Market Commentary

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Deep Learning + Global Macro

www.qplum.co

1620 Plaza 5 Jersey City, NJ 07311

(201) 377-2302 contact@qplum.co (201) 604-5422

In this research report, we are advocating a data-driven approach to trading based on global macroeconomic data, a.k.a. "Global Macro". We will explain why discretionary global macro firms are losing money, and why a Deep Learning[14] approach to Global Macro is better positioned for a world awash with actionable data.

Macro Massacre

Saijel Kishan, Bloomberg, writes that Markets No Longer Make Sense to Macro Managers[1]. After years of underperformance[3], and unfairly high fees, there is a growing stigma in firms about calling themselves "global macro". The quant buzzword is winning the popularity awards today among allocators. Digging deeper, nationwide traders and quants are losing jobs and AI and FinTech jobs are skyrocketing[12].

In the report, we will look at the short sighted business models of macro hedge funds and why they have contributed to the current malaise. In this section, we will see that the failure of macro versus data science is not because of any intrinsic market factors but mostly due to the lack of business foresight. You will see how the discretionary macro versus data science fight is similar to the struggles of Walmart against a technology and AI driven approach[13] like Amazon.

Most importantly, we will provide a blueprint to global macro portfolio managers as to how they can turn things around

What is global macro?

Global Macro is about seeing the investing implications of all sorts of data, and not limiting ourselves to just market prices or companies' balance sheets. It is typically a top down investing strategy that emphasizes data driven tactical allocation.

- U.S. Q1-2017 GDP number was a soft 1.4%. How should I trade that?
- The volatility index is at thirty-year lows. Does that mean a crash is coming?
- Fed has committed to raising rates again this year. However, inflation is well below 2%. How should I trade this inconsistency?

These are some questions a global macro portfolio manager would grapple with. But this is not where it ends. Macro trading is about factoring in a lot of information, from markets, from macroeconomic data and from data related to investor psychology.

Why are traditional macro-money managers seeing underperformance and eventually, redemptions:

1- A lot of high-quality data but they don't do much with it

Almost in any business, major upheavals can be traced to cheap availability of actionable data. There are many examples of how discretionary macro firms have set up relationships with key people in the past and have been able to sample central bank sentiment before others. However, today, that is no longer the case. Due to increased transparency from central banks, most Central Bank data is available in a fair, equal-access format. Moreover, it is often made electronically available via APIs at no cost!

> "I think what Bob Shiller and I have tried to do is to understand the role of psychology in macroeconomics"
>
> - George Akerlof

Cheap availability of data and technology is the reason why some small companies like qplum now have higher accuracy macro models than large discretionary macro firms with multiple decades of experience in an old relationship-driven trade.

2- Lack of business foresight

Is technology an expense or is it an investment?

Walmart's daily revenue is more than what Amazon pays its developers for a year. Yet, Walmart took a while to wake up to Amazon's technology. It's not like they did not have the means or finances to develop the technology to be a leader.

The reason why old school discretionary macro firms like Brevan Howard have consistently underperformed just about everything else since 2012 is because they did not invest in technology. They have been chasing relationships and traders, as opposed to building an information retrieval process from all the high-quality data that is now readily available.

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3- No simple, big, fast trades left

Most of the successes of discretionary macro managers can be traced to following the huge trends where they are able to capture a major part of a rapid move. Even then, they need the trade to play out fast. Think of a seventy basis points move in two months and a macro fund would try to get thirty bps of that. Today, one needs to have a much larger number of consistent, small wins[4]. These sort of trades have just not been happening for a while and when they have happened the success rate has been 50 - 50 at best.

4- Can I move the markets?

The amount of money invested in old school, gut-feeling based global macro rose very quickly after the crisis. Placing huge bets, a.k.a. "spraying the market", based on privately gathered insights is just not working in size any longer. In 2017 for instance, while the Fed has followed through on policy changes that it has been hinting at publicly, global macro funds are down 5% or so while the overall market is up around 8%.

