Time-Varying Correlations and Sharpe Ratios during Quantitative Easing

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Abstract

Using an econometric methodology from Cappiello, Engle, and Sheppard (2006), we evaluate time-varying correlations between multiple asset classes using an asymmetric-DCC GARCH model. Specifically, we focus on the changes in these correlations during quantitative easing. We then use these conditional correlations, along with conditional means and variances to find optimal investment portfolios using Markowitz mean-variance minimization. Lastly, we compute time-varying Sharpe ratios. Our results show increasing Sharpe ratios during the period of quantitative easing which suggests that the Federal Reserve's programs where successful in minimizing risk—i.e. volatility—across several asset classes during the financial crisis.

Keywords: Multivariate GARCH, Asset Allocation, Sharpe Ratios

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1. Introduction

Typically, academic papers analyzing correlations between asset classes focus on the relationship between two types of assets: bonds and stocks (Cappiello et al., 2006; Anderson et al., 2008; Baur and Lucey, 2009; Baele et al., 2010; Aslanidis and Christiansen, 2010), stocks and oil (Jones and Kaul, 1996; Faff and Brailsford, 1999; Sadorsky, 1999), or stocks and gold (Jaffe, 1989; Johnson and Soenen, 1997; Davidson et al., 2003). A handful of other papers have also looked at other asset classes including high-yield bonds and investment-grade bonds (Briere et al., 2008; Reilly et al., 2009; Tuysuz, 2013). Few papers have investigated correlations between multiple asset classes. We estimate correlations between multiple asset classes using an econometric methodology from Cappiello, Engle, and Sheppard (2006). This methodology allows for asymmetries in the correlation dynamics and the conditional variances. Once we obtain conditional returns, variances, and correlations across our asset classes, we estimate time-varying Sharpe ratios using the conventional Markowitz mean-variance minimization strategy. Our results seem to lend support to the idea that QE was effective in stabilizing markets across a broad range of asset classes.

The Federal Reserve ended its quantitative easing (QE) program near the end of 2014, but the effect and success of the program continues to be a widely-debated issue in the media and academia. There are conflicting opinions on the effects quantitative easing has had on various markets. The first theorizes that since the Federal Reserve purchases do not represent a large portion of the overall bond market, the effect of quantitative easing is probably minimal. However, the counter argument is based on the fact that many market participants mimic the Federal Reserve when making asset allocation decisions. The phrase “don’t fight the Fed” has become a popular expression that conveys this idea. It could be the case that market participants attempting to profit by anticipating and tagging along with Federal Reserve actions can produce drastic changes.

Some in the academic world recognize the first theory as most plausible. They are skeptical that large scale asset purchase programs can be an effective monetary policy tool once the zero lower bound is reached. For example, Goodhart (1992), Walsh (2009), and Levin et al. (2010) argue these types of programs have no strong, significant effect. Kuttner (2004) provides evidence from the Japanese economy suggesting that an expansion of a central bank's balance sheet, such as quantitative easing, is not particularly effective in stimulating aggregate demand.

Bernanke (2012) argues for the second theory. He says the likely mechanism through which QE affects the economy is the portfolio balance channel:[1]

> The key premise underlying this channel is that, for a variety of reasons, different classes of financial assets are not perfect substitutes in investors' portfolios. […] Imperfect substitutability of assets implies that changes in the supplies of various assets available to private investors may affect the prices and yields of those assets. Thus, Federal Reserve purchases of mortgage-backed securities (MBS), for example, should raise the prices and lower the yields of those securities; moreover, as investors rebalance their portfolios by replacing the MBS sold to the Federal Reserve with other assets, the prices of the assets they buy should rise and their yields decline as well. Declining yields and rising asset prices ease overall financial conditions and stimulate economic activity through channels similar to those for conventional monetary policy.

So Federal Reserve purchases may spark large changes in markets even when the zero lower bound is reached.

