Vignette

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2/19/2017

Literature Review

High Returns from Low Risk By Pim van Vliet and Jan De Koning

One of the most widely believed tenants of finance is the concept that with more risk comes more reward. However, looking at historical market returns, this does not appear to be the case. Over an 86-year period from 1929, low volatility stocks outperformed high volatility stocks by a factor of 18. If both portfolios started off with the same $100, the low volatility portfolio end value would be $395,000, while the high volatility portfolio would be worth just $21,000. Low risk stocks returned 10.2% annually whereas the high risk stocks returned just 6.4% annually. This difference of 3.8% is striking, and presents an anomaly in the field of finance.

This begs the question of how a portfolio of lower volatility stocks can outperform higher volatility stocks over a long period of time. The primary way this occurs is that the low volatility portfolio loses less during times of financial stress. For example, in 1932 following the Great Depression, it was observed that the high volatility portfolio shrunk from $100 in value to $5 in value, while the low volatility portfolio shrunk from $100 to $30. Since the low volatility portfolio is able to lose less money, it is able to grow capital more effectively than the high volatility portfolio. In this example, the annualized volatility of the low risk portfolio was 13%, and the annualized volatility of the high risk portfolio was around 2.5 times that, at 36%. In addition to being more risky, the high volatility portfolio was outperformed by 18 times.

Thus, it seems very counterintuitive that fund managers and investors would not only invest in low risk stocks. Part of understanding this comes from interpreting what risk is defined as in the financial community. Risk is not necessarily defined as losing money, as it may be for an individual, but instead underperforming a benchmark. Volatility is also an important concept to understand. Volatility is an important measure of financial risk, as it comes from the price fluctuations of a stock or investment. Volatility is also one of the best indicators of bankruptcy. Taking some risk does pay off, as the relationship between risk and return starts off slightly positive before leveling off and becoming negative. Many researchers focus on short-term periods when analyzing stock returns instead of longer term for a couple of reasons. The first reason many focus on "single period returns", which in most academic studies is just a one month period, is because this takes away the significance of compounding. The longer the investment period, the more risk one takes in hurting long term returns through compounding. By not fully including the magic "return upon return" effect of compounding, a high-risk portfolio in this book performs more than 6% better per year. For example, if in month a portfolio worth $100 drops 50% to $50, then the next month increases 50% to $75, the investment return is dependent on how one divides the time period. Looking at it on a monthly basis, even though the portfolio lost $25, the net return would be -50% +50%, or 0%. Looking at it on a long term basis, the net return was -25%.

David Blitz, the head of quantitative equity research at Robeco, discusses this different perspective as somewhat due to the need to benchmark the performance of an investment manager. This is a concept known as "relative" risk. In the examples above, everything has been in respect to absolute risk - that is how much money is being gained or lost due to overall stock movements, with regard to the starting amount of money invested. Volatility, in itself, captures these changes in the price of a stock, and is an absolute risk measurement. Many institutional investors do not look at risk on an absolute level, as a retiree or mom and pop investor may, but instead look at the risk of a portfolio with respect to market or some other widely accepted benchmark. For these investors, the risk is not as much about losing money, rather is more about lagging the market or their peers. Investing is very much a relative game. If a portfolio drops 20% while the market drops 40%, this is seen as a much better outcome than if a portfolio goes up 20% while the market goes up 40%. Thus, a portfolio that moves closely with the market has a very low relative risk. This risk can be calculated as volatility by looking at the relative price movements, instead of the absolute price movements.

Investment professionals focus on relative risk for a number of reasons, one of which is the fact that they are not managing their own money. They need to prove to their bosses and clients that they are above average in their job. If a particular benchmark cannot be beaten by these investors, clients may ask why pay for them to manage their money when they could put it in a low-fee or no-fee mutual fund. This is one of the reasons that institutional investors need to compare their performance to some benchmark. Thus, the focus for investors is return and relative risk. Adding low risk stocks to the portfolio causes relative risk to increase a lot, making it an unappealing investment because low absolute risk inherently causes high relative risk. A low risk portfolio only makes sense if absolute risk is what one cares about. Thus, for those investors who don't care about relative risk and just absolute risk, low risk stocks are a great investing opportunity.

In addition to the reasons mentioned, there are several additional reasons why some investors are not attracted to low-risk stocks. Eric Falkenstein, a renowned author in the low volatility investing realm, wrote that "envy is at the root of the investment paradox." Some investors don't recognize the significance of compounding returns. Others do, but are unable to utilize the paradox due to relative risk and career pressures. Analysts who choose big winners are more likely to get recognized than those who pick safer stocks with lower upside potential, and funds that pick the right high risk stocks also see more reward in an increase in AUM. Moreover, some people do not invest in low risk stocks because they have less appeal of high risk stocks, where they think they can make money easily and quickly. These high risk stocks are more "sexy" and have a "lottery ticket" element that attracts investors with the appeal of a big payday.

Betting Against Correlation: Testing Theories of the Low-Risk Effect

A recurring phenomena in finance, is the observation of the "low-risk effect." This is the idea that lower risk or lower volatility stocks, tend to have higher alpha than higher risk or higher volatility stocks. In trying to understand the reason this anomaly occurs, are two possible explanations. The first looks at at whether this is caused by leverage constraints, meaning measurement using systematic risk. The second focuses on the behavioral effects, or idiosyncratic risks. One of the main issues with prior research, is that a lot of the low-risk factors are correlated and interrelated, making it hard to isolate certain factors or effects. In this paper, the global data was used, with a couple new factors meant to control for existing factors.

Previous studies, like one by Adrian, Etula, and Muir in 2014, showed a link between return to the BAB (Betting Against Beta) factor and financial intermediary leverage. Many of these factors, though, including BAB, generally exhibit the "low-risk effect" and are thus very hard to differentiate between. Thus, this paper decided to do just that, by breaking down BAB into two other factors: betting against correlation (BAC) and betting against volatility (BAV). BAC is accomplished through longing stocks with low correlation to the market, and shorting those with high correlation to the market, while trying to match the volatilities of both the long and short portfolios. BAV is achieved in a similar manner, except instead of longing and shorting correlation, volatility is used, and correlation is kept constant.

To address the behavioral explanation, the paper looks at some prior factors from studies done by Ang, Hodrick, Xing, and Zhang in 2006 and 2009. The first study found stocks with low idiosyncratic volatility (IVOL) have a greater risk-adjusted return, while the second found that a low maximum return (LMAX), a measure of idiosyncratic skewness, is associated with greater risk-adjusted returns. This paper kept the focus on LMAX and IVOL, but added another factor, scaled MAX (SMAX), which longs stocks with a low MAX return divided by ex ante volatility, and then shorts stocks with a high MAX return divided by ex ante volatility. This focuses on the lottery demand, holding volatility relatively constant and only focusing on the distribution of the returns. Margin debt held by investors, and investor sentiment were also noted.

