THREE QUANT LESSONS FROM COVID-19

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Background

COVID-19's patient zero has been traced back to an individual who showed symptoms on December 1, 2019. However, the virus was not isolated and named SARS-CoV-2 until February 11, 2020.[3] On February 19, the Standard and Poor's 500 index reached an all-time close level at 3393.52. As we write this note, the index has suffered a 35% drawdown in a little over a month, and, after an unprecedented 2 trillion intervention, is 24% below its peak. Many quantitative firms have suffered substantial losses, even in the equity market neutral space. What lessons can we learn amid this crisis? Among several, we highlight the following three.

More Nowcasting, Less Forecasting

Traditionally, quant strategies have focused on forecasting prices, based on price time-series dynamics (e.g., stat arb), or based on cross-sectional data (e.g., factor investing). Forecasting made a lot of sense years ago, when datasets were limited, mostly covering price series, and disclosures were infrequent, typically quarterly accounting statements. Today, we have access to a wide range of real-time data sources that allow us to "nowcast" the value of relevant financial variables.

The critical difference between forecasting and nowcasting is that forecasts use structured data to make long-range predictions, while nowcasts rely on unstructured observations to make short-range predictions. For instance, nowcast predictions of inflation, based on web-scraping millions of online prices every day, are much more accurate than the forecasts derived from complex econometric models.[4,5] Similarly, satellite images of parking lot occupancy provide nowcasts of earnings of retailers, engineering datasets are used to nowcast the next refinery production or auto production numbers, etc.

[FIGURE 1 HERE]
[FIGURE 2 HERE]

Nowcasting is relatively new to finance, however it is a well-established approach across the sciences. For instance, it is virtually impossible to predict the time and location of an earthquake.

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[3] https://bit.ly/2WHQmao
[4] https://bit.ly/2WGOhvb
[5] https://bit.ly/2UvhAyc

Instead, scientists have developed early warning systems, where even a few seconds of warning can save thousands of lives. Once the earthquake is detected, it is possible to determine with high accuracy, the cities that will be impacted by the shockwave, and the coastal cities that will be impacted by tsunamis.

[FIGURE 3 HERE]

The point in case is that days before the COVID-19 selloff started, there were plenty of warning signs that the virus was disrupting critical supply chains in China. This selloff may have been a Black Swan to market forecasters, but to market nowcasters, it was a predictable outcome. It is time for quants to pay less attention to crystal balls and add nowcasting to their arsenal.

[FIGURE 4 HERE]

Develop Theories, Not Trading Rules

It is common for academics and practitioners to run tens of thousands of backtests in order to identify a promising investment strategy. The best performing backtest is then reported as if a single trial had taken place, and selected for publication or for launching a new fund. As a result of this selection bias, most published discoveries in finance are false, even if we cannot know exactly which.[6] This fact easily explains why many funds have not performed as expected, including but not limited to the recent performance of many quant funds during the COVID-19 crisis.

In the scientific method, testing plays a critical role in attempting to refute a false hypothesis. In finance, however, researchers have used backtesting for the opposite objective, i.e., for building a hypothesis. The implication is that backtesting is wrongly considered part of the research process, instead of being part of the validation process. This situation extends beyond the realm of investing, and includes all economic modelling. For example, macroeconomic theories are widely recognized as useless (if not downright dangerous), and provide little help to financial modelers.[7]

The solution to this problem is to develop theories without backtesting, using feature importance analysis methods that are robust to overfitting.[8] To quote the great English scientist Sir Isaac Newton: “As in mathematics, so in natural philosophy, the investigation of difficult things by the Method of Analysis, ought ever to precede the Method of Composition.” A functional theory explains a phenomenon by exposing a precise cause-effect mechanism. The validity of this cause-effect mechanism can be tested with more powerful validation tools than backtesting. For

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[6] http://www.ams.org/notices/201405/

[7] Lipton, A. 2016 “Macroeconomic theories: not even wrong”, Risk Magazine.

