Strategic Risk Management:

Out-of-sample evidence from the COVID-19 equity selloff

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ABSTRACT

Over the 2016-2019 period, we released a series of research papers on the topic of "strategic risk management", or the embedding of risk management into investment strategy design. We show that key risk controls that we introduced materially helped during the sharp equity market selloff in February-March 2020, when the COVID-19 pandemic accelerated. First, faster trend following and long-short profitability stock strategies performed well during the equity market selloff. Second, responsive volatility targeting reduced positions dramatically ahead of the most volatile period in March 2020, and so improved both the return and risk profile at that time. Third, strategic rebalancing rules helpfully called for keeping an underweight in equities (not rebalancing back to target) at the end of February 2020, regardless of using 1-, 3-, or 12-month trend systems to base the rebalancing rule on.

Keywords: *Systemic risk, COVID-19, Pandemic, Drawdowns, Rebalancing, Tail risk, Hedging, Risk management, Volatility targeting, Trend following, Moving-average crossover*

JEL codes: G11, G23, G01, C58.

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Introduction

For both asset managers and institutional investors, there is often a degree of separation between the investment and risk management functions. This separation promotes suboptimal outcomes. An investment manager may dismiss a diversifying strategy based on its standalone expected return or performance in normal market conditions, ignoring any beneficial impact it may have on the tail risk of the overall portfolio. A risk manager may not be in a position to press for an allocation to the diversifying strategy if the investment manager sticks to pre-defined risk and exposure limits.

Another challenge is that popular risk metrics, like skewness, kurtosis, and value-at-risk, are expressed for a single period (day, week, or month). Therefore, these metrics fail to pick up on price trends during crises that arise from a "going from bad to worse" environment often observed during prolonged periods of market distress.

Over the 2016-2019 period, we wrote a series of six research papers on the topic of "strategic risk management", or the embedding of risk management into investment strategy design. In Hamill, Rattray, and Van Hemert (2017) and Harvey et al. (2019), we studied time-series momentum (or trend-following) strategies and noted that faster formulations tend to be more defensive in nature. In this paper, we update the main analysis of Harvey et al. (2019) and confirm that this result also held over the February-March 2020 equity market selloff, which was triggered by the COVID-19 pandemic. Consistent with Hamill, Rattray, and Van Hemert (2017), the good performance during the COVID-19 equity market selloff does not just come from following trends in equity markets, but other asset classes contribute materially as well.[2] Among the long-short quality stocks strategies considered in Harvey et al. (2019), profitability in particular continued to show defensive characteristics during the February-March 2020 equity market drawdown. Low risk (or safety) long-short stock strategies are vulnerable to tightening of credit conditions, as noted in Harvey et al. (2019) in relation to the 2007-2009 financial crisis. Credit concerns also surfaced during the recent COVID-19 equity selloff, and low risk strategies performed less well.

In the volatility targeting analysis of Harvey et al. (2018), we argued that sizing positions in proportion to volatility, rather than holding a constant notional exposure, creates a more balanced return stream. Empirically, in case of risk assets like equities, volatility targeting resulted in a higher Sharpe ratio of returns. In this paper, we show that volatility targeting led to a reduced drawdown and higher cumulative returns for equities over 2020Q1 as well.[3]

Finally, in Rattray et al. (2020), we proposed a rule to postpone the rebalancing of a 60-40 equity-bond portfolio after equity market selloffs. The "strategic rebalancing" rule tends to reduce drawdowns of 60-40 portfolios during extended equity market selloffs. In this paper, we extend the sample period to include 2020Q1, and find that the strategic rebalancing rule would have

[2] In Harvey et al. (2017), we study monthly returns of hedge funds and find that, in aggregate, macro funds are long volatility, a defensive property.

[3] In Van Hemert et al. (2020), we focus on the drawdown statistic and find that heteroscedasticity (time variation in volatility) tends to lead to larger drawdowns.

called for postponing rebalance trades during the COVID-19 equity market selloff, and so helped reduce the drawdown of a 60-40 equity-bond portfolio.