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[1] The portfolio balance channel is based on the ideas of Tobin (1965, 1969), Modigliani and Sutch (1966), and Brunner and Meltzer (1973). Recent papers to discuss the portfolio balance channel include Nelson (2011) and Andrés, López-Salido, and Nelson (2004).

The Federal Reserve led the U.S. to the zero lower bound when it began cutting the federal funds rate. This started soon after U.S. financial markets began to feel the effects of a bloated subprime mortgage disaster in late summer 2007. Between September 2007 and December 2008 the federal funds rate went from 5.25% to a target range of 0% to 0.25% where it remained for an extended period. Besides keeping interest rates extraordinarily low for a long period of time, the Federal Reserve also added liquidity to the financial system through direct lending and purchases of Treasury and government sponsored enterprise (GSE) securities. This practice, known as quantitative easing, more than quadrupled the size of the Federal Reserve's balance sheet since the beginning of the financial crisis.

The beginning of quantitative easing started in late November 2008 when the Federal Reserve announced a massive, large-scale asset purchase (LSAP) of mortgage-backed securities (MBS) of up to $600 billion. By March 2009, the Federal Open Market Committee (FOMC) had substantially expanded its purchases of agency-related securities and longer-maturity Treasury securities. At the time, total asset purchases were $1.75 trillion. A second round of quantitative easing soon followed in November 2010 when the Federal Reserve announced it would buy an additional $600 billion of Treasury securities by the end of the second quarter of 2011. The third round of quantitative easing began on September 13, 2012 with the announcement of an open-ended bond purchasing program of MBS totaling $40 billion per month. The Federal Reserve increased this to $85 billion per month on December 12, 2012. Purchases ended on October 29, 2014 with the cumulative total of assets purchased through QE totaling $4.5 trillion. These three rounds of quantitative easing have come to be known as QE1, QE2, and QE3, respectively.

Much of the scholarly work to date has looked at the effects of many of these LSAPs on the specific asset classes targeted by the Federal Reserve.[2] Relatively few papers have looked at the effects in a larger context. As Bernanke (2012) points out, with the Federal Reserve changing the supply of various securities available to private investors, this likely affects not only directly affected asset classes but also other asset classes as investors rebalance their portfolios. Thus, this paper seeks to answer how successful LSAPs and QE were by looking at time-varying Sharpe ratios. Specifically, we argue that if these programs were successful, we expect the Sharpe ratio to increase after implementation of the programs.

Our empirical analysis begins using Cappiello, Engle, and Sheppard's (2006) framework to analyze the time-varying correlations between asset classes using monthly data from 1992-2014. One question of interest is the following: has the Federal Reserve substantially changed the correlations between asset classes by engaging in quantitative easing? Section 3 attempts to answer this question. We use our estimates of conditional correlations, variances, and returns to calculate time-varying Sharpe ratios in Section 4.

2. Data

We are interested in measuring the effect of quantitative easing across a broad range of asset classes. For this reason, we choose the following asset classes: stocks (i.e., equites)[3], three bond funds composed of U.S. government bonds (long, intermediate, and short), two corporate bond funds (investment grade and junk), the Case-Shiller home price index, gold, oil, and the six-month Treasury bill rate (i.e., our measure of the risk-free rate). For all variables, we use monthly data with a sample period beginning in January 1992 and ending in November 2014. All

[2] For example, Gagnon et al. (2010) find that the impact of the Federal Reserve's large-scale asset purchases during the global financial crisis lowered long-term bond rates relative to short rates on the order of 50 basis points, and lowered interest rates on mortgage-backed securities by improving liquidity in this market.

[3] We use the total monthly return of the S&P 500 index.

variables, except the S&P 500 total monthly return and the six-month Treasury bill rate, are defined as 1200 times the monthly percentage change. Figure 1 displays all of the time series variables. Shaded portions of the figures are NBER recession dates.

