QARM - Project
PCA and systemic risk

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1 Abstract

In this project systemic risk of the world stock markets is measured by using a principle component analysis (PCA). The main principle components are used like in Kritzman, Li, Page, and Rigobon (2010) to define a measure of commonality of the stock market called the absorption ratio (AR). For risk management purposes, the AR can be used as indicator but not a sufficient condition for crashes. After having defined a technique to detect spikes in the AR we implement it in a rule based dynamic portfolio strategy approach in order to time the market and avoid extreme losses. Additionally, during the period not invested in the stock market, we test different alternative investments in terms of performance and risk contribution.

2 Introduction

2.1 Objective

The main objective of this report is to show the evolution of systemic risk over the last 20 years. Furthermore, we determine a risk management strategy that allows investors to time the market in order to avoid extreme draw-downs. In a first step, we discuss systematic risk and PCA as well as its computation. Then we apply it to global equity market indices. Afterwards, a risk management strategy based on the PCA will be defined and analyzed. We show how the strategy is back-tested, optimized and put key trigger events into historical context. Finally, we critically reflect our method and compare it to the underlying paper of Kritzman, Li, Page, and Rigobon (2010).

2.2 Systemic Risk

Systemic risk is the possibility of an event impacting the entire financial system or market and leading to the collapse of whole industries or economies. It is not limited to an individual entity but affects the total system and is therefore non-diversifiable risk. In terms of equity portfolio management, this implies that no matter how many different stocks an investor holds, there remains always some systemic risk. This risk is often referred to as the market risk. A very popular example for systemic risk is the 2008 financial crisis. Financial markets became globally more and more connected and dependent such that the failure of big individual entities could lead to a domino effect, carry down others and eventually the entire system, market or economy. This issue is commonly known as the 'Too big to fail' problematic and synchronizes with a 'Too interconnected to fail' problem. Thus, one key driver of systemic risk is interconnections between markets, which can be analysed by using a PCA. The higher the dependencies within markets, the more the system is susceptible to shocks and the higher their speed of propagation.

2.3 Principle Component Analysis

The principle component analysis is a statistical technique to manage big data and to reduce it to few efficient orthogonal linear combinations capturing most of the variance. The idea behind the orthogonality is to determine uncorrelated factors throughout the data. These are called principal components and are obtained as followed: Suppose that one has a matrix of data $p \times n$ (for example a matrix of returns of n assets for p periods) where $p >= n$ and wants to determine its principal components.

First, the mean of each asset X is computed:

$$\overline{X}_n = \frac{1}{p}\sum_{k=1}^{p} X_{k,n}$$

Therefore, the centered data is the matrix C given by:

$$C = X - \overline{X}_n$$

The covariance matrix of C is defined by:

$$B = cov(C) = C^T C$$

One can proceed then to the eigen-decomposition of the squared matrix B sized n such as:

$$B = Q\Lambda Q^{-1}$$

where Q represents the eigen-vectors and Λ is the matrix of eigen-values of the matrix B.
We can now, as following, determine the principal components squared matrix P sized n where the columns represent the principal components. Note that their variance are equal to the eigen-values.

$$P = CQ$$

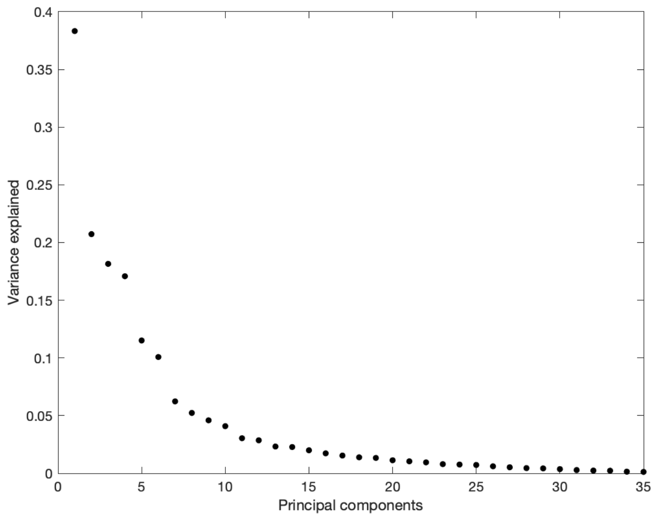

Figure 1: Percentage of the total variance explained by each principal components

In the figure above, one can observe the impact or explanatory power of each component (35 here) of the total variance. The explanatory power decreases exponentially. In this example the first component explains almost 40% of the total variance. This characteristic of principle components suggests that by only using a few components one can explain a large percentage of the total variance.

3 Dataset and time-period

3.1 Data

The data used for this project has been retrieved from Thomson Reuters and Yahoo Finance platform. International stock markets total return indices respectively MSCI's have been retrieved on a monthly basis from Thomson Reuters all quoted in USD. In total, they represent 35 different countries corresponding to a T*N matrix with N the number of columns = 35 assets and T the number of rows = 389 months. The period extends between 01.01.88 to 01.05.20. Note that the weekly basis does not include dividends, for that reason the whole strategy and analysis will be on a monthly basis only. For the PCA we use a rolling window of 120 months. Data for gold, treasury bonds and USD/JPY have been retrieved from Yahoo Finance on a monthly basis for the same period. With regard to the selection of the appropriate treasury bond, a proxy for a risk free asset is needed and therefore the 10-year US treasury appears to be suitable. Although gold isn't a risk-free asset, it will be included because it is considered to be a safe haven besides having a negative correlation with the market. Lastly, we also include a safe haven currency in our analysis namely the Japanese Yen.