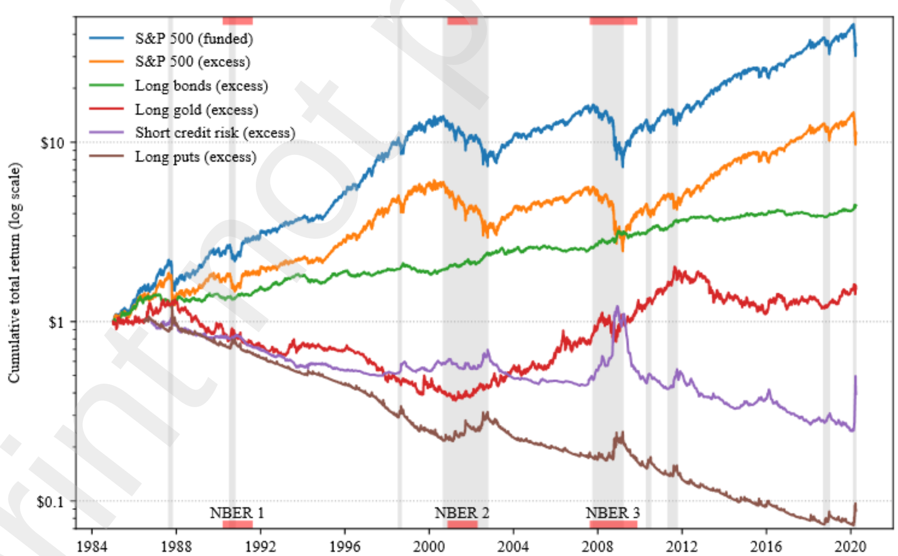
1. The best strategies during the COVID-19 equity selloff

In Figure 1 and Table 1, we extend the analysis in the Harvey et al. (2019) "Best Strategies" paper to the end of March 2020. Importantly, this gives us a ninth drawdown of -15% or worse for the S&P500, which we refer to as "COVID-19" and runs from the close of 19 February to the close of 23 March, 2020.

We note that the COVID-19 selloff in the S&P500 was much faster than most other selloffs. Buying puts provided a good offset, but short credit risk was more potent with a +102% return (in excess of T-bills) over this period. As in Harvey et al. (2019), the credit portfolio employs leverage to obtain a 10% long-term volatility, and this amplifies the good performance over the COVID-19 equity selloff period. Treasury bonds provided only a modest payoff, and gold was slightly down over the COVID-19 selloff period.

Figure 1: Passive investment total return over time

We show the cumulative return of the S&P 500 (funded and in excess of cash), as well as the excess return of long puts (one-month, at-the-money S&P 500 puts), short credit risk (duration-matched US Treasuries over US investment grade corporate bonds), long bonds (US 10-year Treasuries), and long gold (futures). We highlight in grey the eight worst drawdowns for the S&P 500. NBER recessions are indicated on both the top and bottom of the figure. The data are from January 1985 to March 2020.



Moving on to the dynamic strategies, also reported on in Table 1, we note that all time-series momentum (MOM) strategies did well over the COVID-19 equity selloff period. As could be expected for a fast selloff, 1m MOM did best. Position caps on equity positions (only allowing shorts) further improves the performance over this period by 5 to 9 percentage points for the three trend speeds considered.

Of the various quality strategies, profitability held up well during the recent selloff, as did growth. Safety did not do well, particularly when implemented as a beta-neutral strategy. This is similar to the Financial Crisis episode in 2007-2009. We argue this is due to tightening credit conditions. For example, if leverage is used to boost the returns of low risk stocks, then a rise in borrowing costs can be damaging, both as additional up-front cost and indirectly by forcing the unwinding of positions. Payout shows a small negative return over the recent selloff period.

Table 1: Performance over drawdown periods

We report the total return of the S&P 500 and various strategies during the nine worst drawdowns for the S&P 500, the annualized (geometric) return during drawdown, normal, all periods, and the hit rate (percentage of drawdowns periods with positive return). The annualized standard deviation ranges between 6.4% for bonds to 16.5% for the S&P 500, with dynamic strategies all scaled to 10%.The row 'Peak = HWM' indicates whether the index was at an all-time high before the drawdown began. The data are from January 1985 to March 2020.

