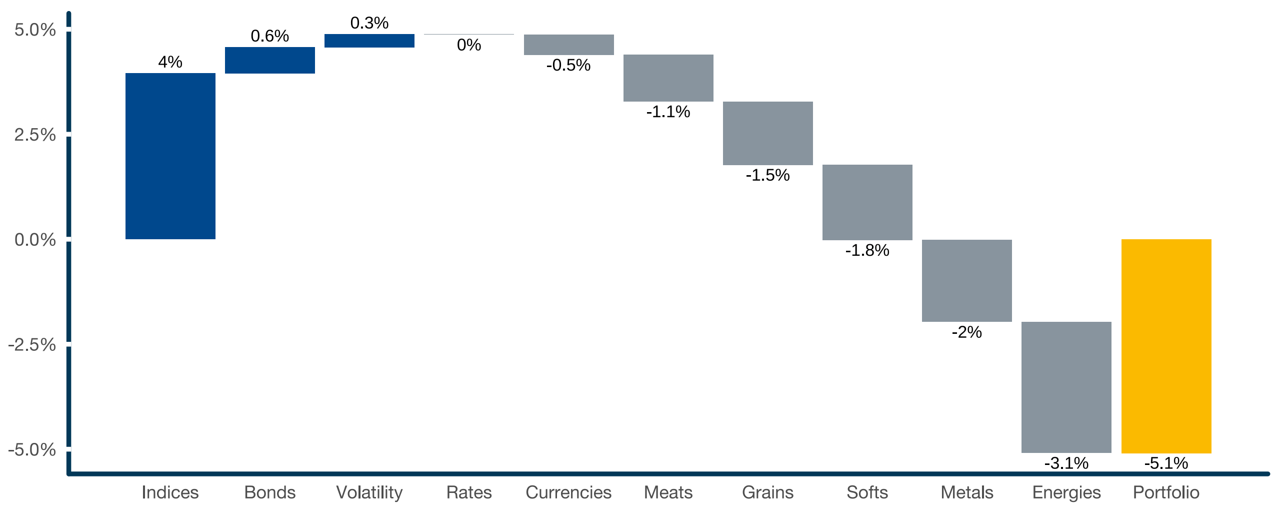
PERFORMANCE REVIEW

The ReSolve Evolution fund endured a total loss of -5.1% in the third quarter of 2020, with the lion's share of losses occurring in August, stemming almost entirely from our exposures to commodities.

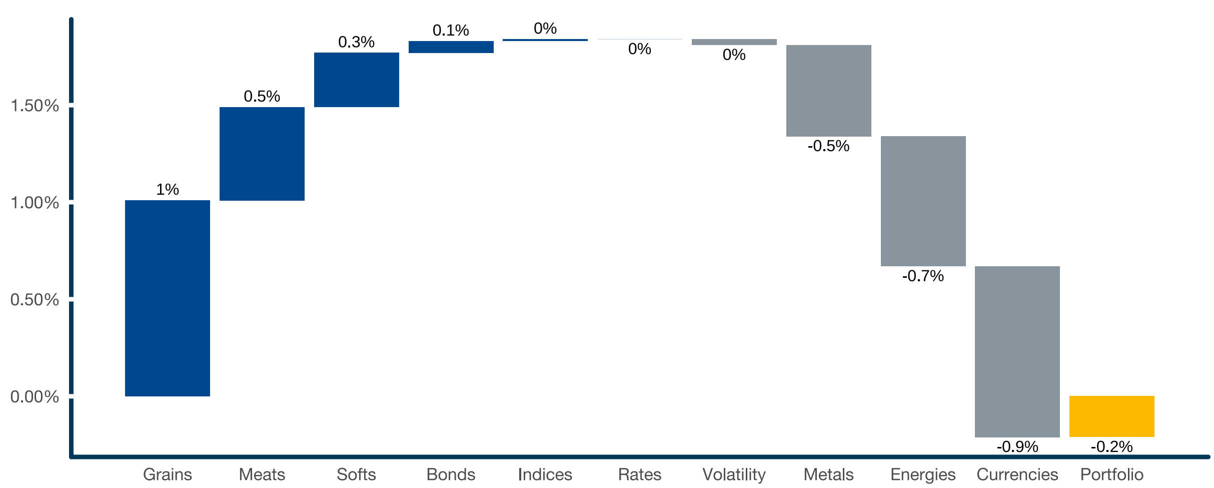
Figure 1. Q3 2020 Performance Attribution by Sector