The right way to use global macro: Deep Learning

With petabytes of new data impacting markets today, a global macro portfolio manager needs to find an AI driven method[9] to derive useful information from data. These might have different frequencies of getting updated. Many of these data sources might be closely related to each other. Think of the two hundred or so data series released by BLS in the monthly employment report. They are all related but they are all distinct observations.

We will need to find these relationships via a deep recurrent neural network. We are showing an illustration of this here.

How to setup a Deep Learning based Global Macro trading strategy?

In the schematic shown in Fig.1 we are taking a number of different data sources. Let's say we take five thousand data sources, and pass them through a seven layered autoencoder, where each successive layer has one-third the number of nodes as the previous layer. This means in each layer we are forcing ourselves to make summaries of the data of the previous layer. Then after seven layers we will be left with three to four nodes.

Now we can use these summary features in two ways:

1. Normalization trade: We can try to infer what prices should have been now given the data we have received so far. This will help us find discrepancies and trade on them.
2. Prediction trade: Instead of predicting every single asset class, we should predict the future value of the summary features, since we will have a much higher out of sample accuracy in doing so.

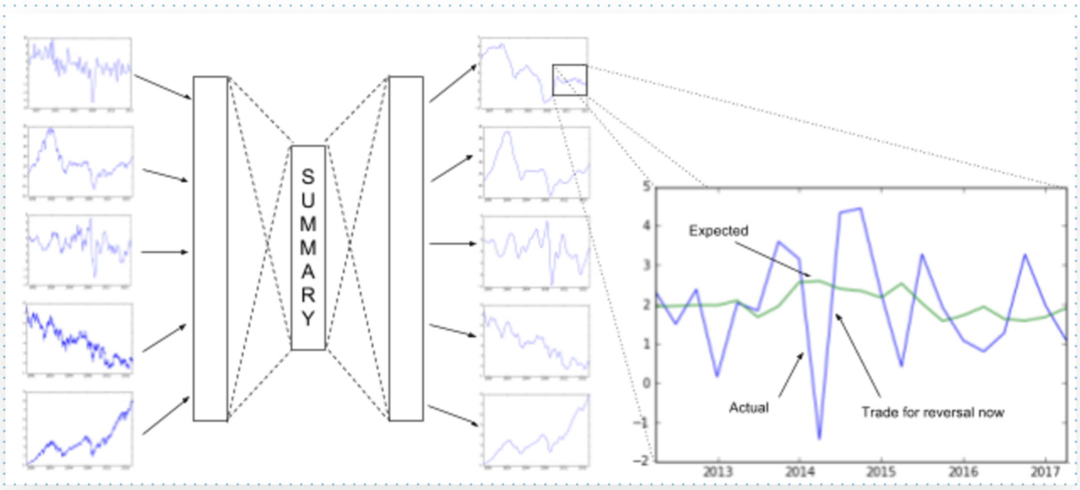


Fig 1: A Deep Learning based setup for a global macro trading strategy

In the rightmost part of Fig 1, we are showing the normalization trade. The green line shows what should have happened and the blue line shows what really happened in that product. This allows us to place trades to correct the discrepancies in current prices.