Table 1 displays the unconditional correlations between our asset classes. The correlations range from as high as 0.89—the correlation between short-duration and intermediate-duration U.S. Treasury bond funds—to as low as -0.12. In general, it appears the commodities, oil and gold, could potentially act as suitable hedges to stocks and bonds since the correlations are relatively low and, in some cases, negative. These unconditional correlations can provide investors with useful information, but correlations that are allowed to vary across time are potentially more useful. The popular model developed in Engle (2002)—known as the dynamic conditional correlation (DCC) generalized autoregressive conditional heteroskedasticity (GARCH) model—has the ability to produce time-varying correlations between series.

3. Time-Varying Correlations

Since many financial variables have been shown to exhibit heteroskedasticity,[4] we choose to model our asset classes within a multivariate GARCH framework.[5] In particular, we adopt Cappiello, Engle, and Sheppard's (2006) three-step econometric model allowing for time-varying correlations between our data series. Not only does Cappiello, Engle, and Sheppard's (2006) methodology allow for conditional asymmetries in volatilities, but also in correlations. It is based off a generalization of the DCC-GARCH model of Engle (2002).[6]

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[4] We test for heteroskedasticity by implementing McLeod-Li tests and calculating Ljung-Box Q-statistics of the squared residuals. We are able to reject homoskedasticity for at least one of the tests for all of our series.
[5] See Enders (2013) for a detailed explanation of multivariate GARCH models.
[6] This methodology has several advantages over other multivariate GARCH methodologies. Several papers utilize a variant of Bollerslev's (1990) methodology. They parameterize time-varying covariances, but correlation coefficients are assumed to be constant over the sample period. See, for example, Koutmos and Booth (1995), Booth, Martikainen, and Tse (1997), Scruggs (1998), and Christiansen (2000). Although this simplifies estimation, this assumption is neither theoretically correct nor robust to empirical evidence. Another class of models exists without the assumption of constant correlation coefficients. See Kroner and Ng (1998), Bekaert and Wu (2000), and

Let y_t be a k x 1 vector containing the data series. The conditional mean equations may be represented by the following reduced-form VAR:

$$A(L)y_t = \varepsilon_t \text{ where } \varepsilon_t \sim N(0, H_t) \qquad t = 1, \ldots\ldots T \tag{1}$$

where *A(L)* is a polynomial matrix in the lag operator L, and ε_t is a vector of innovations. The ε_t vector has the following conditional variance-covariance matrix:

$$H_t = D_t\, R_t D_t$$

where $D_t = diag\{\sqrt{h_{it}}\}$ is a k x k diagonal matrix containing the time-varying standard deviations from univariate GARCH models, and R_t is the time-varying correlation matrix.

The DCC model allows for three-stage estimation of the conditional covariance matrix. In the first stage, Engle and Sheppard (2001) use univariate GARCH models to model the variances and obtain estimates of h_{it}. We select our univariate volatility specifications based on the Bayesian information criterion (BIC).[7] The second stage consists of transforming the data by their estimated standard deviations and estimating the intercept parameters of the conditional correlation. Finally, during the last stage, conditions on the correlation intercept parameters are used to estimate the coefficients governing the dynamics of correlation.[8] Engle's (2002) framework uses the following *DCC(M,N)* structure:

$$R_t = Q_t^{*-1}\, Q_t\, Q_t^{*-1}$$

where

Scruggs and Glabadanidis (2003), but these papers suffer from dimensionality, which limits their scope for application.

[7] There are several information criteria to choose from, as well as, likelihood ratio tests. However, the BIC leads to the correct model specification asymptotically. The BIC is calculated as -2L + Nln(T) where L is the maximized log likelihood and N is the number of parameters in the specification.

