. Figure 8 shows the performance for all trade dates on a portfolio level during the out-of-sample period. Portfolio 4 performs the best as it has the highest average autocallable performance across the full period.

Additionally, the relationship between portfolios and return is almost always monotonic, meaning that portfolio 1 has the worst performance and performance increases with every portfolio. This indicates that our model does a very good job in classifying the attractiveness of a stock for an autocallable trade. The monotonic difference shows that the model is capable of identifying good trades both in upward- and downward-moving markets.

Figure 8 - Performance of the different portfolios

Illustration of the research process to identify stocks suitable for autocallable issuance. Note that performance figures do not include any costs incurred.

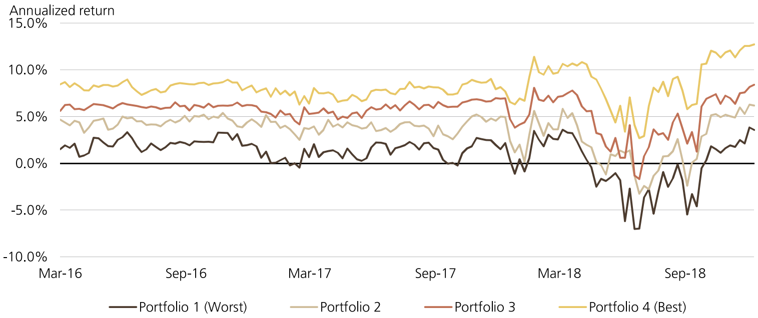

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Table 1 shows the corresponding summary statistics for the four different portfolios. It shows that portfolio 4 has better characteristics not only in terms of return, but also in terms of risk. These results can be strengthened via a z-test to test whether portfolio 4 has a significantly different average return. We find that the null hypothesis, that the two average returns are the same, can be rejected in all three cases.

Table 1 - Portfolio statistics for the four autocallable portfolios

Return statistics on a portfolio level. The time frame includes the out-of-sample period from 2016. All figures are annualized. Note that performance figures do not include any costs incurred.

	Worst			**Best**
Portfolio	**1**	**2**	**3**	**4**
Average return per portfolio	0.9%	3.5%	5.5%	8.2%
Median return per portfolio	2.8%	4.7%	6.1%	8.2%
Standard deviaton per portfolio	2.1%	1.9%	1.7%	1.7%
Z-Test against portfolio 4	32.6	22.6	13.5	

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Table 2 analyzes the single trades within each portfolio and summarizes the return characteristics for each portfolio. It shows that the preferred portfolio 4 has the lowest share of losing trades (5.2%) and that losses are on average smaller than in the other portfolios.

Table 2 - Return statistics across all trades

Return statistics on a portfolio level across all trades for the out-of-sample period from 2016. All figures are annualized. Note that performance figures do not include any costs incurred.

	Worst			Best
Portfolio	1	2	3	4
Average return	0.9%	3.5%	5.5%	8.2%
Standard deviation of returns	10.9%	9.7%	9.3%	9.1%
Frequency of losing trades	9.6%	8.5%	6.6%	5.2%
Average loss	-24.3%	-20.3%	-19.7%	-17.4%

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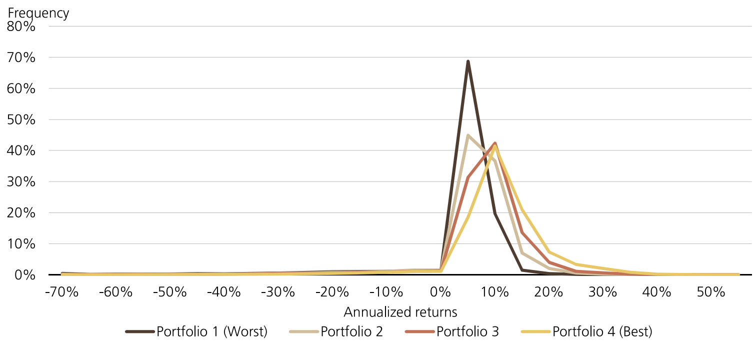
These findings are visualized in figure 9 which shows the distribution of all trades for the four different portfolios. It underlines that the distribution of portfolio 4 is the most attractive as high positive returns are much more likely than in the other portfolios, while adverse situations, such as negative returns are less likely.