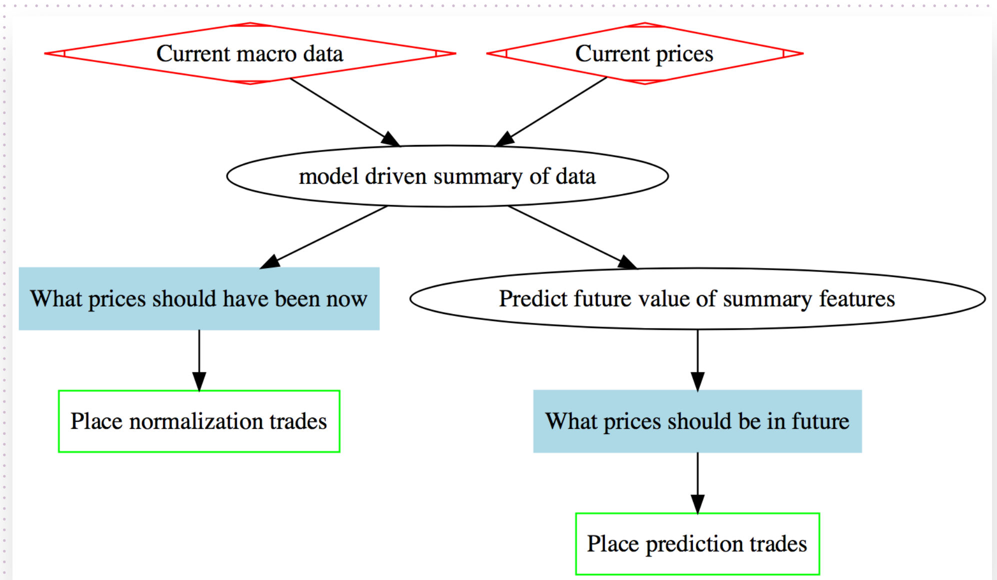


Fig 2: The workflow of a Global Macro - portfolio manager

The flowchart above shows the workflow that a portfolio manager needs to follow in deriving trading information from all new data. As new data emerges of any form, they will need to process it using a data-driven system. Then a PM will want to use the two trades, a market neutral normalization trade for a short trading horizon and/or a directional prediction trade for a longer trading horizon.

What is the ideal way to test an idea without overfitting to the past?

The only way to build trading strategies without a possibility of overfitting is walk-forward-optimization [11]. We show the workflow in the diagram below.