Source:ReSolve Asset Management. PAST PERFORMANCE IS NOT NECESSARILY INDICATIVE OF FUTURE RESULTS.

Consistent with the research we have been highlighting in our commentaries over the last 18 months, the research team !nally deployed the much anticipated hybrid factor approach on September 1st with several novel features. Given these substantial changes, it is informative to single out September for a closer look:

Figure 2. September 2020 Performance Attribution by Sector



Source: ReSolve Asset Management. PAST PERFORMANCE IS NOT NECESSARILY INDICATIVE OF FUTURE RESULTS.

While the strategy had a sizeable allocation to equity indices coming into September, our systems sidestepped the selloff and avoided losses in the space. Most of our gains for the month came from commodities – particularly grains, meats and softs. Currencies, energies and metals were the main detractors. It's also interesting to point out that, while Evolution's older systems would have produced a combined loss of approximately -2%, the fund ended practically flat in September.

EVOLUTION REQUIRES ADAPTATION

"When the facts change, I change my mind. What do you do, sir?"
– John Maynard Keynes

Over the years, ReSolve's principals have experienced several major leaps in their understanding about markets.

First, we had learned the hard way that markets can't be *solved* like a traditional mechanical system. We'd learned this by trying our hand at global macro trading based on a fundamental thesis about the emerging middle class in Brazil, Russia, India and China (the so-called BRICs); knock-on effects in global commodity prices; and the impending collapse of developed market real-estate and ultimately the banking system in 2008. While this thesis played out and a great deal of profits were realized in 2006, 2007 and early 2008, the collapse of the emerging markets / commodity complex in late 2008 and the subsequent coordinated bail-out of the global banking system served up valuable lessons about reflexivity – the interaction between cause and effect in complex adaptive systems like capital markets.

Second, we recognized the folly of seeking alpha from stock-picking. This conclusion was ultimately informed by two factors. First, the observation that almost no traditional mutual funds had demonstrated an ability to deliver sustainable alpha, and that this phenomenon had strengthened over time. Second, we realized that the structure of investment companies and institutions presented essentially zero barriers to arbitrage in the domain of security selection. On the other hand, most investors have very limited ability to take active risk in the domain of asset allocation. Obviously, it makes sense to seek alpha where there are major barriers to arbitrage, so we decided to focus on active asset allocation.

Over time we realized that maximizing in-sample back-test performance[1] wasn't the same as maximizing expected live trading performance . This was our third major leap in thinking. We added new markets and diversified our signals in an effort to close the gap between in-sample results and live trading profits. We embraced *ensembles of ensembles of ensembles*, resampling every conceivable step in the portfolio formation process (more on this topic **here**).

In 2017 we embarked on a journey to evolve our investment universe from Exchange Traded Funds (ETFs) to include global futures markets. Futures trading offers substantial tax advantages over trading ETFs in certain jurisdictions, as well as very cheap leverage and a breathtaking diversity of markets across equity indices, bonds and credit, currencies and commodities. In addition, futures offer a rich ecosystem of data on term structure, sentiment and other factors so that we could diversify our strategy lineup.

We launched the Evolution fund in late 2017 with a trend-following strategy, and the promise to seed investors that we would be adding several additional strategies over the following years. In selecting new strategies, we prioritized edges, like skewness, seasonality, and cross-market value strategies that had not already been widely adopted by style premia funds.