[8] https://ssrn.com/abstract=3544431

instance, we could investigate if persistent order flow imbalance precedes panic selling, like the one observed during the COVID-19 selloff, or during the Flash Crash of May 6, 2010. Microstructural theory tells us that imbalanced order flow adversely selects market makers, who initially hold the prices by providing liquidity in the form of bids, but eventually become sellers themselves, causing sharp price falls.[9,10] To test this theory, we can investigate which market makers lost money during these panics, whether they monitored for order flow imbalance, and we can search for evidence of their sudden retreat in the FIX messages of those days. No historical simulation of a trading rule (i.e., a backtest) can provide us with this level of insight. In conclusion, backtests are only useful to assess the economic value of a trading rule, assuming that the underlying theory is correct, but cannot prove a theory. [11]

Avoid All-Weather Strategies

Academics and practitioners usually search for investment strategies that would have performed well across many different market regimes. That search implies the assumption that such strategies do exist. But why would that be the case? Why would that source of alpha exist continuously, regardless of the underlying market and economic conditions? To quote Napoleon Bonaparte: “One must change one’s tactics every ten years if one wishes to maintain one’s superiority.” We all know what happened to him when he stopped following is own advice.

This “all-weather” assumption is not necessarily valid, as demonstrated by the fact that many successful funds have floundered under the new norm of zero interest rates, and more recently, during the COVID-19 crisis. The unprecedented transformation of the Federal Reserve from the narrow to the fractional-reserve *modus operandi* puts paid to many, if not all, all-weather postulates. Given that markets are adaptive, and investors learn from mistakes, the likelihood that genuine all-weather algorithms exist is rather slim (an argument often wielded by discretionary portfolio managers). And even if all-weather algorithms existed, they are likely to be a rather insignificant subset of the population of algorithms that work across one or more regimes.

Instead, asset managers should focus their efforts on searching for investment strategies that perform optimally under well-defined market regimes. Each regime is characterized by a particular data generating process (DGP). We can nowcast the probability that current observations are being drawn from each DGP, and use those probabilities to build an ensemble portfolio of those optimal strategies.[12] As these probabilities shift from one DGP to another over time, the ensemble portfolio is dynamically adjusted and adapts to the prevailing market conditions. For example, during the COVID-19 selloff, the ensemble portfolio would have

[9] http://ssrn.com/abstract=1695596

[10] Lipton, A., Pesavento, U., Sotiropoulos, M. 2014 “Trading strategies via book imbalance”, Risk Magazine.

[11] https://ssrn.com/abstract=3558728

[12] https://ssrn.com/abstract=3459866

reduced allocations to models optimized for economic expansions and increased allocations to models optimized for economic recessions and market turmoil.

We hope that the quant community will adopt these three lessons. The COVID-19 crisis could help launch a new era of quantitative models that take advantage of more comprehensive datasets, are better aligned with the scientific method, and are more adaptive.

FIGURES

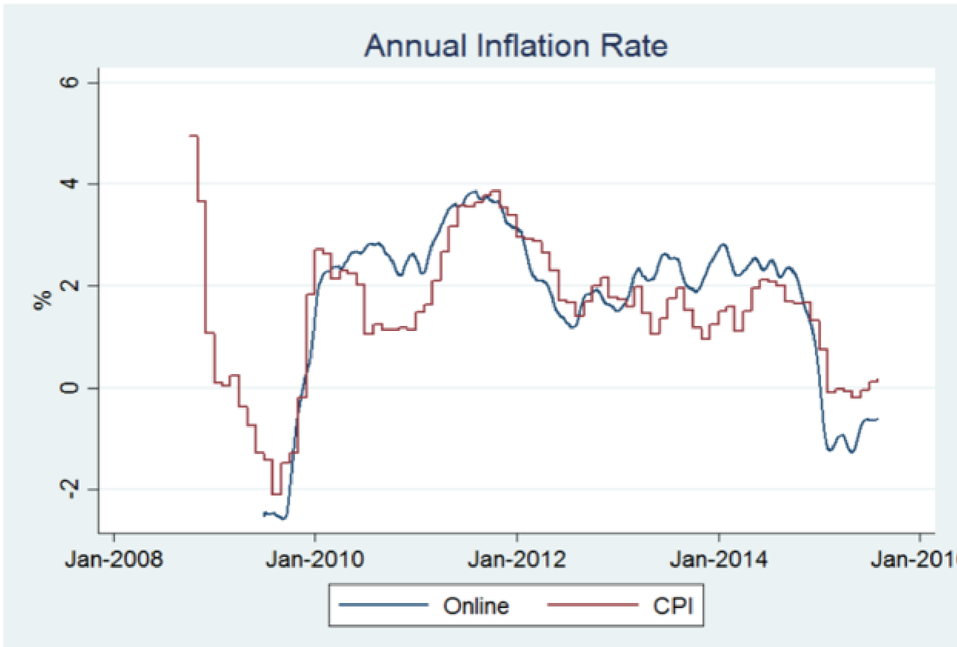

Figure 1 – BPP's nowcasting of U.S. inflation
Source: Cavallo and Rigobon [2016]