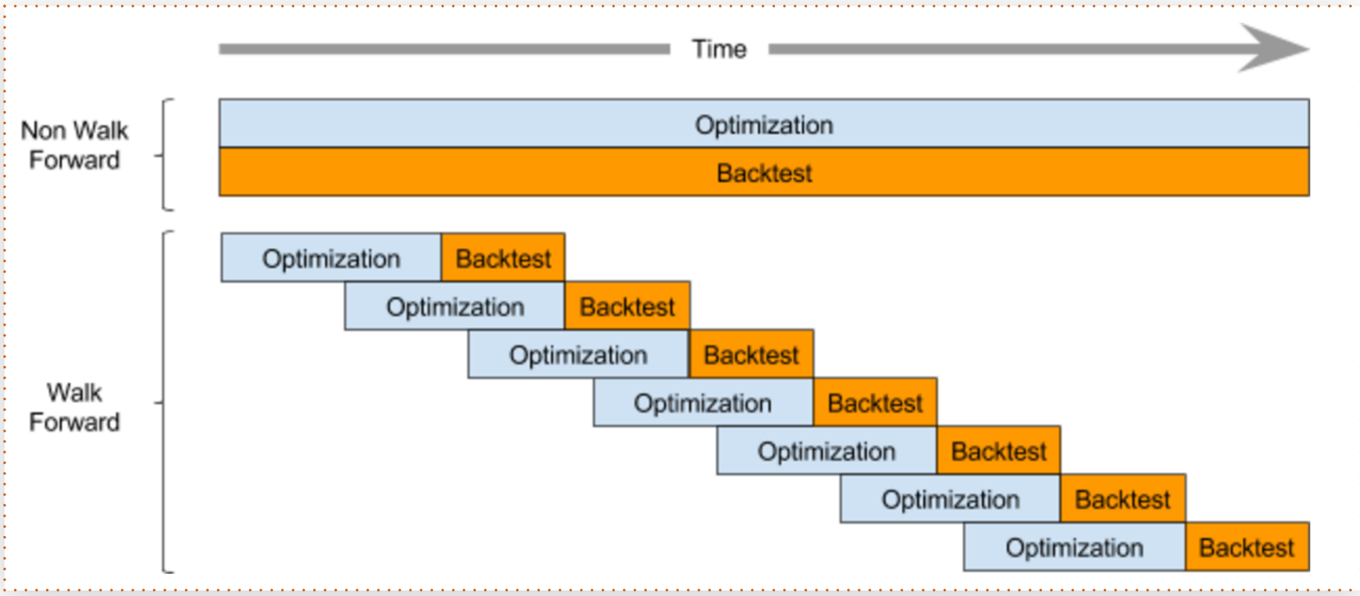


Fig 3: Walk-forward strategy construction ensures that we never overfit

As you can see in Fig 3, a walk forward optimization isn't actually one optimization but a series of them. At any point in time, we use only the data available till then to optimize the strategy parameters (or the model parameters, or hyperparameters), and backtest using these parameters till the next optimization. In the next optimization, we have two choices: 1) add the data accumulated since the last optimization to data from previous optimization or 2) replace some of the older data with the new data (which is what is happening in the illustration above). Now we can optimize again using this data and come up with parameters to be used till the next optimization.

In a non-walk-forward setup, i.e. traditional quant research, researchers would test a strategy over all the data. They would also use the same data to build strategies. This leads to over-fitting on past data. In a walk-forward setup, we would make a new strategy every day using all available data till that time and use the newly built strategy the next day. This ensures that we are never testing a strategy on day (d) using parameters that have been learned on day (d) or any day post that day

Illustrative example: Using nonfarm payroll data

In the chart below we show the risk-adjusted returns backtest of a walk-forward payroll data based strategy.

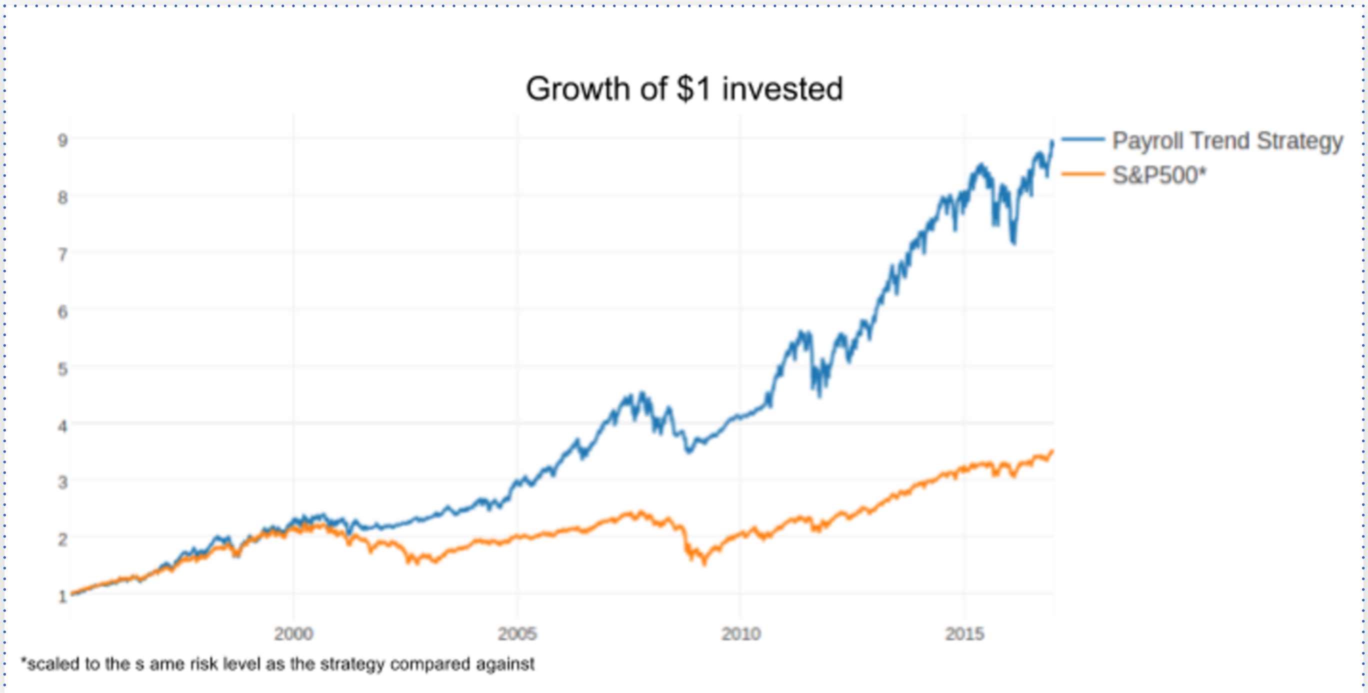


Fig 4: Performance of a trading strategy based on unemployment data vs US stock index

The chart above shows that a walk-forward approach to learning an optimal allocation from payroll data is a great investment strategy. With similar risk as the US stock market, it would have been able to achieve a much higher return. The outperformance continues if we look at other benchmarks like 60-40.