AN OVERGRAZED LANDSCAPE

After a challenging calendar 2018, ReSolve's investment team observed that markets appeared to be changing in meaningful ways that could impact the future performance of our strategies. Trend – by far the most popular strategy in the futures space – had failed to produce profits for many years. In addition, the character of volatility clustering in markets had changed to produce highly skewed, rapidly mean-reverting dynamics which, when combined with trend and other factors, resulted in acute loss cascades and V-shaped recoveries in the face of extreme localized volatility.

In the spirit of adaptation, the investment team got to work identifying potential sources of performance decay and sought alternatives to improve profitability. We also reconnected with an old acquaintance, J.P. Belanger, who had been leading a proprietary trading team at a boutique investment

1 We discuss at length how many analysts abuse back-tests to draw precise conclusions below.

firm in Chicago. J.P. had been highly successful trading and making markets in a variety of liquid futures contracts using a proprietary high-frequency automated process.

Over many months it became clear that J.P. was ready to take on a new challenge, and that ReSolve was the right platform for him to realize his ambitions. As the partnership crystallized, J.P. attended ReSolve's research meetings and shared some of his thinking. In the meantime, ReSolve's Head of Quantitative Research, Andrew Butler, and a new member of the research team, Maciej Zawadzki, both of whom already had a strong background in machine learning techniques, picked up the torch and spent the next year completely re-imagining the experimental methodology that the team would use to identify and test investment strategies. This process resulted in a new framework that would reinvent, from first principles, how ReSolve thinks about harvesting excess returns.

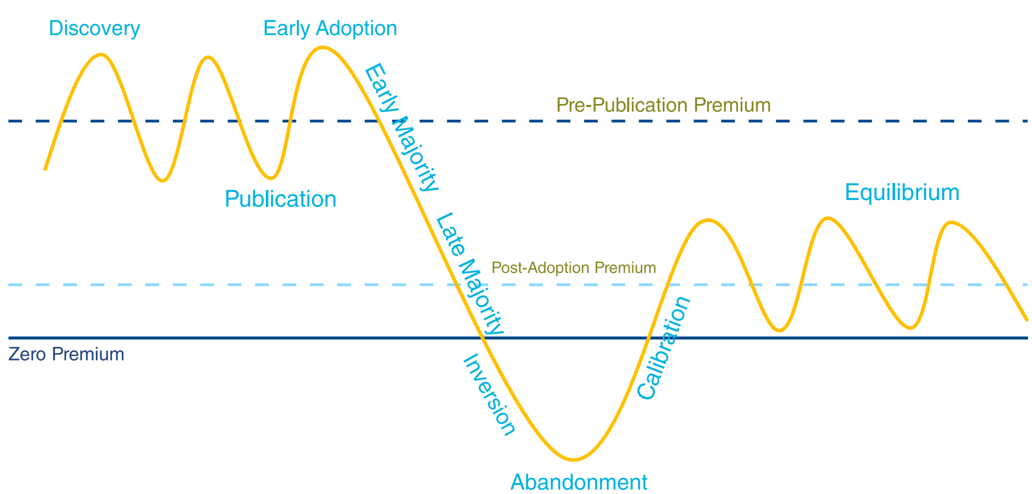
A POST-FACTOR WORLD

"You never change things by fighting the existing reality. To change something, build a new model that makes the existing model obsolete."
- Buckminster Fuller

In some ways, investment strategies are like any new technology. The progenitors of any early technology typically earn extraordinary profits, until competition heats up. Eventually, competition drives down profit margins and the technology becomes commoditized.

But investment technology has a special quality that arises from the reflexive nature of markets. This property means that the profitability of investment concepts conforms to a unique trajectory, which most investors haven't accounted for. We call this trajectory the Factor Life Cycle.

Figure 3. Factor Life Cycle



Source: ReSolve Asset Management

Empirical finance is predicated on the idea that an investment opportunity exists because securities with certain characteristics are systematically mispriced by a cohort of investors. This may occur because these investors are influenced by unique preferences or perceptions of risk.