3.2 Time-period

The time-period stretches from the late 80's to the present day. Indeed, several major crises are in this sample (dot-com bubble, subprime crisis and the Euro-debt crisis), as well as the beginning of the COVID-19 crisis that the world is facing these days. A 10 years rolling window for the PCA includes always some major crisis around the globe. Hence, the data provides a solid empirical basis to test the performance of a risk management strategy under real life conditions.

4 Risk Management Strategy

When uncertainty raises like in crisis, systemic risk becomes suddenly more present. During market turmoil and crashes asset returns are higher correlated than usual and diversification strategies often fail. Investors can suffer huge losses in short periods of time leaving painful memories behind regardless of long term positive expected returns. As Kahneman and Tversky (1979) already showed in their prospect theory investor's utility functions are usually asymmetric (concave in positive and convex in negative domain) requiring higher gains in compensation for small losses. Thus, the benefit of active portfolio risk management could not only lead to better performance, but also increase psychological utility, by minimizing extreme losses. Since predicting future market behaviour in the short run is very difficult, most strategies during distressed market periods are reactive like rebalancing or late hedging. However, by measuring the evolution of the degree of connectivity, one can estimate the level of systemic risk in the market. The underlying idea is, the higher the co-movements in markets, the faster shocks can spread through the financial system, which determines the level of vulnerability. Using a PCA to estimate the degree of connectivity, we define a measure like Kritzman et al. (2010) to anticipate and avoid market crashes.

4.1 Absorption ratio

The measure for the degree of connectivity in financial markets by Kritzman et al. (2010) is called absorption ratio (AR). It is the fraction of the total variance explained by an arbitrary number of eigenvalues (principle components).

$$AR = \frac{\sum_{k=1}^{k} \sigma_{P,i}^2}{\sum_{k=1}^{N} \sigma_{A,j}^2}$$

In our case, N is the total number of indices and k the number of principle components. There is a trade-off between reducing the dimension of the system to an adequate number of eigenvalues used for the AR and its explanatory power. For this project we used the first five principle components which leads to an AR of about 60% up to 80%.

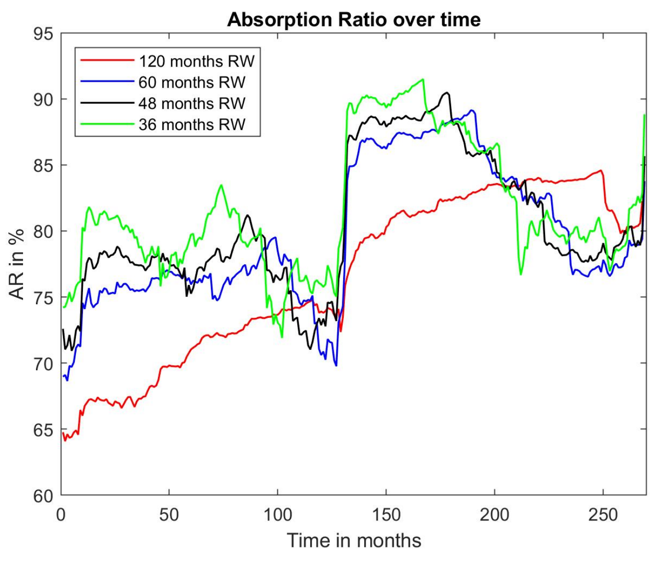

Figure 2: Absorption ratio with different rolling windows all starting in beginning of the year of 1998.

The graph above compares different rolling window periods all starting in January of 1998. The longest 10-year rolling window is pretty smooth and seems to only increase. Just before passing the 250 months mark, there is a sharp drop due to the financial crisis of 2008 falling out of the rolling window. However, just recently at the end of the observation period, all AR spiked again due to the beginning of the COVID-19 crisis. Other rolling windows with shorter periods are more volatile, but provide useful insights of the short term evolution. The Asian-crisis and the Russian default of late 1998, seem to drive the AR up even though the Russian and Chinese stock markets are not included in the PCA due to lack of historical data. The next spike is the dot-com bubble burst in late 2002. As already suggested by Kritzman et al. (2010), the AR seems to be a good predictor of crashes. The longer the rolling window, the less fluctuation one can observe and also the longer the AR remains high after a spike. This is a common issue of rolling windows and also known as the 'ghost-effect'. The choice of an adequate period for the AR rolling window depends on the usage of this information. Hence, there is a trade-off between short term reactivity and having data of previous crisis in the rolling window.

4.2 Kritzman et al.'s market-timing strategy

Accurately defining the exit point in order to avoid extreme losses is the key for success of such a strategy. Kritzman et al. (2010) define the exit point by using the one-standard deviation increase or decrease in the 15-day moving average AR relative to the one-year moving average AR as signal for exiting the market. Since their strategy is based on daily data, it makes sense for them to use a much sorter rolling window of 500 days. In our case, we are dealing with monthly data and want to evaluate a market timing strategy over a longer time horizon using also a longer rolling window. In order to not completely replicate their strategy with monthly data and global stock market indices, we consider an alternative based on spikes in the AR only.

4.3 Implementation of an alternative market-timing strategy

For risk management purposes the AR can be used as predictor of market crashes. A spike in the AR is not a sufficient condition for a market crash, but can be used as predictor. Minimizing extreme losses leads to outperformance, but also to lower volatility, which is important for risk management. One way to do so, would be to exit the stock market, if the AR spikes, implying a fragile system and a lot of co-movements. Such a strategy is also known as market-timing.