In the paper, 58,415 stocks from the MSCI World Index, from 24 countries between January 1926 and December 2015 were covered. BAB and BAC ended up being very successful in controlling for the other factors that could influence the "low-risk effect." For all stocks, the BAC factor produced a significant six-factor alpha that was nearly independent of the other low-risk factors studied. In terms of explaining the behavioral side with factors, SMAX was the only truly great, resilient measure used. The rest generally had higher turnover, and were consequently very susceptible to microstructure noise. SMAX attained positive risk-adjusted returns in the U.S. but negative risk-adjusted returns globally, which was seen with some other idiosyncratic risk factors. The paper showed that systematic low-risk factor generally tended to outperform behavioral risk factors, especially when considering turnover and time period length. All in all, the low-risk effect was believed to be driven by multiple factor effects, meaning both leverage constraints and the demand for lottery could play a role in effecting this. However, leverage constraint effects were a bit stronger, especially internationally.

Price Response to Factor Index Additions and Deletions

Some of the driving fundamental assumptions of finance is the flat demand curve for stocks, where risk is the main driver and each stock has a perfect substitute. However, this concept has been questioned for the past few years, with literature picking up on stocks with show supply shocks and checking how this affects their price. The literature has shown several instances where large block sales of stock has negatively affected its price. This was often due to information contamination, which is new, significant information about the company in the market. This information often reflects fundamental changes in the company, and if is is negative, will understandably trigger block sales. Thus, the price change is less due to the supply shock, and moreso due to the fundamental change in the company's value (like a scandal or earnings report).

However, interesting patterns that have not yet been fully explained have been observed regarding S&P 500 company addition and deletions. When companies are added or removed from the index, it is purely mechanical, and usually not due to some drastic fundamental change in the company. Assuming the market is efficient, the demand for stocks should not change due to being added or removed from an index, but several studies have shown that it does. Harris and Gurel (1986), Shleifer (1986), Beneish and Whaley (1996), Chen, Noronha, and Singal (2004) all show how new additions to the S&P come with higher than normal returns for that company. Though they agree on the price movement, the studies tend to have a hard time agreeing on the reason for this price movement. Some possible explanations include compensation for providing liquidity, better monitoring for investors when a company is added to a reputable and large index, and higher analyst coverage leading to more information and analysis available on the company. One primary concern is whether or not index reshuffling is an information-free event - that is, whether a company being added or removed adds information to the market about the company.

In this paper, the authors look at factor index rebalancing for an information-free event. Factor indices are part of a parent index of many other stocks, and are constructed in a mechanical way that is publically available and usually based on ranking stocks off a particular ratio of characteristic. Looking at the MSCI Minimum Volatility index, stocks returns were recorded for the stocks that had been added/dropped. It was found that the cumulative return from announcement to the effective day was 1.07% for stocks added with a significant t-statistic of 7.16, with 62% of the stocks exhibiting a positive cumulative abnormal return. Of the 1.07% increase, 0.63% of it was gained the following day, indicating that a large part of the increase is from an increase in demand from index funds. 0.31% of the return is lost five days after the rebalancing, but generally the price tends to stabilize afterwards after ten days. Thus, 68% of the price increase is permanent, while the other 32% is temporary and lost after a few days. This can be due to a number of reasons including a liquidity premium charged by the stock's owner or arbitrage activity. Average trading volume was also significantly more for stocks that were recently added to the index. Between the announcement and actual day of adding the stock, the average trading volume was 30% higher than normal, with a significant t-statistic of 3.81. Moreover, there is a 74% increase in volume for the day prior to the actual adding of the security. A very similar phenomena occurs with stocks set to be dropped from the MSCI Minimum Volatility Index. From the announcement of a stock being dropped to the day before it is actually deleted from the index, the total cumulative abnormal return is -0.91%, and -0.57% of this comes the day right before. After the stocks are deleted, 64% of them have a negative return the following day, and only 0.49% of the -0.91% is regained after three weeks. Trading volume also spikes 46% on the day prior to removal from the index. After three weeks, it returns back to within 1% of the normal trading volume.

These findings imply that once a security is added to a factor index, the demand curve shifts to the right, moving the equilibrium. The trading volume change is likely due to index funds buying or selling massive amounts of the stocks that will be added or removed. Moreover, it was found that the amount of the return is also directly related to the weighting of the volume of stocks entering or leaving the factor index. All in all, these findings suggest an index arbitrage opportunity if the index additions or deletions can be predicted.