[8] Engle and Sheppard (2001) and Engle and Sheppard (2005) study the efficiency of this three-stage estimation process and find that estimation of the univariate models makes little difference relative to a one-step, maximum-likelihood estimation. However, the correlation estimates will be consistent only if the univariate GARCH models are well specified.

$$Q_t = (1 - a - b)\overline{Q} + a(\varepsilon_{t-1}\acute{\varepsilon}_{t-1}) + bQ_{t-1}. \quad (2)$$

$\overline{Q}$ is the time-invariant variance-covariance matrix obtained by estimating the univariate volatility models, and Q_t^* is a k x k diagonal matrix containing the square root of the diagonal elements of Q_t.

Cappiello, Engle, and Sheppard (2006) add to the Engle (2002) methodology to allow for asymmetries and modify the correlation evolution equation. It becomes

$$Q_t = \left(\overline{Q} - A'\overline{Q}A - B'\overline{Q}B - G'\bar{\mathrm{U}}G\right) + A'\varepsilon_{t-1}\acute{\varepsilon}_{t-1}A + G'u_{t-1}u'_{t-1}G + B'Q_{t-1}B, \quad (3)$$

where *A*, *B*, and *G* are *k* x *k* parameter matrices, $u_t = I[\varepsilon_t < 0] o \varepsilon_t . I[\cdot]$ is a k x 1 indicator function which takes on a value of 1 if the argument is true and 0 otherwise, while "o" indicates the Hadamard product. Equation (3) is referred to as the asymmetric generalized dynamic conditional correlation (AG-DCC) model. There are two other models that Cappiello, Engle, and Sheppard (2006) develop. The asymmetric DCC (A-DCC) is obtained if the matrices *A*, *B*, and *G* are replaced by scalars. Similarly, the generalized DCC (G-DCC) is another special case of the AG-DCC when *G* = 0.

The first step in the estimation procedure involves selecting well-specified univariate GARCH models. We select our univariate volatility specifications based from the following types of GARCH models:[9] GARCH (Bollerslev (1986)), EGARCH (Nelson(1991)), and GJR-GARCH (Glosten, Jagannathan, and Runkle (1993)). Then, the four parameterizations of the

[9] We select the GARCH model with the smallest BIC from the following models:

GARCH: $h_t = \omega + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1}$

GJR-GARCH: $h_t = \omega + \alpha\varepsilon_{t-1}^2 + \gamma I[\varepsilon_{t-1} < 0]\varepsilon_{t-1}^2 + \beta h_{t-1}$

EGARCH: $\ln(h_t) = \omega + \alpha\frac{|\varepsilon_{t-1}|}{\sqrt{h_{t-1}}} + \gamma\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} + \beta\ln(h_{t-1})$

DCC model are estimated for the dynamics of the correlation. The first and simplest model is a standard scalar DCC model where no asymmetric terms are included. Second, the AG-DCC model is considered. Next, the two other asymmetric models, the A-DCC and the G-DCC are estimated. The A-DCC model has the lowest BIC of the all of the estimated models. Therefore, the remainder of the paper uses the correlation results estimated from the A-DCC model.

Figure 2 shows time-varying correlations for three of our asset classes with stocks. Correlations have been relatively stable over time except for the large spike that occurs during the Great Recession. The correlation between stocks and oil has historically been about 0.05 with brief periods of negative correlation. However, during the Great Recession the correlation spiked to almost 0.3. The vertical lines in Figure 2 represent the start of QE by the Federal Reserve. As can be seen, the start of QE was the beginning of the correlation between stocks and oil returning to historical levels. The other correlations—stocks and corporate bonds—display a similar pattern. The historical correlation between stocks and corporate investment grade bonds hovered around a historical average of 0.15 before spiking to a high of 0.35 in late 2008. Again, the start of QE returns the correlation between these asset classes to historical levels. Our final correlation in Figure 2 shows the time-varying correlation between stock and corporate junk bonds. The correlation was about 0.4 before spiking to a high of 0.55 during the financial crisis. The start date of QE appears to signify the beginning of the return to historical levels.

