Quantitative Frameworks for Scalable Data Modeling and Alpha Extraction

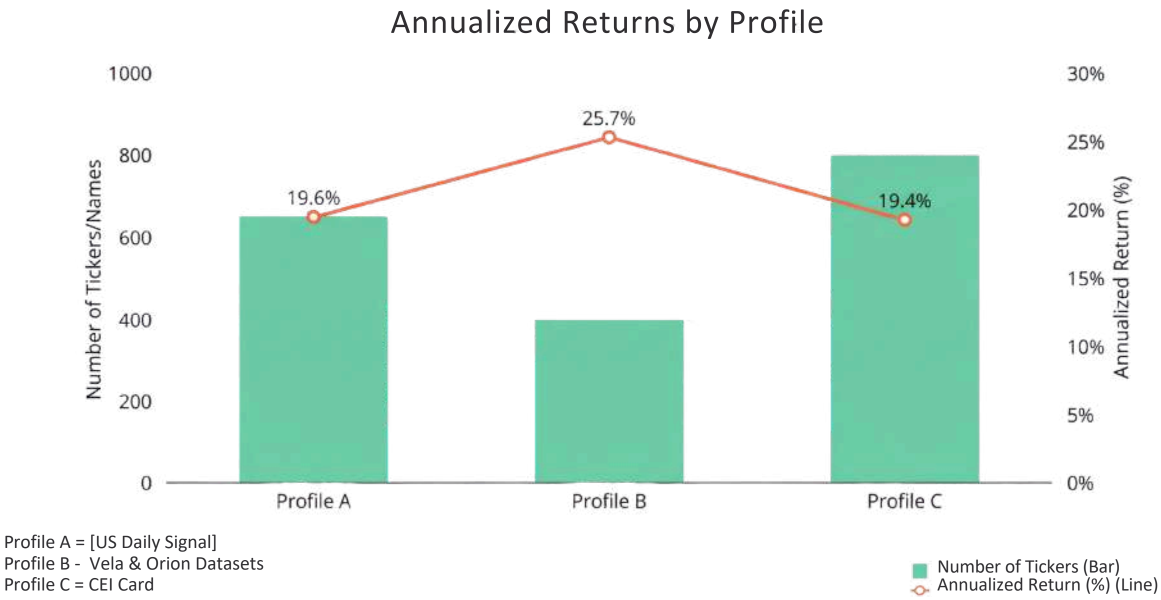
Maiden Century

In Collaboration with Consumer Edge

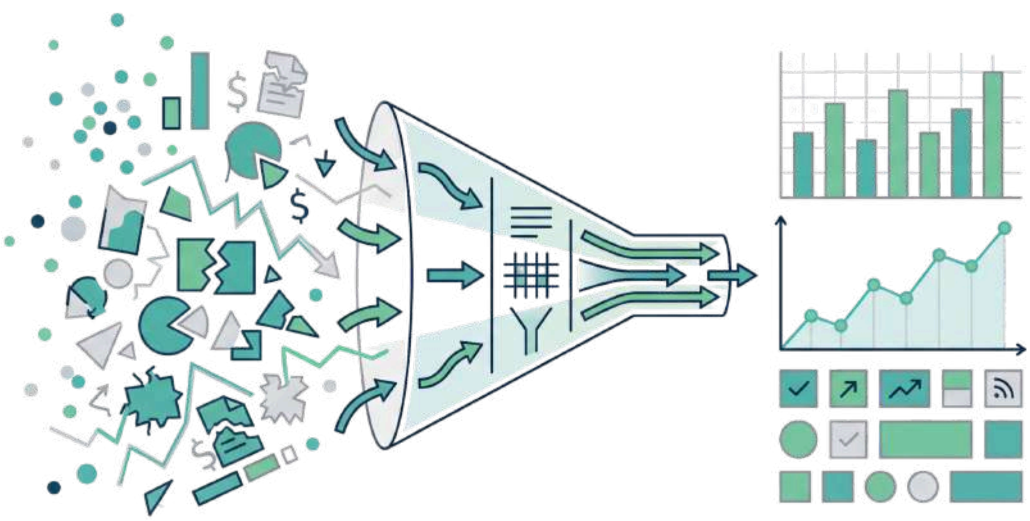
Table of Contents

Introduction

Alternative data has become a proven source of alpha—and Consumer Edge's datasets are delivering the type of performance that quants can no longer afford to overlook. Across three distinct strategy profiles, Consumer Edge signals have generated 19–25% annualized market-neutral returns with Sharpe ratios of 2–3x, far surpassing what traditional market data can support.



This paper explains how to use Maiden Century's QTIP platform in combination with Consumer Edge's highly accurate, quant-ready data to test, validate, and scale strategies capable of achieving these levels of performance. For quant funds still rooted in legacy data inputs, the takeaway is clear: the next era of alpha will belong to those who embrace richer signals—and the infrastructure to extract their full value.



Issues for Quants When Evaluating Alternative Data

The very features that made market data so easy for Quants to model off of are the same cages that have made those models so inflexible.

Point-in-time data: Market data by its very nature is point-in-time. What was the specific price or trading volume of an asset on a specific date or at a specific hour? This makes it very easy to model how the price of a stock at a specific time responded to those input variables. In contrast, most alternative datasets are acquired by the providers from intermediaries who are able to furnish a history that was not available to be traded on or move markets until much more recently.