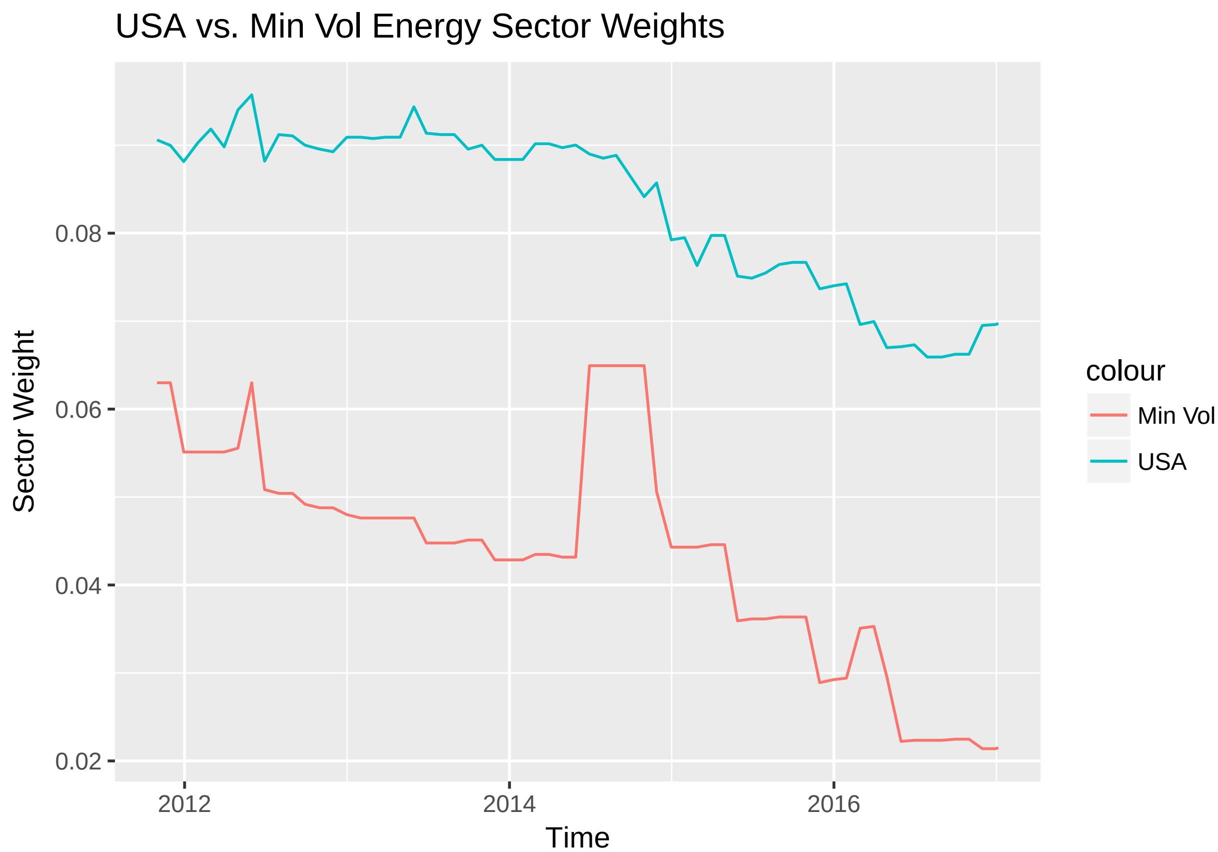
```r
library(mscidata)
library(ggplot2)
data(minvol_percent)
data(usa_percent)

## Summary statistics of EUSA Data
summary(usa_percent)
```

```
##                    sector_name  sector_count          total
##  Cash and/or Derivatives: 64   Length:832         Length:832
##  Consumer Discretionary : 64   Class :character   Class :character
##  Consumer Staples       : 64   Mode  :character   Mode  :character
##  Energy                 : 64
##  Financials             : 64
##  Health Care            : 64
##  (Other)                :448
##     percent             date
##  Min.   :0.00000   Min.   :2011-10-31
##  1st Qu.:0.01426   1st Qu.:2013-02-21
##  Median :0.06820   Median :2014-06-14
##  Mean   :0.07692   Mean   :2014-06-14
##  3rd Qu.:0.12236   3rd Qu.:2015-10-07
##  Max.   :0.19293   Max.   :2017-01-05
##
```

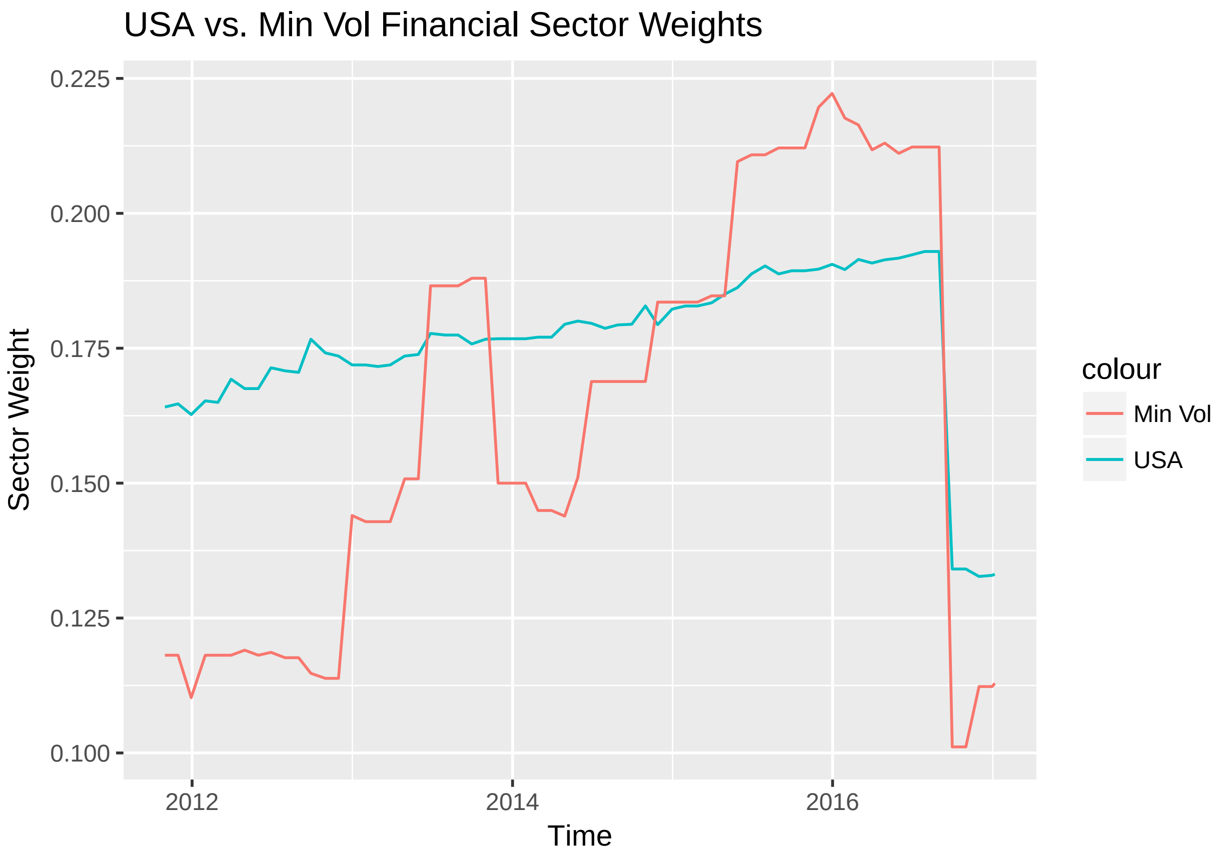
```r
## Summary statistics of USMV Data
summary(minvol_percent)
```

```
##                    sector_name  sector_count          total
##  Cash and/or Derivatives: 64   Length:832         Length:832
##  Consumer Discretionary : 64   Class :character   Class :character
##  Consumer Staples       : 64   Mode  :character   Mode  :character
##  Energy                 : 64
##  Financials             : 64
##  Health Care            : 64
##  (Other)                :448
##     percent             date
##  Min.   :0.00000   Min.   :2011-10-31
##  1st Qu.:0.02235   1st Qu.:2013-02-21
##  Median :0.06349   Median :2014-06-14
##  Mean   :0.07692   Mean   :2014-06-14
##  3rd Qu.:0.13043   3rd Qu.:2015-10-07
##  Max.   :0.22222   Max.   :2017-01-05
##
```