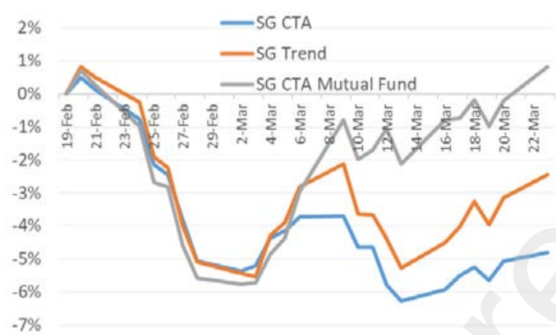
	Black Monday	Gulf war	Asian crisis	Tech burst	Financial crisis	Euro crisis I	Euro crisis II	2018Q4	COVID-19	Drawdown (14%)	Normal (86%)	All (100%)	Hit rate
Peak day	25-Aug-87	16-Jul-90	17-Jul-98	1-Sep-00	9-Oct-07	23-Apr-10	29-Apr-11	20-Sep-18	19-Feb-20				
Trough day	19-Oct-87	11-Oct-90	31-Aug-98	9-Oct-02	9-Mar-09	2-Jul-10	3-Oct-11	24-Dec-18	23-Mar-20				
Weekdays count	39	63	31	548	369	50	111	67	23				
Peak = HWM?	Yes	Yes	Yes	Yes	Yes	No	No	Yes	Yes				
Strategy				**Total return**							**Annualized return**		**%**
S&P 500 (funded)	-32.9%	-19.2%	-19.2%	-47.4%	-55.2%	-15.6%	-18.6%	-19.4%	-33.8%	-48.2%	25.3%	10.6%	n.a.
S&P 500 (excess)	-33.5%	-20.7%	-19.7%	-51.0%	-56.3%	-15.7%	-18.6%	-19.8%	-33.9%	-49.6%	21.3%	7.1%	n.a.
Long puts (excess)	38.0%	12.4%	15.5%	44.7%	40.5%	15.8%	13.4%	18.0%	32.8%	49.8%	-14.3%	-6.9%	100%
Short credit risk (excess)	7.6%	3.3%	12.1%	17.0%	127.7%	11.7%	26.1%	9.5%	101.6%	59.8%	-10.8%	-2.7%	100%
Long bonds (excess)	-8.3%	-2.7%	3.0%	24.2%	20.4%	5.7%	10.1%	2.5%	5.5%	11.6%	3.2%	4.3%	78%
Long gold (excess)	4.4%	5.5%	-6.9%	7.5%	18.9%	4.6%	6.3%	4.5%	-2.7%	8.2%	0.1%	1.2%	78%
1m MOM unconstrained	5.6%	19.3%	9.0%	31.3%	28.6%	2.7%	4.9%	8.1%	40.8%	30.8%	5.7%	8.9%	100%
1m MOM EQ position cap	9.5%	22.8%	12.5%	37.4%	34.3%	4.8%	8.4%	9.7%	45.3%	38.4%	2.6%	7.0%	100%
3m MOM unconstrained	10.3%	10.5%	9.3%	50.7%	32.6%	0.5%	10.9%	0.8%	24.1%	30.1%	5.8%	8.9%	100%
3m MOM EQ position cap	15.4%	18.7%	14.4%	61.3%	41.4%	4.7%	13.7%	2.7%	32.2%	42.2%	3.0%	7.8%	100%
12m MOM unconstrained	0.4%	12.2%	7.7%	52.3%	17.3%	-4.0%	-4.1%	-2.8%	9.2%	16.3%	11.0%	11.8%	67%
12m MOM EQ position cap	8.3%	18.7%	16.2%	71.7%	23.7%	2.1%	0.2%	-0.9%	18.2%	30.8%	8.1%	11.0%	89%
Profitability, dollar-neutral	-1.6%	-2.1%	3.0%	161.9%	33.9%	10.5%	10.9%	4.5%	9.5%	37.5%	0.9%	5.4%	78%
Profitability, beta-neutral	2.3%	2.9%	9.1%	160.7%	21.2%	2.4%	3.3%	1.7%	3.7%	32.4%	1.6%	5.4%	100%
Payout, dollar neutral	0.1%	6.3%	9.1%	178.6%	20.5%	7.0%	5.0%	7.6%	-1.3%	36.2%	0.0%	4.5%	89%
Payout, beta-neutral	-2.8%	8.0%	11.9%	196.1%	13.1%	1.2%	1.2%	5.1%	-2.6%	32.9%	3.0%	6.7%	78%
Growth, dollar-neutral		-6.6%	-9.6%	-8.6%	9.0%	10.8%	9.8%	-1.3%	12.3%	2.6%	1.8%	1.9%	50%
Growth, beta-neutral		-3.0%	-5.7%	-16.2%	12.4%	3.1%	2.8%	1.4%	10.7%	0.5%	0.3%	0.4%	63%
Safety, dollar-neutral	5.0%	9.5%	9.1%	90.7%	12.2%	7.9%	13.6%	9.9%	0.9%	29.7%	-4.1%	0.1%	100%
Safety, beta-neutral	-3.5%	4.8%	0.8%	96.9%	-9.1%	1.8%	4.2%	1.9%	-13.9%	11.2%	4.9%	5.8%	67%
Quality All, dollar-neutral	4.3%	7.3%	8.2%	142.9%	26.3%	10.2%	15.2%	4.5%	5.6%	39.2%	-1.4%	3.6%	100%
Quality All, beta-neutral	-3.3%	7.0%	6.6%	164.9%	9.6%	2.4%	4.6%	1.7%	-4.1%	27.4%	5.2%	8.1%	78%

It is perhaps surprising that the MOM strategies did so well over the recent selloff, while the actual performance of trend followers over this period was slightly negative on average, albeit with considerable dispersion across managers, with some doing very well. This is illustrated in Figure 2, which shows that the cumulative return of the Societe Generale (SG) CTA index over the COVID-19 equity selloff period was -4.8%. The trend-focused SG Trend index fared a bit better. And the (mostly simpler) trend-focused SG CTA Mutual Fund index was slightly positive. In particular, the first 10 days of the selloff were negative for these indices.

