Comparing the Great Recession and COVID-19 Pandemic via GARCH Modeling Techniques

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Abstract

This paper seeks to compare two periods of historic financial market volatility: the Great Recession and the COVID-19 Pandemic. In pursuit of this, market data was compiled from beginning of 2005 into June 2020. Market data included Trade-and-Quote (TAQ) data detailing all trades that occurred in all of those years, by the second, for eleven different exchange-traded funds (ETF's). One of these ETF's tracks the market, and the other eleven pertain to specific sectors of the United States economy. This data was analyzed with the use of several GARCH model variations with the goal of calculating and comparing volatility between them. It has been found that, overall, the sheer magnitude of volatility exhibited by the markets during these two periods was similar. However, certain sectors actualized significantly different volatilities between these contractions, both in relative and absolute terms.

I. Acknowledgements

To begin, I'd like to give thanks to Dr. Hansen for taking me on as a research assistant and for requesting funding for me; he's been a tremendous resource, and I am eternally grateful. Additionally, I'd like to thank Chan Kim for his outstanding efforts and willingness to aid me in navigating this new space. He's been remarkably patient with me, and that is an absolute testament his commitment. Lastly, I'm highly appreciative of the Economics Department here at U.N.C. and the Matthew Guest Family Fund for presenting me this opportunity. The department has been a second home to me, and I'll cherish that forever. Having said that, let's begin the academic portion of this paper.

II. Introduction

In early March 2020, the coronavirus had begun to present itself to the world as an extreme threat, with remarkably high infection rates and a significant mortality rate. In response to this, the financial markets experienced a torrential crash. Between March 4th and March 23rd, the S&P 500 index fell approximately 34%, almost instantaneously ending what had been an historic bull-run. In fact, this was the first bear market that the U.S. had experienced since its last recession, the Great Recession of 2008.

In that recession, the causes were somewhat more complex, as it was not simply the uncontained spread of an illness. Relaxed lending standards followed by a plummet in the demand for housing served to destabilize financial institutions and, by extension, their numerous clients. The result was a deleveraged economy in which its downfall was so foundational that the timeline for recovery of said economy was completely uncertain. Financial uncertainty had

reverberated throughout the economy, inciting economic uncertainty, which was, then, sent back into the financial markets. The terminal result was that financial volatility soared.

With regards to the size of volatility, a comparable pattern manifested during the crash in March 2020, even if the movement toward economic distress was more sudden. With seemingly perfect coordination, as the economy was partially shutdown, and the markets took a downturn, the volatility of those markets experienced a drastic upturn. This is a common pattern of volatility spikes in the markets, and, in the case of the recent pandemic, it seems that this uptrend in volatility was no exception.

Nonetheless, another dimension of volatility goes beyond its causes and tracking of the market. That dimension is its measurement, predicated upon an important question: what is volatility, and how do we measure it? According to the Corporate Finance Institute, financial volatility is "a measure of the rate of fluctuations in the price of a security over time". [1]

There are three components to this definition:

1) First is that which comes from the phrase "over time". Here, there is not a specific unit of time provided, implying that there is not an objective time frame over which volatility ought to be measured.
2) Second, the analysis is on the "rate of fluctuations in the price of a security"; this portion of the definition alludes to the first component and adds more information. In addition to mentioning that "the price of a security" is being measured, there is use of the word "rate". Definitionally, a "rate" has two parts: first, a magnitude, and, second, a unit of time by which that magnitude is made relevant. This is because a magnitude cannot be understood without time contextualization, hence why speed is often

measured as the function of an hour. Therefore, any working definition of volatility requires a magnitude and its application to some unit of time.

3) The third component, "a measure", completes the definition and is purposefully innocuous. That is because there is not a perfect method by which the fluctuations of the price of a security can be analyzed. As such, there is not a specific listed, just reference to some type of measurement. However, this deserves more discussion.

Given everything discussed so far, two things are clear. First, financial volatility is highly relevant to everyone and, by extension, worth measuring, as it indicates a damaged economy or will shock the economy itself. Second, great care should be taken to find or create a great metric for financial volatility, and it must include elements of time and magnitude. Thus, these two statements will act as tenants for this research, guiding both the foundational econometrics and the causal arguments presented here.

The study of financial volatility has a rich history, and its relevance to periods of economic and financial instability are unmistakable, especially in cases where the volatility is severe. In turn, it seems appropriate to undertake the measurement of financial volatility during the most pronounced periods of economic uncertainty in recent memory, those during the Great Recession and the COVID-19 Pandemic. This measurement can serve as a basis for understanding the past and predicting future financial and economic conditions for politicians, economists, and traders of the like so as to enable their preparation.

It is an imperative to research financial volatility, and the primary goal of this paper to expand understanding of this abstract concept. To achieve this goal, three variations of GARCH (Generalized Autoregressive Conditional Heteroskedasticity) models will be used to measure the

volatility of index prices representing numerous economic sectors as well as the overall market. From there, correlations will be assessed, and conclusions will be drawn.

It is recognized here that it may appear odd to compare two recessions with such seemingly different causes. This is an understandable reaction: one crash was caused by gradual deleveraging of our central financial system, and the other was incited by a large-scale shutdown of the global economy. However, a crash is a crash, and since the Great Recession contained the last bear market since that which was caused by the recent shutdown, it only seems natural to compare the two. Having said that, this paper contends that, while certain sectors may have behaved differently, the overall volatilities exhibited approaching and at the peak of these two bear markets have similar magnitudes.

III. Literature Review

In this paper, the goal is to measure volatility. Since Professor Peter Hansen, the advisor of this paper, is at the forefront of studying this field, it makes the most sense to use his preferred methods for measuring volatility. Specifically, the methods of immediate interest are variations in GARCH models, so some of Dr. Hansen's previous work, as well as other relevant literature, will be reviewed here.

To begin dissecting types of GARCH models, its foundation from which it comes must be reviewed: the ARCH (Autoregressive Conditional Heteroskedasticity) model. Past econometric modeling in finance had always sought to predict financial volatility exogenously. However, beginning with this model, research started to lean toward the endogenous use of

variance in models, where a factor in the computation of the current period's variance could be at least partially conditional, not just unconditional. [2]

A few years later, a new type of process was created based on the ARCH process: the GARCH model. The ARCH model computed its conditional variance as a linear function of errors in past sample variance, which is the realized deviation from unconditional variance, which conveniently permits changes in the conditional variance. However, this derivative GARCH model is more flexible. This new process allows for two things: 1) flexible lag structuring, and 2) the inclusion of conditional variances in the model as a means to predict future conditional variance, hence why it is "generalized". Now, it is able to be described as a GARCH (p, q) process, where p is the lag placed on conditional variances, and q is the lag placed on unconditional variances. Therefore, if p were to be set equal to zero, the model would revert to an ARCH (q) process, since conditional variances would no longer have been included in the model. [3]

After this breakthrough, it had become commonplace to view GARCH models as the new gold standard of econometric modeling. However, the GARCH model possessed a couple of shortcomings that were enumerated by the developers of the next model in the timeline: the Exponential GARCH process. In the previous process, shock impacts were unmanaged, and patterns were inconsistent. This made correlations between returns and volatility innovations impermissible, made shock impacts indecipherable, and necessitated the use of inequality constraints on parameters. However, by having the natural logarithm of the variance act as the conditional volatility of interest, all of those barriers are removed. Resulting curves are smoothed out, and shock impacts are standardized, affording researchers the opportunity to use unrestricted parameters and calculate active correlations. Additionally, another tremendous benefit, perhaps

the most important one, is that, with the volatility shocks being standardized, much of the noise of the markets is filtered out, improving the model. [4]

While the Exponential GARCH provided a vast improvement to previous models, it was arguably limited with regard to factors. Based on this notion, an entire family of multivariate models was created that sought to add extra predictive power to the relatively straightforward Exponential GARCH, almost like a regression. Thus, the Exponential GARCH-X group of processes emerged. In essence, all that needs to be done is take the standard Exponential GARCH formula and add parameters, like the daily range of logarithmic prices, based on the individual researcher's preference. The result is a multivariate model with, in many cases, greater accuracy. [5]

The final model of interest in this study is a direct innovation of the Exponential GARCH base, and it is known as the Realized Exponential GARCH model. This process is predicated on taking the standard Exponential GARCH model and incorporating realized measures of volatility within it, such as realized variance. In short, a realized measure of volatility is a metric describing movements in markets that have already materialized. They stand separately from implied measures of volatility, which are dependent on the market's assessment of future volatility. One is actualized, and the other is speculative. With the realized measures being actualized, they are more conventionally useful for application to past data, a product of its reduction of the influence of noise. [6]

In total, there are five processes whose histories are presented here, each with individual strengths and weaknesses, ranging from simplicity to efficacy. Regardless, there are numerous other models that have been developed since the original ARCH models were conceived in 1982. Having said that, these methods will serve the purposes of this paper extremely well.

IV. Methodology

On the whole, the general progression will proceed as follows. Data choice, collection, and conversion will be explained. Then, the mathematical procedures undertaken to arrive at all models will be given overview and enumerated. Then, the application itself as well as other actions will be laid out. Having said that, it all begins with the data and the purpose behind collecting that data.

To begin, TAQ data, ranging from January 1, 2005 to June 9, 2020, was collected from Wharton Research Data Services on the following assets: SPY, VNQ, XLB, XLE, XLF, XLI, XLK, XLP, XLU, XLV, XLY. TAQ data provides information about all trades that occur for a given asset, such as the precise time, including extended hours trading if desired, and the price at which the trade was executed. January 5, 2005 was chosen as the starting point for the data because that is the first trading day of the next year after the public release of nearly all of these ETF's. June 9, 2020 was the last trading day available when all of this data was pulled. Additionally, in the initial data collected for this project, extended hours sessions were included so as to gather as much information as possible. As such, all trade data from January 1, 2005 to June 9, 2020 was collected for the S&P 500 as well as suitable ETF's tracking all major sectors of the U.S. economy.

Now that all of the data was present, it became necessary to convert it into a functional form for research. In this way, for technical analysis, a key aspect of the data needed to change. Every day of TAQ data needs comparable time elements, meaning that the time structure of the data needed to conform to one another. There are two reasons for this: first, daily data is needed

for other parts of these processes, and, second, intraday operations will be performed on it. Consistently timestamped intraday data is imperative for these purposes.

In turn, it was decided to shrink the data into five-minute intervals where, within each block of five minutes, a low, high, open, and close (OHLC) price would be computed. In addition to this, if there was not a movement in the price during a given interval, that block would simply be removed. As such, over the course of any trading day, from the beginning of pre-market hours through after hours, prices would be assigned at every five-minute mark and consolidated in the event that nothing changed. From there, intraday operations could be performed much more easily, such as calculating realized measures of volatility. Nonetheless, most procedures in this framework are applied to daily data. Therefore, concurrent daily data needed to be created from this intraday data. Fortunately, pulling daily information from intraday data is straightforward. First, establish the desired timeframes, which would only include open market hours here. Second, collapse the data across all available timeframes each day. With that, concurrent intraday OHLC data and daily OHLC data have been obtained. With this, logarithmic returns can be calculated, and volatilities may be computed.

Having alluded to volatilities, it makes sense to explain their use in this study. For starters, the three most advanced models mentioned, the Exponential GARCH, Exponential GARCH-X, and Realized Exponential GARCH model, will be applied to the data, and the results will be shown in graphs with a timeline of significant events for each recession. In terms of the models themselves, while their conceptual relevance was mentioned in the introduction, their mathematical development is here in the methodology section, starting just below with the ARCH model.

The ARCH (1) framework is written as such:

$$(\sigma_t)^2 = \omega + \alpha(Y_{t-1})^2$$

Here, Y_{t-1} is the error in sample variance as it deviates from the pre-established unconditional variance in time period (t – 1), and ω is the ever-present unconditional variance. The desired outcome of this regression is an accurate $(\sigma_t)^2$, which is simply the financial volatility in the time period (t), which would commonly be referred to as the conditional variance. As can be seen here, there are two parts to this model: the unconditional variance and the conditional variance. At this point, the conditional variance was a new innovation, and it serves as a dynamic way to calculate ever-changing volatility. As such, the way it is calculated is the unconditional variance plus the square of the error in its application.

From here, the transition over to a GARCH (1, 1) framework is straightforward:

$$(\sigma_t)^2 = \omega + \alpha(Y_{t-1})^2 + \beta(\sigma_{t-1})^2$$

Now, with this innovation, volatility is no longer purely a function of unconditional variance and its errors. It now includes the previous period's conditional variance, $(\sigma_{t-1})^2$. As such, the model is much more whole now, with a terminally dynamic system for calculating the current period's volatility. All of the elements that went into the previous period's computations will be applied to the coming period.

From here, it is possible to derive an EGARCH (1, 1) framework:

$$\ln(\sigma_t)^2 = \omega + \beta(\ln(\sigma_{t-1})^2) + \tau(z_{t-1})$$

This model changes quite a bit from the previous model. To begin, invoke natural logarithms on the conditional variance for the current and previous period to smooth out curves and standardize

shock impacts. After this, remove the past errors portion of the GARCH model, Y. Then, a leverage function will be added, τ, where $\tau(z_t) = \tau_1 z_t + \tau_2((z_t)^2 - 1)$. This is an effective means to include standardized and studentized returns in this EGARCH process, and, with that, this new model is complete.

From EGARCH (1, 1), we can obtain the EGARCH-X (1, 1) framework:

$$\ln(\sigma_t)^2 = \omega + \beta(\ln(\sigma_{t-1})^2) + \tau(z_{t-1}) + \delta(\ln(x_{t-1}))$$

The extension onto EGARCH that this model brings is in the addition of a realized measure of volatility, x. That realized measure of volatility could be one or more the many measures available. Some of these include the daily range squared, realized kernel, or realized variance. In this model, the daily range squared is that realized measure. However, one important thing to note is that this purely a daily measure, which will come into play when discussing a more accurate variation of this current model.

A great additional framework is the Realized EGARCH (1, 1) framework:

$$\ln(\sigma_t)^2 = \omega + \beta(\ln(\sigma_{t-1})^2) + \tau(z_{t-1}) + \gamma'(u_{t-1})$$

This model is similar to EGARCH-X (1, 1), but u_{t-1} differentiates it. In essence, let's imagine a matrix storing multiple realized measures called x. Now, take the matrix x and combine it with returns to create a filtration function. This function, then, is used to calculate expected conditional returns for the next period. In short, $\mu_t = E(r_t|F_t - 1)$. Given this, γ' could be seen as the marginal informative value that group of realized measures has pertaining to future volatility. Nonetheless, only one realized measure will be used in this model, realized variance, which is computed here by summing the squared intraday returns at five-minute time blocks. Thus, in practice, this will operate similarly to the EGARCH-X (1, 1).

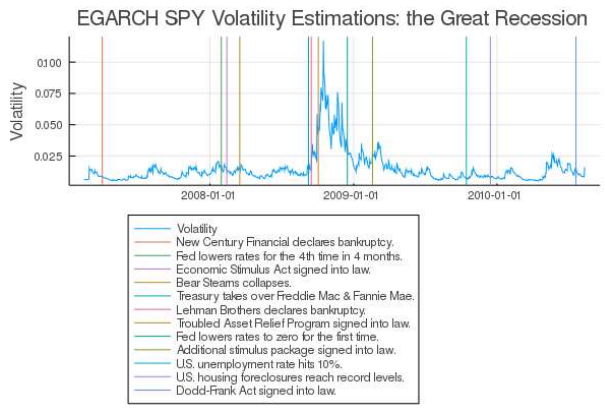
One important thing to note about GARCH models is their purpose. While the prerequisite ARCH process is actually a regression model, the GARCH processes are all members of a family of models known as likelihood models. [2, 6] In these models, coefficients are determined so as to maximize some likelihood estimator, which is sometimes referred to as a score. What these estimators do is attempt to measure the likelihood of a model working, as observed, on the dependent variable, $(\sigma_t)^2$. As such, these formulas are able to avoid operating on false OLS assumptions, and, instead, they choose to focus on how likely it is that the formulas are useful.

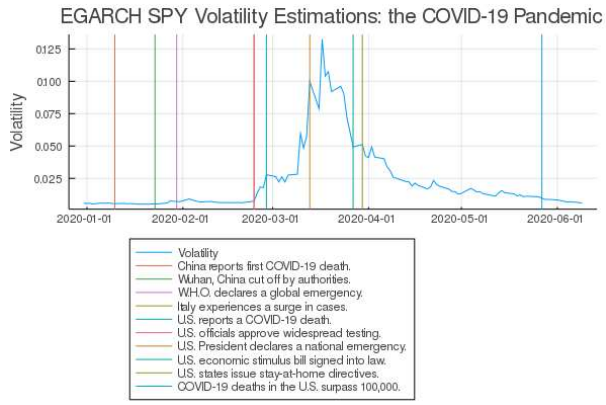
The last three frameworks will be used to calculate volatility separately, with regards to both the models themselves as well as the time periods to which they are applied. Then, those calculations will be displayed in graphs with corresponding events as they relate to the time periods of interest for context. From that point, the analysis will be causal, and differentiations in the results of the differing GARCH processes will attempt to be explained. In addition, the 50-day simple moving average of three-month rolling return correlations will be generated for the Realized EGARCH Model, as it would be inconsistent to compare standardized return correlations if deviations by which they are standardized were computed differently. Significant results from those correlation generations will be displayed in the body of the paper while the rest will be placed in the paper's appendix.