Figure 9 - Return distribution of trades across

Distribution of all trades per portfolio in out-of-sample periods. All returns are annualized. Note that performance figures do not include any costs incurred.



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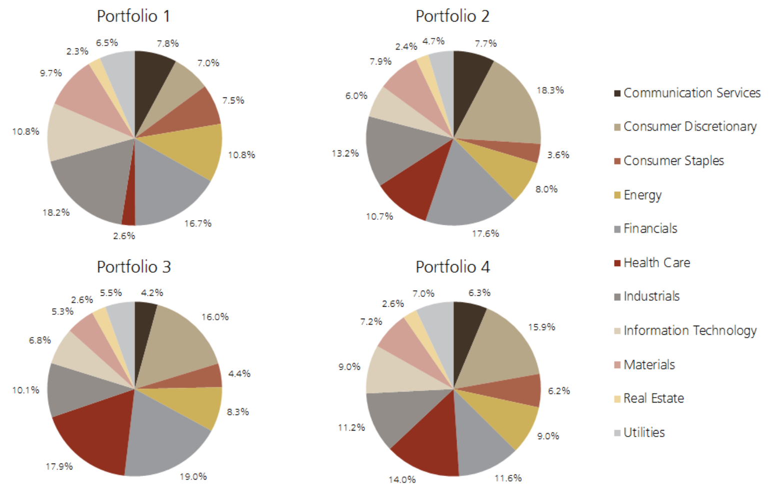
In order to further analyze the results, we take a look at the relative importance of sectors across the portfolios. As we normalize explanatory variables across sectors, the sector tilts of the four portfolios should not be too extreme. Some sectors, such as Utilities or Energy, are distributed relatively evenly across the four portfolios. Others, such as Information Technology or Health Care, are more often picked by the better performing portfolios 3 and 4. Industrials on the other hand are more often allocated to portfolios 1 and 2. Figure 10 illustrates the sector allocation across the four portfolios. As all portfolios are of the same size, the total share of a sector is just the average across the four portfolios.

Figure 10 - Sector allocation across the four portfolios

The timeframe includes the out-of-sample period from 2016 to 2019.



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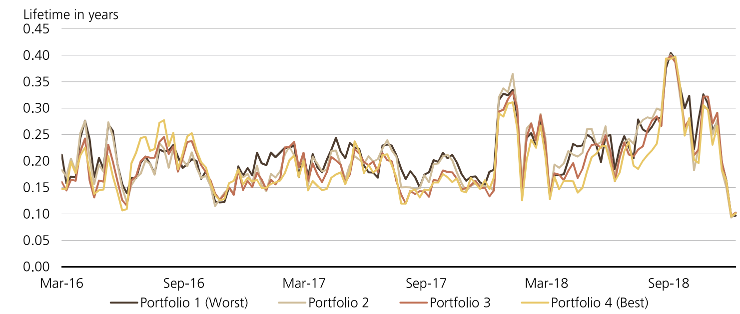
An attentive reader might claim that there are underlying dynamics other than sector allocation which vary across the four portfolios. One might be product lifetime. Our preferred stocks might autocall quicker than the others, and hence we would be comparing apples and oranges. In figure 11 we compare the average lifetime across the four portfolios.

Figure 11 - Average lifetime of autocallables across portfolios

The time frame includes the out-of-sample period from 2016 to 2019. The chart shows the average lifetime of an autocallable per portfolio in years.



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The illustration shows that typically the average lifetime of products is very similar. The variation in the lifetime of an autocallable is much more dependent on a common factor, i.e. the market performance, as the average lifetime does not differ across the four portfolios.