Entity mapping: Quants often trade on the market data of an entity itself. How does the price and volume of stock XXX on day t influence the price of stock XXX on day t + 1? The entity is circularly connected to itself, feeding on its own progeny. Alternative datasets may alternatively use different conventions across stocks, defaulting to the naming used by other services such as Bloomberg or their own unique labelling. This is in the best case where tickers are included at all - many datasets will publish data at a level below the parent company such as a URL or retail banner and force the end user to aggregate up to a tradeable entity.

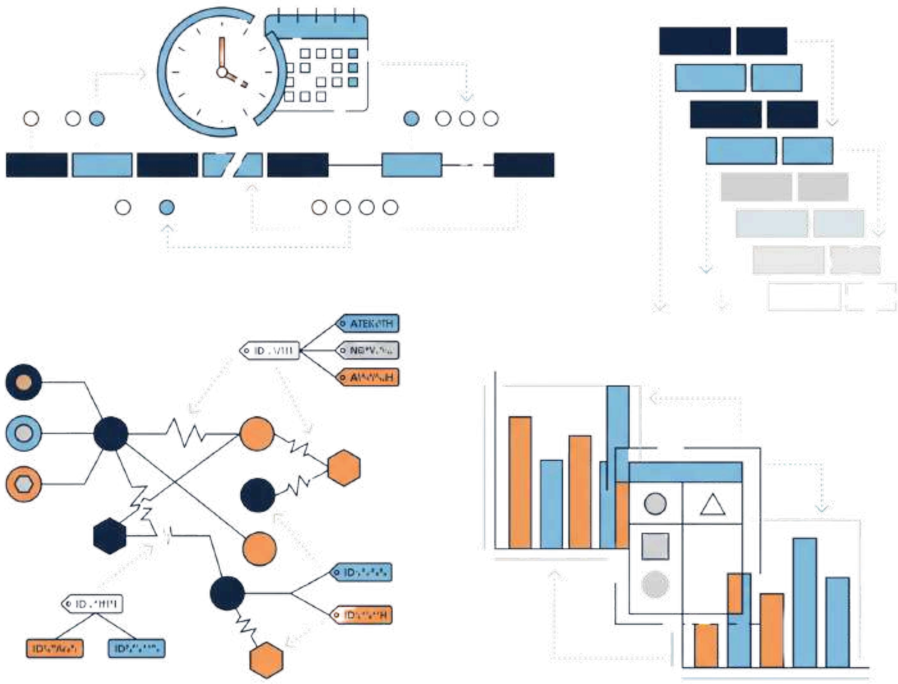
Survivorship bias: Quants like that market data encompasses anything that was traded on that market at a given time - this provides a long in-sample history that captures even (and perhaps especially) firms that are trending towards bankruptcy. Would this model have correctly predicted XXX's nosedive? Many alternative datasets will instead contain only the tickers most relevant when they launched, and remove any that become delisted to save space and compute. This can be limiting for Quants who are looking point-in-time across an entire data history and want as many companies in their models as possible.

A direct y variable: Quants build their models to predict stock prices, and there is an extremely direct relationship between market data and that price. How much of the variation in the price of XXX is explained by my model? Alternative data is more likely to predict company performance like revenue or SG&A, which is sometimes very closely tied to stock price and sometimes very far removed, especially if the company is experiencing exogenous shocks. Indeed, these variables should be considered an instrumental variable for stock price and not directly correlated. Even most quant funds who recognize the disconnect between revenue and stock price often look at only the highest-level revenue for a company, like Total Global Sales. Alternative datasets are often much more limited in scope, and the instrumental variable is more likely narrowed to a specific geography or reporting segment. That instrumental variable may not even be relevant to stock price movement, or its relevance may be obscured with consensus already incorporated into pricing.

Unquestionable accuracy: Quants can be confident of the accuracy of market data -apart from a major technical glitch, a stock price is a factual piece of information. There is no accuracy question needed. Alternative data, on the other hand, will vary significantly in accuracy across tickers as it only captures a small portion of what it's trying to measure and that portion is subject to ticker-specific biases based on the data collection methodology.

Limited variables: Quants can build relatively simple and scalable models off of narrow market data restricted to price and volume, which is available for all tickers. What is the impact of the variables across the entire dataset?

Alternative data contains much more richness, with the ability to dig into multiple factors that may differ substantially in accessibility even within the coverage of a single dataset and even more so across datasets. The importance of each of these factors can also vary from company to company (eg direct to consumer sales may be more important to a retailer's outlook than to a company that derives most of its revenue through wholesale channels), and from one period to another (eg if a company makes an acquisition that suddenly makes a new product category much more critical to its growth).



How Providers Handle These Issues

Alternative data providers who have worked with Quant clients understand these issues and do their best to address them. Consumer Edge—supported by years of buyside and sellside experience across its leadership—is widely recognized as best-in-class in developing products that reduce friction for Quants accustomed to market data workflows. At the same time, fully unlocking the power of any alternative dataset often requires additional refinement on the Quant side to adapt existing models—work that ultimately strengthens performance but may not deliver immediate returns in early testing or evaluation

Point-in-time data: Consumer Edge maintains all data published and gives Quant clients access to data as produced on a given day. Yet, there is no time machine for newly acquired datasets and the history must build over time. Although CE is sensitive to the consistency required for backtesting and tries to limit schema and panelization changes, almost all alternative data providers at times produce product enhancements that sometimes require a break in continuity.