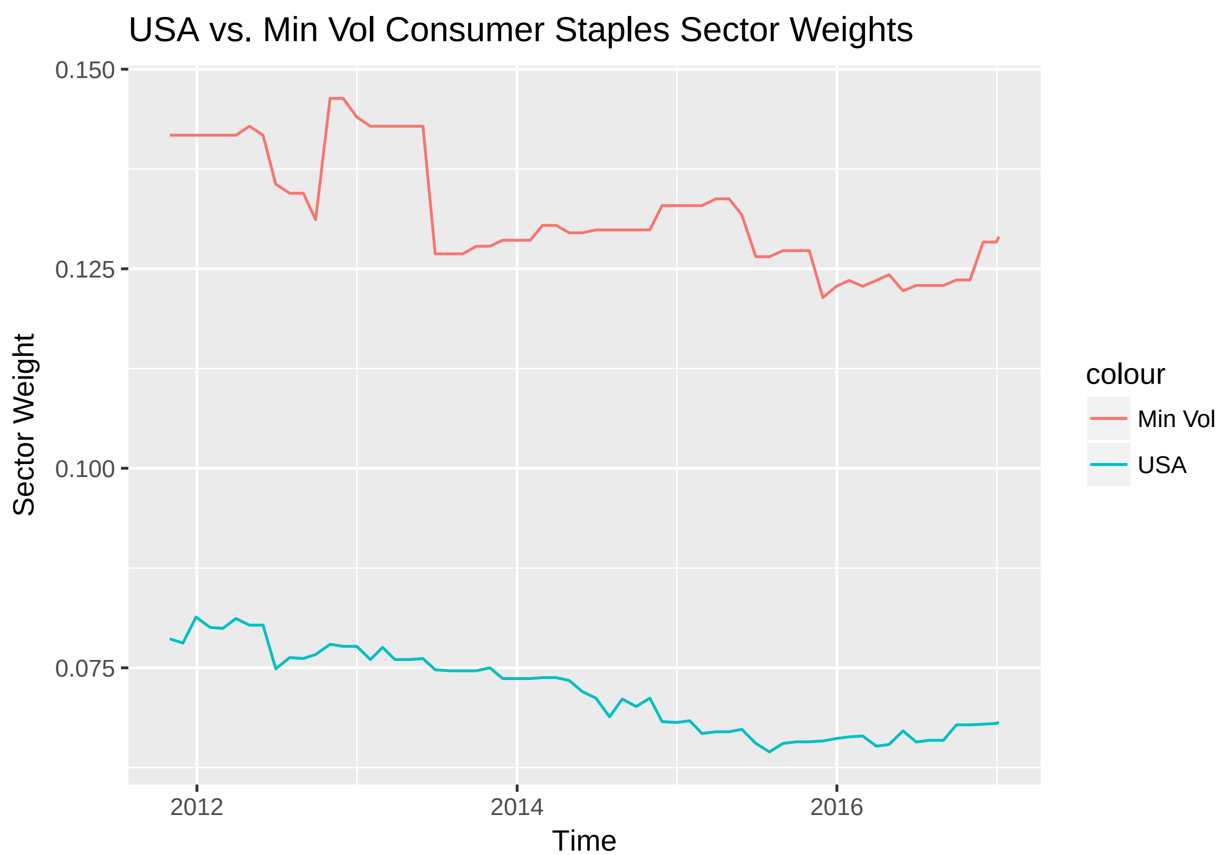
```
## Energy
Eng1 <- usa_percent[which(usa_percent$sector_name=="Energy"), ]
Eng2 <- minvol_percent[which(minvol_percent$sector_name=="Energy"), ]
ggplot(Eng1, aes(date, percent, colour = "USA")) + geom_line() +
ggtitle("USA vs. Min Vol Energy Sector Weights") + xlab("Time") + ylab("Sector Weight") +
geom_line(data = Eng2, aes(x=date, y=percent, colour="Min Vol"),show.legend = TRUE)
```



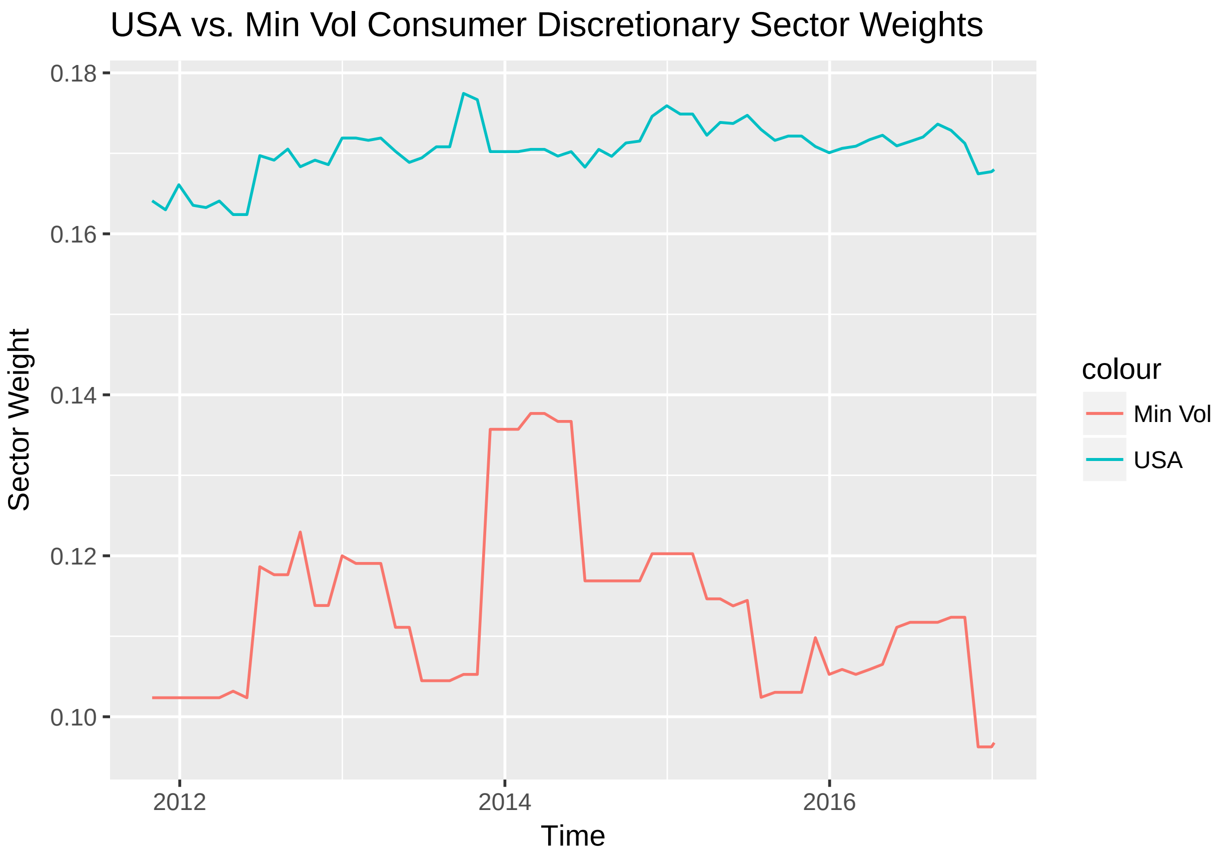

```
## Finacials
Fin1 <- usa_percent[which(usa_percent$sector_name=="Financials"), ]
Fin2 <- minvol_percent[which(minvol_percent$sector_name=="Financials"), ]
ggplot(Fin1, aes(date, percent, colour = "USA")) + geom_line() +
ggtitle("USA vs. Min Vol Financial Sector Weights") + xlab("Time") +
ylab("Sector Weight") +
geom_line(data = Fin2, aes(x=date, y=percent, colour="Min Vol"),show.legend = TRUE)
```