V. Results

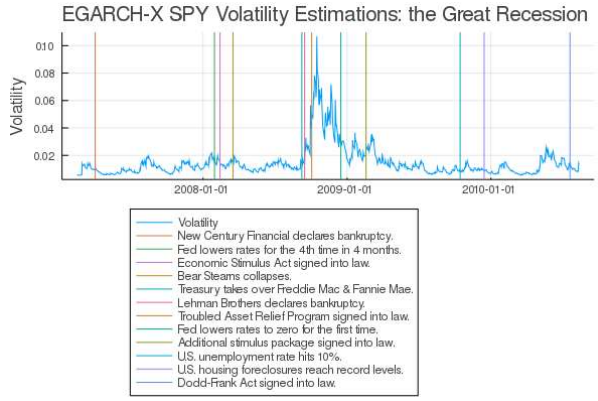
In this section are the visualizations of all model volatilities and notable return correlations. Commentary will be made on these visualizations as they appear.

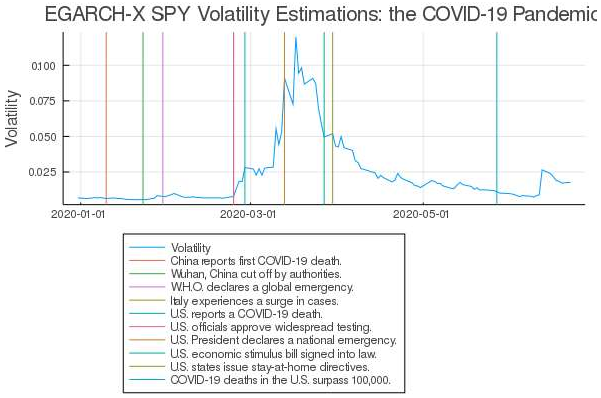
SPY Volatilities



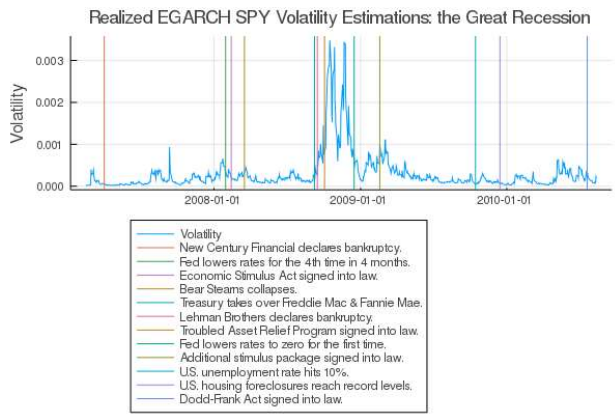


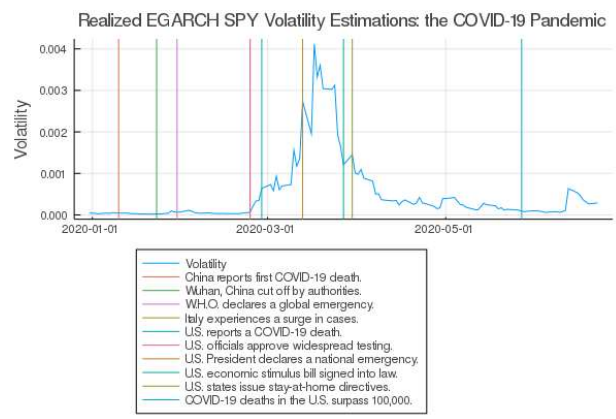
According to the standard EGARCH model, SPY's volatility in the initial onset of the COVID-19 Pandemic was comparable to the volatility peak of the Great Recession. More precisely, both volatility graphs maxing out somewhere between .12 and .14, representing increases of greater than several hundred percent in each case.





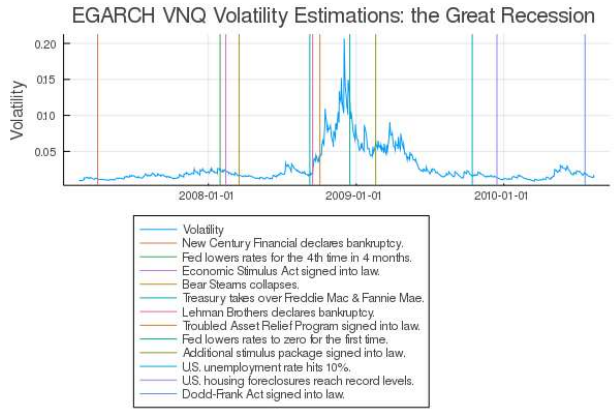
Somewhat differentially, the EGARCH-X model posits that greater volatility was present in March 2020 than in late 2008, likely on the account of certain days in March 2020 days experience extreme high and low prices, perhaps associated with those days' circuit breakers. In terms of relative volatility, though, the output here is still similar to the output of the standard EGARCH model.

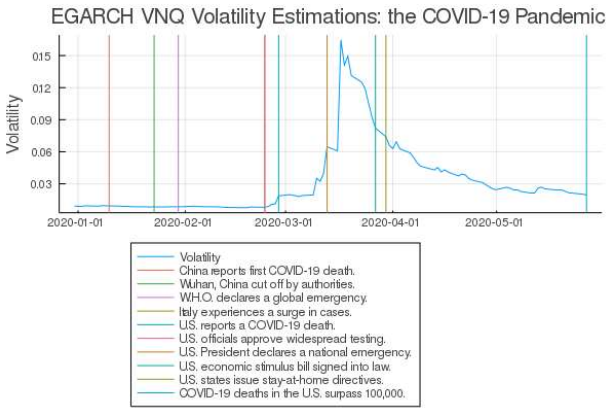




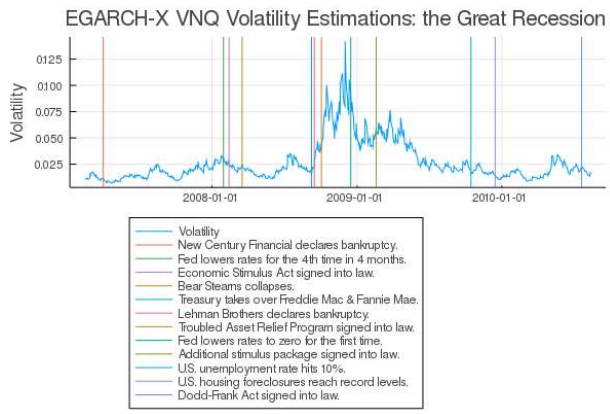
The Realized EGARCH model behaved very differently, as its realized measure, realized variance, permits the detection of multiple intraday price movements. As such, volatility spikes are more pronounced and more numerous. One other facet of this Realized EGARCH is how much is demonstrates the relative change in volatility, with SPY's moving well over 1000%.

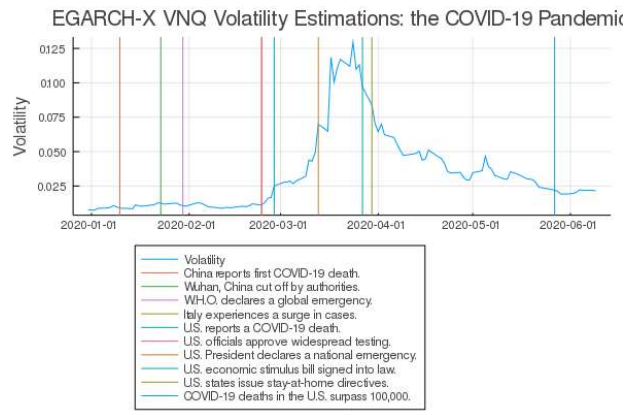
<u>VNQ Volatilities</u>



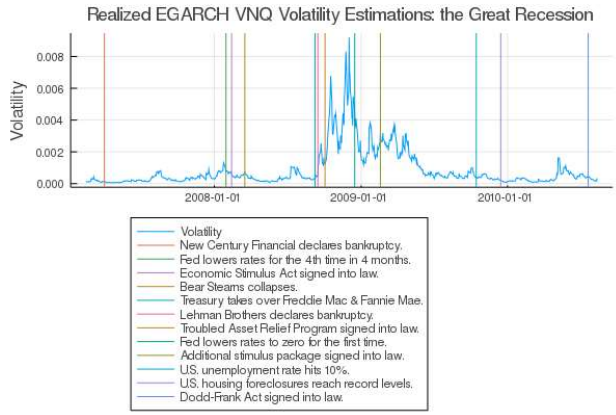


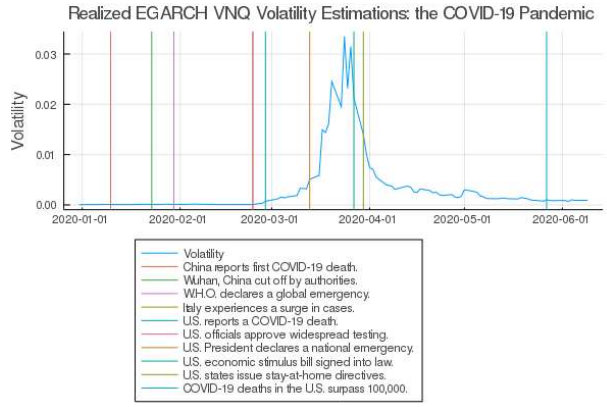
In the base model, EGARCH, VNQ behaves somewhat conventionally in terms of direction, but it exhibits much greater volatility than other sectors. However, while the peak early on during the COVID-19 here was around .16, the Great Recession broke above .20, which is the greatest volatility to occur among all assets studied.





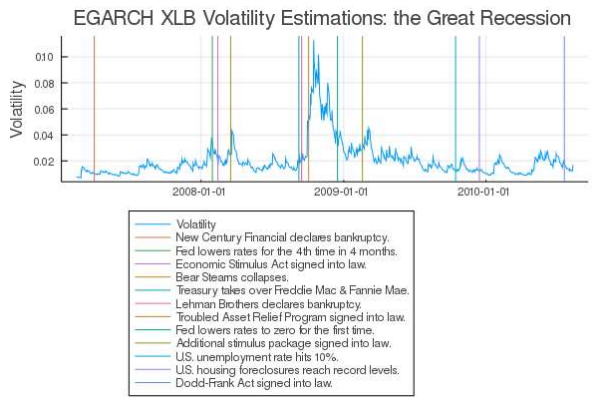
Interestingly, VNQ's volatility presented in the EGARCH-X innovation asserts two things: first, the maximum volatility present in both crises were comparable in magnitude, and, second, the volatility is less severe than what EGARCH makes of it, with both scenarios peaking near .13. One other detail is that heightened volatility appeared to linger in March 2020 instead of quickly diminishing like the other models.

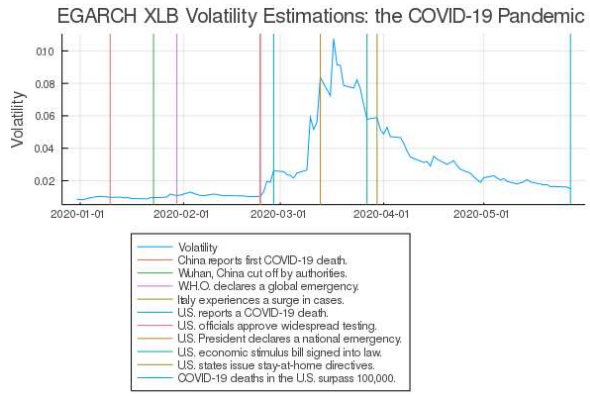




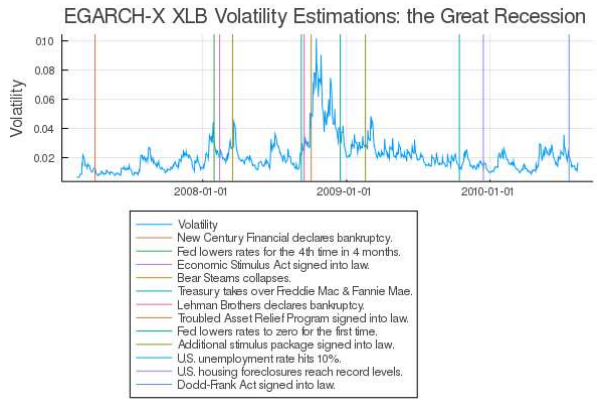
The Realized EGARCH model, as will become a recurring theme, behaved very uniquely. To begin, the COVID-19 Pandemic's peak, according to this output, realized greater than three times the volatility during the Great Recession, as that appeared to be a slower burn, metaphorically speaking. However, with regards to the other sectors, VNQ was extremely stable by comparison, with only about 25% of the magnitude volatility realized by SPY.

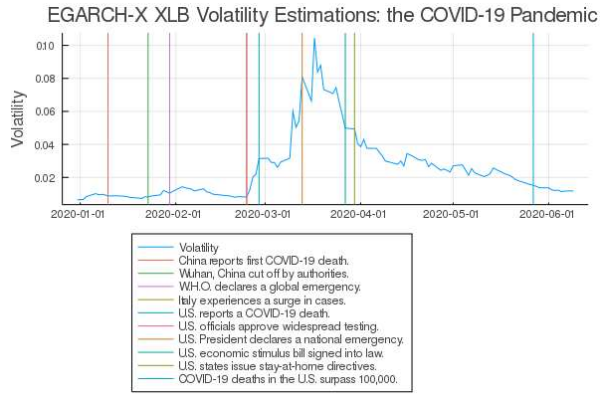
XLB Volatilities



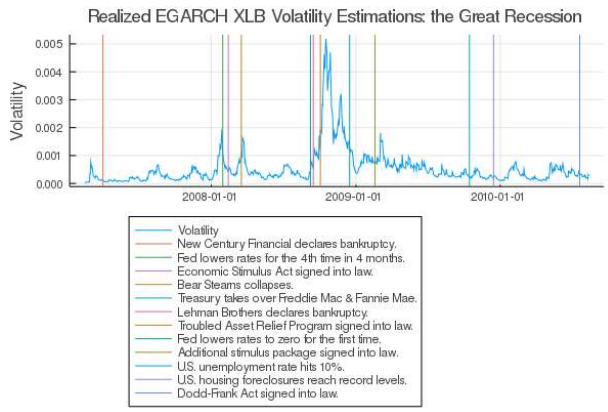


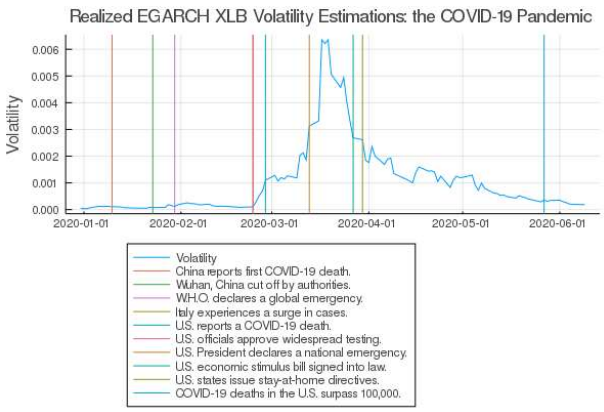
According to the EGARCH model, the peaks of volatility for XLB are almost precisely the same between the periods of late 2008 and March 2020, with both scenarios maximizing at values of approximately .11. In terms of relative change, though, COVID's onset prompts an increase in volatility of around 1000%, while the change is only approximately half that in the Great Recession.





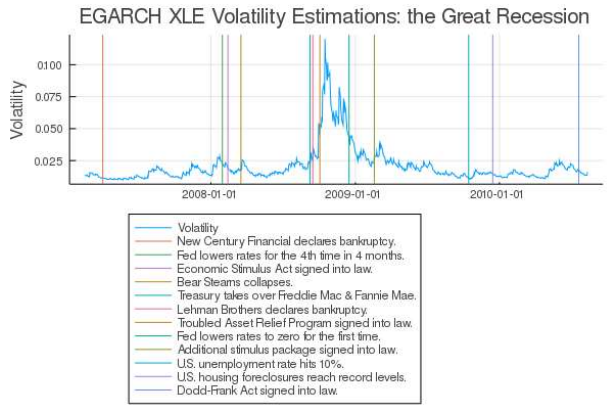
Oddly enough, although the addition of daily ranges to the model tends to have visible effects, the EGARCH-X model's output aligns very closely with the base EGARCH model. The measured volatility spikes at the same date and manifests very similar values at just above .1. Even the "recovery" period is extremely similar between the models for XLB.