There are a couple of explanations as to why our MOM strategies perform so much better than the SG indices over the COVID-19 equity drawdown period. First, asset managers who purport to employ trend following strategies often allocate to other strategies too, like carry, and anecdotally these non-trend strategies have not done well over the recent crisis period. This is consistent with the SG CTA index performing the worst in Figure 2. Second, simpler trend strategies (like MOM) seem to have worked better during this particular selloff, consistent with the SG CTA Mutual Fund index performing best in Figure 2. Third, trend followers typically employ slower models, and it is faster trend models, like the 1-month trend model in our case, that performed best.

Figure 2: Performance SG CTA indices over the 2020 equity drawdown period

We show the cumulative performance of over the COVID-19 equity selloff period from 19 February to 23 March 2020 for the SG index, the SG Trend sub-index, and the SG CTA Mutual Fund index.



The second point deserves some elaboration. The simple time-series momentum (MOM) strategies introduced in our paper use as signal the past return, divided by the volatility of returns to create a value that is approximately unit standard deviation. We limit values to be between -2 and 2 to prevent extreme views. For security k, at time t, the N-day momentum signal is given by:

$$\mathrm{mom}_t^k(N) = \frac{\prod_{i=0}^{N-1}(1+R_{t-i}^k)-1}{\sigma_t^k(R^k)}. \quad [1]$$

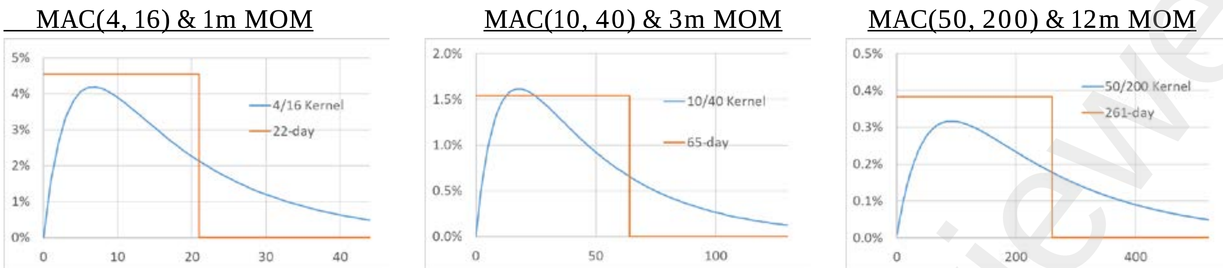
For the purpose of analysis, we consider 1-, 3-, and 12-month momentum strategies to capture short-, medium-, and long-term momentum trading. That is, N in [1] is set to 22, 65, and 261 days, respectively.

In practice, trend followers often employ moving-average crossovers (MACs), rather than the simpler MOM strategies. On this particular occasion, the simpler MOM construction turned out to be a virtue. To illustrate this, we define a moving-average crossover of prices, where the two moving averages use exponentially decaying weights, one with a fast (short) and one with a slow (long) half-life. We divide by a volatility estimate for the difference of moving averages to again create a value that is approximately unit standard deviations, and limit values to be between -2 and 2.

$$\mathrm{mac}_t^k(f,s) = \frac{\mathrm{ma}_t^k(f)-\mathrm{ma}_t^k(s)}{\sigma_t^k\left(\mathrm{ma}^k(f)-\mathrm{ma}^k(s)\right)}. \quad [2]$$

If we use fast and slow half-lives of 4 and 16 days, respectively, the MAC behaves similar to the 1-month MOM model; see Figure 3, where we compare the effective weight given to different lagged returns. Similarly, we can find MACs that match the 3- and 12-month MOM models reasonably well.

Figure 3: moving-average crossover (MAC) vs momentum (MOM) weight to lagged returns
We show the weight effectively given to returns at different lags (in days) for MAC and associated MOM strategies.



In Table 2, we see that correlations between paired MAC and MOM strategies are 0.9 or higher. However, one crucial difference is that MAC models put relatively low weight on the most recent returns, and for that reason are more gradual (and thus slower) in their response to a sudden selloff. The more gradual profile of MACs helps to keep transaction costs under control. However, as can be seen in Table 3, for the recent, very fast, equity selloff, the more gradual trading led to substantially lower crisis performance compared to the simple MOM strategy. For example, the MAC(50, 200) is barely positive over the crisis period, while the associated 12m MOM had a +9.2% return.

Table 2: moving-average crossover (MAC) vs. momentum (MOM) correlations
We report correlations between the three moving-average crossovers (MAC) and three momentum (MOM) strategies considered.