Entity mapping: Consumer Edge uses a consistent entity model across all of its data products, for linkage to other sources. Even with RIC and ISIN though, mapping still requires another step and other datasets may not match how CE incorporates M&A.

Survivorship bias: Consumer Edge does maintain history and continues tracking on a pro forma basis any ticker that it has ever covered since the launch of a dataset (including those that have gone bankrupt or been acquired). Yet, most alternative data providers including CE have not engaged in any large scale effort in the launch of a new dataset to make sure to map tickers that no longer exist.

A direct variable: Consumer Edge provides recommended KPIs that its analysts believe most closely correspond to what each dataset is tracking. It makes sure to include consensus for these metrics where available, which is not always the case. Other providers may recommend other KPIs (or no KPIs) for similar datasets due to differences in the data they offer.

Unquestionable accuracy: In addition to correlation and MAPE analysis of each ticker, Consumer Edge publishes any data blind spots that may affect accuracy in a standardized machine readable file.

Limited variables: The Consumer Edge Quant offering provides data at the parent company/ticker level for an easy first pass of the data. However, more intensive models are likely to extract additional alpha from the cuts provided in Daily Signal, with different weights for credit vs. debit or online vs. offline spend. Daily Signal also offers additional KPIs like same-store-sales and subscription metrics that are likely to be more relevant to stock price movements.

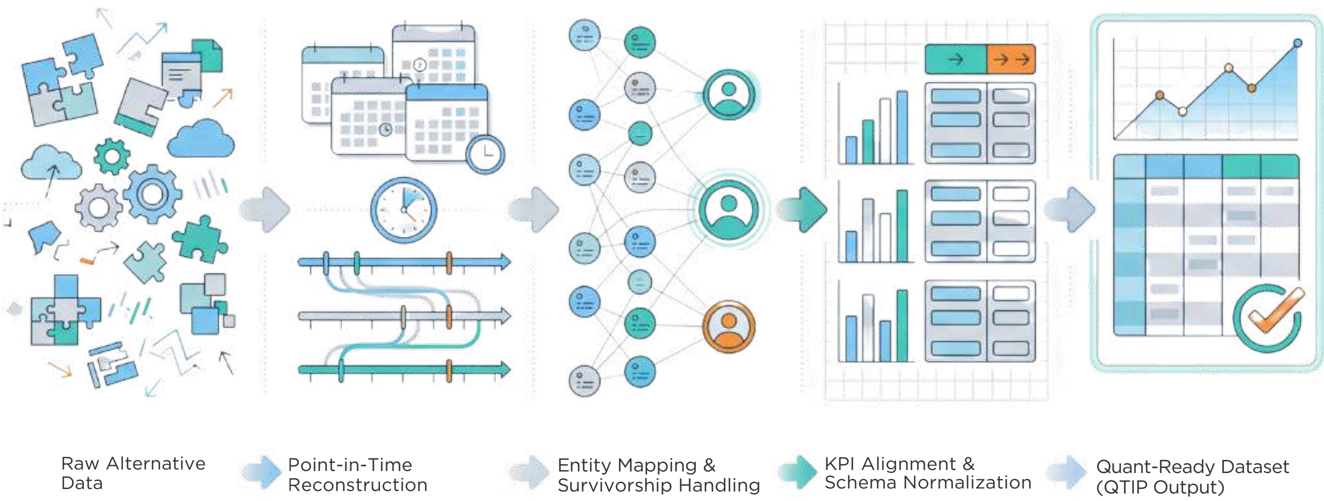
How QTIP bridges these gaps

Maiden Century's QTIP (Quantitative Solutions for Investment Professionals) is a product born on the buyside, envisaged as a tool to solve some of the intractable problems outlined in the earlier sections, and to lay the groundwork for bridging the historical divide between discretionary and systematic investing.

At its core, QTIP takes the 'mile deep' process discretionary investors follow and scales it up to become a 'mile wide' as well. QTIP takes the process discretionary investors follow on a single name basis, and leverages machine learning, advanced statistical modeling and an intimate knowledge of each company's business model to scale this process up a thousand-fold.

The resulting product, which is highly repeatable, reliable and scaleable, is the result of a decade's worth of iteration and learning. Maiden Century's team of data scientists, research analysts and statistical modelers add value along a number of areas to convert raw alternative data signals into highly alpha-generative, easily back-testable signals. Slippage around any of these areas can easily derail the entire process.

QTIP Data Harmonization Pipeline



Some of the key steps involved include:

Ingestion: Alternative data comes in many shapes and sizes, and in many different. delivery forms, ranging from Excel to PDFs to AWS shares. Maiden Century builds extensive and versatile ingestion pipelines with QA to ensure a consistent and timely data lake for training and modeling purposes.

Entity resolution: Alternative data is rarely clean from an entity resolution perspective. Geographic footprints, web domains, app store IDs, merchant descriptions, brand names and SKUs all need to be mapped to companies, and onwards onto tickers. Maiden Century maps every single application 'entity' available across a wide variety of datasets to public tickers to create common join keys across disparate sources.

Corporate actions: Companies are not static. They are constantly undergoing changes, ranging from their listing status to M&A. As those changes take shape, the nature of the company's relationship with a particular dataset can change quite dramatically as well. For instance, a US based retailer that acquires a Chinese manufacturer will no longer correlate as well to US-only consumer facing data. Maiden Century's research team tracks all of these moves and makes relevant changes to entity mappings as well as metric / feature selections (discussed below) to account for all such actions in near real-time.