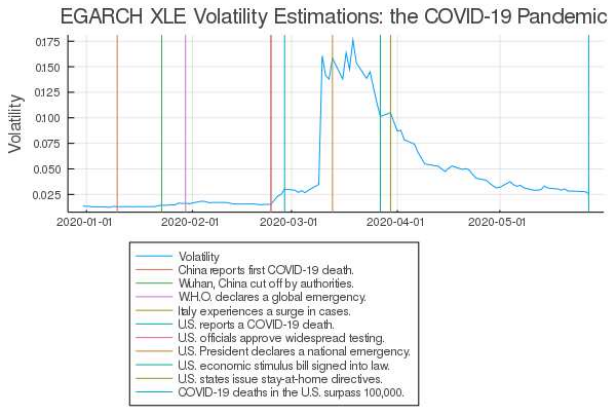




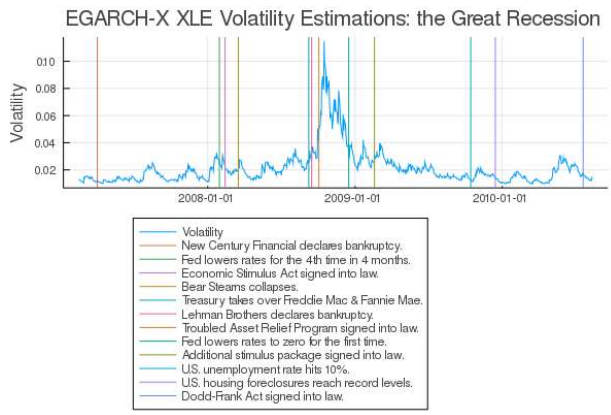
The spike dates may be comparable for XLB as measured by Realized EGARCH innovations, but the values suggest a different conclusion. Here, the exhibited volatility of March 2020 is approximately 20% greater than what was exhibited at the height of the Great Recession. In addition to that, there appear to be two absolute maxima being achieved during March, a stark differentiation between this and the other metrics.

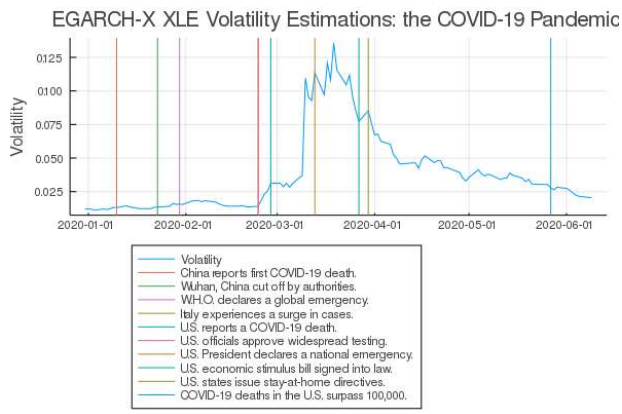
<u>XLE Volatilities</u>



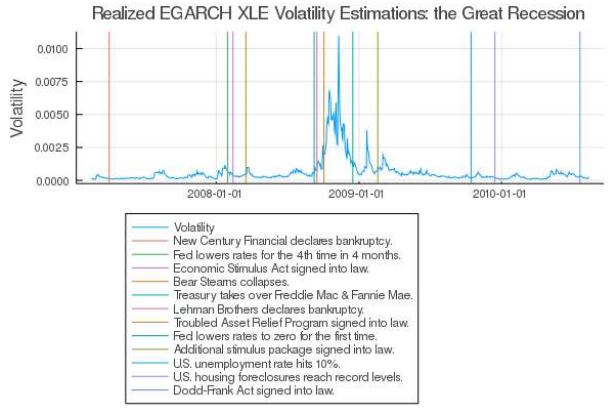


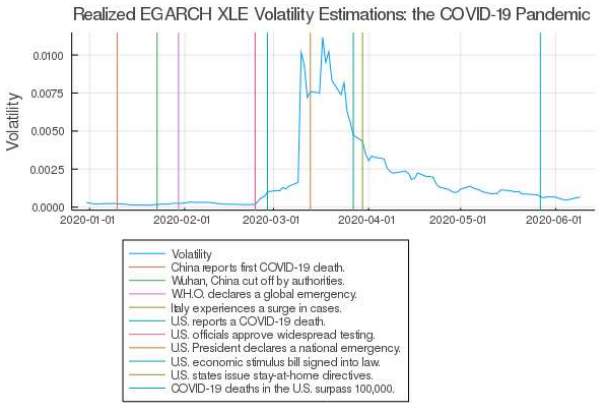
As seen with the other models, the general XLE volatility levels experienced during the early panic of COVID-19 were higher than experienced during the Great Recession. This was primarily caused by travel being halted in March 2020, decreasing the demand for oil, and, as such, XLE's volatility momentarily plateaued around 50% higher than in the previous recession.





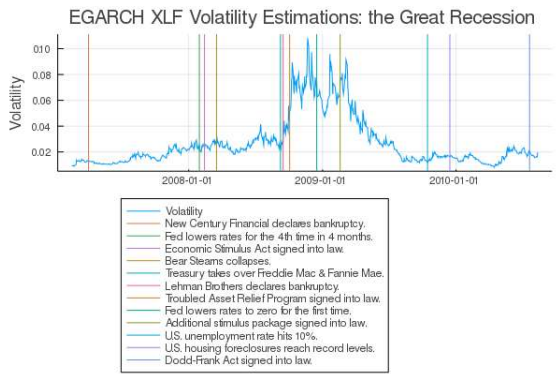
Like what was just mentioned, the EGARCH-X model similarly demonstrates that the general volatility present in March 2020 is greater than it was in 2008. However, the level here at which the volatility lingers is lower than in the standard EGARCH model, with this situating around .05 or so lower, and the volatility experienced earlier this year is relatively smaller as compared to the Great Recession.

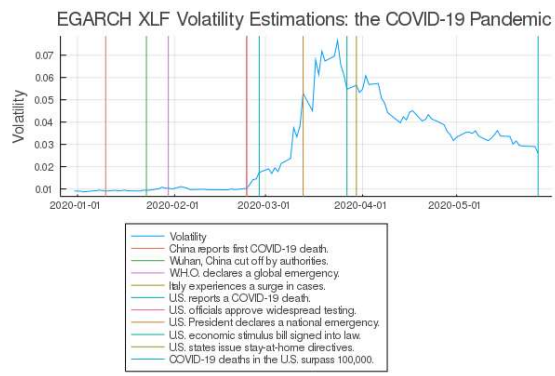




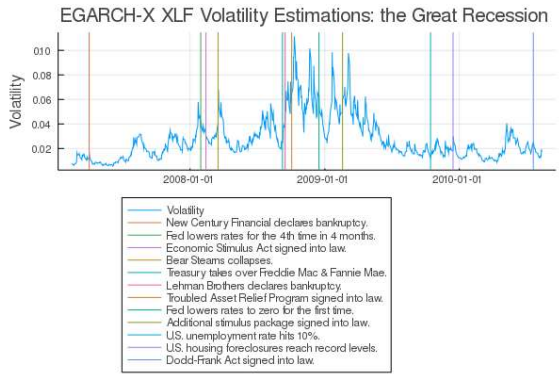
Almost like clockwork, the Realized EGARCH has produced another visibly different result. However, this time, the difference pertains more to orientation as opposed to relative volatility. The COVID-19 Pandemic preceded a greater than 1000% increase in volatility, and its level hovered above 2008 by around 20%, but the difference comes from the initial peak in volatility, the momentary comedown, and the resurgence to push it to its maximum.

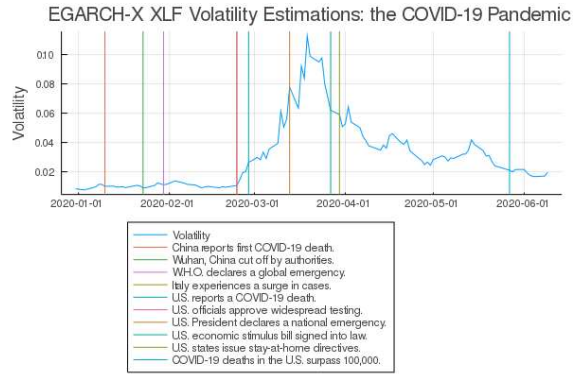
XLF Volatilities



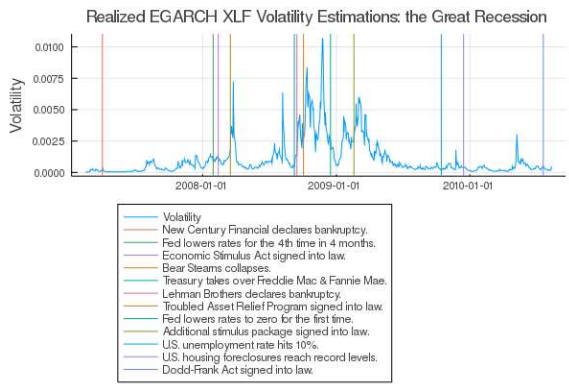


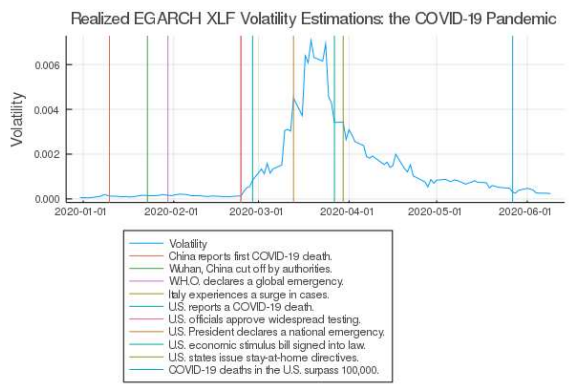
Given that the Great Recession in 2008 primarily emerged from issues in the financial sector, it is unsurprising that the peaks in XLF volatility were higher than present in 2020. Based on the EGARCH output for XLF, the maximum in late 2008 was almost 50% higher than the maximum in 2020. Moreover, there were several clearly defined peaks during the Great Recession whereas there was one clear upward trend that occurred this year.





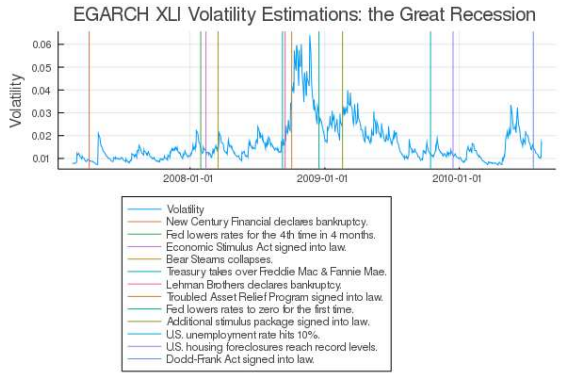
The EGARCH-X model's results heavily distinguish them from the results of the base EGARCH innovation. Its maxima between the two bear markets are extremely close in magnitude at about .1, and the dates on which maxima occurred have changed. Output of this model is clearly more prone to exacerbating movements in volatility as they occur, and it manifests by producing significantly more peaks.

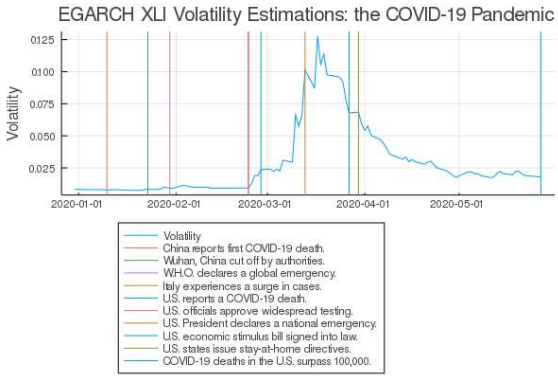




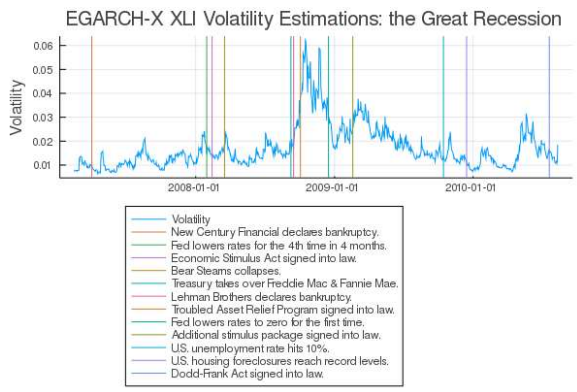
While volatility in the other two models was increased drastically during certain periods, the relative amount of change in volatility exhibited as measured by the Realized EGARCH model is comparatively massive. In the calm times, volatility was almost nonexistent, causing bad times to be more severe. Additionally, while the general levels of volatility are close, the peaks are much more pronounced in 2008 and up to about 50% above the maximum in 2020.

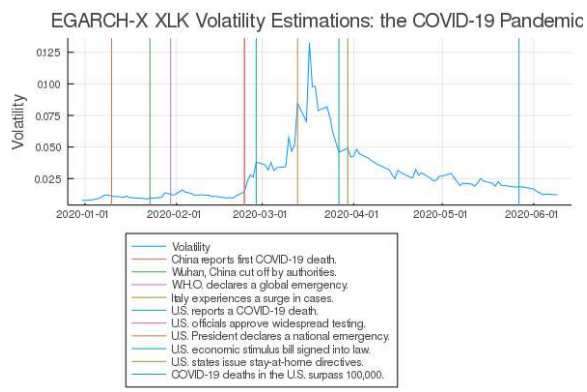
<u>XLI Volatilities</u>



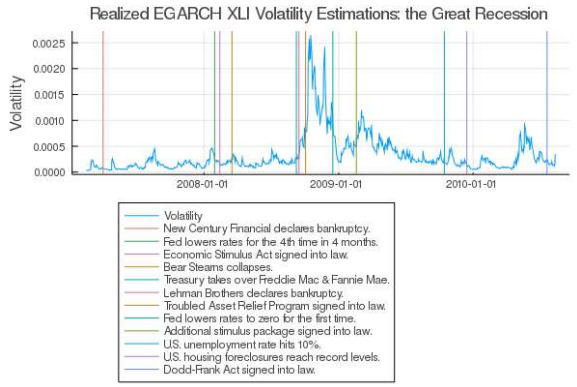


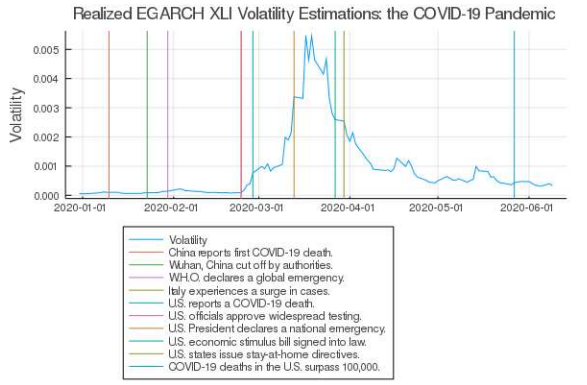
Thus far, it's been somewhat rare for the EGARCH model to produce vast differentiations in volatility between the time periods of COVID-19 and the Great Recession. Nonetheless, in this case, the volatility of XLI in March 2020 is measured to be about .125 at its peak, which is twice that of the maximum during 2008 at around .06.





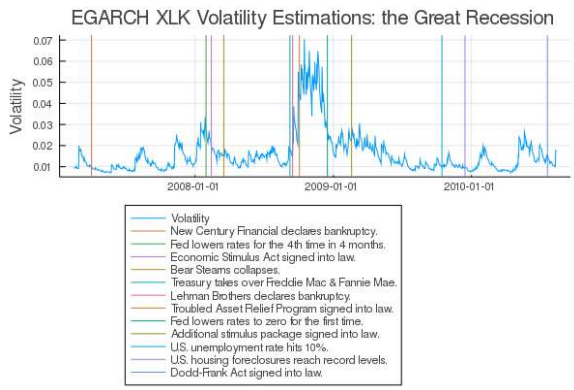
Interestingly enough, the peaks in the graphs produced by the EGARCH-X model have different dates and are more pronounced from the standard EGARCH model, which implies greater relative movements in volatility. However, the maximum volatility values themselves are almost exactly the same as the previous model, with maxima during 2008 occurring at close to .06 and during March 2020 at just above .125.