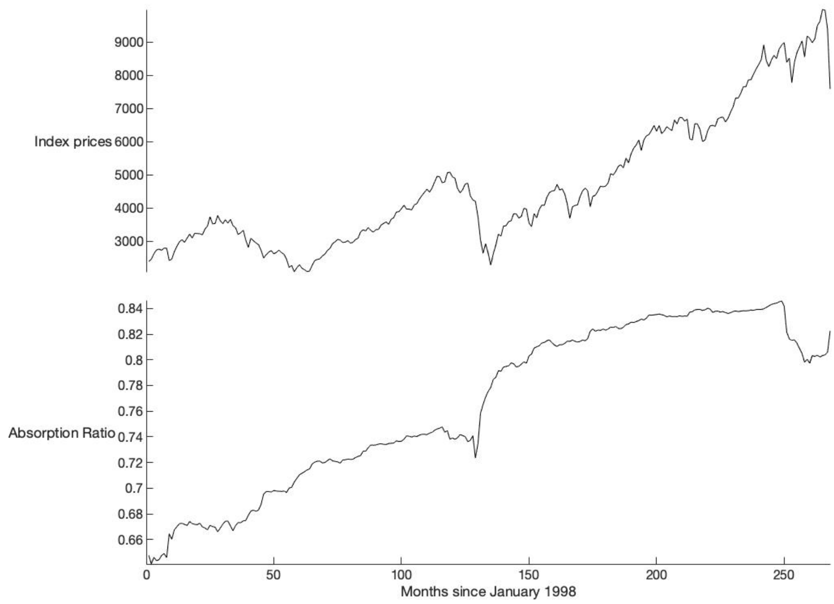

Figure 3: MSCI world index and the AR (10y RW) between January 1998 and May 2020

As one can see in the figure above, it is not that obvious to spot spike in the AR with a 10 year rolling window, since it seems to be too smooth and not reactive enough to predict market crashes. However, comparing the relative changes in value of the AR to the maximum of the past period, could detect sharp spikes.

4.3.1 Market draw-downs

Therefore we compute the changes Δ of the AR following its 10 years rolling window.

$$\Delta AR = \frac{AR_t - AR_{t-1}}{AR_{t-1}}$$

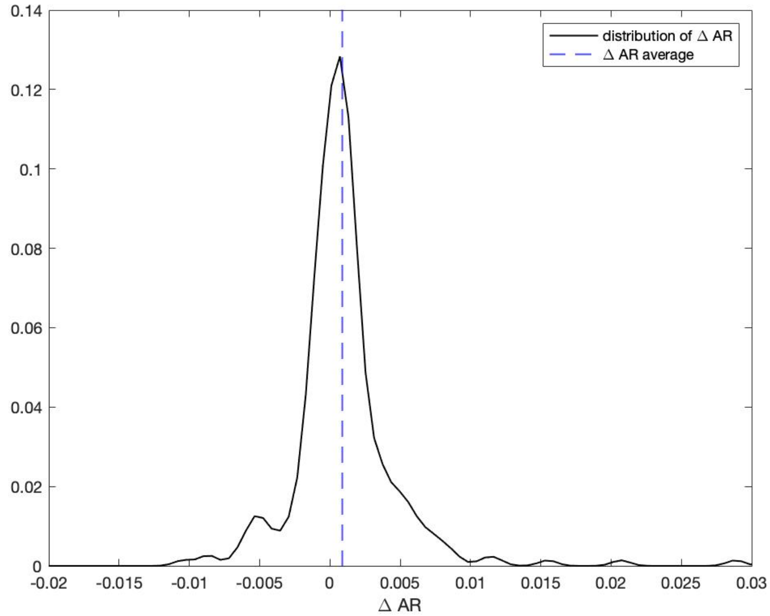

Figure 4: Distribution of ΔAR with a 120 months rolling window

In the ΔAR distribution above, one can notice the way the ΔAR is positively skewed with a positive average as figure 3 would suggest. Moreover, here comes one useful property of a long rolling window for the AR into play. Since the ΔAR does not fluctuate as much as the AR by itself if computed with shorter rolling windows, large changes above a certain threshold can be interpreted as signals.

Table 1: Largest ΔAR 1%, 5% and 10%

Percentile	ΔAR	n
99% ΔAR	1.98%	3
95% ΔAR	0.68%	13
90% ΔAR	0.48%	27

As the paper of Kritzman et al. (2010) suggests, a spike in the AR is an indicator of market fragility, but not a sufficient condition for a draw-down. Therefore, we want to analyse where the mentioned highest spikes of the ΔAR occurred between January 1998 and May 2020.