Metric selection: As a group, alternative data can track a wide variety of things, but asingle dataset is typically only good at a subset of the dimensions it tracks. Transaction data, for instance, excels at tracking sales for companies that sell directly to consumers. But for a company that has a mostly wholesale distribution model, this data would be next to useless. Similarly, app usage data is great for ecommerce companies but largely irrelevant for an Industrials company that sells through a direct sales channel. Having looked at over 500 datasets by now, Maiden Century's research team understands the nuances of each time series and finds only the most appropriate companies and metrics to model each source against. This way, there's a fundamental thesis behind all of its predictive models, and overfitting risk is significantly diminished.

Fiscal periods: Most alternative data is inaccurate or heavily biased, which means backtesting the data against ground truth reports from companies is essential to sift the wheat from the chaff. To run those backtests accurately, a key building block is the alignment of daily / weekly / monthly data against the fiscal periods of each company. Those fiscal periods can vary widely from company to company, especially in the case of companies that follow unorthodox calendars, which require special adjustments every few years. While this may sound innocuous, even minor mistakes in maintaining accurate fiscal period tables can lead to inaccurate conclusions about backward looking backtests, or more crucially, forward looking estimates. Maiden Century's research team meticulously analyzes corporate filings for every ticker covered to accurately map fiscal period logic against each model.

Feature & entity selection: Traditional data is relatively easy to backtest. There's really one measure for a company's share price, or trading volumes, or reported earnings. Alternative data, however, is much more complex and multi-dimensional. As an example, if you're looking to test the correlation of web traffic into a company's websites to its reported sales, you don't just have a single index to backtest. The company likely has multiple domains (or entities), some of which are more relevant to the company's sales than others. Web traffic can also be measured along a number of features: desktop vs mobile; US vs Japan vs China vs worldwide; unique visitors vs time spent vs pages viewed; and so on. Depending on the combination of features and entities selected, you could get very different perspectives on historical accuracy or future predictions. Maiden Century's research team meticulously matches the right entities and dataset features to each KPI model, bearing in mind each dataset's characteristics as well as the accounting policies that define each company's KPI reporting standards. The strong fundamental intuition that underpins all of Maiden Century's models helps mprove modeling accuracy and minimizes false positives.

Metric relevance: Most public companies will report hundreds of financial and operating metrics each year. Some will be more influential in driving stock price behavior than others. Maiden Century's team spends considerable time understanding the key drivers of each company's business model, through a study of its filings, following its earnings reports, and daily interactions with our discretionary clients. Maiden Century has even developed quantitative measures for determining the relative value of each metric in relation to others, and our QTIP model is trained to prioritize those metrics with higher 'Metric Relevance' scores than others.

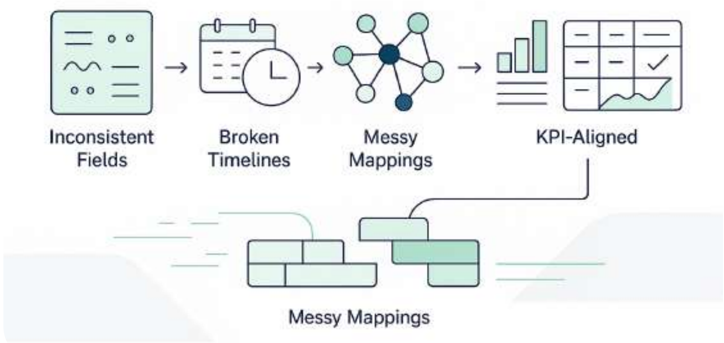
Modeling: By its nature, alternative data generally has limited history, with many datasets not going back further than 3-5 years. Even those that have been around longer regularly restate their panel composition, rendering longer lookbacks futile. Combined with the fact that most companies report on either a quarterly or semi-annual cadence, investors are left with just a handful of observations on which to train their predictive models. The multiple ‘feature combinations’, or cohorts in Maiden Century terminology, further compound the risk of overfitting. Maiden Century’s statistical models are purpose built with all of these challenges in mind. They studiously avoid both overfitting and look-forward bias through a ‘model of models’ approach that ensures both accuracy and auditability.

Precast: One of the most vital components of Maiden Century’s solution is the ability to predict earnings outcomes up to 6 months in advance of a company report. In a world where alternative data has become more widely used by investors, the ability to look further into the future with confidence, and confidently make investment decisions ahead of the broader market, is key to QTIP’s alpha generation. Central to this is Maiden Century’s ‘Precast’ algorithm, which predicts the alternative data that in turn underpins all of our metric forecasting models. Precast allows us to establish a view not only on the current period, but even on the risks to forward looking guidance. Maiden Century’s research has shown that it is this guidance risk that is often a greater predictor of stock price performance than whatever a company may report in the current earnings period. Precast is central to our ability to confidently monetize risks to that forward looking guidance from management teams.

Street expectations: Acceleration or deceleration in alternative data on a given company, when viewed in a vacuum, provides very little value add. A company experiencing a 10pp acceleration in web traffic, eg, could well see its stock price tank if it fell short of expectations already discounted into the share price (potentially because the management team had guided to even greater acceleration from a new product launch). Maiden Century systematically pulls in Consensus (sell side) estimates to understand market expectations. Maiden Century’s metric forecasts are then benchmarked against these very sell side estimates to determine whether a modeled outcome is positive or negative.