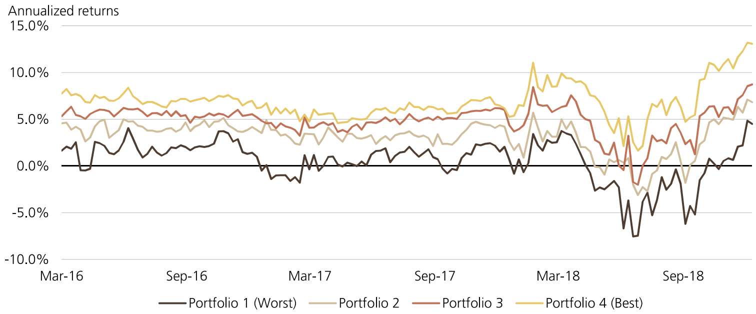
A further consideration, is that the products have different strike levels to adjust for the riskiness of the underlying. Hence, autocallables on less risky stocks might have a higher strike combined with a higher coupon level. These products would do well during most of the time as markets generally trend upwards.

In order to test that the product structure is not the main driver of the outperformance of portfolio 4, we rerun the same analysis and price all autocallables with a fixed strike at 85% of spot. An autocallable on a certain stock might perform differently as it has a different strike level and, hence, also pays a different coupon.

Nevertheless, our model still prefers the same stocks, as the explanatory variables across stocks do not change. Figure 12 illustrates the performance using the same methodology if all autocallables have a fixed strike level of 85%. The results are encouraging portfolio 4 still performs the best across the out-of-sample period and the relationship across all portfolios remains monotonic for the vast majority of trade dates.

Figure 12 - Performance across portfolios using the same strike level for all products

All products have strike level of 85% of spot, independent of skewness and implied volatility. The time frame includes the out-of-sample period from 2016 to 2019. Note that performance figures do not include any costs incurred.



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This is the case for bull markets, for example during 2017, as well for market sell-offs, as in the fall of 2018. These findings support the notion that our model selects suitable stocks for autocallables and does not load on product specific features.

What makes a good trade?

Machine learning models are often criticized as black boxes, where the relationship between explanatory variables and output cannot be reconstructed unequivocally. Nevertheless, we know which variables are important to select stocks for autocallable trades. Additionally, we can use LIME as proposed by Ribeiro et al. (2016) to further analyze the results. LIME is an algorithm which aims to provide an explanation of a prediction by approximating the machine learning model with an interpretable model.

Figure 13 - Approximated result using LIME

Illustration of factor loadings for two exemplified trades. Note that a skew below average indicates that the 20% out-of-the money volatility is relatively high compared to the at-the-money volatility.

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Figure 13 shows the results when using LIME to decode our model and displays the drivers for a positive selection for two exemplified trades. It shows that many different variables have a positive effect on viewing a trade positively. For one, companies should have favorable default metrics meaning that default risk and hence, a downward jump in the stock price, is unlikely. Above average profitability metrics and a high skew, indicating higher coupons, make stocks more attractive. The price-to-sales ratio seems to have a strong weight. However, our model performs similarly well if we remove it and recalculate the analysis with the 11 remaining variables.

Conclusion

Autocallables are a viable tool to enhance yields in a portfolio. We show that investors can use a systematic approach to select stocks as underlyings for autocallable notes. Our approach uses a random forest classifier in order to select the single stocks. A portfolio of autocallables on the selected stocks outperforms in terms of return as well as drawdown metrics. While we used an advanced method to pick our preferred stocks, the recipe to select a stock are relatively intuitive. The model prefers stocks which have a high skewness, but still healthy leverage figures, good solvency measures and an above average profitability. These findings can also be used for a bottom-up approach to select stocks for autocallables. Our model just uses a more systematic approach to do so.

Appendix

Autocallable pricing
In order to price autocallables on single stocks for the time period from 2008 to 2019 we have used a static replication approach. The investor is long a portfolio of up-and-out digital call options (one for each observation date) and short one up-and-out put option with a tenor of six months. In the process of building the pricer we have compared our prices to others generated with Bloomberg models in order to ensure fair prices. Data source for pricing data is Bloomberg, with the exception of CDS spreads which are sourced from Citi.

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Appendix

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