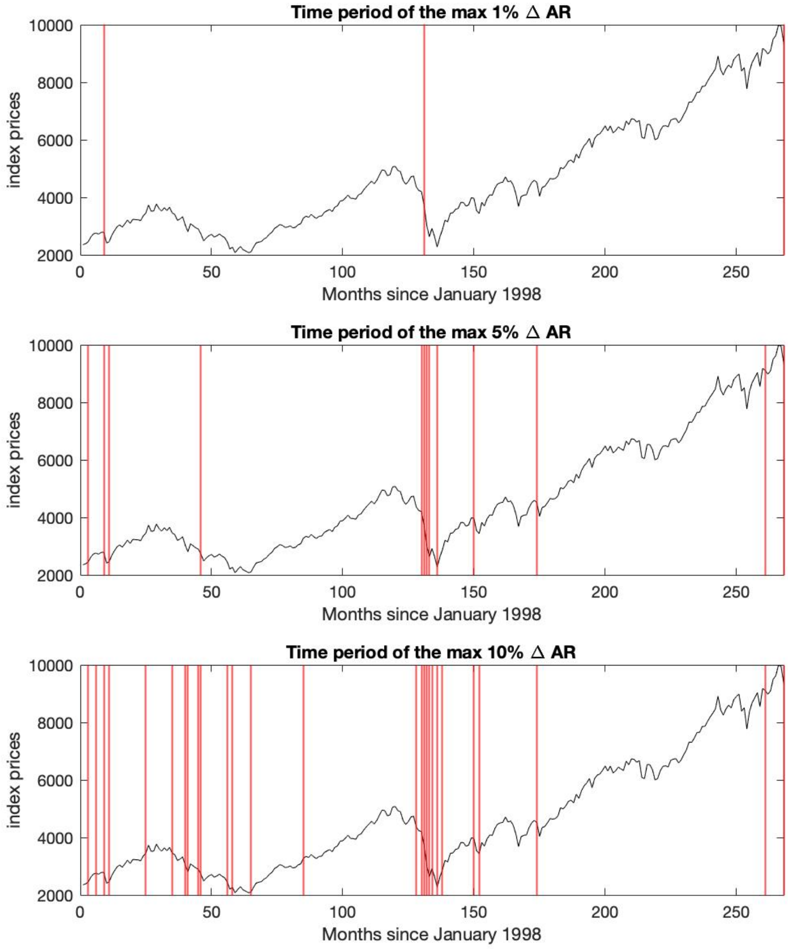

Figure 5: Time period of the maximum ΔAR

The highest ΔAR match well the worst draw-downs over the last 22 years. This strengthens the hypothesis to use the change in AR as signal to exit the market. However, it does not spot all crashes. A spike of Δ AR is neither a necessary nor a sufficient condition for extreme losses.

4.3.2 Strategy to exit and re-enter the market

With this approach of predicting draw-downs using the spikes in ΔAR, we determine a strategy telling the investor when to exit the stock market in order to avoid extreme losses. For this purpose, we are comparing the maximum ΔAR to the one of the previous period using a new rolling window. Investors should exit the market if the maximum ΔAR of the actual time period is superior to the maximum ΔAR of the previous period such that:

$$max(\Delta AR)_t > max(\Delta AR)_{t-w} \tag{1}$$

where t is the time of the actual period and w the rolling window used for comparison. If the investor already left the market and the condition from equation 1 again is satisfied, the agent will obviously not take it into account.

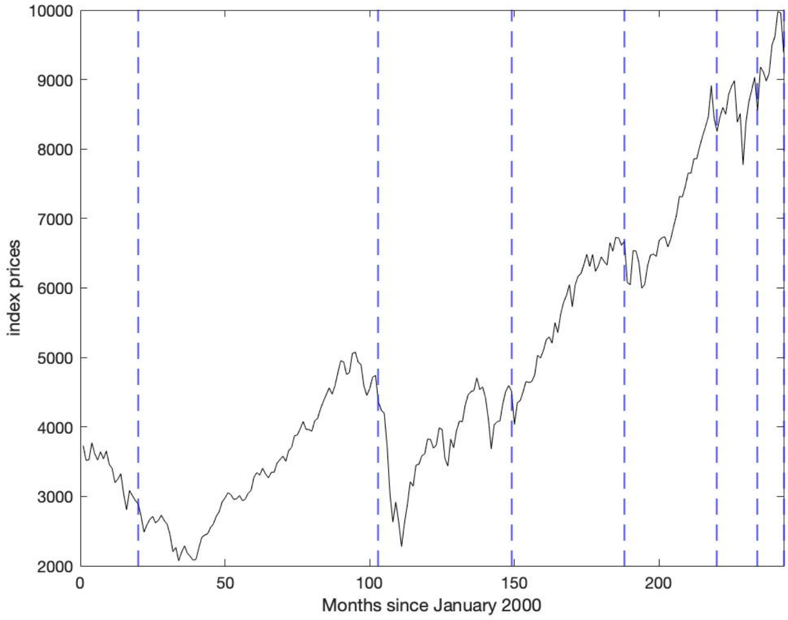

Figure 6: Times exiting the market using a 24 months rolling window

The figure above shows the number of times the implemented strategy tells the investor to exit the market with the maximum ΔAR on a rolling window of 24 months as threshold. Meaning the period that equation 1 has to satisfy is rolling over time. This allows to spot a single spike in the ΔAR as signal on a short-term period. The underlying assumption being that big crashes occur not as frequently and no more than once every two years. After having triggered the exit rule, only an even bigger move in ΔAR could lead to a new exit if the market has been re-entered. We observe that this strategy leads to exit the equity market 8 times, namely during the dot-com crisis (beginning of 21th century), the 2008 financial crisis, the Greek debt crisis (2012), the European debt crisis (2015) and most recently the Covid-19 pandemic crisis (2020).

Table 2: Number of time exiting the market

Rolling window	$n_{exit,w}$
w=6 months	21
w=12 months	14
w=24 months	7
w=48 months	4

The table above 2 shows the number of times that an investor would exit the market using the described strategy with respect to different rolling window periods. The longer the rolling window, the higher the spikes in the ΔAR will need to be to exceed the threshold.