	1m MOM	3m MOM	12m MOM	MAC(4, 16)	MAC(10, 40)	MAC(50, 200)
1m MOM		0.72	0.45	0.93	0.69	0.24
3m MOM	0.72		0.66	0.83	0.93	0.52
12m MOM	0.45	0.66		0.56	0.75	0.90
MAC(4, 16)	0.93	0.83	0.56		0.83	0.36
MAC(10, 40)	0.69	0.93	0.75	0.83		0.63
MAC(50, 200)	0.24	0.52	0.90	0.36	0.63	

In Table 3, we also report the asset class attribution of performance. Across all nine equity market selloffs, trends in fixed income are most profitable. In the most recent COVID-19 selloff, a main driver of the performance difference between MAC and MOM strategies is that MOM strategies do better in equity indices.

Table 3: Performance of moving-average crossover (MAC) vs momentum (MOM)

We report the total return of the S&P 500 and various trend (MOM) and moving-average crossover (MAC) strategies during the nine worst drawdowns for the S&P 500, the annualized (geometric) return during drawdown, normal, all periods, and the hit rate (percentage of drawdowns with positive return). The data are from January 1985 to March 2020.

	Black Monday	Gulf war	Asian crisis	Tech burst	Financial crisis	Euro crisis I	Euro crisis II	2018Q4	COVID-19	Drawdown (14%)	Normal (86%)	All (100%)	Hit rate
Strategy				**Total return**							**Annualized return**		**%**
S&P 500 (funded)	-32.9%	-19.2%	-19.2%	-47.4%	-55.2%	-15.6%	-18.6%	-19.4%	-33.8%	-48.2%	25.3%	10.6%	n.a.
S&P 500 (excess)	-33.5%	-20.7%	-19.7%	-51.0%	-56.3%	-15.7%	-18.6%	-19.8%	-33.9%	-49.6%	21.3%	7.1%	n.a.
1m MOM	5.6%	19.3%	9.0%	31.3%	28.6%	2.7%	4.9%	8.1%	40.8%	30.8%	5.7%	8.9%	100%
Commodities	0.2%	8.1%	0.5%	-2.9%	8.1%	-0.1%	-1.6%	1.8%	5.3%	3.8%	1.6%	1.9%	67%
Currencies	-0.3%	4.9%	0.9%	9.4%	7.1%	0.2%	-2.2%	-0.2%	5.6%	5.0%	1.1%	1.6%	67%
Equity indices	3.2%	5.8%	0.4%	7.1%	5.4%	-2.0%	1.1%	1.9%	19.3%	8.3%	0.6%	1.6%	89%
Fixed income	2.5%	-0.2%	7.1%	15.9%	6.1%	4.9%	8.0%	4.5%	6.7%	11.2%	2.5%	3.7%	89%
3m MOM	10.3%	10.5%	9.3%	50.7%	32.6%	0.5%	10.9%	0.8%	24.1%	30.1%	5.8%	8.9%	100%
Commodities	0.4%	5.8%	1.3%	1.6%	10.2%	-0.8%	-2.1%	0.0%	3.6%	3.9%	1.6%	1.9%	78%
Currencies	0.6%	7.4%	2.4%	10.3%	7.9%	-0.8%	-0.5%	-0.7%	6.6%	6.6%	1.2%	2.0%	67%
Equity indices	5.3%	0.0%	-1.9%	8.2%	3.3%	-3.2%	3.0%	2.3%	8.4%	5.0%	0.9%	1.5%	67%
Fixed income	3.7%	-2.6%	7.4%	24.8%	8.7%	5.6%	10.6%	-0.7%	4.0%	12.2%	2.0%	3.4%	78%
12m MOM	0.4%	12.2%	7.7%	52.3%	17.3%	-4.0%	-4.1%	-2.8%	9.2%	16.3%	11.0%	11.8%	67%
Commodities	2.2%	3.4%	1.8%	4.4%	4.6%	-2.5%	-2.6%	-1.5%	2.4%	2.4%	2.0%	2.1%	67%
Currencies	1.8%	7.4%	2.5%	10.2%	2.3%	-2.6%	-2.3%	1.3%	4.1%	4.9%	2.3%	2.7%	78%
Equity indices	-6.2%	-0.7%	-4.2%	8.3%	4.9%	-5.7%	-4.1%	-1.0%	-3.0%	-2.5%	3.0%	2.2%	22%
Fixed income	2.8%	1.9%	7.7%	22.5%	4.7%	7.1%	5.1%	-1.7%	5.7%	11.1%	3.3%	4.4%	89%
MAC(4, 16)	4.9%	16.1%	9.5%	47.4%	31.7%	2.9%	3.6%	5.1%	30.5%	30.6%	6.4%	9.5%	100%
Commodities	0.2%	7.3%	1.0%	-1.4%	11.1%	-0.9%	-1.3%	1.4%	4.3%	4.2%	1.7%	2.1%	67%
Currencies	0.2%	6.1%	1.6%	13.5%	6.7%	0.3%	-2.1%	-1.3%	4.4%	5.8%	1.5%	2.1%	78%
Equity indices	0.7%	4.2%	-0.8%	10.4%	5.0%	-1.7%	-0.6%	1.6%	12.6%	6.2%	0.5%	1.3%	67%
Fixed income	3.7%	-2.0%	7.6%	19.9%	6.3%	5.5%	8.1%	3.4%	6.9%	12.0%	2.7%	4.0%	89%
MAC(10, 40)	2.3%	11.1%	7.5%	52.0%	36.5%	1.0%	4.2%	2.9%	12.2%	25.4%	7.3%	9.7%	100%
Commodities	0.5%	4.9%	1.7%	1.3%	11.6%	-1.2%	-2.5%	0.0%	3.0%	3.8%	1.6%	1.9%	78%
Currencies	0.4%	7.3%	2.4%	11.1%	7.7%	-0.7%	-1.2%	0.2%	3.1%	6.0%	1.6%	2.2%	78%
Equity indices	0.4%	0.4%	-3.4%	10.6%	5.5%	-3.0%	-0.5%	1.7%	2.1%	2.1%	1.4%	1.5%	67%
Fixed income	3.6%	-1.6%	6.9%	22.7%	8.2%	6.2%	8.8%	1.0%	3.7%	11.9%	2.6%	3.9%	89%
MAC(50, 200)	-8.1%	4.9%	6.5%	32.1%	5.4%	2.3%	-3.3%	-4.7%	0.3%	6.2%	9.2%	8.8%	67%
Commodities	1.3%	2.7%	2.6%	2.4%	1.6%	-0.8%	-3.3%	-2.3%	1.1%	1.0%	1.1%	1.1%	67%
Currencies	1.8%	6.3%	3.4%	1.8%	-1.6%	-1.1%	-1.8%	1.9%	3.3%	2.8%	1.9%	2.0%	67%
Equity indices	-10.8%	-4.4%	-6.0%	8.5%	2.2%	-2.5%	-5.1%	-3.2%	-7.1%	-5.9%	3.4%	2.1%	22%
Fixed income	-0.2%	0.4%	6.8%	17.1%	3.2%	6.9%	7.3%	-1.1%	3.3%	8.7%	2.5%	3.4%	78%