Buyside expectations: In some cases, sell side estimates aren’t enough to anticipate likely share price reactions post earnings. Partially due to the growing popularity of alternative data itself, we are increasingly seeing buy side expectations shift away from the widely available sell side models. In such cases, QTIP uses several methods to anticipate buy side whispers, and incorporate them into its own dynamic scoring.

How QTIP Bridges These Gaps



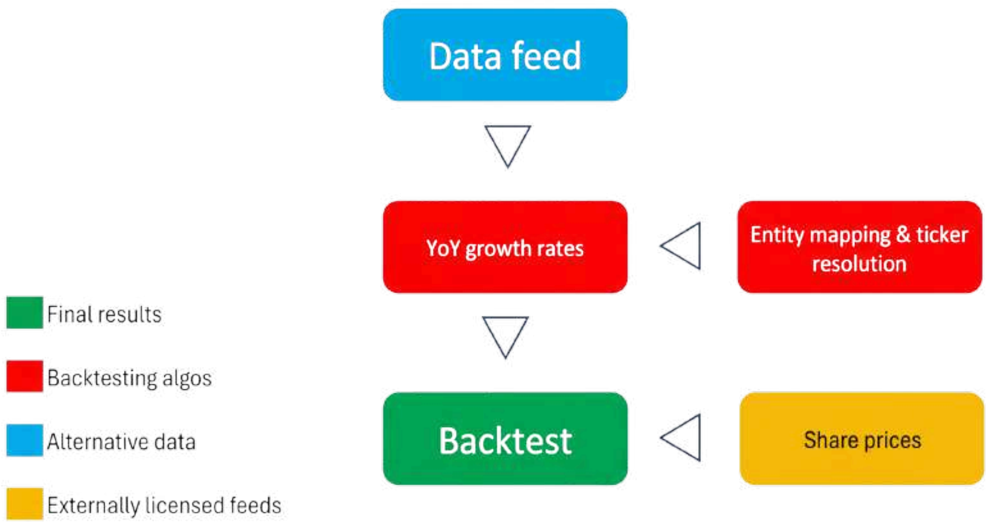
QTIP Workflow

Without a tool like QTIP, systematic investors typically follow a traditional and relatively simple backtesting process, which is summarized in the figure below. This process skips several essential steps that we feel are central to extracting optimal value from alternative data. The workflow illustrated on the next page illustrates the numerous steps Maiden Century adds to the workflow in order to optimize returns from your alternative data feeds. The contrast is stark.

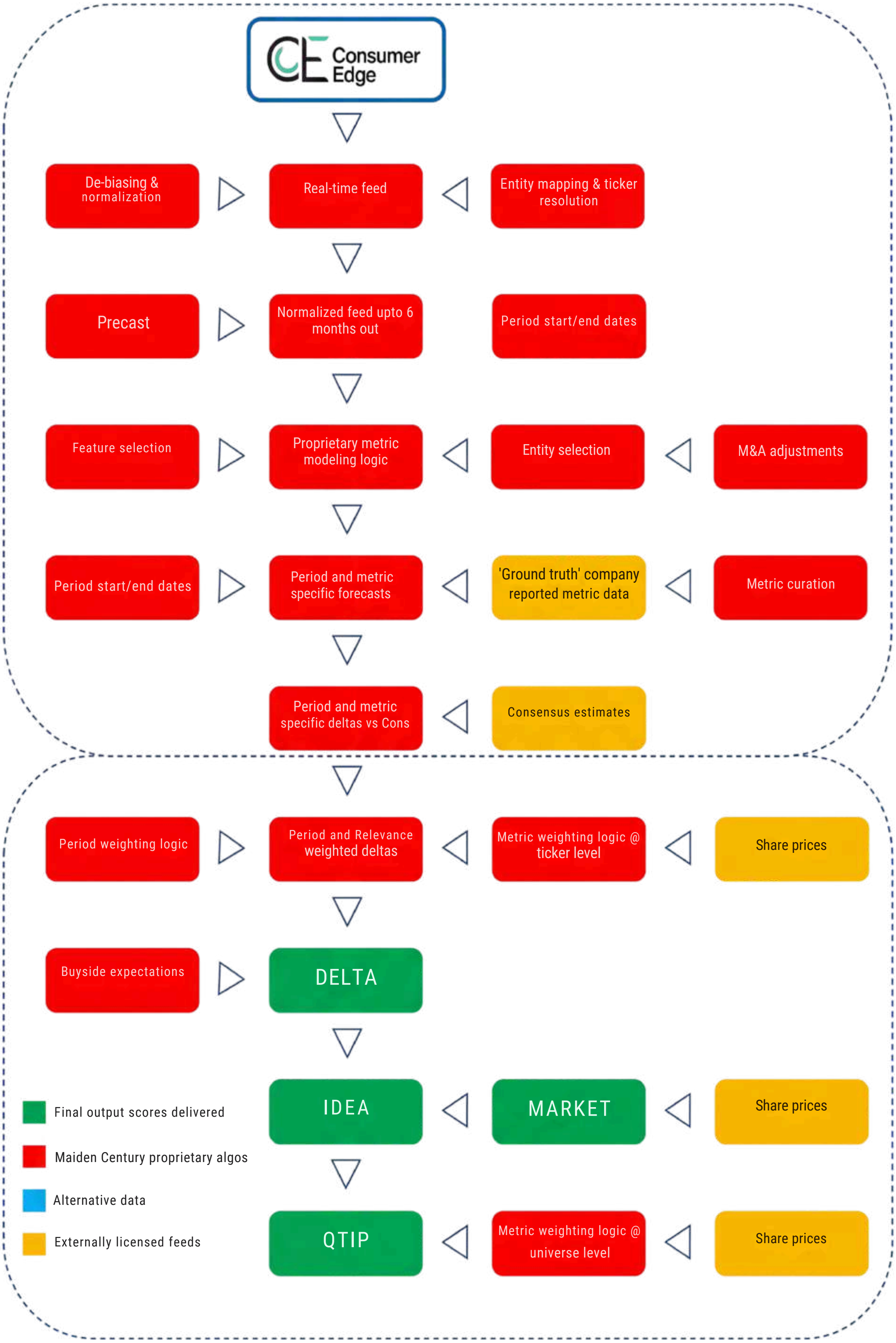
The QTIP output today primarily consists of four principal scores, called Delta, Market, IDEA and QTIP. A detailed explanation can be found in the Data Dictionary section of this document, while their relative positioning in the workflow is explained in the diagram below. Our process is generally broken out into two 'phases'. The first phase stems from the work we do for our discretionary (IDEA) clients in translating multiple data feeds into reliable period and metric specific forecasts, benchmarked against Consensus / sell-side estimates. The second phase is specific to QTIP clients, and converts the significant amounts of metadata generated for discretionary clients into synthetized, ticker level point-in-time scores that are primed for backtesting algorithms.