Now that a way has been found to accurately estimate the time to leave the market, how does one know when it is time to reinvest. As the AR is constantly increasing due to the ghost effect, it is difficult to measure if it has recovered from the most recent spike due to the draw-down. Since we need to stick to the 10 years rolling window, an alternative approach is to set arbitrary time frames to re-enter the market. The idea is that the investor will, each time he exits the market, wait the same amount of time until he invests again. The underlying assumption is that so called bear markets last for about one year on average. Such a strategy is very simple and proves to be appropriate for big draw-downs like the 2008 financial crisis, but less beneficial for smaller crashes. Therefore we test different exit periods such as 4, 8 or 12 months. Then we determine which period is the best suited based on the empirical data according to risk management measures.

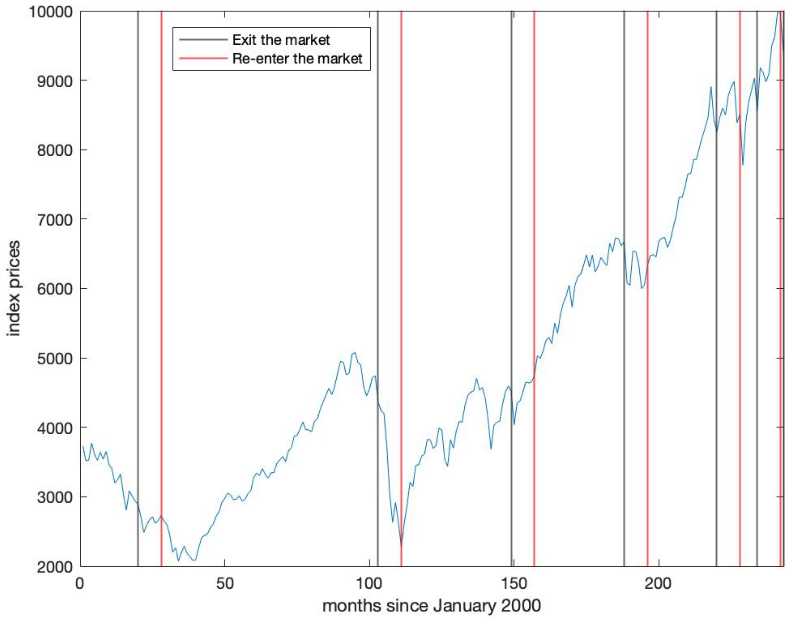

Figure 7: Exiting/Re-entering the market

Figure 7 shows the time period, that will be named τ, where the agent is not invested in the stock market for a period of 8 months. At glance, one can see that each black line is followed by a fall in the market price and an increase in volatility. However, it can be observed that the point in time of re-entering the market does not always results in 'buying the dip' which corresponds to perfect market-timing after a crash. As discussed before, the down-side of waiting a fixed amount of time after exiting is not always advantageous for the investor, because not all crises have the same length. However, when a spike in ΔAR occurs, it is assumed that the investor following this strategy does not have additional information at the time to estimate the magnitude of a potential future market crash. Thus, for risk averse investors, to exit the stock market for a fixed period of time is assumed a safe strategy.

5 Results and Interpretation

In this section, the most important results are presented and analyzed. The illustrations will be based in particular on the number of exits and entries into the market and the performance of the strategy from a risk point of view. Additionally we analyze the effectiveness of the AR in correctly forecasting a market draw-down. Finally, alternatives for the period not invested in the stock market will be proposed. Let's first take a look at the distribution of the monthly returns of the MSCI world index and its worst draw-downs (DD) between 2000 and 2020.

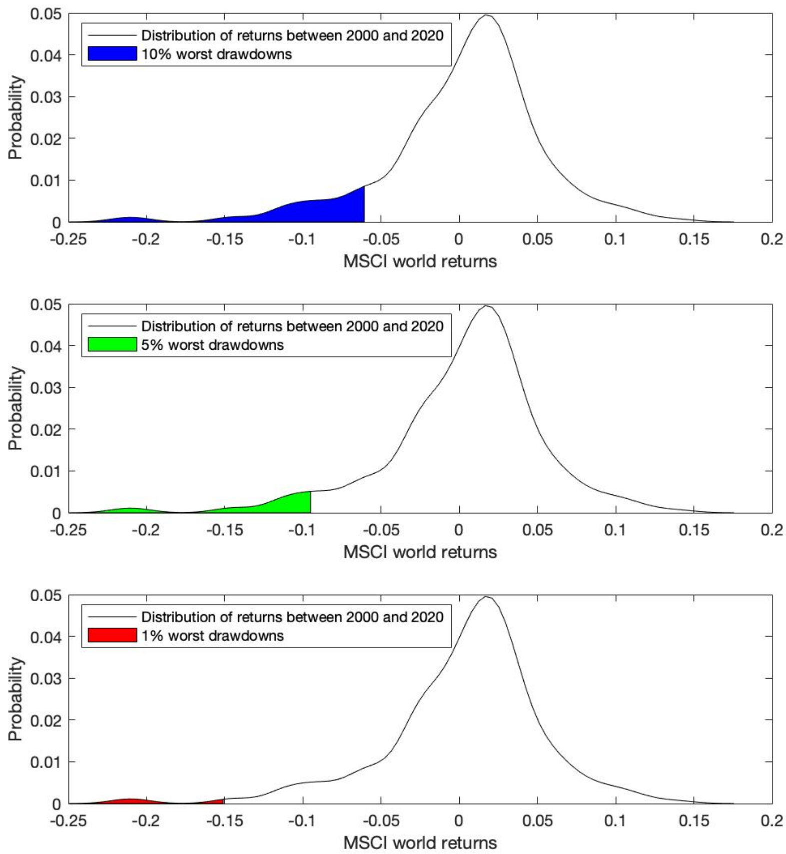

Figure 8: Distribution of the MSCI World monthly returns and the 1%, 5% and 10% worst draw-downs

Table 3: Worst 1, 5 and 10% draw-downs

Percentile	Returns	n_{DD}
1%	-14.90%	2
5%	-9.14%	13
10%	-5.89%	26

The table above shows how many times the respective percentile has been exceeded for the 1%, 5% and 10% worst monthly returns. In fact this represents the empirical value at risk of the MSCI world.