So-called *Alternative Premia* or factor strategies typically derive their credibility from academic credentials and peer reviewed journals. A paper is published, describing an investment strategy with an intuitive origin story. A back-test and comprehensive analysis are presented with strong economic and statistical significance.

Word spreads about the new investment concept. A few big institutions jump on board. Innovative managers launch funds, which do well for a few years and catch the eye of more adventurous investors and advisors. A few more years pass. Now most institutions are running the strategy internally. Index providers launch a mosaic of interpretations of the previously novel concept, many of which go on to inform new index ETFs.

There comes a point when the arbitrage dollars begin to *crowd out* the investors who were creating the opportunity in the first place. The securities that were underpriced become *overpriced*. The sign of the edge inverts - it is now a *money-losing investment.*

What happens next? Investors eventually *cry uncle* and abandon the strategy in droves. At some point, the market finds a new equilibrium premium that is just large enough to keep the most disciplined investors engaged, but much smaller than the original pre-publication premium.

Many of you will recall that a few of the most sophisticated institutions and hedge funds started running systematic alternative premia strategies in the mid-2000s to harvest the size, value, low volatility, trend, momentum, carry and other so-called *factor* strategies. These innovators and early adopters harvested rich premia for a few years before the ideas went mainstream.

By 2011-2012 the investment banks had launched *alt premia* indices and major investment managers launched funds, attracting tens of billions of arbitrage capital from the Early Majority investors. These billions were typically levered up 5x-10x.

By 2015 most major institutions had built or were building internal desks to harvest these premia and eliminate fund fees, while retail investors were getting in on the action via an array of index funds.

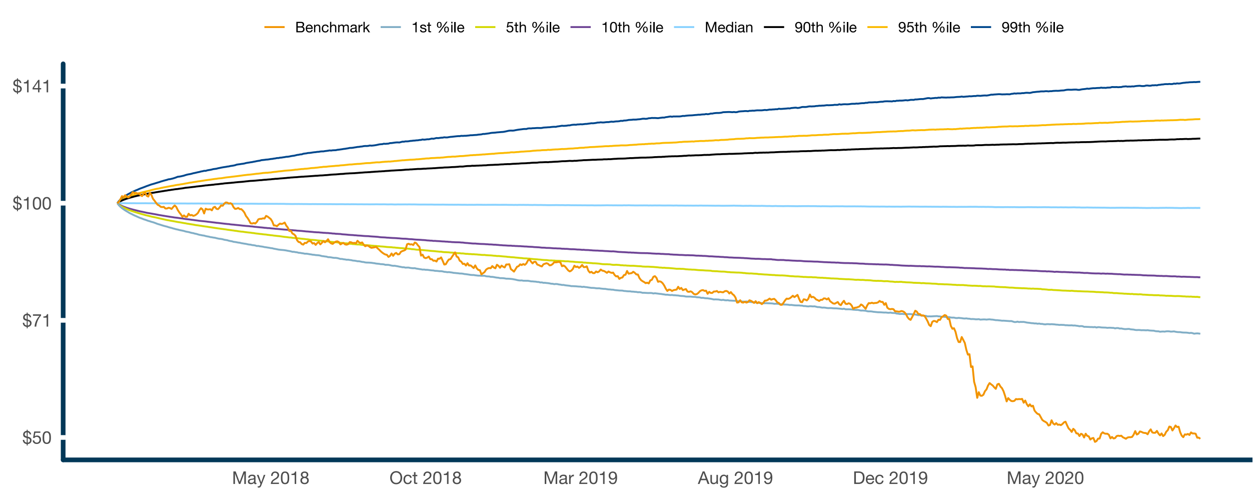
Fast forward to 2016-2017. *Alt premia* strategies were broadly adopted and many of the largest Style Premia funds started to close to new investors. The Late Majority *was all-in*. Peak Alt Premia. What happened after 2017?