As a general rule, we recommend clients use the QTIP score for backtesting, since it incorporates the most inputs into its computation. That said, in some cases, clients may find more value in the more upstream Delta and IDEA scores. The market score is merely an input into the QTIP score calculation, and is not recommended for backtesting.

Traditional systematic investor backtesting evaluation workflow:



QTIP Workflow



Backtest setup and performance benchmarks

Ultimately, none of this matters if the resulting strategy generates poor returns. While every institutional investor will want to test signal efficacy through their own backtesting methodology, we have provided our own, more basic backtests here as a jumping off point. For instance, the backtests below are based on three unique profiles that leverage one or more Consumer Edge data offerings. As more datasets are blended together, we see an improvement in coverage, returns and sharpe ratios.

The three profiles we test here include:

- Profile A: US Daily Signal
- Profile B: Vela & Orion Datasets
- Profile C: CEI Card

To achieve these results, we have made the following assumptions:

- All point in time data
- Market neutral portfolio
- Top quartile (i.e. scores of +50 to +100) long, bottom quartile (i.e. scores of-50 to -100) short
- Half of eligible investment universe in portfolio at any given point in time
- QTIP scores used as ranking criteria
- Daily rebalancing
- Trading costs are not included in these returns
- No restrictions on market cap, ADV or listing exchange
- No factor or sector neutralization
- Weighted positions based on ticker score (i.e. ticker with +60 score will have a 20% larger position size than a ticker with a +50 score)

While the underlying feeds are quite different, QTIP delivery schema is identical in all cases, allowing for rapid testing of various iterations of Consumer Edge's data offerings. The ease of use across Consumer Edge datasets becomes amplified as other datasets that are less quant-friendly get added to the models as well.

A summary of our backtest results are shown in the following section(s). All returns are based on a market neutral portfolio, meaning they represent pure alpha. They are also based on true point in time data, meaning tickers are only added into the universe from the time we had models on them, and all signals are based on the data as received from the data partner at that point. All subsequent revisions to historical data are ignored.

Exhibit 1 below highlights ITD returns from three distinct Consumer Edge profiles. Each of these profiles has generated annualized market-neutral returns in the 19–25% range, with Sharpe ratios in the 2–3x range. Profile A, based on the core US Daily Signal dataset, has compounded at 19.6% since early 2021 while covering nearly 650 names. Profile B, based on the Vela and Orion datasets, covers fewer names (just over 400) but provides much higher returns (25.7% CAGR since the beginning of 2021). Finally, Profile C—which encompasses both US and EU transaction datasets—has yielded returns of 19.4% annually since May 2019 while covering nearly 800 tickers.

We make a few observations from these results. One, as you add more datasets into the QTIP ensemble, coverage goes up, which in theory should reduce volatility through more diverse portfolio construction. Second, even datasets covering the same universe of names, with the same type of data (transaction spend) and covering the same region (US), but using different underlying sources (Orion and Vela), can produce improved performance through the combination of idiosyncratic signals that help overcome each individual source's biases and weaknesses. Thus, while individual dataset backtests may be a good way to start the QTIP evaluation process, we believe the optimal risk-adjusted returns will only come from combining multiple datasets, while keeping the evaluation framework consistent.