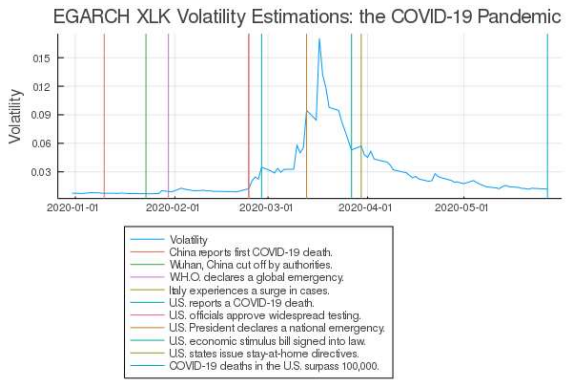




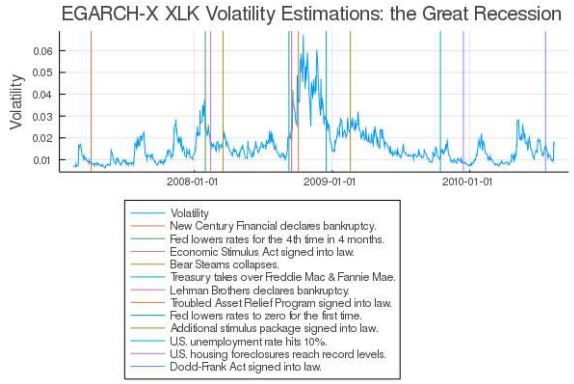
The recurring theme of the Realized EGARCH model holds true for XLI as two unique conditions are met here: first, additional peaks in volatility are produced in these graphs, and, second, the relative change in volatility seen is greater than that exhibited in the normal EGARCH and EGARCH-X. However, what is unique is that, just like those models, the maximum volatility measured during the onset of COVID-19 is almost exactly twice what was measured during the Great Recession.

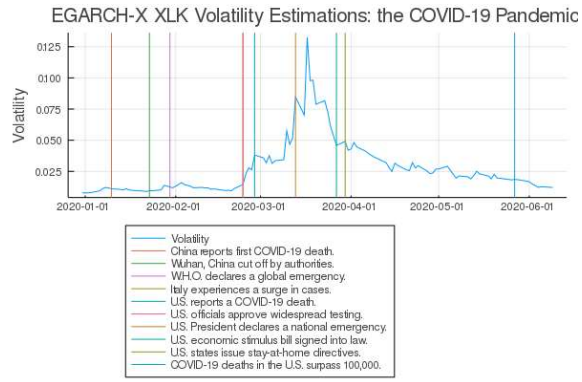
XLK Volatilities



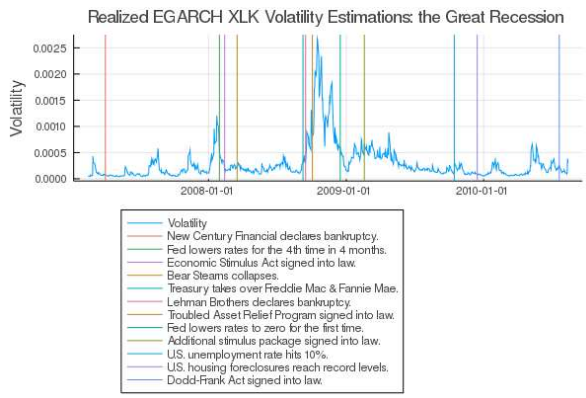


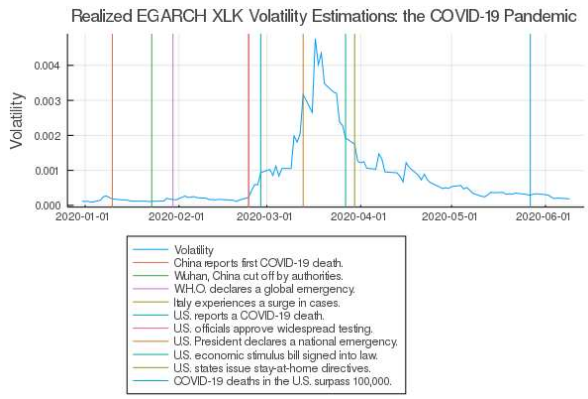
With the EGARCH model applied to XLK, the COVID-19 period peak volatility of XLK comes in at about .16 and quickly returns to near pre-COVID levels. Similarly, once the panic calms, XLK's volatility during the Great Recession somewhat quickly reduces to normal levels. However, near peak, the volatility lingers near its top for a while, between .05 and .07, which is around one-third of the peak in 2020.





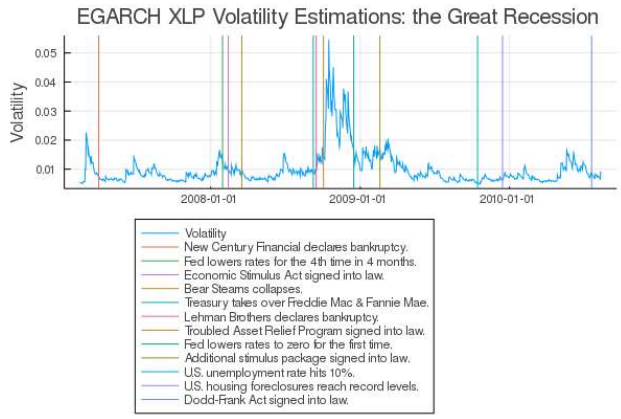
In this case, the EGARCH-X model produces comparable results: the general movement patterns shown here are highly reminiscent of what was produced by the regular EGARCH model, and the periods of severe volatility in 2008 hang around the magnitude one-third or so of the peak volatility produced in 2020. However, the volatilities here come out about 20% lower.

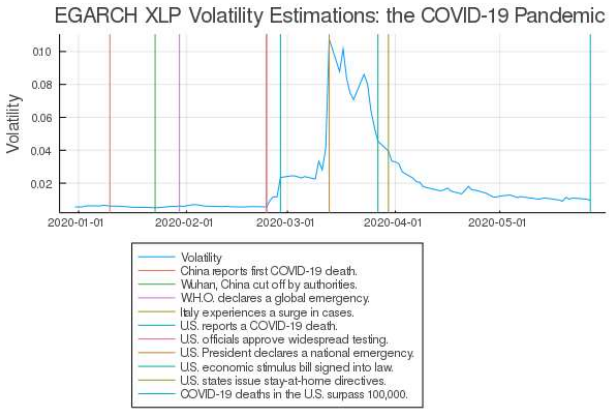




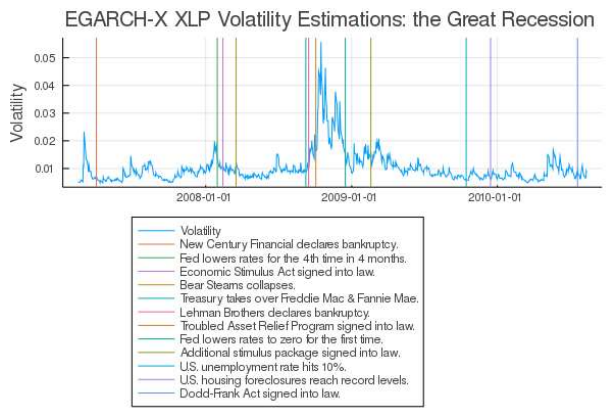
The Realized EGARCH model, once again, provides somewhat differential results for XLK. To begin, while it is in agreement with the other models by suggesting that 2020 volatility maxed out at a higher level than in 2008 by a factor of approximately 2, the 2008 volatility spike here didn't linger like the other models. Also, the volatility movements present in the Realized EGARCH are more pronounced, with volatility increasing ten-fold or greater in each crisis.

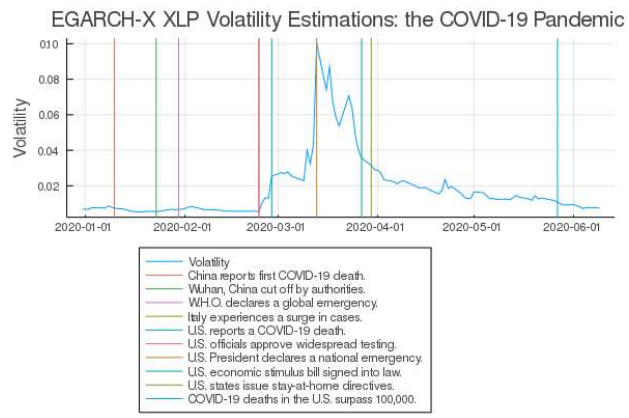
<u>XLP Volatilities</u>



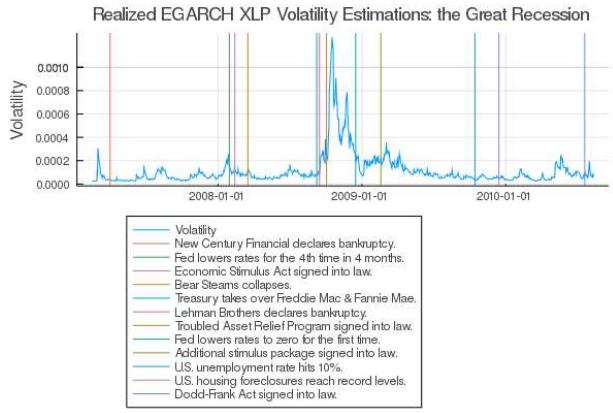


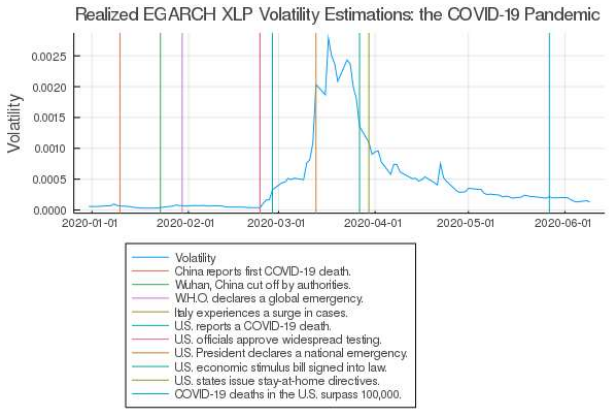
According to the base EGARCH model, XLP was significantly more volatile, at about two-fold, during the onset of COVID-19 than what was seen during the Great Recession. Nonetheless, as expected, the volatility of XLP is still on the lower side among all ETF's studied here, with peaks at .05 and .1 for the two unstable time periods, respectively.





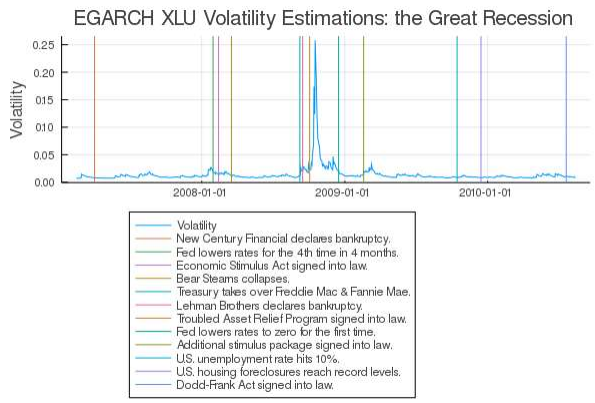
As with the past couple of assets, the extended EGARCH model, EGARCH-X, exhibits similar results to the standard EGARCH, with likewise patterns, maximums, and maximum dates. Even the relative increase in volatility of about 400% from normal levels is seen in both of these innovations, a striking similarity.

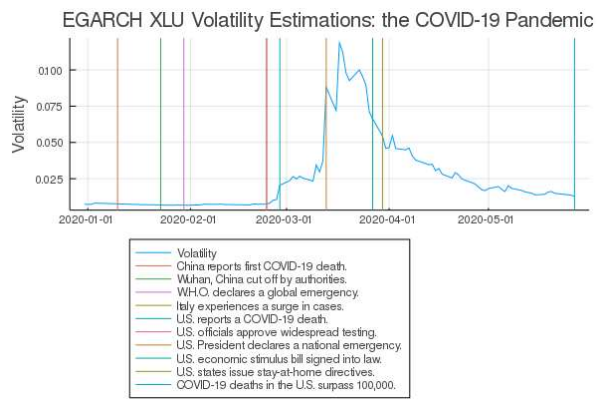




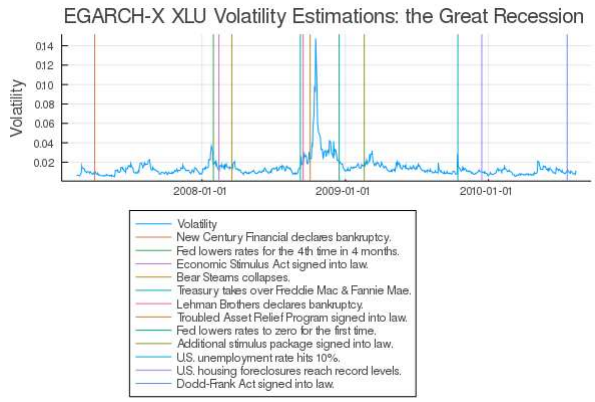
For a change, it appears that the results of applying the Realized EGARCH model to XLP yields results that are close to what is observed in the EGARCH and EGARCH-X applications. Like the other instances of Realized EGARCH, the volatilities produced are radically different, but, the patterns and the ratio of maximum volatility between March 2020 and late 2008 is two-to-one, which is almost exactly the same as what the other models produced. However, a difference is that the relative volatility change is about twice what was shown previously.

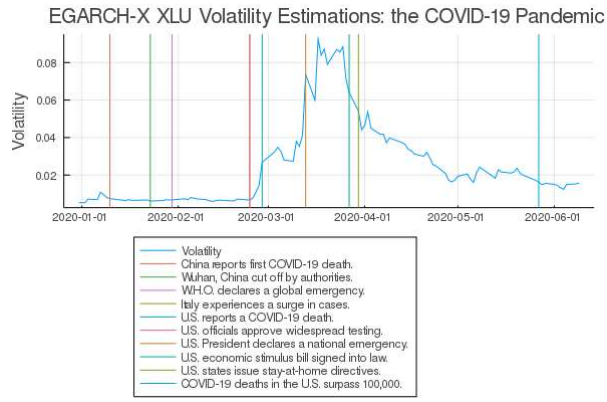
XLU Volatilities



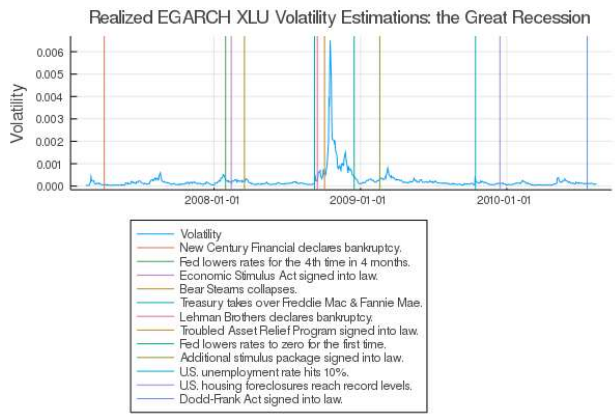


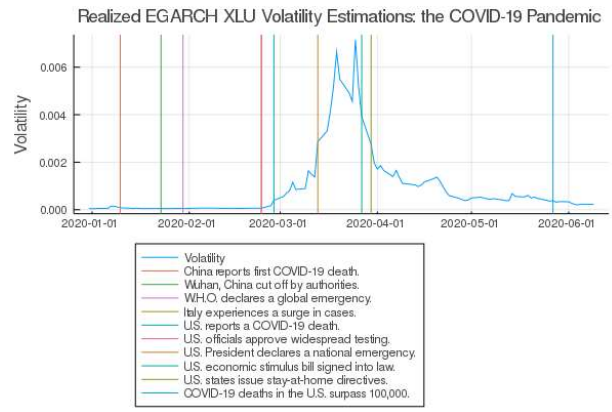
Typically, when using EGARCH, volatility is clearly present in the returns of an asset, even when the economy and financial markets are under duress. However, with XLU, volatility is almost nonexistent before its respective spikes in both time frames. Another unique facet of XLU is that volatility appears to have been more severe during 2008 by a factor of two, the greatest difference seen thus far.





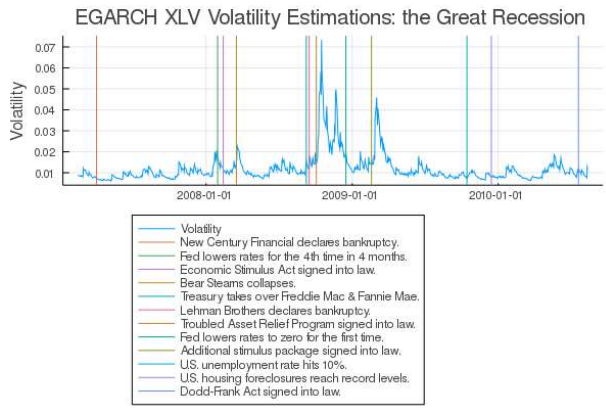
Unexpectedly, given that the EGARCH-X model adds another dimension to volatility in the form of the daily range, in both scenarios, the Great Recession and the COVID-19 panic, less volatility was exhibited. .14 and .09 were the maximum volatilities in 2008 and 2020, respectively, and the difference between the two sectors was smaller as well.