Figure 2 – Measurable AI's nowcasting of retailers' sales

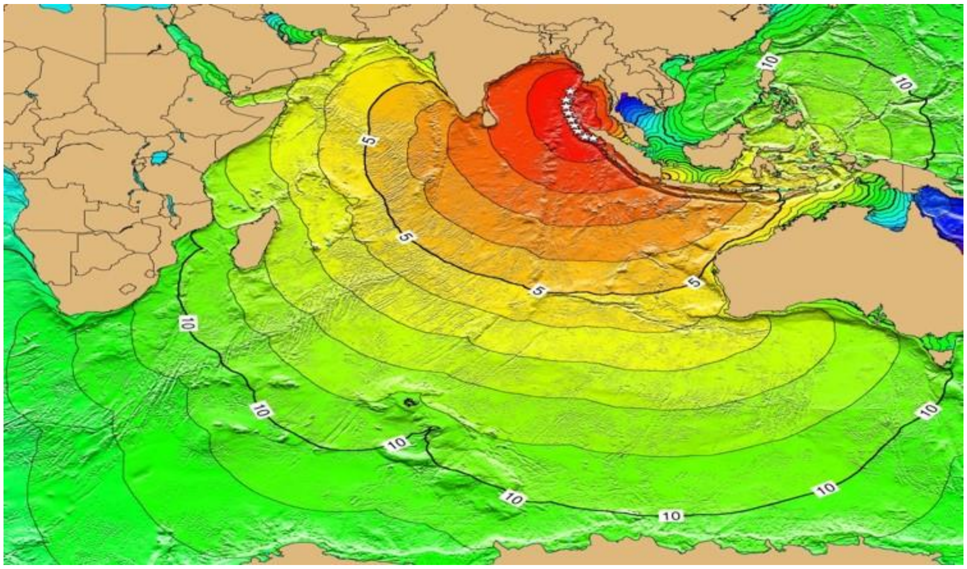

Figure 3 – Expansion of the December 26, 2004 Sumatra tsunami
Source: [NOAA]()

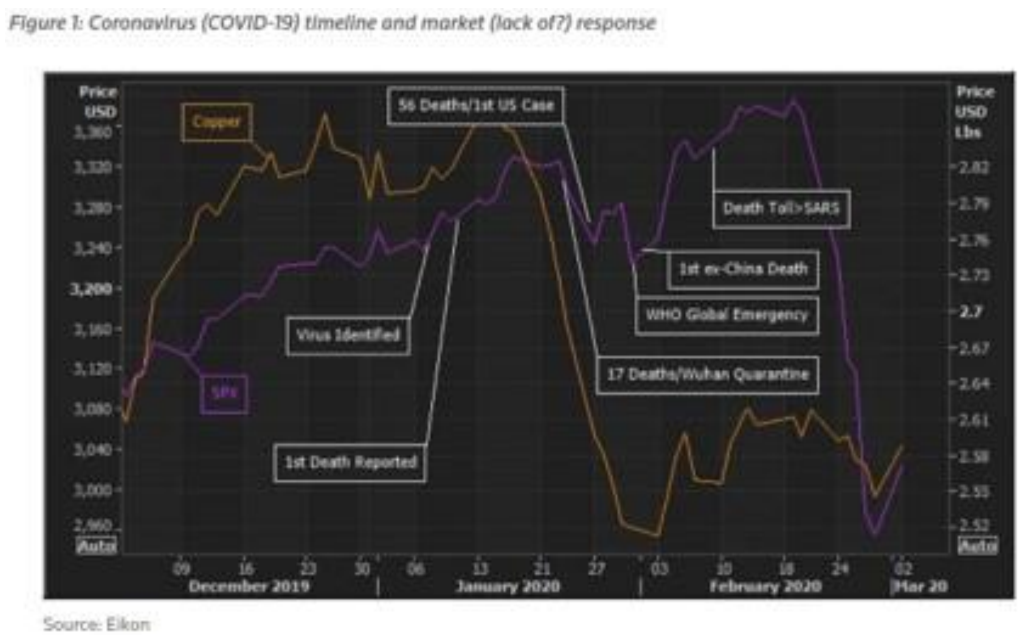

Figure 4 – Nowcasting of COVID-19’s market response