Market-Neutral Returns Across Three Profiles:

- **Profile A:** 19.6% annualized since 2021 (~650 tickers)
- **Profile B:** 25.7% annualized (~400 tickers)
- **Profile C:** 19.4% annualized since 2019 (~800 tickers)
- Sharpe Ratios: 2-3x across all profiles

Exhibit # 1: Sample returns for three distinct Consumer Edge QTIP profiles

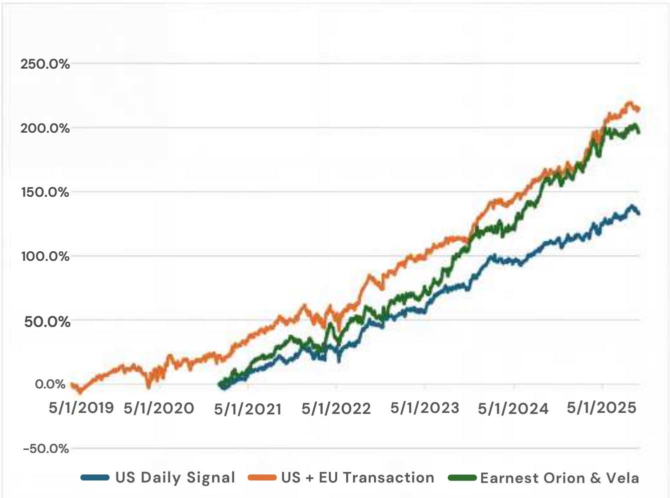
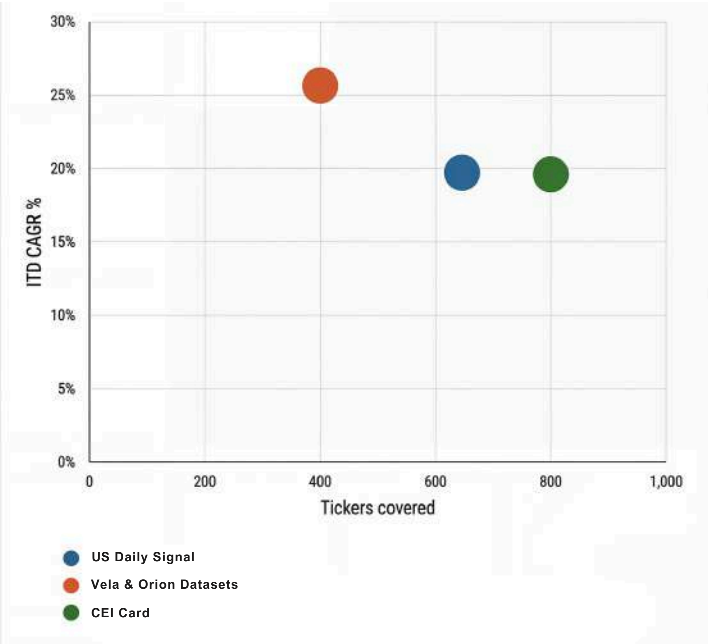


Exhibit # 2: Risk-adjusted returns vs coverage



Overcoming limited history challenges with SPIT

In an ideal world, investors would be able to test alternative data signals over multiple economic cycles. In plainspeak, this usually translates into 10+ years of true point in time datapoints.

In practice, this is very hard to achieve with alternative data. The vast majority of alternative datasets only came to life over the last 5-7 years. Even some of the longer tenured datasets have seen significant changes to their underlying composition over their lifespan, rendering signal quality from even the earlier part of this decade an imperfect proxy at best for current data quality.

To overcome these challenges, Maiden Century has developed a synthetic point in time signal ("SPIT"). This approach takes historical data from the most recently delivered tables, builds in known delivery lags into the data, and painstakingly rebuilds the entire history of the QTIP signal, going back as the data permits. As an example, SPIT would take today's file, find the value for a date in the past (say, July 16, 2022), apply a known delivery lag to the date (say, 7 days), and then assume that we would've seen the data for July 16th, 2022 on July 23rd, 2022. We would then proceed to build a KPI forecast for the next two quarters based only on the data we would've seen until July 23rd, and benchmark it against Consensus expectations on that date as well.

While SPIT doesn't meet the academic purity of a true point in time ("PIT") backtest signal, we believe it provides the next best alternative, and opens up a much wider universe of alternative datasets for backtesting. Many of Consumer Edge's datasets that were added more recently to the Maiden Century platform (e.g. US Daily Quant, or EU Daily Signal) have limited PIT histories but much deeper SPIT profiles for those interested in longer dated backtests.

One key advantage of a SPIT backtest over PIT is the ability it provides potential users to evaluate a dataset that hasn't been fully discounted into Street pricing models as yet. Generally speaking, more mature datasets tend to get more broadly deployed partially because of their longer PIT histories, which ironically also diminishes their alpha generation potential. By contrast, newer datasets offer far more untapped opportunities, provided investors are willing to adopt a more flexible approach towards historical signal evaluation.

Building a better – and truly proprietary – quant signal

QTIP is a highly synthesized trading signal that summarized dozens, if not hundreds, of underlying data inputs into its creation of a daily, ticker level score. Maiden Century applies a number of rules to convert all of these inputs into a single score. These rules are based on fundamental intuition, but likely leave open room for material improvement by people willing to put the time and effort into it. As investors get more familiar with QTIP, many naturally seek to customize and curate the signals by gaining access to the underlying inputs.

To cater to these needs, Maiden Century provides a number of MRD (machine readable data) tables that serve as the key ingredients into QTIP's creation. Using these MRD tables, investors can build their own set of rules, or integrate other first / third party datasets into the Maiden Century inputs, to further augment (or de-bias) QTIP signals. Each of these files is available for subscription standalone or as part of a bundle. Point in time histories tailored to each dataset or profile (combination of datasets) are available for backtesting purposes. Regardless of the dataset or profile used, the underlying schema and field definitions remain consistent across all Maiden Century MRD files, enabling scalable testing and deployment in production environments.