5.1 Anticipating draw-downs

This section is analyze the impact of some variables such as the rolling window period "w" of 1 and the period of being not invested. For that purpose three computation methods will be introduced:
-% of anticipated draw-downs
-Anticipation efficiency
-Opportunity costs

5.1.1 Percentage of anticipated draw-downs

We define the % of anticipated draw-downs (ADD) as the percentage of draw-downs (10%, 5%, 1% worst) that one is avoiding by using the strategy defined in the previous section. Tables 3 gives us the number of draw-downs for each percentile that occurred between 2000 and 2020 for the MSCI World index. It is computed as followed:

$$ADD_{x\%,\tau,w} = \frac{\sum 1_{\{r_t \leqslant q_{x\%}\}} 1_{\{t \in (t_{exit};t_{exit+\tau})\}}}{\sum 1_{\{r_t \leqslant q_{x\%}\}}}$$

Where :

$$1_{\{x\}} = \begin{cases} 1 & \text{if condition x true} \\ 0 & \text{else.} \end{cases}$$

And r_t is the log-return of the MSCI world at time t and $q_{x\%}$ represent the quantile at x% of the MSCI world index returns. Furthermore, t_{exit} and $t_{exit+\tau}$ represent the times when one exits and enters the market respectively. Thus, τ corresponds to the period when one is not invested in the stock market after a spike in AR.

Table 4: % anticipated draw-downs for w=12

Out-market period (τ) $\longrightarrow$	**4 months**	**8 months**	**12 months**
$ADD_{1\%}$	50%	50%	100%
$ADD_{5\%}$	33.33%	25%	58.33%
$ADD_{10\%}$	32%	40%	60%
% of time out of the market	22.39%	41.79%	49.25%

Table 5: % anticipated draw-downs for w=24

Out-market period (τ) $\longrightarrow$	**4 months**	**8 months**	**12 months**
$ADD_{1\%}$	50%	50%	100%
$ADD_{5\%}$	25%	41.67%	58.33%
$ADD_{10\%}$	16%	36%	48%
% of time out of the market	10.45%	20.90%	31.34%

In table 4 and 5 the percentages of draw-downs are shown which the strategy previously presented is actually anticipating and avoiding. It also shows the relative time one would not be invested in the stock market over the whole observation period depending on the actual length of the period he is leaving such that:

$$S_{w,\tau} = \frac{n_{exit,w} \times \tau}{m}$$

where $n_{exit,w}$ is the number of times exiting the market as defined in table 2 and τ the period where the investor is not invested in the stock market is defined through figure 7. "m" is the number of months from the analyzed period. The longer the investor remains not invested, the higher the percentage of draw-downs which can be avoided. However, one has to take into account the efficiency of his exit and the opportunity costs of leaving the market. Therefore, two more measures will be presented in order to determine the efficiency in anticipating draw-downs due to a spike in the AR.

5.1.2 Anticipation efficiency

We define the anticipation efficiency (AE) as followed:

$$AE_{\tau,x\%,w} = \frac{ADD_{x\%}}{S_{w,\tau}}$$

It represents the percentage of draw-downs that have been anticipated over the time fraction the investor is not invested in the stock market. The more accurate an investor's market-timing, the higher the AE ratio. This measure depends on the quantile $x\%$ of draw-downs avoided, the rolling window period for the analysis of AR spikes and the length τ of the period being not invested in the stock market. For comparison, we use the weighted average of the AE which is computed using the n_{DD} from table 3.

Table 6: Anticipation efficiency for the rolling window of 24 months

Out-market period (τ) $\longrightarrow$	**4 months**	**8 months**	**12 months**
1% worst DD	4.34	2.17	2.89
5% worst DD	2.17	1.81	1.69
10% worst DD	1.39	1.56	1.39
Weighted average	1.72	1.67	1.53

Table 7: Anticipation efficiency for the rolling window of 12 months

Out-market period (τ) $\longrightarrow$	4 months	8 months	12 months
1% worst DD	2.03	1.08	1.84
5% worst DD	1.35	0.54	1.07
10% worst DD	1.3	0.87	1.10
Weighted average	1.35	0.80	1.13

In tables 6 and 7, one can see that the most efficient combination of variables to analyze the ΔAR is a 2 years rolling window period and τ=4 months, the period an investor should leave the market after a spike, maximizing the AE.
The table must be read such as: If one use w=24 and τ=4, he will anticipate 2.17% of the worst 5% draw-downs ($ADD_{x\%,\tau,w}$) per percent an investor will stay away from the market ($S_{w,\tau}$).

5.1.3 Opportunity costs

One would also be interested into what are the cost in term of returns from exiting the market at certain time and for a specific period.