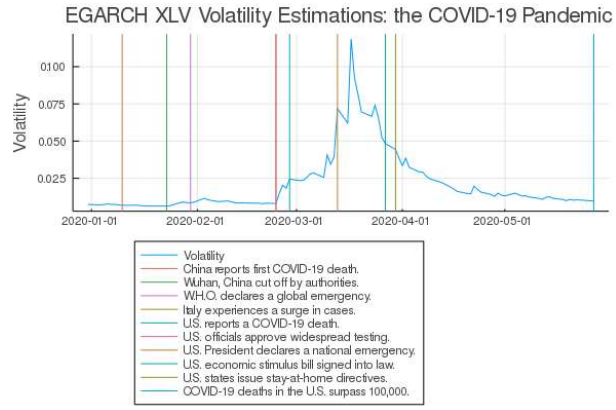




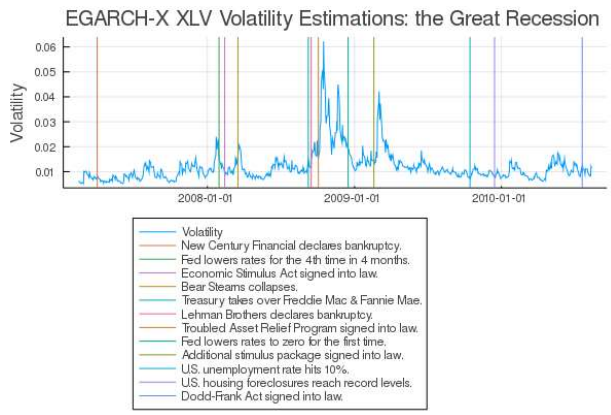
As per usual, in general terms, the Realized EGARCH innovation is suggesting extremely small values for volatility in general when compared to the other models. However, the most unique part of this model's application to XLU is the relative difference in peak volatility between 2008 and 2020: there is almost none. Here, both situations max out at around .006 whereas there was a much higher 2008-to-2020 ratio previously.

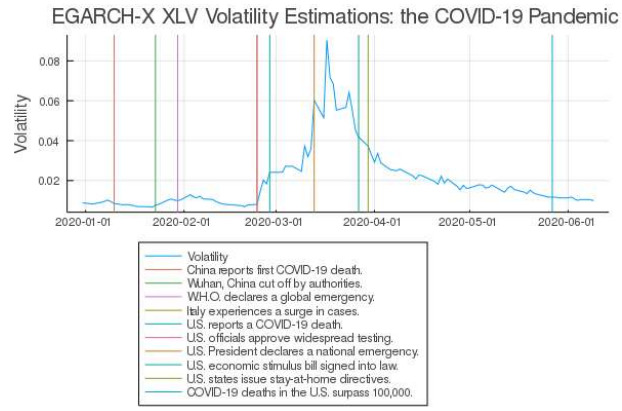
<u>XLV Volatilities</u>



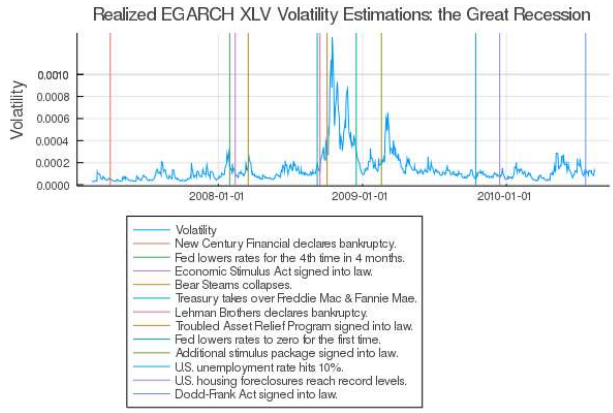


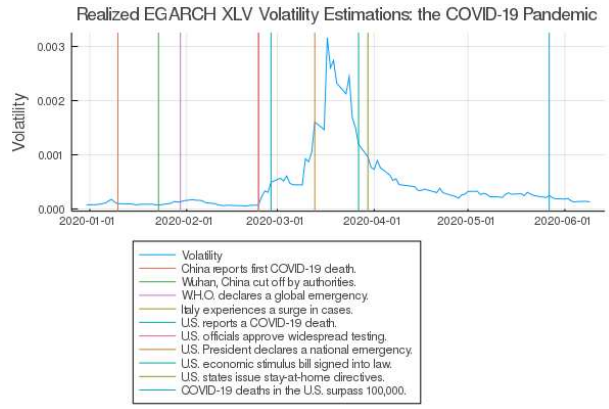
XLV appeared to exhibit average to above average stability as measured by the EGARCH method, hitting a .07 peak during the Great Recession and a .12 peak during March 2020. The relative increase in volatility is high here with it changing by several hundred percent or more in both scenarios.





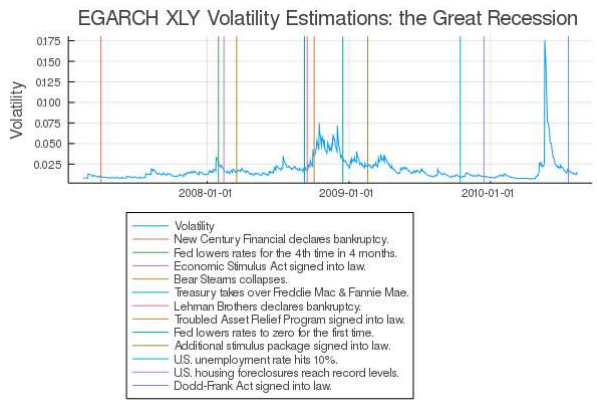
With regards to this particular asset, XLV, the EGARCH-X behaves uniquely, as it differs strongly from the results of the EGARCH implementation. The 2008 maximum volatility is higher, yet the 2020 maximum volatility is lower by comparison, and, because of this, this extended model estimates they both periods exhibited similar volatility for this asset. Additionally, the separate, relative change in volatility is much greater here too.

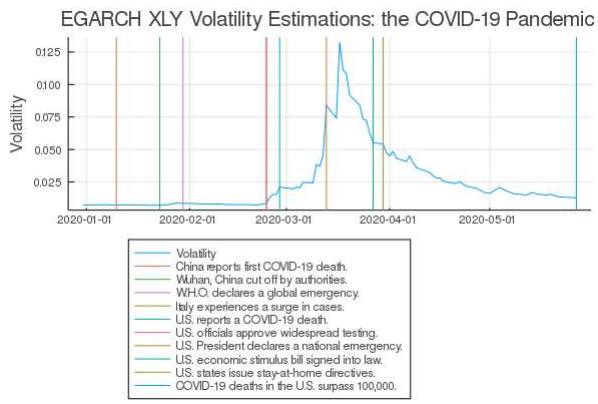




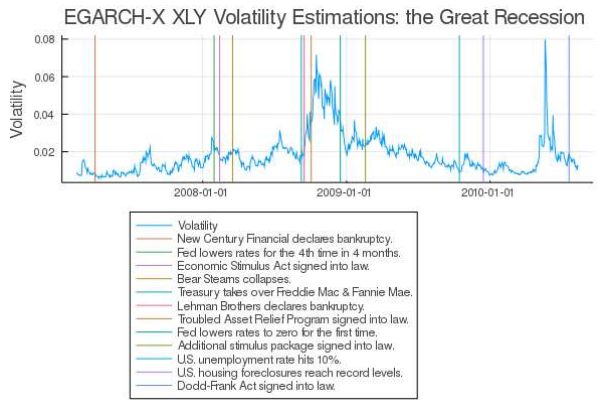
Very differentially, the Realized EGARCH model suggests that the greatest volatility exhibited in March is almost three times the greatest volatility exhibited back in 2008, a much greater disparity than in the other models. Also, to an even greater extent than was present in the extended EGARCH model, there is an extreme change in relative volatility during the onset of COVID-19. In the case of XLV, volatility appears to have increased by well over 1000%.

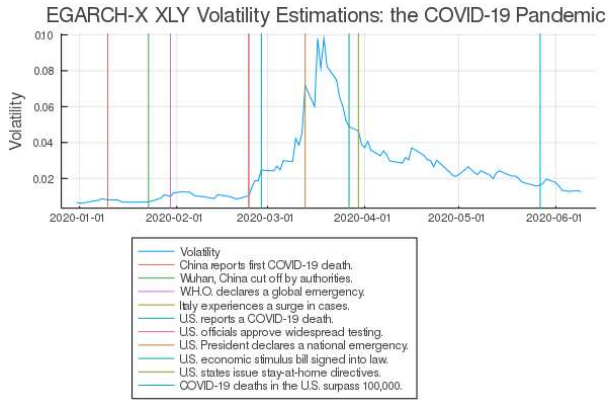
XLY Volatilities



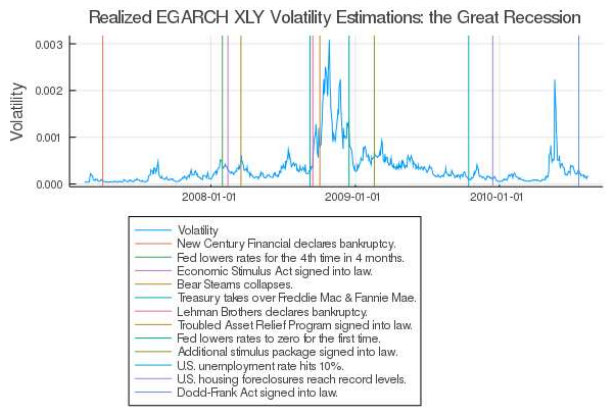


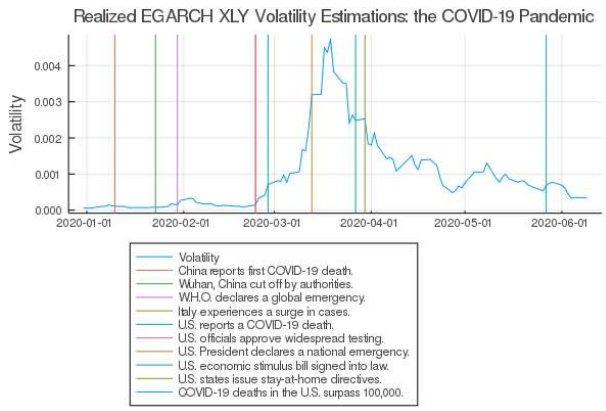
The final ETF, XLY, is quite unique with regards to volatility. The EGARCH model posits that it was less volatile than average during prime Great Recession and close to average back in March 2020. Additionally, the relative increase in measured volatility experienced in the more recent recession was several times greater than what was experienced in 2008. This is all, of course independent of the massive spike in mid-2010, likely caused by European debt.





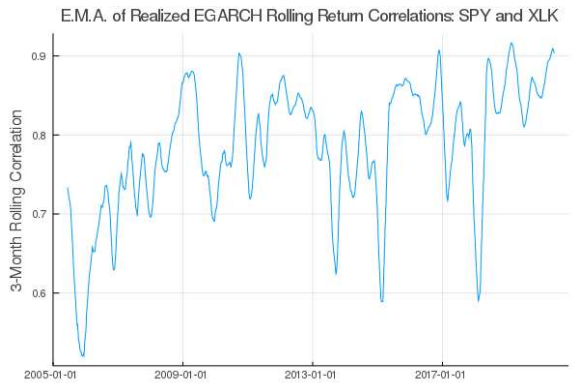
On account of the lack of intraday volatility witnessed in 2010, the EGARCH-X model does not appear to heavily favor the momentary XLY volatility spike in 2010 over that which occurred in 2008 and maxed out at around .07. However, while EGARCH contended that the COVID-19 panic was much more unstable, this model suggests that it is only slightly greater.





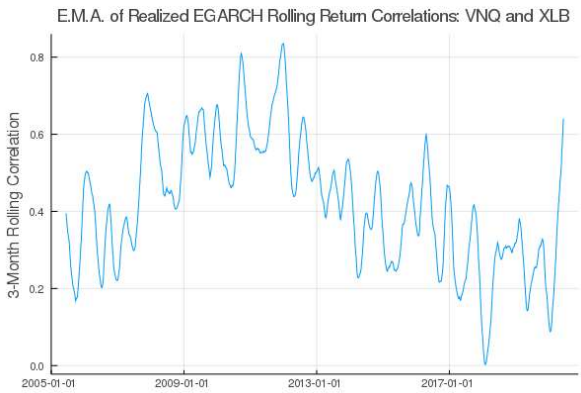
The Realized EGARCH model appears to line up with the results of the EGARCH-X innovation, relatively speaking. According to this, the measured volatility during the beginning of COVID-19's onset was about 25% higher than the maximum reached during the Great Recession, and the relative change in 2020 is observed as greater than 2008. However, unlike the EGARCH-X model, the 2010 spike is measured to be less severe than what occurred in 2008.

<u>Notable Correlation - SPY</u>



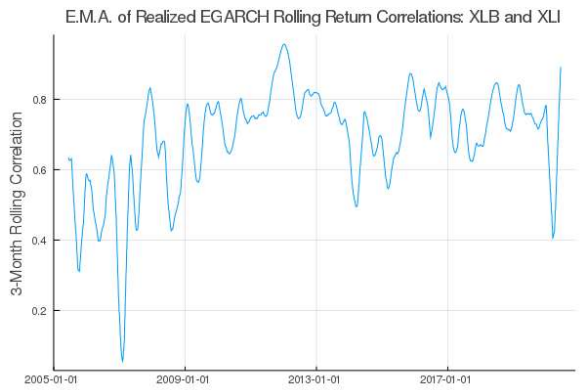
The most apparent reason for the upward trend between SPY and XLK since the Great Recession is that, throughout the 2010's, technology stocks have grown tremendously. As these stocks, which already populate XLK, the tech sector ETF, grow, their respective weightings within SPY increase, causing SPY to more closely align with XLK's performance.

Notable Correlation - VNQ



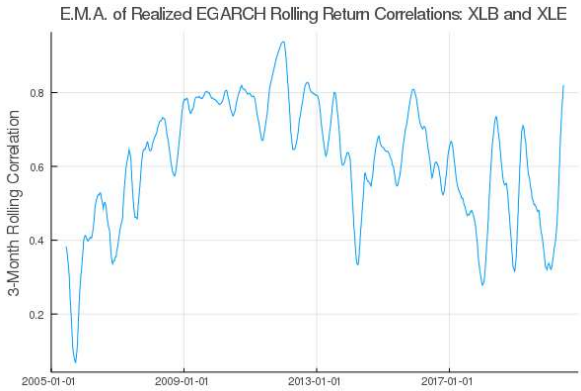
Logically, since companies present in XLB contain the inputs of the goods that are sold in VNQ, this relationship deserves analysis. Interestingly enough, though, correlation seemed highest when the housing market was at its worst, signaling that, during housing recessions, supply side factors appear to be more impactful on the price of real estate.

Notable Correlation - XLB



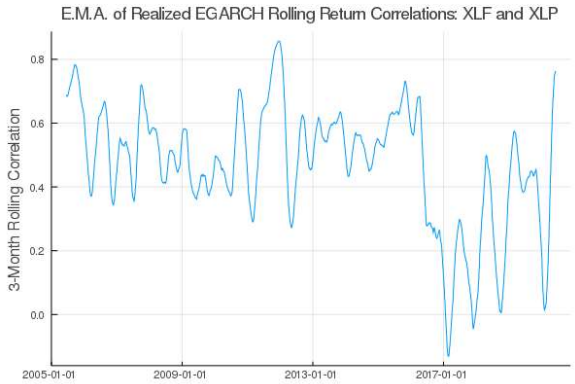
Another interesting correlation is that between XLB and XLI, the industrials sector ETF, where there was a solidly positive overall trend. This is for two reasons: 1) both of them serve as heavy supply side indicators for the economy, and 2) the basic materials sector likely holds the inputs for industrials, where economic activity in these two sectors is likely to coincide.

Notable Correlation - XLE



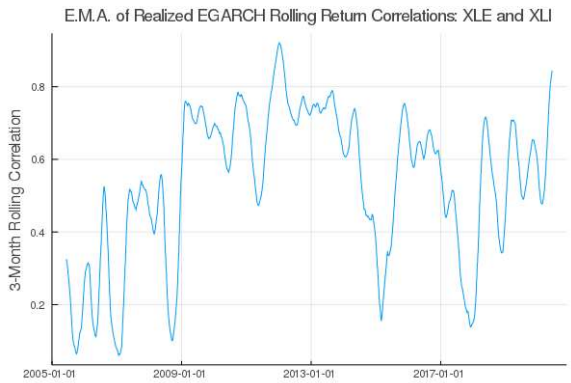
Similar to the case above is the correlation between XLB and XLE, the energy sector ETF, where the companies in these industries act as inputs for most of the rest of the economy. Interestingly enough, the association between them was weak during the Great Recession, but as the markets recovered, the correlations increased, even as they became more erratic.