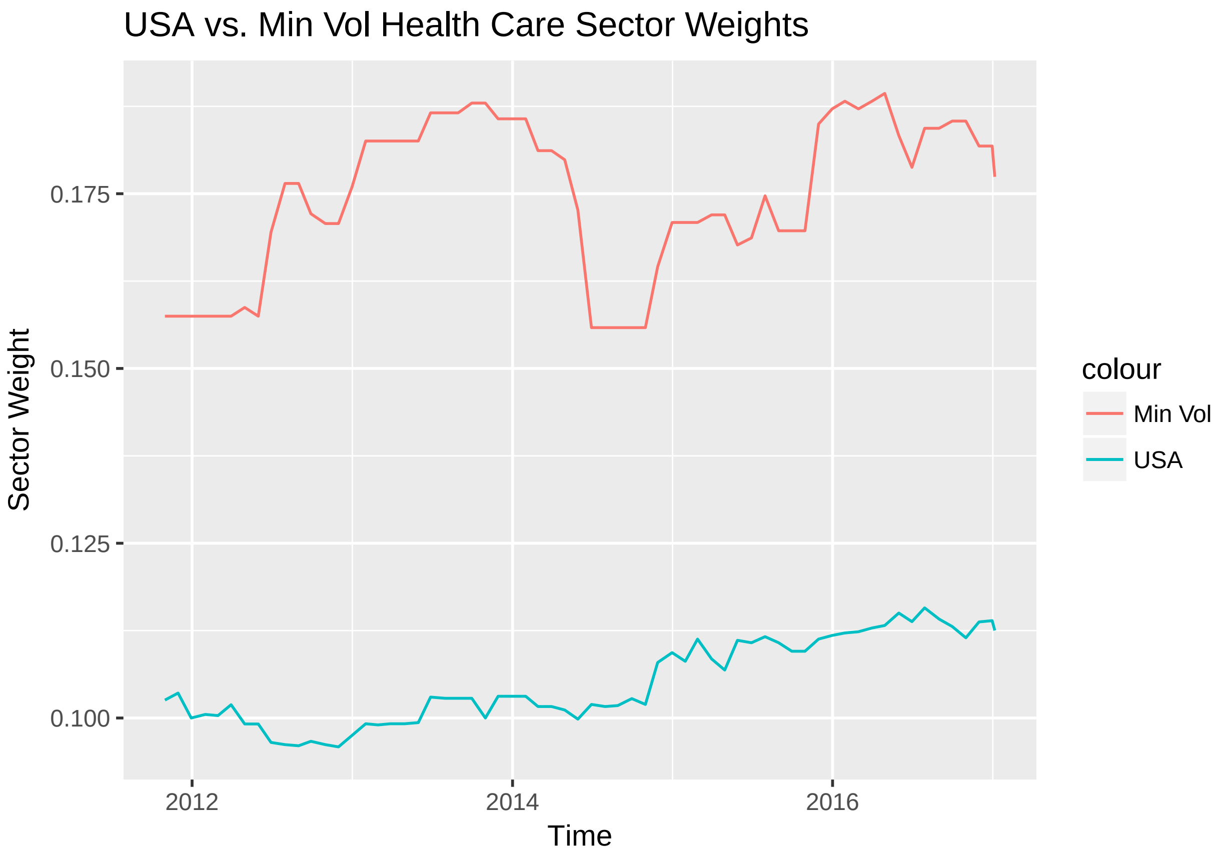

```r
## Consumer Staples
ConStap1 <- usa_percent[which(usa_percent$sector_name=="Consumer Staples"), ]
ConStap2 <- minvol_percent[which(minvol_percent$sector_name=="Consumer Staples"), ]
ggplot(ConStap1, aes(date, percent, colour = "USA")) + geom_line() +
ggtitle("USA vs. Min Vol Consumer Staples Sector Weights") + xlab("Time") +
ylab("Sector Weight") + geom_line(data = ConStap2, aes(x=date, y=percent,
colour="Min Vol"),show.legend = TRUE)
```