2. Volatility targeting

In the Harvey et al. (2018) paper on volatility targeting, we showed that sizing holdings in an asset to target a constant the ex-ante volatility, rather than targeting a constant notional exposure, leads to improved risk characteristics.[4] The intuition is that "left-tail" events tend to occur at times of elevated volatility, when a volatility targeting portfolio has a relatively low notional exposure. In addition, for risk assets, such as equities and credit, we find that volatility targeting tends to improve the long-term Sharpe ratio of investment returns.

The 2020Q1 period provides an interesting out-of-sample period to evaluate how volatility targeting performs. In Figure 4, we contrast the cases of constant notional (left panels) and

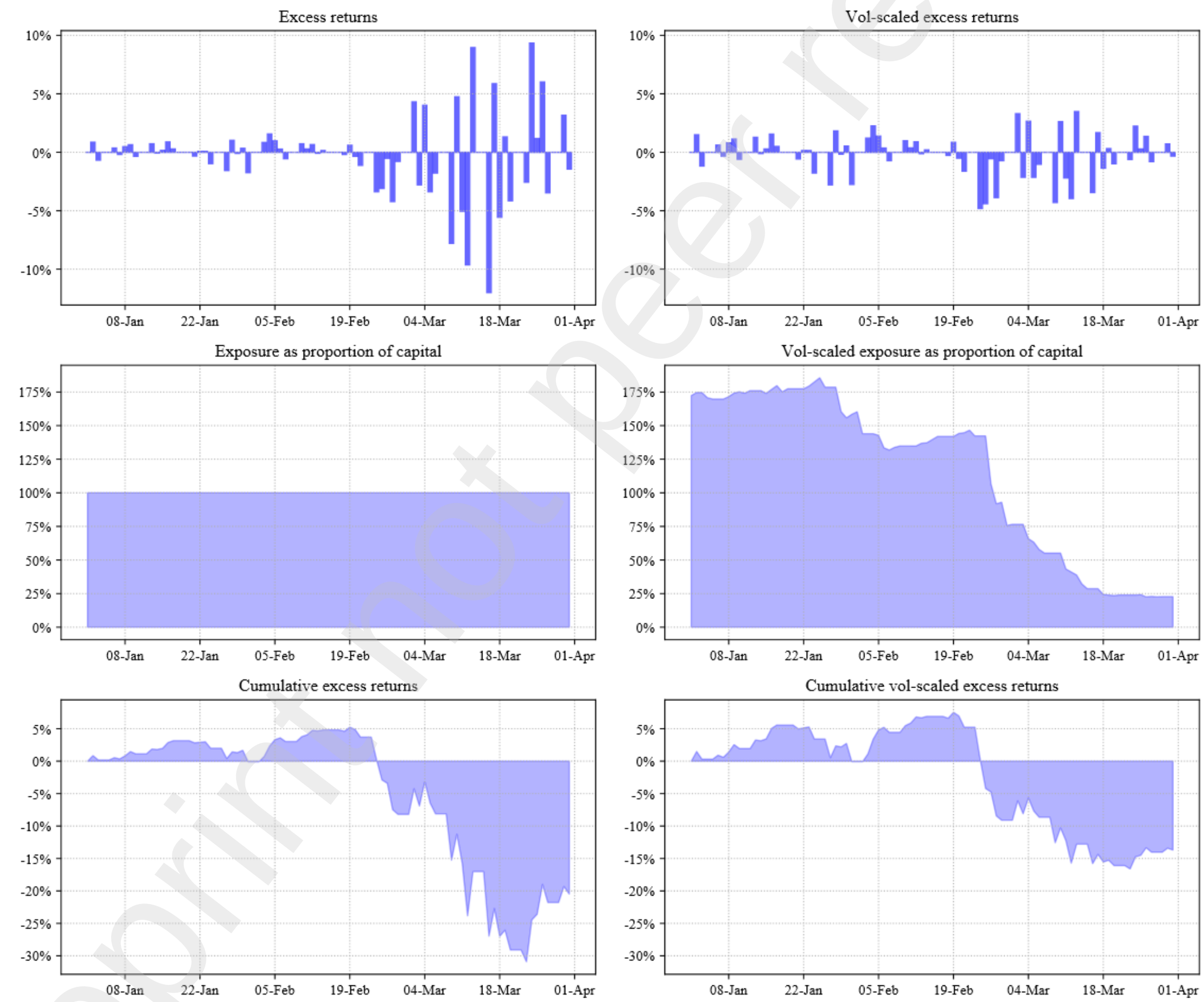
[4] Volatility targeting is also referred to as volatility scaling, since it involves sizing positions inversely proportional to the volatility of asset prices.

volatility targeting (right panels) for US equities. We use exponentially-decaying weights for the volatility estimate with a half-life of 20 days.

The top panels show that the volatility-scaled returns (in excess of T-bills) are indeed more stable. This is achieved by holding more than a 100% exposure in January, when our volatility estimate is below the long-term value of 19.1%, and holding less than 100% exposure from the end of February, when volatility starts to pick up. From the lower panels, a constant notional exposure leads to a much worse drawdown, with the cumulative return dipping below -30%, while for target-volatility investing, the trough is only around -17%.

Figure 4: Volatility scaling of equity returns during 2020Q1

The left panels show the statistics for investing a constant notional amount in US equities, while the right panels show the case of volatility targeting. The top panel display daily returns (in excess of the T-bill rate) for the 2020Q1 period. The middle panels show that notional exposure taken. The bottom panels show the cumulative returns.



3. Strategic rebalancing