Notable Correlation - XLF



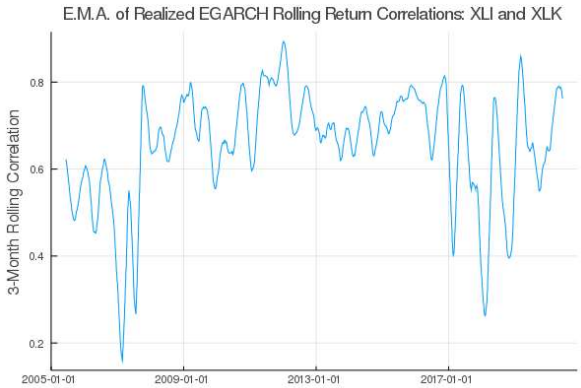
Theoretically, when the economy contracts, people will lean more into the consumer staples sector, XLP, whereas financial activity from mergers, acquisitions, trading, and banking should decrease. However, up until 2016 where the market as a whole changed in anticipation of the presidential election, there was a steadily positive correlation.

Notable Correlation - XLI



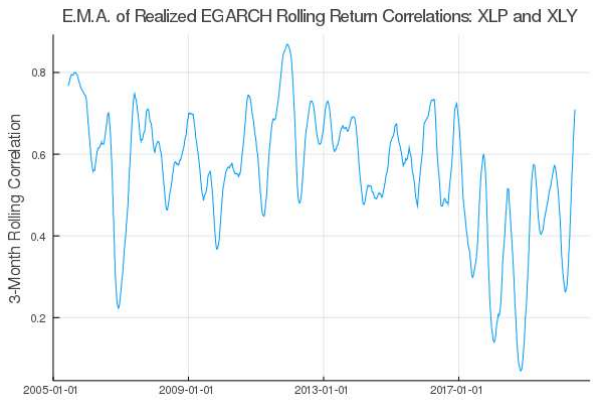
Since the return correlations were assessed between XLB and XLI, where an input sector is connected to the industrials, it seems fitting to compare another input-related sector, XLE, with industrials. However, while the trend is upward trend like with XLB and XLI, this trend is less steady and more volatile, likely do the XLI input costs and general XLE volatility.

Notable Correlation - XLK



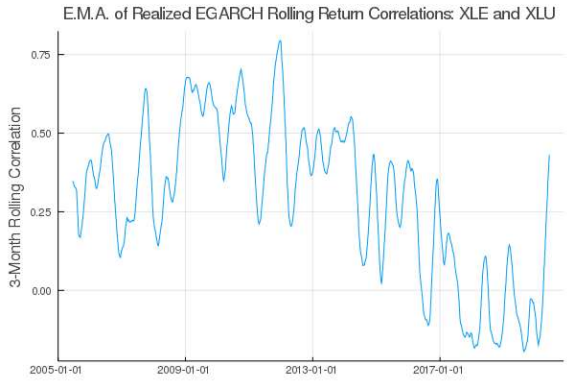
Two different ways in which economies develop are production and innovation. XLI represents production whereas XLK is tied to innovation, and the general relationship appears be positive. Nonetheless, there have been bouts of instability to occur in that relationship, such as the Great Recession and massive growth of the tech sector over the past several years.

Notable Correlation - XLP



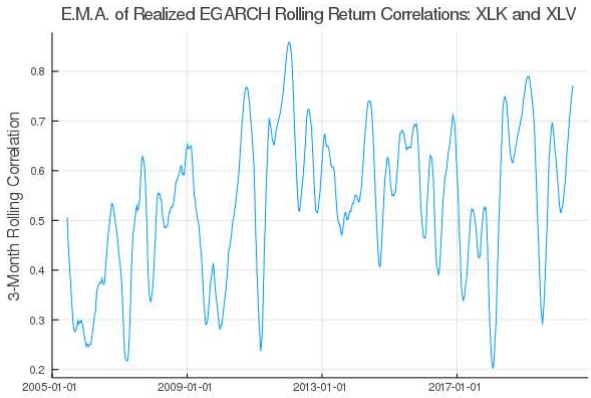
As a more punctual version of XLF to XLP, a comparison between XLP and XLY seems worthwhile, as it could provide insights into individual income allocation. In this regard, the correlation appears lower during the Great Recession and the past couple of years in which the consumer discretionary sector has greatly expanded.

Notable Correlation - XLU



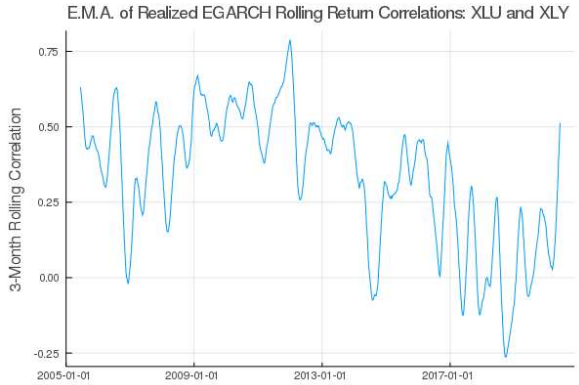
The utilities sector, XLU, relies on energy in order to provide its services. Given this, it could have a fascinating relationship with the energy sector, represented by XLE. Here, it is observed that their rolling correlations have trended downward overall. This makes sense since energy prices represent revenue for the energy sector but represent costs for the utilities sector.

Notable Correlation - XLV



A topic of great importance right now is that of medical technology, and, given this, it stands to reason that things affecting XLK could also affect XLV, the health care sector. The correlations are positive, likely due to technological innovation benefiting the health care sector, but still pretty unstable, signaling that the relationship is less established.

Notable Correlation - XLY



Since utilities are seen as the ultimate staple for consumers, it would seem reasonable that, during economic contractions, the utilities sector would be more stable than the consumer discretionary sector. This held true in the Great Recession, but, more recently, consumer discretionary stocks appear to have performed so well that their correlations have decreased.

VI. Conclusion

Broadly speaking, there are three primary conclusions that can be drawn from this paper:

1) Empirically, in anticipation of, or during, economic contractions, the general volatility level of the financial markets overwhelmingly increases. The amount by which volatility increased differed from sector to sector; for example, the real estate sector's relative volatility increases in 2008 was much greater than any other case measured. Nonetheless, for SPY as well as all studied individual sector ETF's of the U.S. economy experienced massive volatility shocks in both 2008 and 2020.
2) With regards to performance around the times of these downturns, no sector group of equities is spared; all of these ETF's are highly likely to drop, regardless of placement in the economy. Throughout almost the entire sampling period, including the Great Recession and COVID-19 Pandemic, all ETF's in the sample exhibited positive return correlations with the other ETF's. Given the presence of these correlations, systematic risks are unavoidable in the sector ETF asset class.
3) Empirical models that include intraday volatility measures, such as realized variance, clearly recognize additional instances of heightened volatility. There were several occasions in which additional volatility spikes appeared in the Realized EGARCH model since it picks up rapid changes in price during the trading day in five-minute intervals. Because of this trait, it is evidently the best model of the group, and, going forward, variations of this particular innovation are preferable and should be applied to other asset classes and instances of financial instability.

VII. References

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5. Engle, R. F., 2002. New frontiers for arch models. Journal of Applied Econometrics 17, 425–446.

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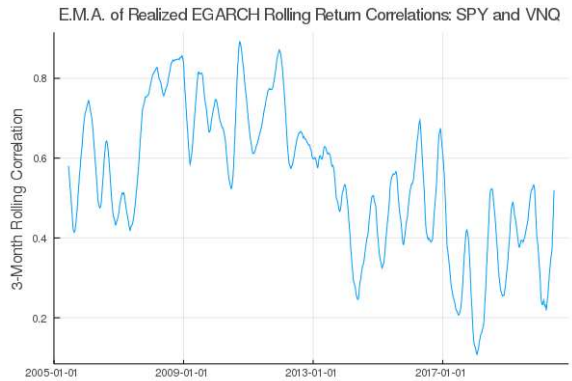
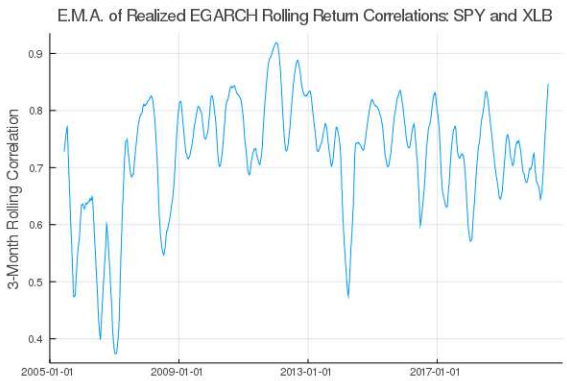
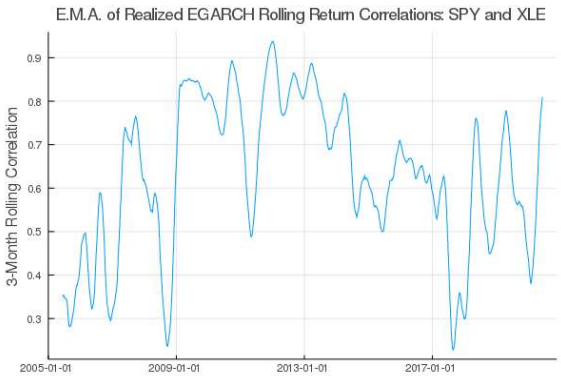
VIII. Appendix