This is just an example. Similar to this, we have extended the work of Sumit Chopra, Yann LeCun, et. al[24] in predicting house prices in "A multi-factor RNN model for house price prediction"[8] with a multi-factor RNN model.

Letters from the community

We are publishing anonymous excerpts of what our readers wrote this month about our past research.

We would love for you to email your thoughts and articles at community@qplum.co and we will feature as many of them as possible in future letters.

Purple Bowtie from New York about the ten-year cycle in trading[2]:

"I thought you were particularly observant in noting the shift in stat-arb from a model-based research methodology akin to physics to a purely data-driven methodology in HFT. I remember internal discussions on the topic. "data mining!" was a phrase that would shut down all discussion on a topic. Our focus at the end ceased to be finding new sources of alpha and simply on streamlining and perfecting existing sources.

My thoughts on the quant crisis have more to do with misaligned incentives present in the traditional financial management framework. Firms run by quants (TS, Shaw, Renaissance, etc...) pulled through and are still performing well. Places like Highbridge, Goldman, etc... which were managed by suits did not. I think in the time leading up to the crises individual incentives for profit knowingly took on risks that were borne by the investors, not the managers."

Blue Table from Upper East Side about the Nvidia Podcast on Deep Learning in Trading[15]

"I was impressed by your June AI podcast interview. I'm a head trader at one of the largest long short hedge funds and much of what you had to say struck a chord with me. The point about why technology is the reason for a change in the trading landscape makes a lot of sense to industry insiders, while outside usually talk about vague statistics like correlation and volatility."

Dark Horse from Montclair about the Humans vs AI article (Andrew Ng and Gaurav)[16]

"Congrats on the fascinating, brain stretching "Humans vs AI" piece. "

Blade Runner from Jersey City about Modern Portfolio Theory does not work[10]

"I loved your piece illustrating the weaknesses of Modern Portfolio Theory. I want to write something similar, albeit less technical, to help CIOs of pension funds stop using an age old formula, that can easily be bettered by risk parity and even equal allocation[23] "

What did we work on at qplum this month?

We refined our work on the US investor index[7]. Our readers will recall that the US investor index is a measure of the real investment performance of US investors. This looks at data directly collected by the Federal Reserve about assets, liabilities, asset allocation, income, expenses, taxes, earnings in each asset class and every little detail about the balance sheets and income streams of all US households.

We have since been able to extract an investing strategy that uses US investor data.