In the Rattray et al. (2020) "Strategic Rebalancing" paper, we introduced a rebalancing rule for 60-40 stock-bond portfolios: only rebalance the portfolio back to the target 60-40 stock-bond mix if the 1-, 3-, or 12-month trend in the stock-bond relative return is above its long-term historical average of 0.8%, 2.3%, and 9.1%, respectively. Moreover, if rebalancing, only move half of the distance back to a 60-40 mix.

In Table 4, we illustrate how our rule played out in 2020Q1, assuming a 60-40 stock-bond mix at the start of the year. In Panel A, we show the stock, bond, 60-40, and stock-bond return. In all three months of 2020Q1, bonds outperformed. The only case where the stock-bond return differential is above its long-term average is for 3-month trend in January, and so, in that case, Panel B shows a 50% rebalance back toward the target mix. In the first column, we also include the baseline case of always rebalancing 100% back to target. Panel C shows the allocation to stocks after the end-of-month rebalancing trade, where applicable. Finally, Panel D reports a cumulative return of -8.0% for the baseline case at the end of March, versus -7.2% to -7.4% for the strategic rebalancing rules. That is, the strategic rebalancing rules reduce the drawdown by 0.6 to 0.8 percentage points (or, nearly 10% in relative terms). The impact of the rule is not as large as during the 2007-2009 financial crisis (about 5 percentage points then), when equities experienced a more gradual and larger underperformance. But the strategic rebalancing rule did reduce the 2020Q1 drawdown, despite the suddenness of the crisis.

Table 4: Strategic rebalancing in 2020Q1

In Panel A, we report the monthly stock, bond, 60/40, and stock-bond returns for the US. In Panel B, we show the percent rebalancing toward a 60-40 equity-bond target mix at month end for the baseline case of always rebalancing as well as when using strategic rebalancing rules based on the 1-, 3-, and 12-month trend in the stock-bond return. Panel C shows the resulting equity-bond mix after the rebalancing trade. Panel D reports the cumulative returns for the baselines case and under the strategic rebalancing rules. The data are monthly for the 2020Q1 period.