<u>Realized EGARCH Roling Correlations</u>



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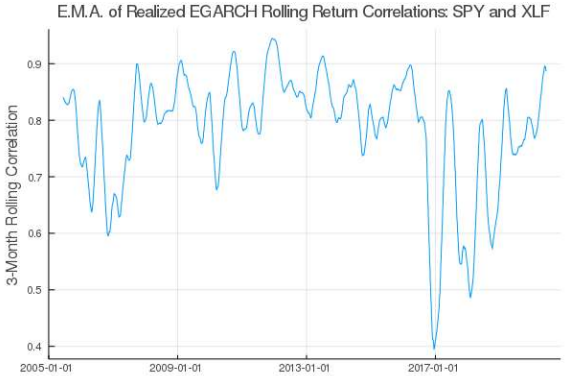
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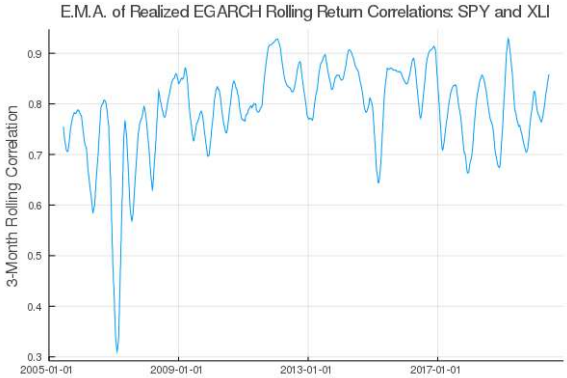
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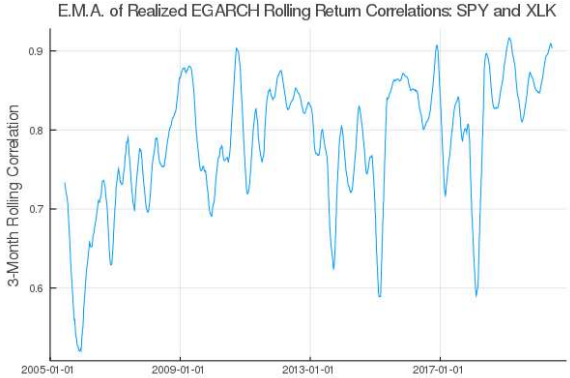
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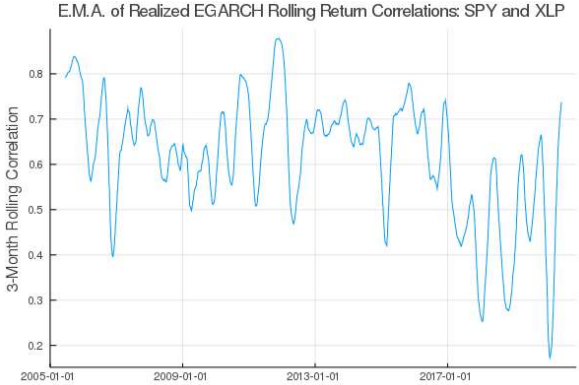
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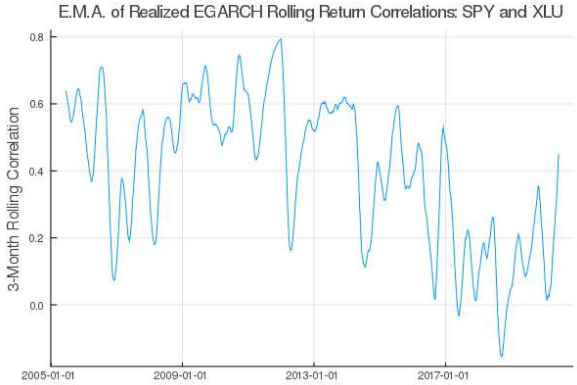
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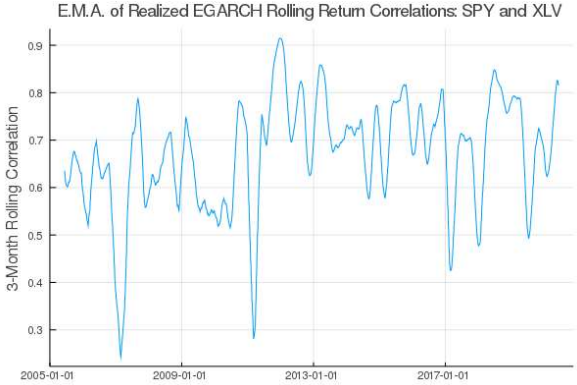
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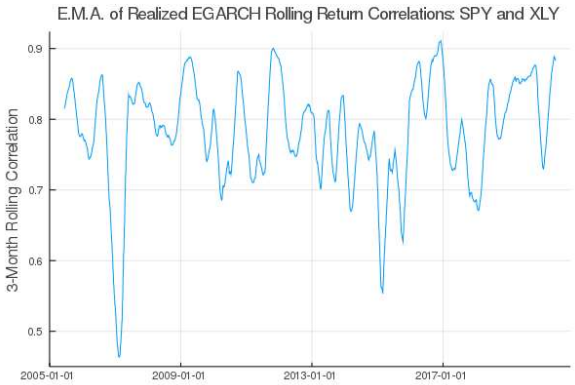
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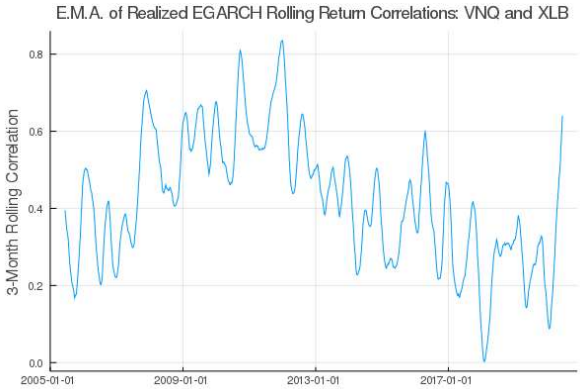
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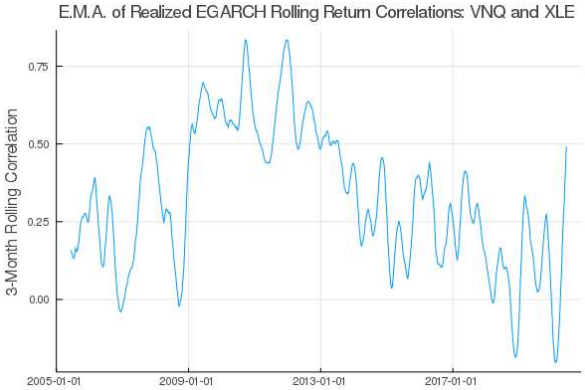
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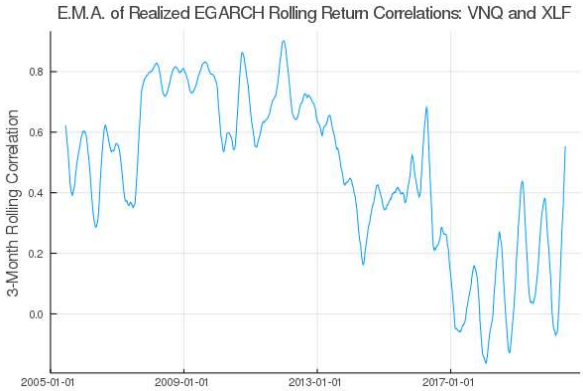
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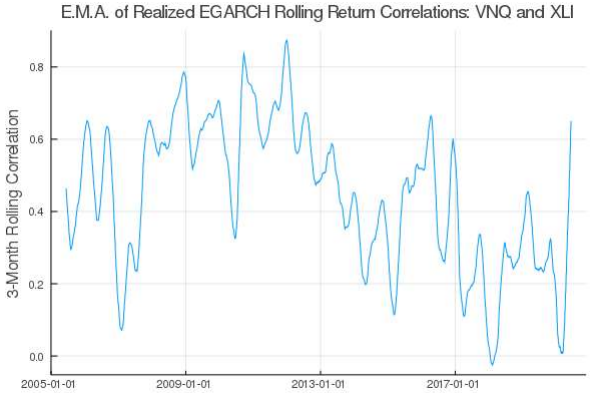
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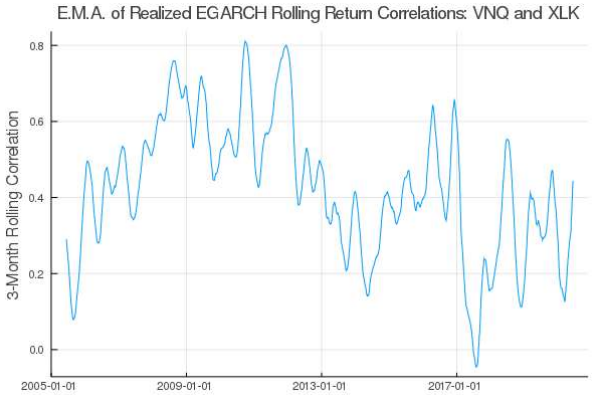
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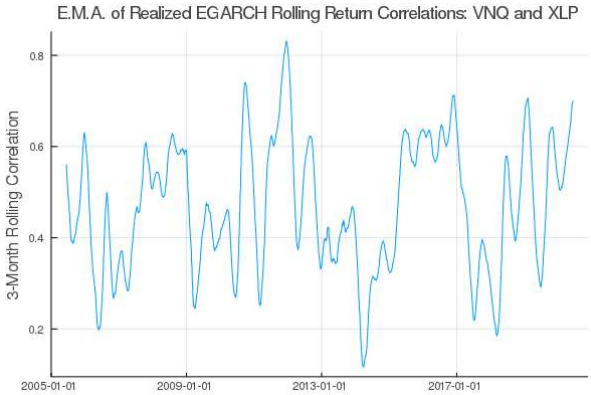
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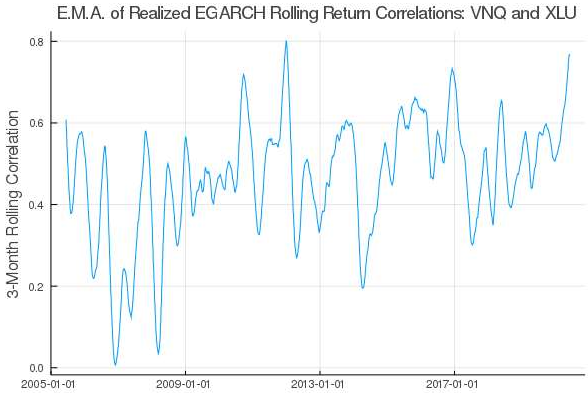
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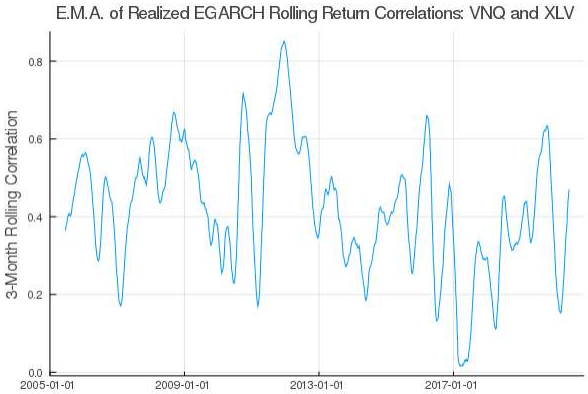
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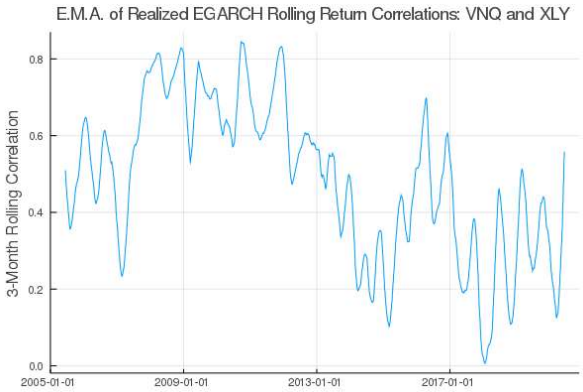
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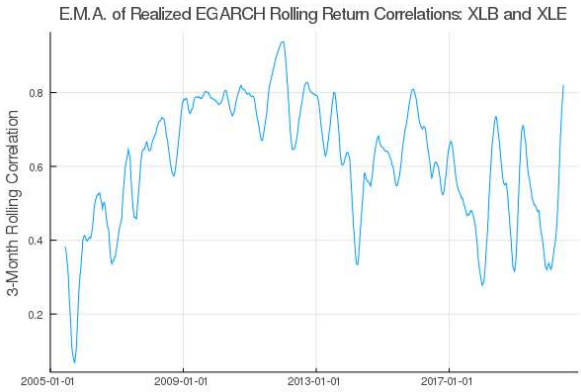
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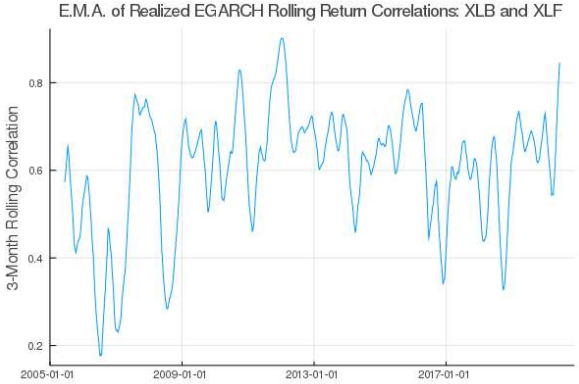
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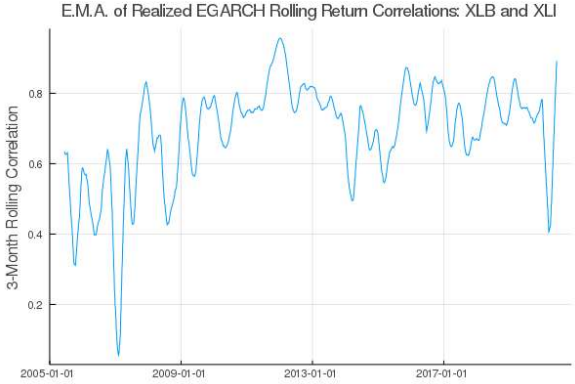
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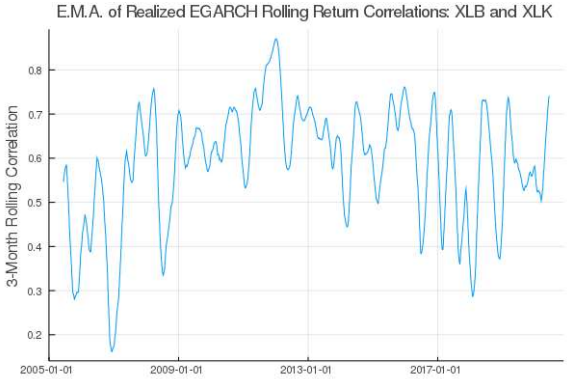
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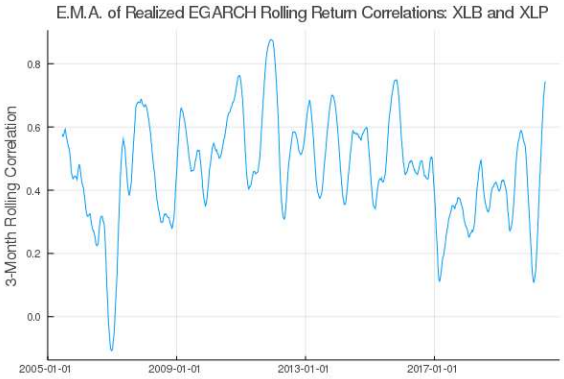
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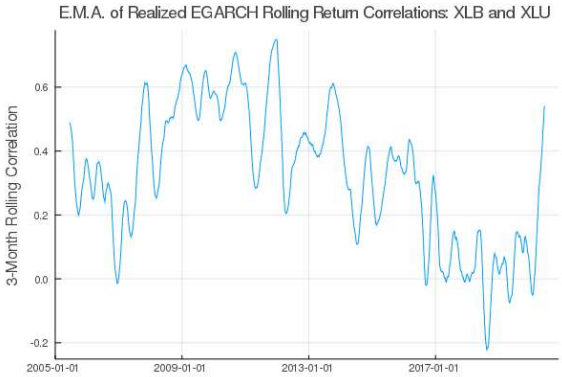
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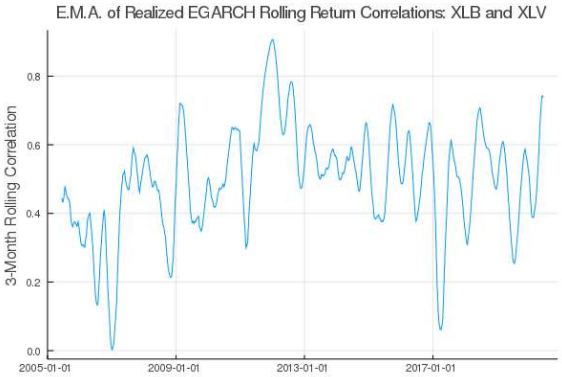
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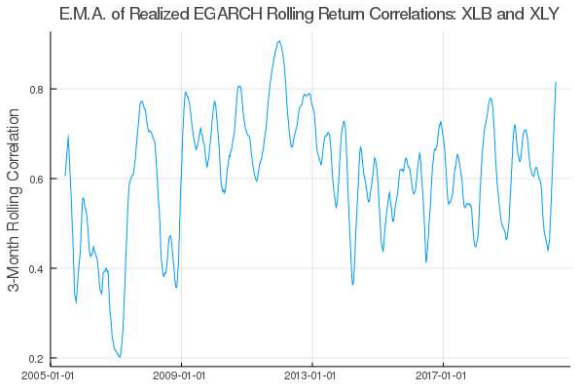
E.M.A. of Realized EGARCH Rolling Return Correlations: XLB and XLY
3-Month Rolling Correlation
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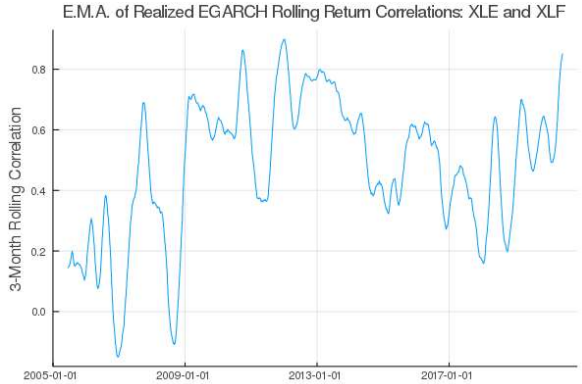
E.M.A. of Realized EGARCH Rolling Return Correlations: XLE and XLF
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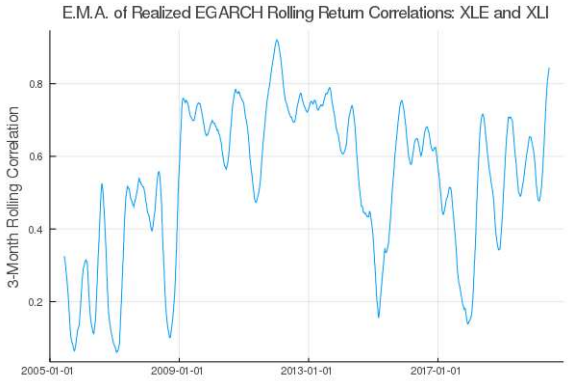
E.M.A. of Realized EGARCH Rolling Return Correlations: XLE and XLI
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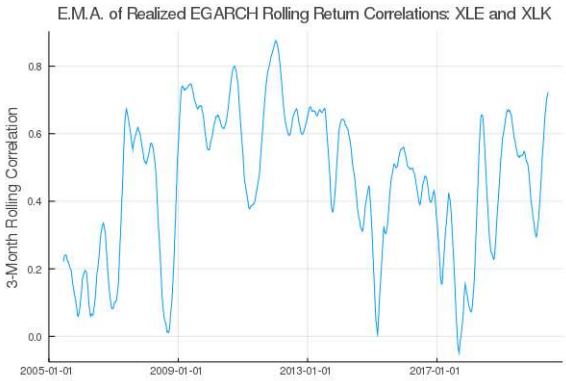
E.M.A. of Realized EGARCH Rolling Return Correlations: XLE and XLK
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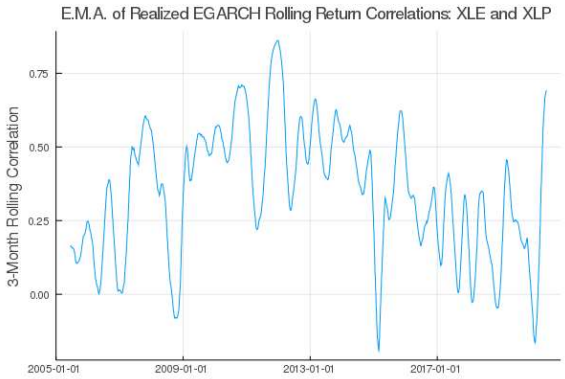
E.M.A. of Realized EGARCH Rolling Return Correlations: XLE and XLP
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0.25
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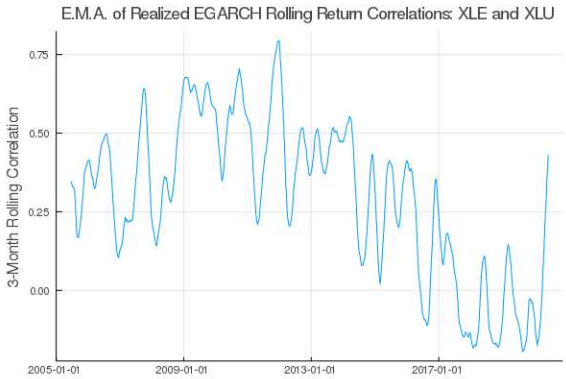
E.M.A. of Realized EGARCH Rolling Return Correlations: XLE and XLU
3-Month Rolling Correlation
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0.50
0.25
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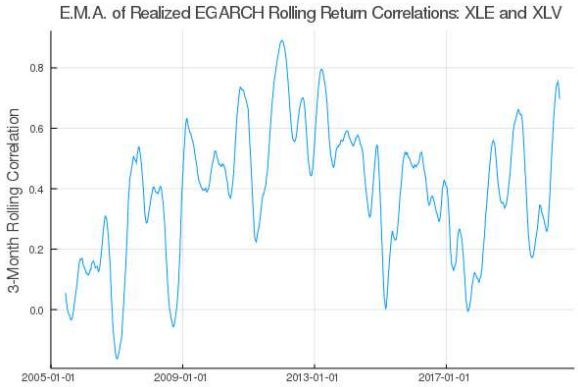
2017-01-01


E.M.A. of Realized EGARCH Rolling Return Correlations: XLE and XLV
3-Month Rolling Correlation
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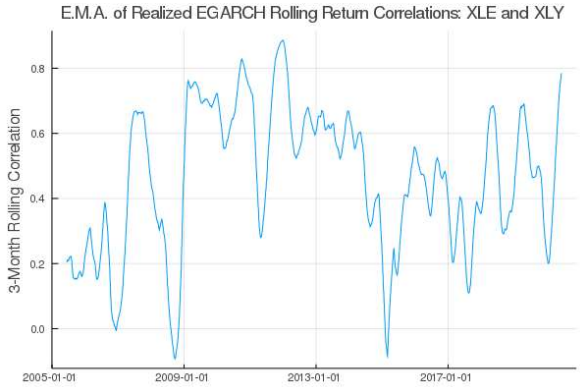
2017-01-01