Figure 3 looks at time-varying correlations between corporate, investment-grade bonds and U.S. Treasury bond funds of three different maturities. All of the correlations display a similar pattern—historically stable correlations followed by large decreases during the Great Recession. In each graph, the correlations decrease in magnitude by approximately 0.25 (e.g., a historical correlation between corporate investment grade bonds and short-term Treasury bonds is around 0.75 and decreases to approximately 0.5 during the Great Recession). Once again, the start of QE appears to signal the return to historical levels.

The main conclusion from Figures 2 and 3 is the fact that historical correlations changed dramatically during the Great Recession (i.e., asset classes that had historically been good hedges—for example, oil and stocks—became more correlated). It appears QE started the process of returning asset classes to their historical correlations. A final point to be drawn from Figures 2 and 3 is the large increases in correlations in Figure 2 and large decreases in Figure 3. During the financial crisis investors sold a broad range of assets and bought safer U.S. Treasury bonds. This likely led to a large increase in correlations between varying asset classes such as stocks, oil, corporate investment grade, and corporate junk bonds that can be seen in Figure 2. Figure 3 illustrates the newly perceived default risk of corporate, investment-grade bonds that were previously viewed as safe. This is likely explained by the "flight to quality" status of U.S. Treasury debt. Investors, it appears, sold corporate bonds and bought Treasury bonds of any maturity to avoid this newly perceived risk leading to a decrease in the correlations.

4. Time-Varying Sharpe Ratios

In this section, we use our time-varying correlations along with the estimated returns and variances to produce optimal minimum-variance portfolios using the Markowitz mean-variance minimization strategy. From these portfolios, we calculate time-varying Sharpe ratios to determine whether the Federal Reserve was successful in minimizing variances (i.e., risk) across a broad range of asset classes.

At its most basic, the optimal portfolio is the solution to a problem that minimizes portfolio variance. Traditionally, we write this problem as:

$$\min 1/2\pi_t' \Sigma_t \pi_t$$

$$\text{subject to (1) } \mu'\pi_t = \mu_p \text{ and (2) } \mathbf{1}'\pi_t = 1$$

where π denotes a portfolio, a vector of weights in time t, Σ is the conditional covariance matrix of returns at the same time, and μ_p is the objective expected return for the portfolio. Constraint (1) imposes an expected return on the portfolio. Constraint (2), where $\mathbf{1}$ is a vector of ones, forces weights of investments in a portfolio to compose no more or less than 100% of the portfolio. We estimate two types of portfolios. In one, the no-shorting portfolio, asset weights are constrained to be non-negative. In the other, the portfolio may have negative asset weights, implying that assets may be sold short to optimize the portfolio. We minimize half the variance as a matter of convenience, and minimizing half variance gives the equivalent solution to minimizing variance. Solving this problem produces:

$$\pi_\mu = \frac{1}{\mathbf{1}'\Sigma^{-1}\mathbf{1}}\Sigma^{-1}\mu.$$

Then π_μ is a portfolio of risky assets. This portfolio represents the least variance combination of weights in all assets in the portfolio for some expected portfolio return given historical returns to the assets.

Solving this minimization problem for many different expected portfolio returns produces a curve in "expected return-standard deviation" space that represents the frontier of portfolios that have the least possible risk for any level of return. The best of these minimum-variance portfolios is the one that is the tangency point of the frontier and a line starting from the y-axis at the risk-free rate. Thus, the best minimum-variance portfolio is the one with the highest slope of this tangent line—the Capital Market Line (CML). In our analysis, we repeat the Markowitz mean-variance minimization for every month from January 1992 to November 2014. This yields optimal portfolio weights for each month.