Table 8: Average monthly return and volatility of the MSCI world index while not invested

	w=12 months		w=24 months	
τ	**Return**	**Annualized volatility**	**Return**	**Annualized volatility**
4 months	0.13%	19.05%	-0.69%	24.98%
8 months	0.18%	18.29%	0.22%	21.75%
12 months	0.30%	17.36%	0.50%	19.99%

Above table 8 presents the average monthly returns of the MSCI world index during the period not invested in the equity market based on the strategy. Once again, w=24 and τ=4 seem to be the best combination of variables to implement the strategy. Indeed, the return of the MSCI world are negative which means one had not missed anything by not being invested. Also, the avoided volatility is the highest compared to any other combinations.

5.2 Alternatives to not being invested

In this section we propose different alternatives to the stock market during draw downs. Once the stock market has been left based on a spike in the AR, alternative assets like gold, treasury bonds or even safe haven currencies could outperform in the short run and most importantly reduce the portfolio volatility by avoiding extreme losses.

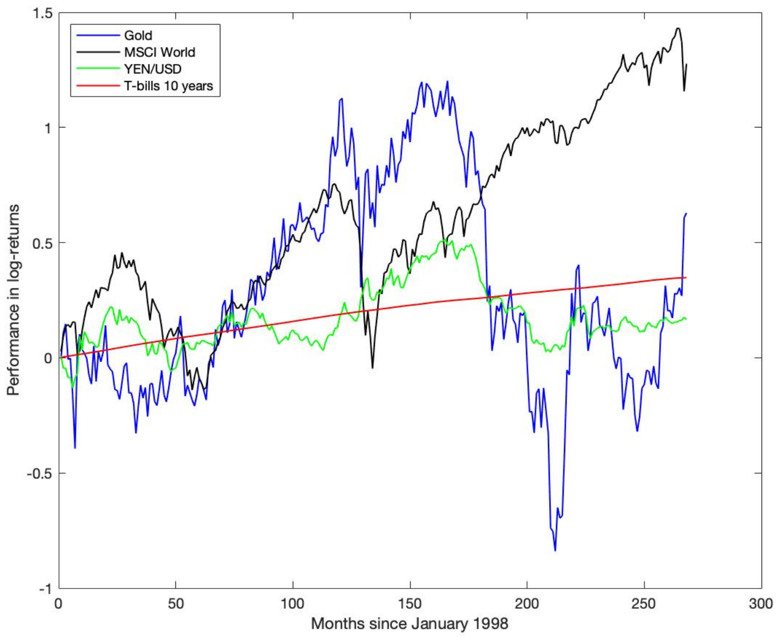

Figure 9: Overall performance since January 1998

The figure above shows the cumulative performance of the MSCI world compared to three alternative assets, namely gold, YEN/USD and 10 year US T-Bonds. By involving different alternative investments into our strategy, the idea is to switch into another asset class if the MSCI world does not perform well. The different properties of these assets have a direct impact on the risk adjusted performance. Next, we analyse which one among these three assets could be the best solution to invest in while we are not invested in the MSCI world index. The intuition behind choosing safe haven assets is their low correlation with respect to equities in general and especially during market turmoils.

5.3 Risk measurement

In order to evaluate the strategies from a risk management perspective, the value-at-risk (VaR) and expected shortfall (ES) are computed by using the actual empirical out-of-sample returns. Since there are several severe crisis in the observation period the distribution of returns has not to be modeled or estimated. The table below shows the different VaR for the strategy chosen by using a rolling window of 24 months to determine the spikes in the AR following a period of 4 months not invested in the market, but in the alternative asset. The monthly VaR is computed for the 1%, 5% and 10% percentile.

Table 9: Monthly Value at Risk

Value at Risk	1%	5%	10%
MSCI	-14.55%	-9.11%	-5.75%
10Y-US-T.	-11.26%	-7.82%	-4.21%
YEN	-11.26%	-7.82%	-8.38%
Gold	-15.72%	-9.12%	-4.66%

If one would have stayed invested in the MSCI world index the VaR over the last 20 years was about -15% on a 1% level. The strategy with alternatively investing in 10 years US-Treasury bonds during the period not invested in the stock market, performs better especially towards the end of the tail with a 1% VaR of about -11%. This strengthens the hypothesis that our strategy works avoiding extreme losses given the chosen lengths for the rolling window as well as the 4 month period not being invested. Surprisingly, a safe haven currency like the Japanese YEN does not perform better than the 10 years US-Treasury bond and has very similar values. This is due to the low volatility of the JPY and a risk free treasury bond compared to stocks. The big losses driving the VaR come from the same underlying namely the MSCI world index. Thus risk measures as the VaR and the ES for a strategy using a low risk alternative investment during the period not invested, will always be quite close. On the other hand this shows that although gold is considered to be a safe haven as well, it is very volatile. The monthly VaR at the 1% percentile for the strategy using gold as an alternative investment is even higher than the one of the MSCI world. Our hypothesis that switching to gold might lead to overall lower volatility has been disproved.

Table 10: Monthly Expected Shortfall

Expected Shortfall	1%	5%	10%
MSCI	-21.02%	-13.08%	-10.14%
10Y-US-T.	-14.45%	-10.54%	-8.32%
JPY	-14.45%	-10.54%	-8.38%
Gold	-31.98%	-14.83%	-11.06%

A similar pictures arises when comparing the ES. The gap between the different alternative investments is even wider for the ES. Over the whole observation period, the MSCI world index had a monthly ES of 21% at the 1% level. The strategy involving gold, however, an ES of about 32% for the same level. This further highlights the volatility of commodities even if gold is considered a safe haven asset. An explanation for such a draw down considering gold as alternative might be, that as soon as the stock market bottomed out, gold prices tend to decrease again. The negative correlation between equities and gold can only be used to further reduce volatility with perfect market timing. Yet, the strategy with 10Y US treasury bonds or Japanese Yen performs clearly better than if one remains invested in the stock market.