Panel A: monthly returns (US)

	Stock	Bond	60/40	Stock-Bond
1/31/2020	0.0%	4.0%	1.6%	-3.9%
2/29/2020	-8.0%	3.7%	-3.3%	-11.7%
3/31/2020	-13.4%	4.2%	-6.4%	-17.6%

Panel B: Rebalance toward 60-40

	Always	1m mom	3m mom	12m mom
1/31/2020	100%	0%	50%	0%
2/29/2020	100%	0%	0%	0%
3/31/2020	100%	0%	0%	0%

Panel C: %stocks after EOM rebal

	Always	1m mom	3m mom	12m mom
1/31/2020	60.0%	59.1%	59.5%	59.1%
2/29/2020	60.0%	56.1%	56.6%	56.1%
3/31/2020	60.0%	51.6%	52.0%	51.6%

Panel D: cumulative returns

	Always	1m mom	3m mom	12m mom
1/31/2020	1.6%	1.6%	1.6%	1.6%
2/29/2020	-1.8%	-1.6%	-1.7%	-1.6%
3/31/2020	-8.0%	-7.2%	-7.4%	-7.2%

Concluding remarks

A few years ago, equity and bond markets were booming. The US economy was in a historically long period of uninterrupted growth. Volatility was low and confidence high. We believed the time was right to undertake a research program on the topic of "strategic risk management", which involves the integration of risk management and the investment function. Given that many markets were at all-time highs, it seemed prudent to develop investment programs that seek crisis alpha, i.e., outperformance during the inevitable drawdown.

The COVID-19 pandemic is the type of risk realization that provides an out-of-sample test of some of our papers.[5] We summarize three key ideas.

First, we examined various investment strategies and assessed how they performed during both drawdowns and recessions. For example, a program of buying put options performed very well during drawdowns but was infeasibly expensive during normal times. We found that gold was unreliable. Our research identified two strategies that were notable: allocation to trend following, and certain long-short equity strategies focused on quality, in particular, profitability. We update our results for February and March of 2020 and find that these two strategies performed particularly well during the pandemic selloff.

Second, we undertook a study of volatility targeting, which is both a risk management program (targeting constant risk exposure) as well as an investment strategy. Our research suggested this type of portfolio management was particularly beneficial for risk-oriented assets, such as equity and credit, over our sample. When we extended the sample through the first quarter of 2020, volatility targeting significantly outperformed, reducing drawdowns by one half. The spike in volatility led to sharp reductions in allocation to risk assets – at the right time.

Finally, we examined an important aspect of portfolio construction – rebalancing. We argued that rebalancing is an active strategy, since assets are sold after they rise in value and bought when they fall in value. Buying (rebalancing) when stocks are in a downtrend leads to larger drawdowns. We explored various different heuristics to mitigate these larger drawdowns. We introduced the concept of strategic rebalancing. Here, the rebalancing decision is conditioned on a trend-following signal. If the market is in a downtrend, then delay the rebalancing. At the end of February 2020, all of the trend signals we studied said to delay rebalancing. As such, the strategic rebalancing method outperformed a mechanical rebalancing rule.

[5] We note that for the Harvey et al. (2019) "Best Strategies" paper, the 2018Q4 selloff also can be considered an out-of-sample data point, as we wrote the first version of the paper in 2017 (and posted it online at SSRN.com).

References

Hamill, C., S. Rattray, and O. Van Hemert (2016), "Trend following: equity and bond crisis alpha", SSRN working paper https://ssrn.com/abstract=2831926.

Harvey, C. R., E. Hoyle, Russell Korgaonkar, S. Rattray, M. Sargaison, and O. Van Hemert (2018), "The impact of volatility targeting", *Journal of Portfolio Management*, 45(1), 14-33.

Harvey, C. R., E. Hoyle, S. Rattray, M. Sargaison, D. Taylor, and O. Van Hemert (2019), "The Best of Strategies for the Worst of Times: Can Portfolios be Crisis Proofed?", *Journal of Portfolio Management*, 45(5), 7-28.

Harvey, C. R., S. Rattray, A. Sinclair, and O. Van Hemert (2017), "Man vs. Machine: Comparing Discretionary and Systematic Hedge Fund Performance", *Journal of Portfolio Management*, 43(4), 55-69.

Rattray, S., N. Granger, C. R. Harvey, and O. Van Hemert (2020), "Strategic rebalancing", *Journal of Portfolio Management*, forthcoming.

Van Hemert, O., M. Ganz., C. R. Harvey, S. Rattray, E. Sanchez Martin, D. Yawitch (2020), "Drawdowns", working paper https://ssrn.com/abstract=3583864.