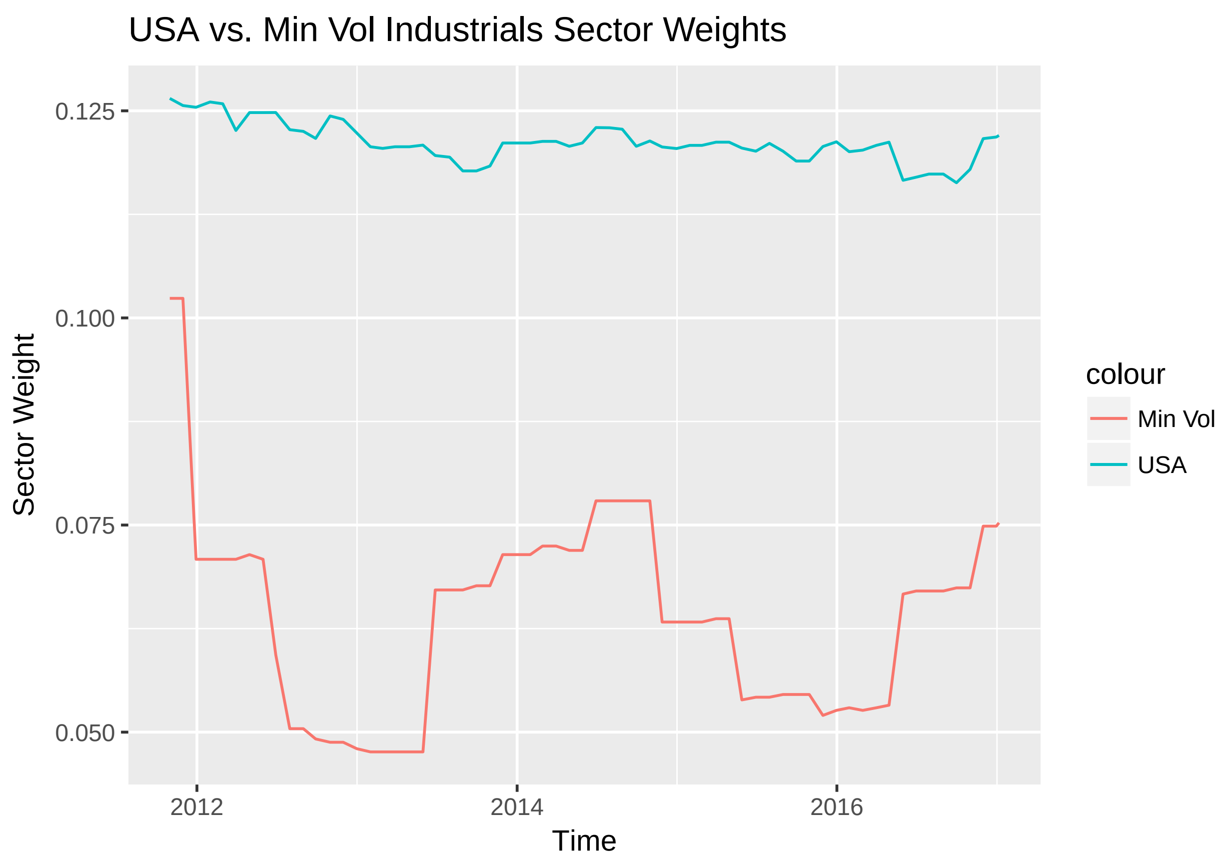

```
## Consumer Discretionary
ConDis1 <- usa_percent[which(usa_percent$sector_name=="Consumer Discretionary"), ]
ConDis2 <- minvol_percent[which(minvol_percent$sector_name=="Consumer Discretionary"), ]
ggplot(ConDis1, aes(date, percent, colour = "USA")) + geom_line() +
ggtitle("USA vs. Min Vol Consumer Discretionary Sector Weights") + xlab("Time") +
ylab("Sector Weight") + geom_line(data = ConDis2, aes(x=date, y=percent,
colour="Min Vol"),show.legend = TRUE)
```



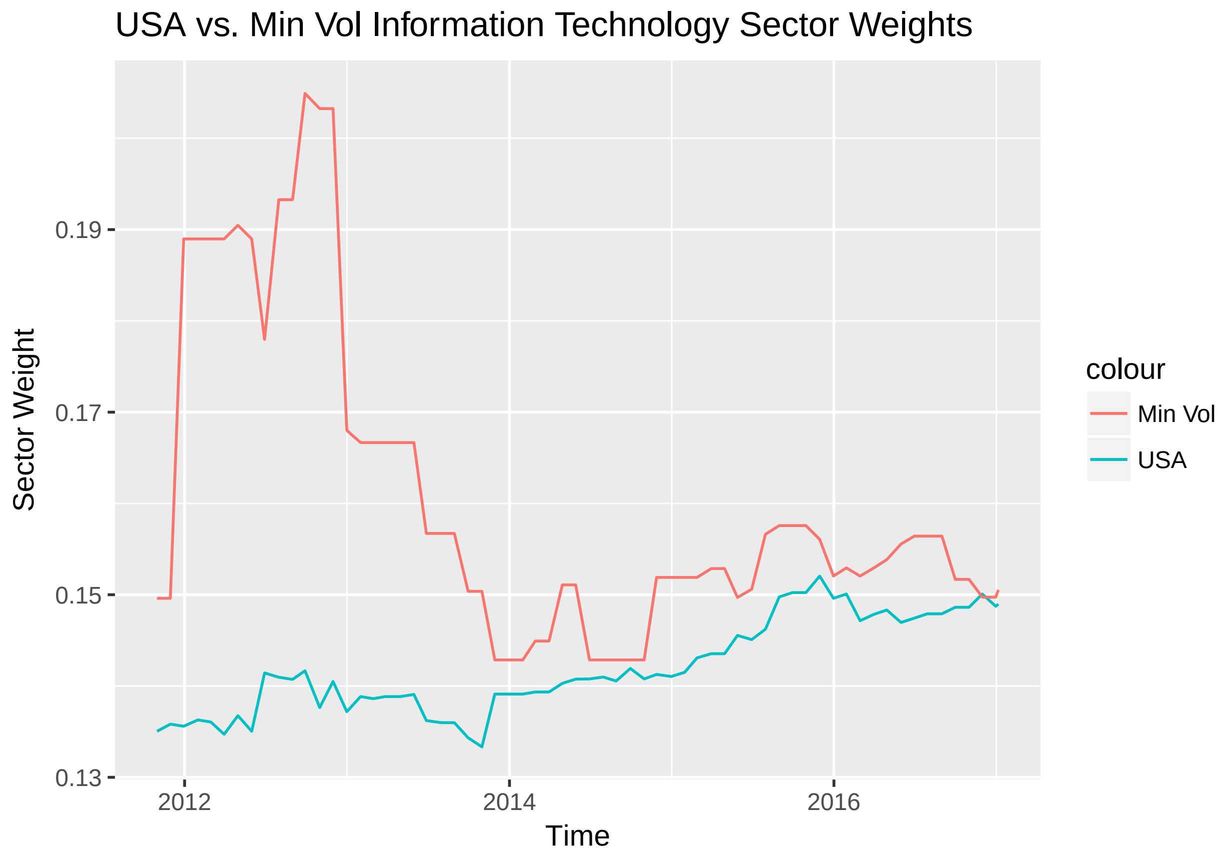

```
## Health Care
Health1 <- usa_percent[which(usa_percent$sector_name=="Health Care"), ]
Health2 <- minvol_percent[which(minvol_percent$sector_name=="Health Care"), ]
ggplot(Health1, aes(date, percent, colour = "USA")) + geom_line() +
ggtitle("USA vs. Min Vol Health Care Sector Weights") + xlab("Time") +
ylab("Sector Weight") + geom_line(data = Health2, aes(x=date, y=percent,
colour="Min Vol"),show.legend = TRUE)
```




```
## Industrials
Ind1 <- usa_percent[which(usa_percent$sector_name=="Industrials"), ]
Ind2 <- minvol_percent[which(minvol_percent$sector_name=="Industrials"), ]
ggplot(Ind1, aes(date, percent, colour = "USA")) + geom_line() +
ggtitle("USA vs. Min Vol Industrials Sector Weights") + xlab("Time") +
ylab("Sector Weight") + geom_line(data = Ind2, aes(x=date, y=percent,
colour="Min Vol"),show.legend = TRUE)
```