INVERSION

The following chart plots the cumulative alpha from a benchmark combination of leading alternative premia and systematic multi-strategy funds from January 2018 through July 2020. The funds purport to allocate across fifteen distinct alternative premia[2]. We scaled the funds to express equal risk in the portfolio and called it the Alt Premia Benchmark.

We overlayed a cone that charts the trajectory of a random walk with zero return and the same volatility as the Benchmark. Over the past 30+ months this composite – representing over fifteen different alternative premia sleeves – has produced a return trajectory that is well below what might be expected, even from a random walk.

Figure 4. Alt Premia Benchmark



Source: Data from Bloomberg. Analysis by ReSolve Asset Management. Chart plots the cumulative alpha (regressed on S&P 500) of an Alt Premia Benchmark that combines an alternative risk premia fund and a systematic multi-strategy fund weighted for equal volatility. See disclaimer for constituents.

2 Event driven, convertible and volatility arbitrage, equity market neutral, dedicated short bias, long/short equity, emerging markets, global macro, managed futures, fixed income relative value. In addition, the benchmark includes value, momentum, carry and defensive strategies across stocks and industries, equity indices, fixed income, currencies, and commodities.

Conversations with institutions and consultants confirm that investors are heading for the exits. Pension and endowment funds are dismantling factor desks and major wire-houses have begun the process of de-listing Alt Premia funds from approved lists.

So, what have we learned?

Investors seek comfort in economic intuition, expert opinions, peer reviewed academia, strong recent performance and most importantly, broad adoption. Sadly, these are the very qualities that destroy future returns. Alpha lives in the crevices and dark corners; lonely places where most investors don't want to go.

If asset owners and investors want to earn sustainable excess returns, then by definition, they must come to grips with the reflexive nature of markets. Where a strategy offers comfort in the form of published research and peer adoption, with simple mechanics, compelling back-tests and intuitive stories, we should expect the market to quickly mediate this opportunity. There is no free lunch!

At ReSolve, we have spent the last 18 months designing systematic strategies for a post-factor world.

Where factors typically have intuitive explanations rooted in economic theory or behavioral hypotheses, we now source edges directly from the empirical data. Where factors are predicated on common relationships across all assets, we are now seeking patterns in the data that are unique to each market. Where factor relationships are simple in structure, we have developed methods to identify complex relationships that are difficult to specify. Where factor strategies rely on long-term average investor behaviour, we now evaluate how asset classes respond under different conditions, including faster moving market dynamics. And perhaps most importantly, where factor strategies are evaluated on typical in-sample back-testing methods, our strategies are now validated by the advanced out-of-sample and hold-out methods used in machine learning.

REIMAGINING THE RESEARCH PROCESS FROM THE GROUND UP

There are two fundamental differences between traditional statistics and data science or machine learning.

The first difference is that traditional statistics allows for the fit of a model to be determined by how well a model performs on *in-sample* data. In contrast, data scientists understand that you can only evaluate models on data that the model hasn't seen yet (out-of-sample data).

The second difference is that machine learning allows models to take a wider variety of shapes to fit the data. This is possible because data scientists have tools to evaluate the trade-off between how completely a model fits the data (the bias), and how well the model generalizes/performs on novel data that the models have never seen (the variance). Traditional statistics lacks the tools to evaluate and tune this trade-off, which is why traditional models severely constrain complexity – think linear regression.

The analysis of time-series adds an extra dimension that data scientists must navigate. Specifically, time-series models must account for the time ordering of events (and potential autocorrelation and information leakage across observations). *Financial* time-series add a further dimension still: the potential for models to change over time as markets adapt and evolve – so-called *non-stationarity*.

Consider the experimental design of any random paper found in traditional tier-one finance journals and utilized by finance PhDs everywhere. Ideally, an economic thesis prompts a hypothesis test that is carried out via simulation. The holdings of a portfolio are conditioned on a certain characteristic (like past returns or book-to-market ratio, for example), and reformed at each time-step to emphasize the target characteristics. Returns from this model are compared against returns from an *unbiased* [3] model using linear regression to determine the significance of the relationship.