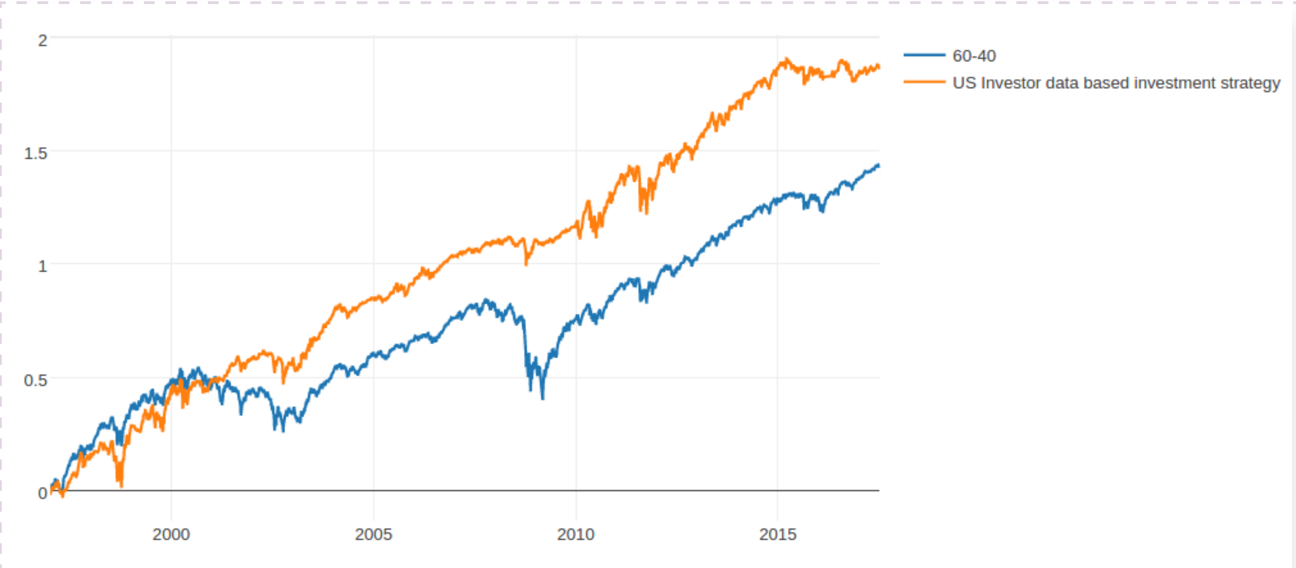


Fig 5: How our US investor index strategy compares to 60-40 institutional benchmark

The chart above shows the performance of qplum's US Investor data based investment strategy (QP-US-Inv-Strat) that uses US investor behavior recorded by the Federal Reserve and made publicly available. We estimate the cost of collecting, cleaning, maintaining and distributing this data would run into hundreds of millions of dollars for the Federal Reserve and shows the commitment they have to their data-driven mission.

QP-US-Inv-Strat would have achieved about 50% better returns than a 60-40 institutional investing benchmark. QP-US-Inv-Strat has a back-tested Sharpe Ratio of about three times that of US stocks in this period, and a maximum drawdown of a fourth of what US stocks had in this period.
We expect to have this included in qplum-Flagship[17] in a month or two.

What happened in markets this month? How does it impact me?

The two biggest stories in June are related.

The first story is the sharp drops in the two biggest hedge fund strategies. As qplum team explained here[3] and as Dani Burger writes here[18], the momentum + risk-parity chill pill is facing its worst time in decades.

Fig 6: How Risk Parity and Trend Following have been falling together

So much so that the head of the world's largest hedge fund, Cliff Asness, got into a "cat" fight with Bloomberg reporter, Dani Burger[6]. We are big fans of AQR's transparency here at qplum. However, at some point, the last three years of not making any money for investors and earning billions in fees had to catch up with AQR.

The second notable story is that, inexplicably enough, an average US investor had a better investment performance than every other index in our table below. This is not an isolated trend. Looking at the entire history since when we have real performance data for both indexes, US investors have outperformed an average investment in hedge funds.

This was not always the case. We think that this is probably incontrovertible evidence that we are all learning together how to invest smarter! Cliff Asness might disagree about investors getting smarter, but data speaks for itself. US Investor Index returns are better than 90% of the funds on AQR's performance page[19].