MRD File	Definition (What It Contains)	Primary Use Cases for QTIP / Quant Signal Construction
Historical Spread	Days-adjusted YoY, YoY2, YoY3, YoY4 growth rates for each cohort within a dataset. Normalizes for period-length differences and aligns trends across datasets.	• Core input for spread-based modeling frameworks. • Helps identify trend momentum and inflection points. • Supports custom rule creation for growth-based signals.
Periodic Index	Days-adjusted raw cohort-level index values for each reporting period, aligned for fiscal calendars, M&A, mapping consistency, and dataset definitions. Includes full history and out-period via Precast.	• Foundational building block for model reconstruction. • Enables dataset linking, feature engineering, and multi-dataset composites. • Useful for validating raw inputs and rebuilding QTIP-style pipelines.
Forecast Summary	Provides forward-looking cohort, dataset, and blended (IDEA) estimates—along with weights, accuracy, relevance, deltas to consensus, beat probabilities, and margins of error. Because we expose estimates and weights at each level (cohort, dataset, IDEA), users can apply their own weighting schemes across datasets or models to build custom blended estimates tailored to their preferred rules or signals.	• Feature set for more advanced forecasting or signal augmentation. • Helps benchmark user-built rules against MC's blended models. • Valuable for constructing sentiment- and expectations-based signals.

Metric Relevance	Measures price sensitivity to relative beats or misses for each KPI, separately for T1 (current quarter) and T2 (next quarter). It provides a forced-rank score (0–100) indicating how strongly each KPI has historically driven post-earnings stock reactions	• Critical for systematic KPI weighting. • Determines which KPIs should drive signal magnitude. • Helps quantify when forward guidance (T2) matters more than current results (T1).
Napkin Math	Compares a simplistic QTD + 1-year spread-based estimate to two benchmarks: (1) Consensus, and (2) a Precasted + 1-year spread estimate, where Precast projects roughly 180 days of future data. The file shows the deltas between these approaches, quantifying how much expectations differ between a naïve early-quarter method and a more complete precast-driven approach.	• Highlights expectation gaps early in the period, when naïve QTD trends can diverge meaningfully from fuller-information Precast models. • Helps users understand how far buy-side expectations might drift relative to more stable projected fundamentals.

Conclusion

Many Quant funds claim that there's no alpha left in alternative data because the most accurate datasets have become table stakes. However, they must remember that since the data predicts earnings and not stock prices, when the macro conditions are such that earnings recede into the background, the signal can go through periods of temporary dislocation. This can help explain some relatively muted performance in recent periods in the context of exogenous factors like AI spending distortions and tariff news which make the relationship between top and bottom line trends more challenging.

But as the QTIP results for CE data show, there's always room to extract value from more nuanced analysis and a smarter trading strategy. Although the upfront investment to accomplish this may seem daunting, the richness of Consumer Edge Data combined with the accessibility provided by QTIP dramatically lowers those barriers by optimizing inputs to allow quants to focus their time value-added alpha extraction.

About Maiden Century

Maiden Century sits between the most widely used datasets in the investment industry and the world's preeminent investors and consumers of data. Our platform has helped investors solve some of their most vexing data challenges and drastically increase the ROI on their existing data ensemble. We help investors consume more data and deploy models that work for them, within their existing process. We understand the stakes of relying on data and have deployed capital as fundamental investors ourselves. We know the benefits of getting it right and the risks of getting it wrong. That is why our platform is trusted by the world's most sophisticated data consumers.

REQUEST A DEMO

About Consumer Edge

Consumer Edge ("CE") is a leading data and insights-as-a-service (IaaS) company specializing in the global consumer, B2B, and healthcare economies. Founded in 2009 by CEO Bill Pecoriello, CE delivers real-time, transaction-based intelligence enriched by deep industry expertise. Its solutions equip corporate and investment leaders with best-in-class tools for strategic decision-making, offering granular insights and benchmarking across products, brands, sub-industries, and industries. CE's unique capabilities turn complex data into clear, actionable insights that drive smarter, faster decisions.

Brand	1wk	12wk	26wk	52wk		YoY
Apple	2.5%	1.3%	0.8%	1.2%	0.4%	0.0%
Amazon	2.5%	1.3%	0.8%	1.3%	0.4%	0.0%
Costco	2.5%	0.8%	0.8%	1.2%	0.4%	0.0%
Bankorama	-0.8%	0.4%	0.0%	0.6%	0.0%	-0.5%
CVS	-0.8%	-1.2%	-0.5%	0.6%	0.0%	-0.5%
McDonald's	0.5%	0.8%	0.8%	1.2%	0.0%	0.0%
Walgreens	0.8%	0.4%	0.4%	0.6%	0.0%	0.0%
PetSzz	-1.2%	-1.3%	-0.5%	0.6%	0.0%	-0.5%
Whole Foods	-0.5%	-0.5%	-0.5%	0.6%	0.0%	-0.5%

	1wk	4wk	13wk
Qys21	1.3%	0.5%	2.5%
13wk	1.3%	1.3%	1.3%
26wk	0.8%	1.2%	0.6%
39wk	0.8%	0.6%	0.6%
52wk	-0.7%	-1.1%	-0.5%
65wk	-0.7%	-0.5%	-0.5%