E.M.A. of Realized EGARCH Rolling Return Correlations: XLE and XLY
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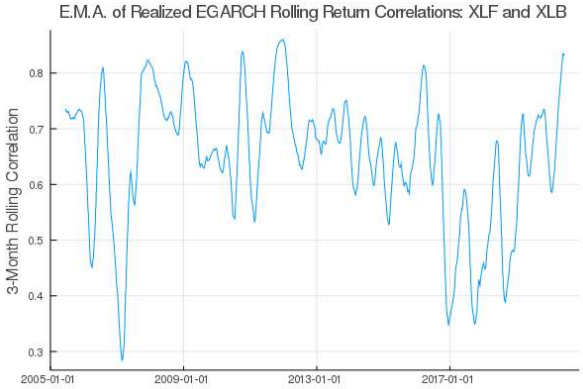
E.M.A. of Realized EGARCH Rolling Return Correlations: XLF and XLB
3-Month Rolling Correlation
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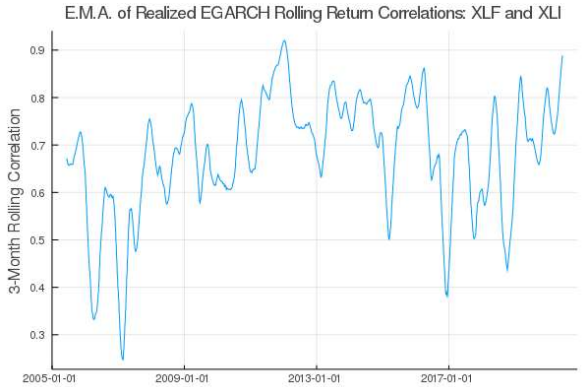
E.M.A. of Realized EGARCH Rolling Return Correlations: XLF and XLI
3-Month Rolling Correlation
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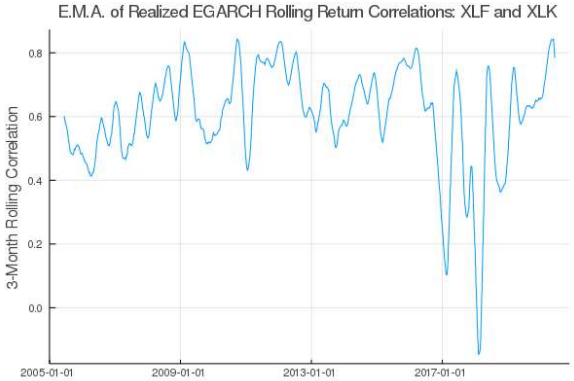
E.M.A. of Realized EGARCH Rolling Return Correlations: XLF and XLK
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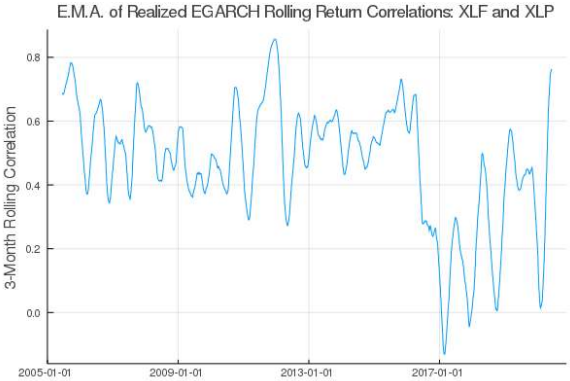
E.M.A. of Realized EGARCH Rolling Return Correlations: XLF and XLP
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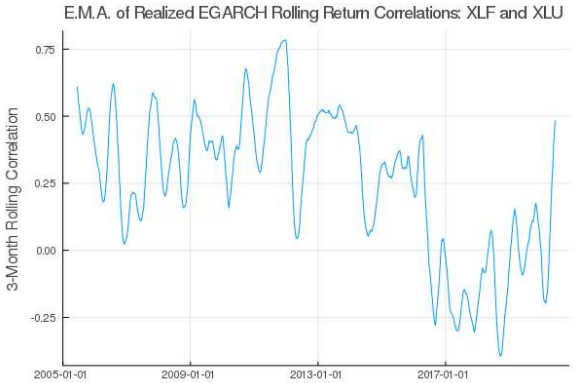
E.M.A. of Realized EGARCH Rolling Return Correlations: XLF and XLU
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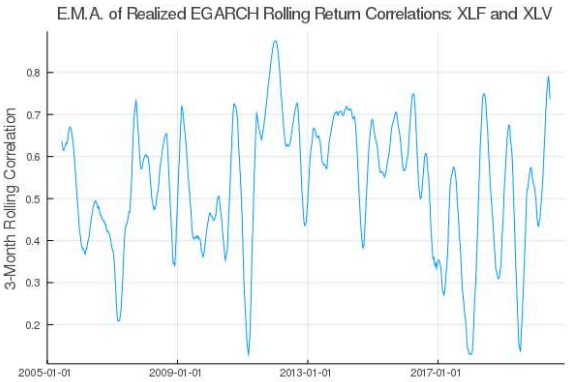
E.M.A. of Realized EGARCH Rolling Return Correlations: XLF and XLV
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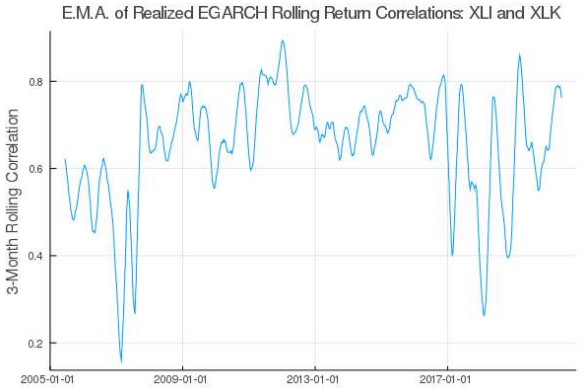
E.M.A. of Realized EGARCH Rolling Return Correlations: XLI and XLK
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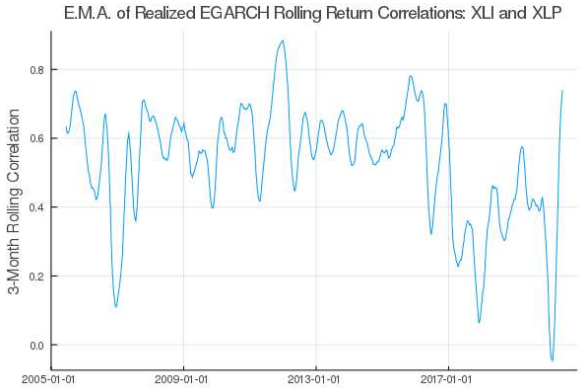
E.M.A. of Realized EGARCH Rolling Return Correlations: XLI and XLP
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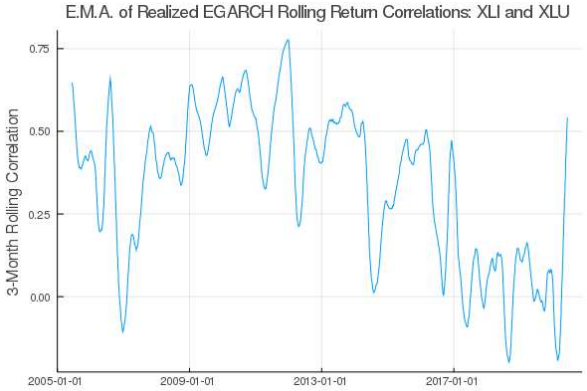
E.M.A. of Realized EGARCH Rolling Return Correlations: XLI and XLU
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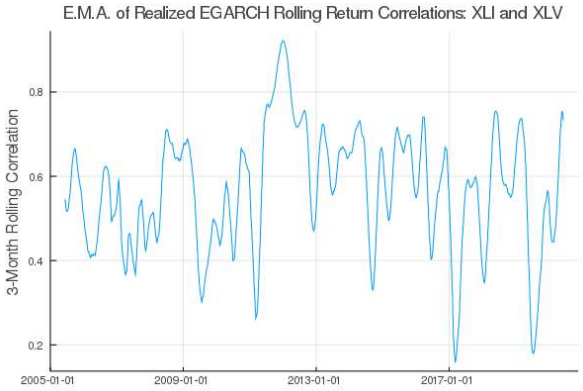
E.M.A. of Realized EGARCH Rolling Return Correlations: XLI and XLV
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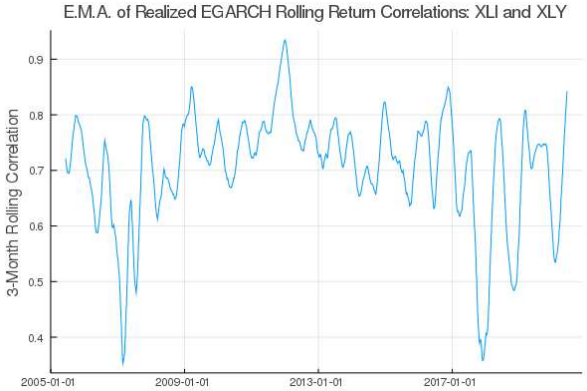
E.M.A. of Realized EGARCH Rolling Return Correlations: XLI and XLY
3-Month Rolling Correlation
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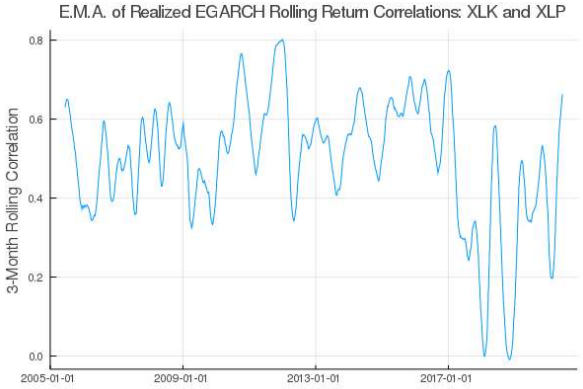
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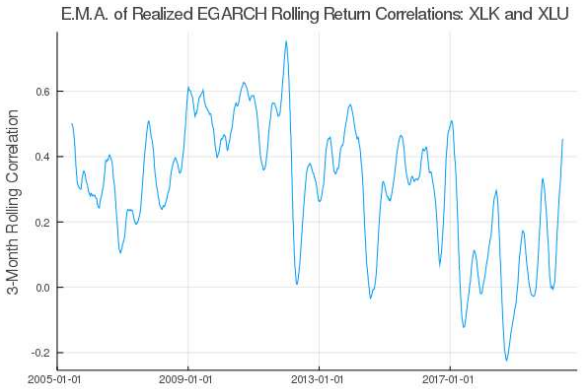
E.M.A. of Realized EGARCH Rolling Return Correlations: XLK and XLU
3-Month Rolling Correlation
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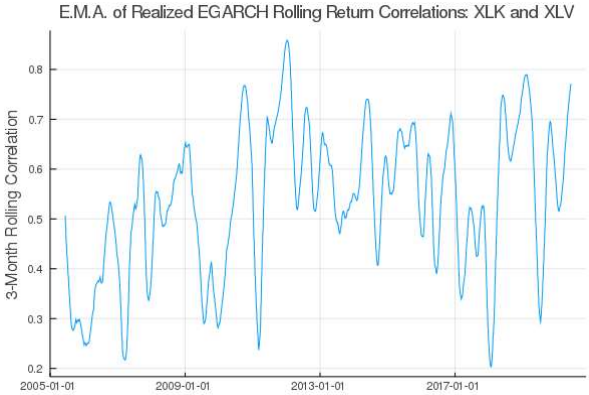
E.M.A. of Realized EGARCH Rolling Return Correlations: XLK and XLV
3-Month Rolling Correlation
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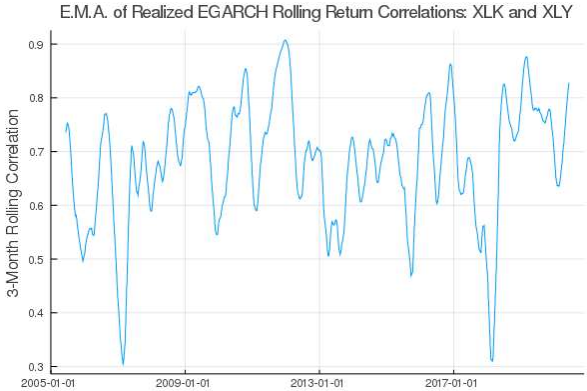
E.M.A. of Realized EGARCH Rolling Return Correlations: XLK and XLY
3-Month Rolling Correlation
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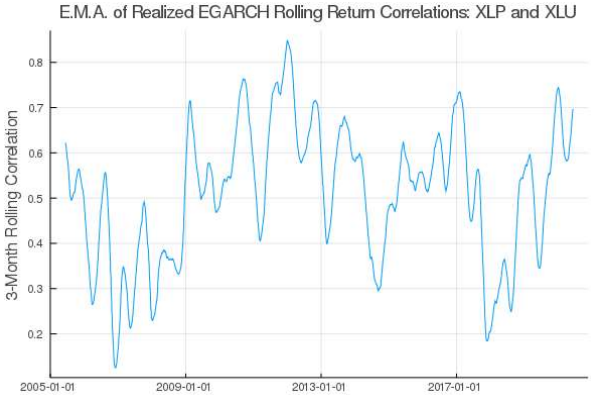
E.M.A. of Realized EGARCH Rolling Return Correlations: XLP and XLU
3-Month Rolling Correlation
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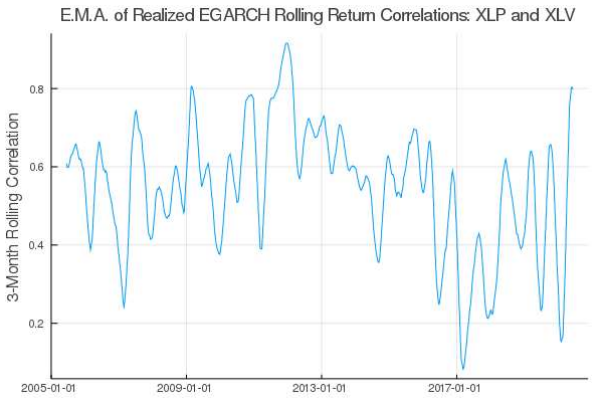
E.M.A. of Realized EGARCH Rolling Return Correlations: XLP and XLV
3-Month Rolling Correlation
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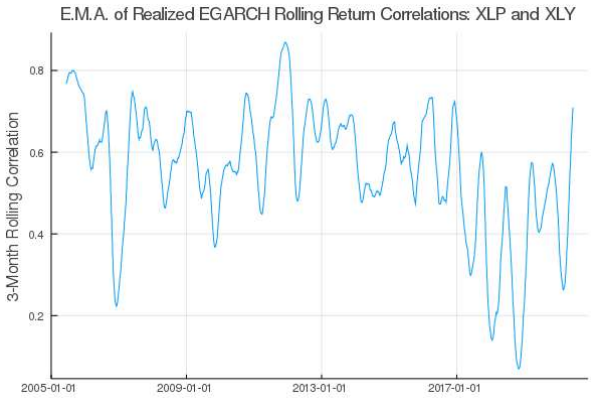
E.M.A. of Realized EGARCH Rolling Return Correlations: XLP and XLY
3-Month Rolling Correlation
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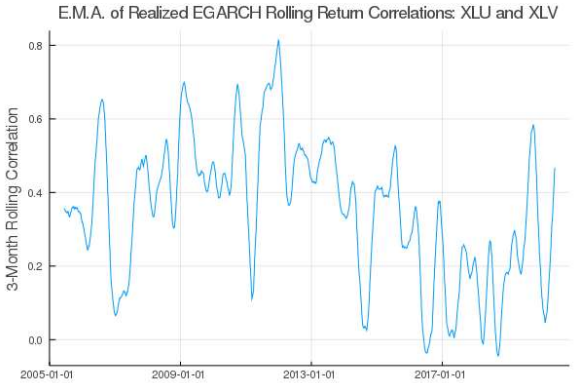
E.M.A. of Realized EGARCH Rolling Return Correlations: XLU and XLV
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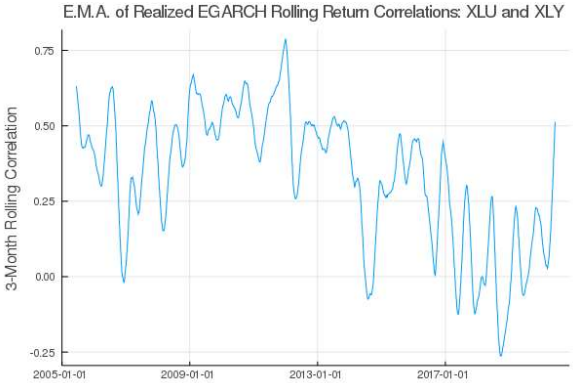
E.M.A. of Realized EGARCH Rolling Return Correlations: XLU and XLY
3-Month Rolling Correlation
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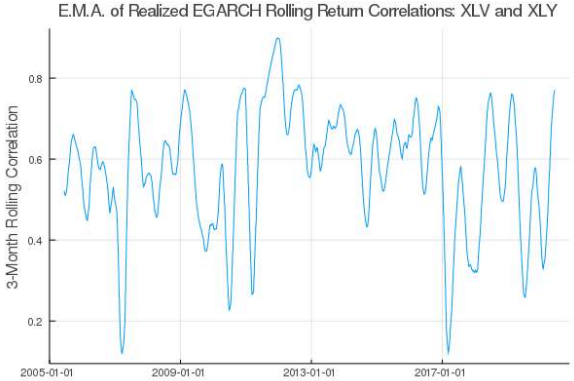
E.M.A. of Realized EGARCH Rolling Return Correlations: XLV and XLY
3-Month Rolling Correlation
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0.4
0.2
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2013-01-01
2017-01-01