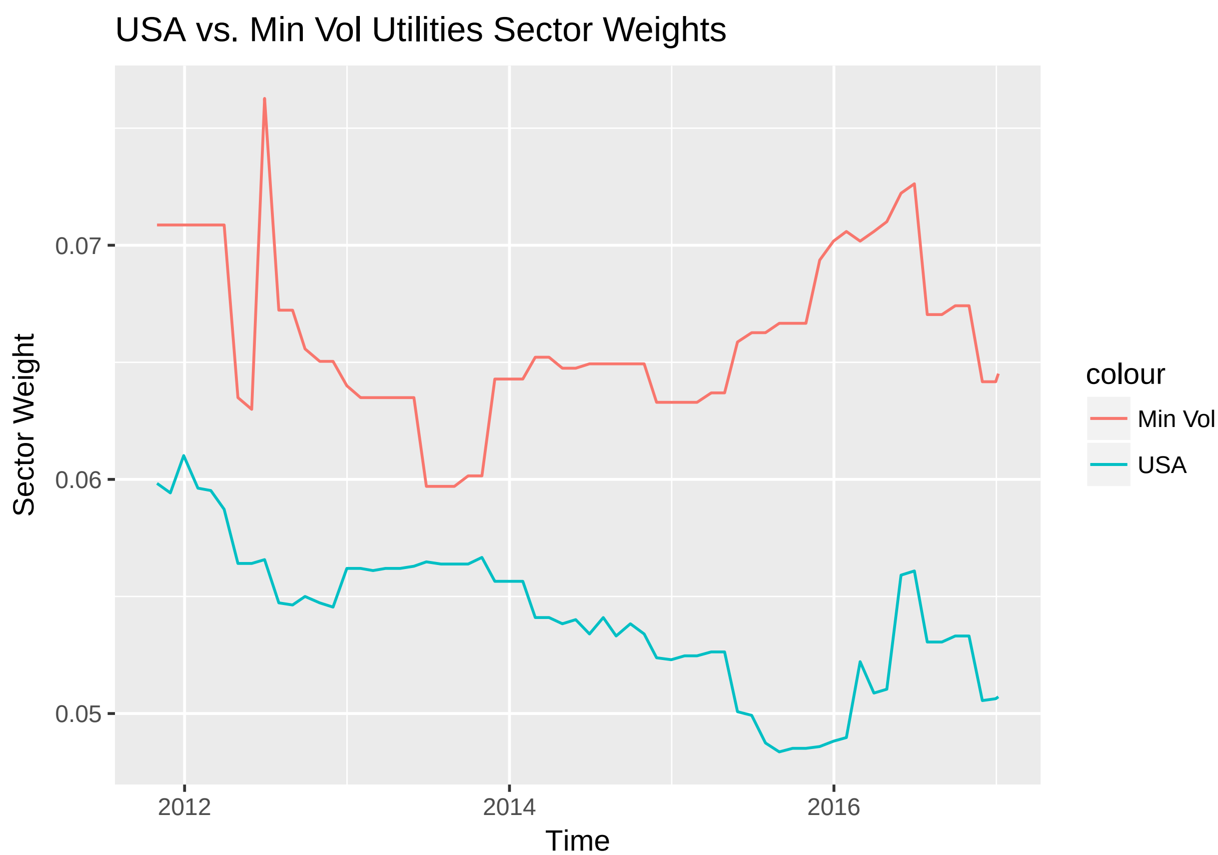



```
## Information Technology
IT1 <- usa_percent[which(usa_percent$sector_name=="Information Technology"), ]
IT2 <- minvol_percent[which(minvol_percent$sector_name=="Information Technology"), ]
ggplot(IT1, aes(date, percent, colour = "USA")) + geom_line() +
ggtitle("USA vs. Min Vol Information Technology Sector Weights") +
xlab("Time") + ylab("Sector Weight") + geom_line(data = IT2, aes(x=date, y=percent,
colour="Min Vol"),show.legend = TRUE)
```

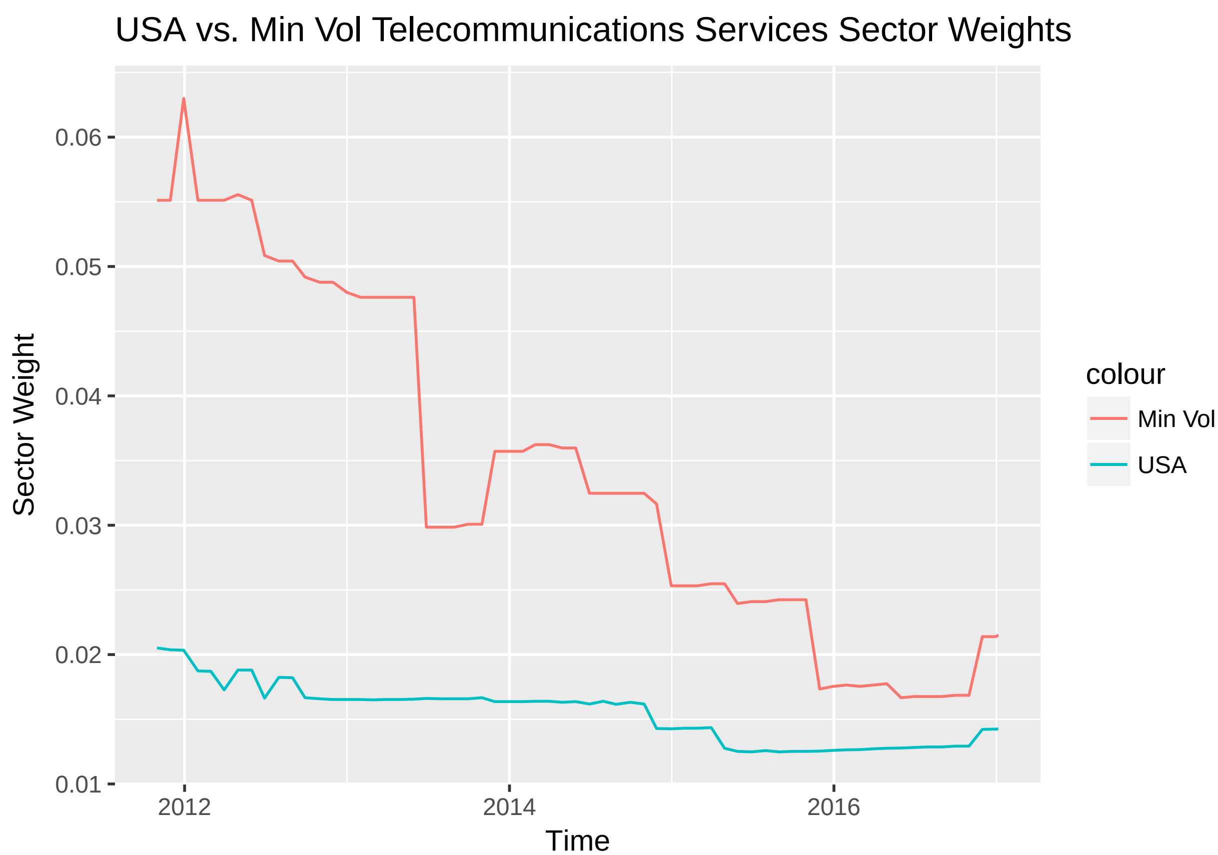



```
## Materials
Mat1 <- usa_percent[which(usa_percent$sector_name=="Materials"), ]
Mat2 <- minvol_percent[which(minvol_percent$sector_name=="Materials"), ]
ggplot(Mat1, aes(date, percent, colour = "USA")) + geom_line() +
ggtitle("USA vs. Min Vol Materials Sector Weights") + xlab("Time") +
ylab("Sector Weight") + geom_line(data = Mat2, aes(x=date, y=percent,
colour="Min Vol"),show.legend = TRUE)
```