5.4 Sharpe ratio and total performance

Switching from a risk management perspective only, to also considering the returns, one can look at the ratio of the excess return to the volatility of the different strategies (using w=24 and τ=4) also known as the Sharpe ratio. Clearly, the best option ex-post would be to invest in treasury bonds if one is not invested in the equity market. However, the gold, the yen and the treasury bond strategies are all more efficient than staying the whole time in a long position in the equity market. Which means that the timing strategy used is working in order to have better returns and avoid volatility.

Table 11: Annualized Sharpe ratio Ex-post with w=24 and τ=4

Strategy out-market	Annualized Sharpe ratio
MSCI	0.2139
10Y-US-T.	0.3668
JPY	0.2680
Gold	0.3047

In the figure below, it can be noticed that the total performance of the gold strategy is more profitable compared to the others. As stated above, this is just compensation for the additional risk, volatility involved. In terms of the Sharpe ratio, the three strategies are quasi-equivalent and dominate the MSCI world.

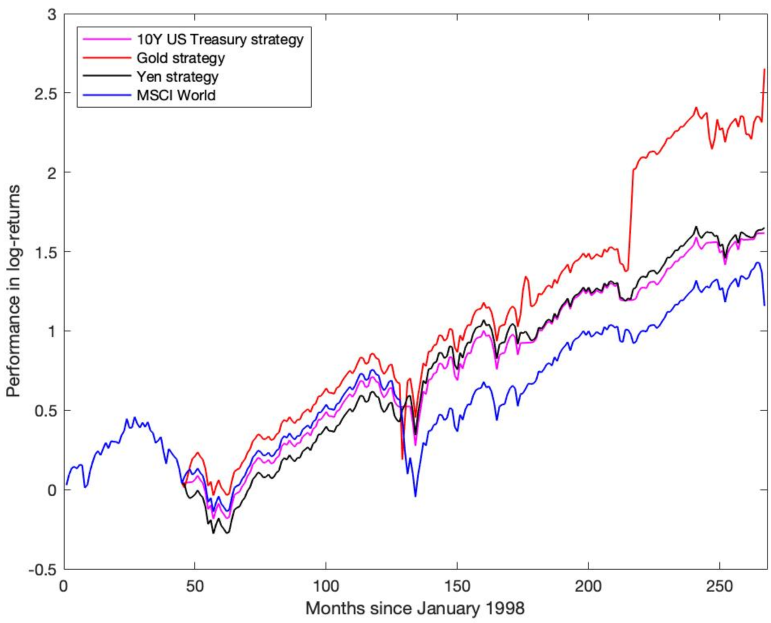

Figure 10: Overall performance of the strategies since January 1998

6 Conclusion

We want to summarize the key insights of this project in two parts. The first one focuses on the AR being an appropriate measure of systemic risk. The second one elaborates the performance and adequacy of the implemented risk management strategy.

By performing a PCA to evaluate systemic risk in global equity markets, we have shown using a 10 years rolling window that the level of systemic risk keeps increasing since the beginning of 1998. By taking the first 5 factors to define the AR between 60% and 80% of the total variance is captured.

Using the AR as indicator for a risk management strategy in order to time the market is a efficient way to reduce extreme losses. The alternative approach to Kritzman et al. (2010) compares the AR on a 10 years rolling window basis to the maximum over the past 24 months. Since we are focusing only on the draw downs the exiting criterion can vary, but the reentering time after 4 months is fixed and maximizes the anticipation efficiency. The strategy outperforms the MSCI world index on a risk adjusted measure, regardless of the alternative investment during the period not invested in the stock market. Although gold is considered a safe haven, it has been proven not to minimize the risk of the strategy, but in fact to even increase it. The benefit of safe haven currency like the JPY is about the same as if investing in 10 years US treasury bonds. To conclude, a strategy investing only into one asset class and market timing using the AR as crash predictor leads to better risk adjusted performance in our observation period.

6.1 Differences to original paper

Before turning to a critical reflection of our project, we want to highlight the differences to the original underlying paper of Kritzman, Li, Page, and Rigobon (2010). The time period analyzed in their paper covers the years from 1997 to 2009, by using daily returns however. This allows them to use a much shorter rolling window for their PCA (500 days) where as we use one of 10 years with monthly returns up to 2020. We find similar results for an increasing AR over time. Our strategy differs by using the maximum of a change in AR over a short period compared to the maximum over a longer horizon. Kritzman et al. (2010) use a the standardized difference in moving averages between a long and a short time horizon. Because the primary purpose was not to find the bottom after crashes, but more from a risk management point of view to avoid extreme losses more weight has been put on the strategy for exiting the critical periods. Moreover, Kritzman et al. (2010) showed that using the AR for reentering the market had less accuracy than for leaving it.

6.2 Critical Reflection

Our analysis is based on some strong assumptions like the following ones:
-No market friction: Investors can buy and sell any fraction of assets.
-No transaction costs: Asset turnover does not reduce the portfolio performance.
-No taxes and no inflation rate: The taxes and inflation does not reduce the performance of a portfolio.

Also, a portfolio consisting of only one asset class might be suitable for illustration, but is far from reality. Therefore, a strategy involving the AR for adjusting portfolio weights in different asset classes might be more realistic. Another approach might be to hedge using futures after a spike in the AR.