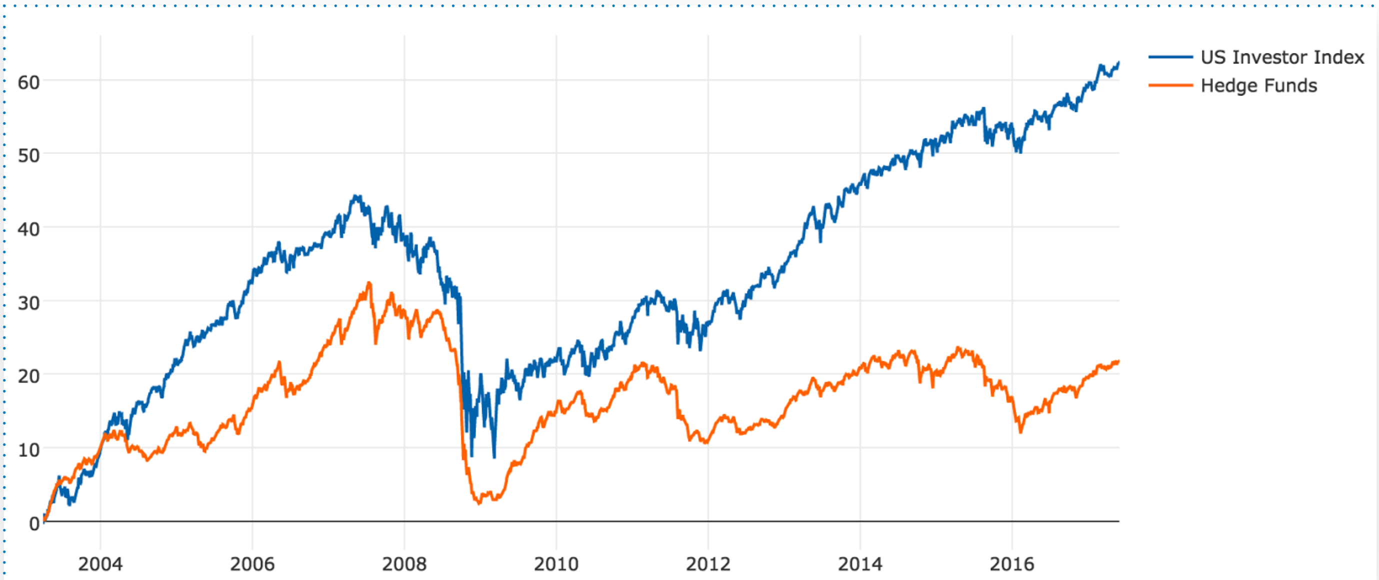
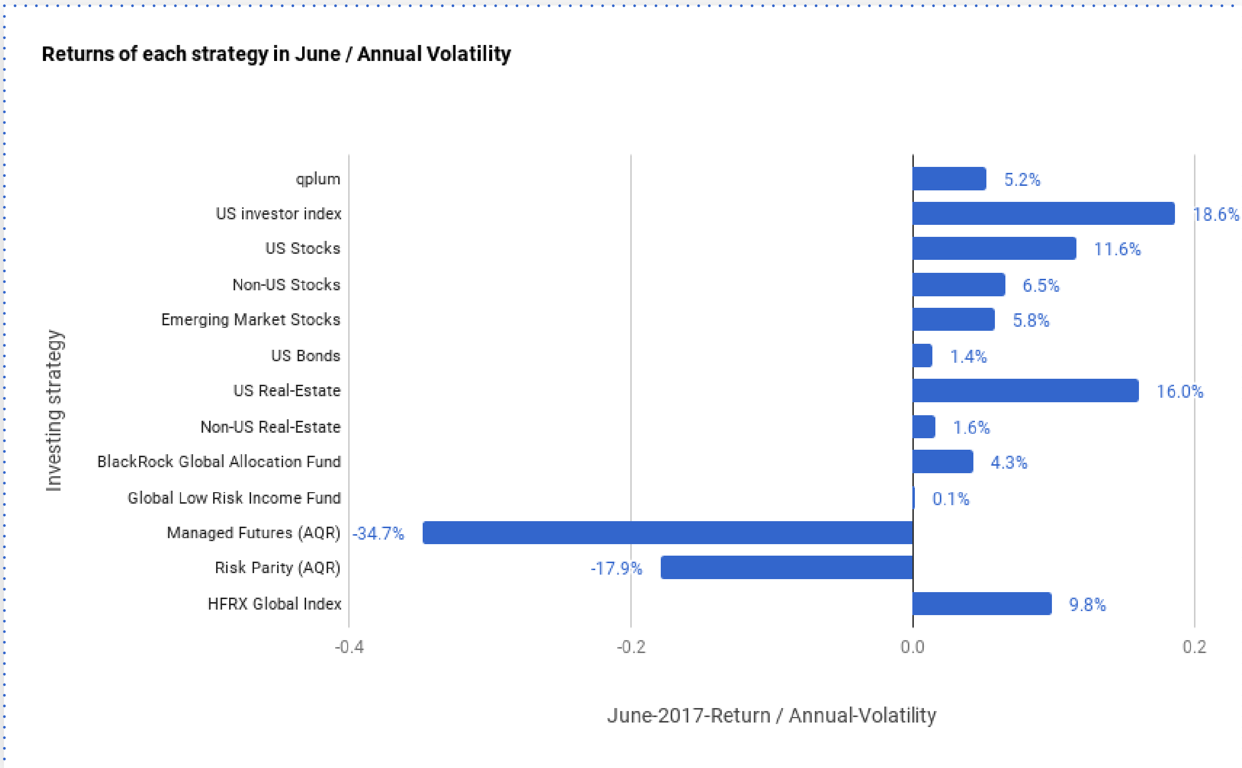