Many investors overlook the fact that many decisions are made along the way. For example, what is the optimal function to convert a characteristic to a portfolio weight? When and how often should one rebalance? How many securities will one hold? The manager must choose. Such decisions represent degrees of freedom – *hyperparameters* in the language of machine learning. How are we to know how sensitive the results are to changes in these parameters? How is one to choose the optimal relationship?

3 Like a capitalization-weighted benchmark, or previously endorsed explanatory models.

Admittedly, authors in recent years also often publish appendices containing results for simulations with different specifications. It's tempting to believe this information might guide an investor's choice of model to trade. But all the published results are based on the full sample of data! How can the investor know whether the criteria used to select the optimal method will generalize to new data?

To glean any meaningful information from the analysis, at a minimum the authors might divide the data into training, validation, and *out-of-sample* test sub-sets. They could then evaluate different criteria to select the best model specifications on the validation set, and test their selection criteria on the out-of-sample test-set. Performance in the out-of-sample test set would offer at least a small amount of guidance about what to expect from the models in live trading.

The experimental design above would make studies more useful, but it still leaves several issues unresolved. For example, the framework only allows for a small range of model specifications (i.e. different quantile sorts, or binary, or linear relationship), and in just one direction (i.e. higher is better or lower is better). And how do we know if the optimal model selection is stable through time?

A robust simulation framework would address all of these questions explicitly, and provide precise guidance of the range of expected outcomes in live trading. Moreover, it would provide a secondary model with similar design to identify which set of models from the first stage of the experiment should be deployed in live trading.

It turns out that there is just one experimental design that addresses each and every one of these challenges. While this experimental design still leaves many details unsettled, these details are at much higher levels of abstraction, with much more manageable impacts on trading outcomes. The result of simulations carried out with this design is a very precise estimate of exactly what to expect from trading strategies in live trading.

THROUGH THE LOOKING GLASS

Sadly, while we are excited to share that we have crafted an experimental design that addresses the challenges highlighted above, we do not feel it is prudent to share material novel elements of our process.

This is, of course, in your best interest as investors. As described above, the enemy of alpha is broad adoption. And perhaps counterintuitively, while we are convinced our experimental design is a quantum leap in understanding how to design, select, and set expectations for investment strategies, the underlying concept is actually rather obvious. Well, obvious in retrospect anyway.

You might rightly wonder, if our shiny new process is so obvious, why shouldn't we expect other firms to have already discovered it, or at very least be hot on our heels? The answer is that there is a very big difference between problems that we must solve from scratch, and problems we solve with hints.

For example, it is computationally intractable with modern computers to find the factors for a 2000 bit number. However, the solution is trivial to confirm once someone gives you the factors.

For this reason, we are going to keep our kimono closed for the moment. But that still means we can describe the kimono.