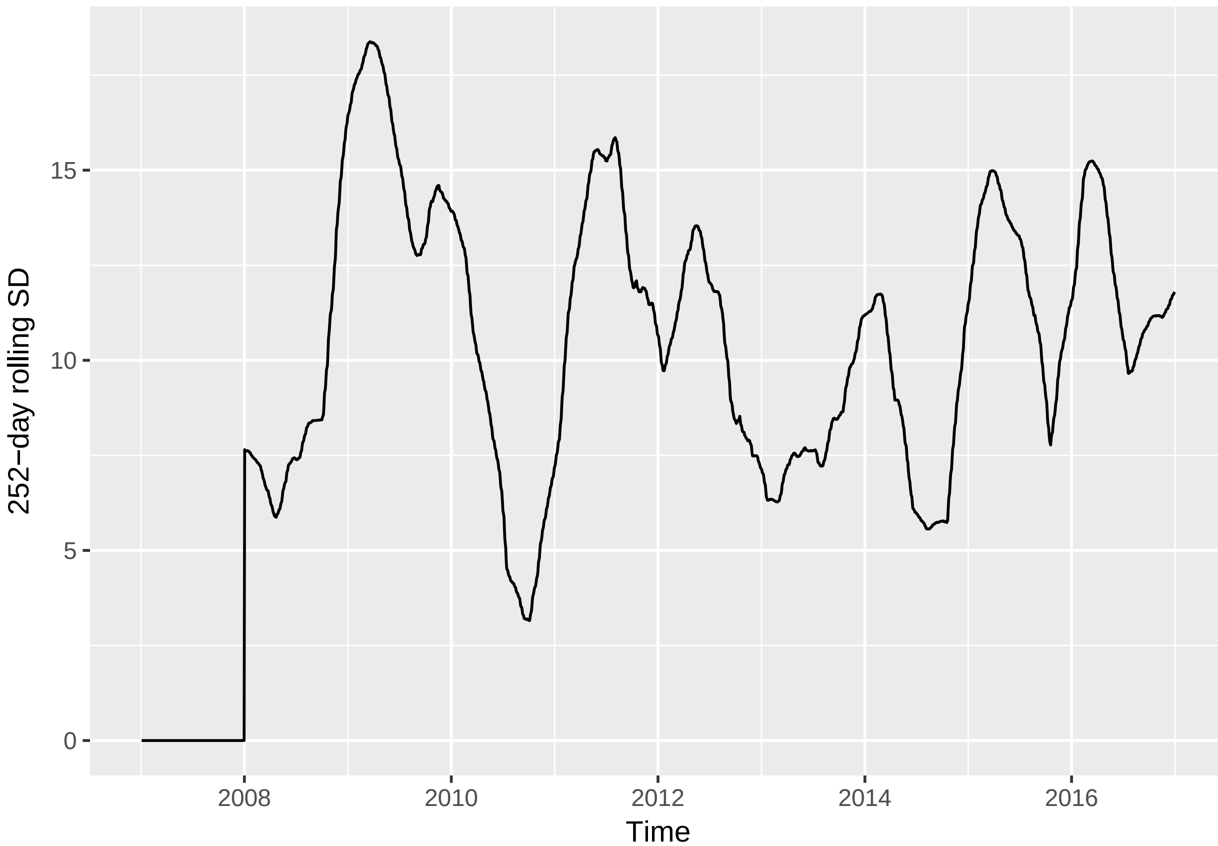

```
## Utilites
Util1 <- usa_percent[which(usa_percent$sector_name=="Utilities"), ]
Util2 <- minvol_percent[which(minvol_percent$sector_name=="Utilities"), ]
ggplot(Util1, aes(date, percent, colour = "USA")) + geom_line() +
ggtitle("USA vs. Min Vol Utilities Sector Weights") + xlab("Time") +
ylab("Sector Weight") + geom_line(data = Util2, aes(x=date, y=percent,
colour="Min Vol"),show.legend = TRUE)
```




```
## Telecommunication Services
Telecom1 <- usa_percent[which(usa_percent$sector_name=="Telecommunications"), ]
Telecom2 <- minvol_percent[which(minvol_percent$sector_name=="Telecommunications"), ]
ggplot(Telecom1, aes(date, percent, colour = "USA")) + geom_line() +
ggtitle("USA vs. Min Vol Telecommunications Services Sector Weights") +
xlab("Time") + ylab("Sector Weight") + geom_line(data = Telecom2, aes(x=date,
y=percent, colour="Min Vol"),show.legend = TRUE)
```




```
ggplot(ibm, aes(Date, sd)) + geom_line() + xlab("Time") + ylab("252-day rolling SD")
```



252−day rolling SD
0
5
10
15
2008
2010
2012
2014
2016
Time