Fig 7: US Investors have actually invested better than the hedge fund index

On a different note, we applaud the initiative by Seema Hingorani, SevenStep Capital, a hedge fund seeding platform that has a focus on investing in women and minority hedge fund managers. Women and minority owned managers make up just 1.1% of the asset management industry[5]

qplum's performance this month

At qplum, we continue to outperform our benchmark[20]. However, we underperformed US investors for the first time in 8 months. We have attributed this to our global exposure, and our partial exposure to trend following[21] and risk parity[22].



Investment Style	June	YTD returns	Annual Volatility	June Return / Annual Volatility
qplum	0.32%	6.9%	6.2%	5.2%
US investor index	0.82%	4.1%	4.4%	18.6%
US Stocks	0.95%	8.9%	8.2%	11.6%
Non-US Stocks	0.63%	14.9%	9.7%	6.5%
Emerging Market Stocks	0.84%	15.1%	14.4%	5.8%
US Bonds	0.05%	2.4%	3.4%	1.4%
US Real-Estate	2.23%	2.6%	13.9%	16.0%
Non-US Real-Estate	0.16%	14.0%	10.2%	1.6%
BlackRock Global Allocation Fund	0.20%	7.7%	4.7%	4.3%
Global Low Risk Income Fund	0.00%	3.6%	2.5%	0.1%
Managed Futures (AQR)	-2.22%	-5.6%	6.4%	-34.7%
Risk Parity (AQR)	-1.30%	5.7%	7.3%	-17.9%
HFRX Global Hedge Fund Index	0.24%	2.6%	2.5%	9.8%

References and Data

1. Markets No Longer Make Sense to Macro Managers - Saijel Kishan
2. The ten year cycle of boom and bust in quant trades
3. Momentum and Risk Parity are losing together and not because of US rates!
4. US interest rates are higher by about 1% since last July but the sky did not fall on our heads
5. Women and minority owned managers make up just 1.1% of the asset management industry
6. Cliff Asness fails to hold his own in a data driven world
7. Qplum US investor Index - the best benchmark for family offices and personal investors
8. A multi-factor RNN model for house price prediction
9. What is Artificial Intelligence really? Is it a fad? Which firms use it?
10. Modern portfolio theory does not work
11. Steps to systematically remove the possibility of overfitting in quantitative trading
12. Nobody wants traders or quants! Huge gains for FinTech and AI
13. Why the move from quant to AI in trading? Why now?
14. An executive summary on deep learning in trading
15. Deep Learning is the future of Investing - Nvidia Podcast
16. Humans vs AI Or Humans-with-AI vs Humans-without-AI
17. Qplum's Flagship AI driven strategy
18. Old school trend following and risk parity quants facing worst loss in a decade - Dani Burger
19. Performance of AQR's funds
20. Qplum's performance since inception
21. What is Trend Following? When does it work? What's a data science way of implementing it?
22. Risk Parity losses similar to May 2015!
23. Optimal Versus Naive Diversification: How Inefficient is the 1/N Portfolio Strategy?
24. Discovering the Hidden Structure of House Prices with a Non-Parametric Latent Manifold Model

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