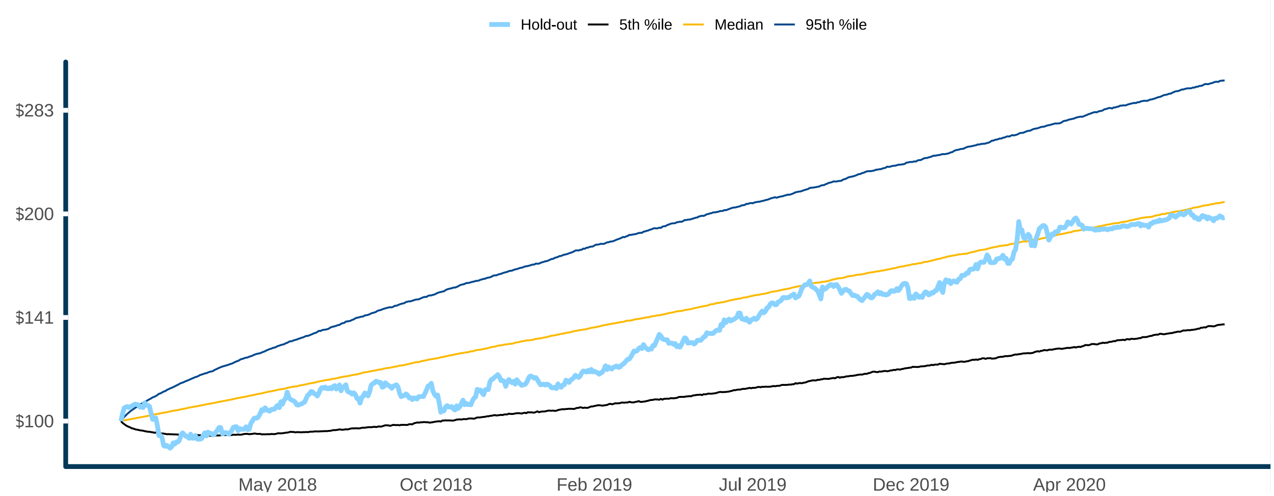
First off, it is true from first principles (you'll have to take our word for the moment) that the current off-the-shelf machine learning methods and software packages are fundamentally unsuited to learning from financial time-series analysis. As such, we built our own custom data-science library. Note that there are two sides to this coin. On the one hand using off-the-shelf libraries would have produced off-the-shelf results. But on the other hand, off-the-shelf software is typically of higher quality.

We addressed the latter issue in two ways. First, our core software was written by a 25-year veteran of software development. In fact he founded a software company that built mission-critical infrastructure for global companies like Wells Fargo, JP Morgan Chase, Walmart, Costco and other major brands (he sold the company to IBM). So the software is tight. But we still took the extra precaution of having another senior researcher build a second implementation of the software in a completely different language, and which yielded exactly the same results!

More importantly, we can evaluate the merits of our process in the most fool-proof way possible. That is, by deploying the models that emerged from our process to data that has been *withheld* from all previous analysis, and observing the resultant performance.

In Figure 5, we plot the cumulative returns for the models selected by our process over the period 1990 – 2017, on the *hold-out data* from January 2018 – September 2020. The cone describes the 90% range of performance outcomes that we would expect to observe if the hold-out results are drawn from the same distribution as the out-of-sample returns.

Figure 5. Performance of models on hold-out data from January 2018 – September 2020, net of expected trading and market impact costs. SIMULATED RESULTS



Source: Data from CSI. Analysis by ReSolve Asset Management. These results are simulated, hypothetical, and for illustrative purposes only. See disclaimer.

You can see that the hold-out results map very closely to the average growth rate observed in the out-of-sample tests, well within the expected cone of possibilities. We can conclude that a) our models are well specified, b) our models are highly explanatory and c) our models generalize to periods in the future.

CONCLUSION

Unlike advancements described in the past, which focused on incremental improvements from additional factor sleeves, what we have outlined here is a substantial leap forward in our alpha generation machine. We no longer focus on identifying possible theoretical anomalies and subsequently surrounding them with ensemble feature sets, hoping our original thesis was correct. Rather we can observe the empirical data itself using the training/validation/holdout process to find the true idiosyncratic signals with a much higher level of confidence that they will persist in live trading. Moreover, we have a better understanding of the cone of the performance that we, and investors, can measure success against.

To say that our team is excited with these changes would be an understatement. This new scientific process sets the table for a major explosion in innovation, adding new tradeable assets like spreads, baskets, and synthetics; and integrating new real-time information sources, such as analytics derived from options surfaces, and alternative data, to navigate modern markets with agility and confidence.

Thank you very much for your commitment to the Evolution strategy. Our team remains at your disposal if you have any questions.

Sincerely,

ReSolve Asset Management

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General information regarding the use of benchmarks. The Alt Premia Benchmark consists of an equal volatility weighted combination of the following U.S. mutual funds: AQR Alt Style Premia Fund (QSPIX), AQR Multi-Strategy Alternative Fund (ASAIX) scaled to 10% annualized volatility.