Figure 4 shows the time-varying optimal weights for the portfolio without shorting. Oil, gold, and long-term Treasury bonds are typically highly weighted throughout all time periods, including recessions and expansions. Corporate junk bonds and stocks also have a number of periods with positive weights. Notice the weighting on stocks is typically very high during expansions, but zero during recessions. The weightings on returns from the housing market are high during the large run-up in housing prices from 2000 to 2006 and during the recovery after the Great Recession from 2012 to 2014 but close to zero during other time periods. Lastly, intermediate Treasury bonds, investment grade corporate bonds, and short-term Treasury bills are weighted very sparingly during the entire time period. The only large weighting for investment grade bonds occurs during the 2001 recession, while the large weightings for short-term Treasury bills occur during the 2001 and 2008 recessions.

The slope of the CML is the Sharpe ratio. This is a risk-adjusted, unitless measure of return to risk estimated by the following:

$$\frac{E\left[\widetilde{R_p}\right] - R_f}{stdev(\widetilde{R_p})} \tag{4}$$

where R_f is the risk-free return and $E\left[\widetilde{R_p}\right]$ is the expected portfolio return. There are essentially two ways to increase the Sharpe ratio. As illustrated in equation (4), one way to increase the Sharpe ratio is by decreasing the risk free rate. Once the Federal Reserve reached the zero lower bound, this option was essentially no longer available. The other way to increase the Sharpe ratio is to decrease the variance of the market portfolio. One way to potentially look at the effectiveness of QE across a broad range of asset classes is to see whether the Sharpe ratio increased during QE. Figure 5 displays our time-varying Sharpe ratios with and without shorting.[10] As can be seen, there's a large spike in the Sharpe ratio at the beginning of QE. The Sharpe ratio remains elevated throughout 2009. This is probably due to a combination of decreasing the risk free rate and decreasing the volatility of the optimal portfolio.

To see how quantitative easing altered the Sharpe ratio, we also take the average of the Sharpe ratios before November 2008 and the average after. Figure 6 illustrates the CMLs before and during quantitative easing in the scenario in which assets may be sold short. It is clear that the slope—the Sharpe ratio—is higher after policy implementation than before. The average Sharpe ratio before is approximately 96 and the average after approximately 117. This increase in the ratio is similar when we constrain portfolio investments to long positions. The average Sharpe before is approximately 63 and after is approximately 78.

5. Conclusion

Using an econometric methodology from Cappiello, Engle, and Sheppard (2006), we evaluate the time-varying correlations between different asset classes from 1992 through 2014. It appears that many correlations across a broad range of asset classes changed substantially during the Great Recession. The beginning of QE coincides with the start of correlations returning to historical levels, which suggests that QE was effective in calming investors' fears.

After estimating conditional time-varying correlations, volatilities, and returns, we calculate Markowitz mean-variance portfolios. Time-varying optimal weights suggest that commodities such as oil and gold act as beneficial hedges to stocks and bonds during expansions and recessions. The results also show little benefit from adding corporate investment grade bonds or short-term Treasury bonds except during recessions. Lastly, we calculate time-varying Sharpe ratios and determine that the Federal Reserve successfully increased the Sharpe ratio during

[10] Tang and Whitelaw (2011) estimate time-varying Sharpe ratios and find that Sharpe ratios are generally low at the peak of the business cycle and high at the trough.

QE—especially during QE1. Our results lend support to the idea that QE was effective in stabilizing markets across a broad range of asset classes.

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Table 1: Unconditional Correlations Between Asset Classes

	S&P	CS Housing	Gold	Oil	U.S. - Long	U.S. - Short	U.S. - Int.	Corp. - Inv.	Corp. - Junk
S&P		0.36	-0.01	0.10	0.07	0.21	0.11	0.26	0.23
CS Housing			-0.03	0.11	0.04	0.11	0.06	0.22	0.14
Gold				0.14	0.11	0.16	0.14	0.15	0.04
Oil					-0.12	0.04	-0.02	0.20	0.12
U.S. – Long						0.67	0.88	0.46	0.09
U.S. – Short							0.89	0.75	0.19
U.S. - Int.								0.64	0.16
Corp. - Inv.									0.63

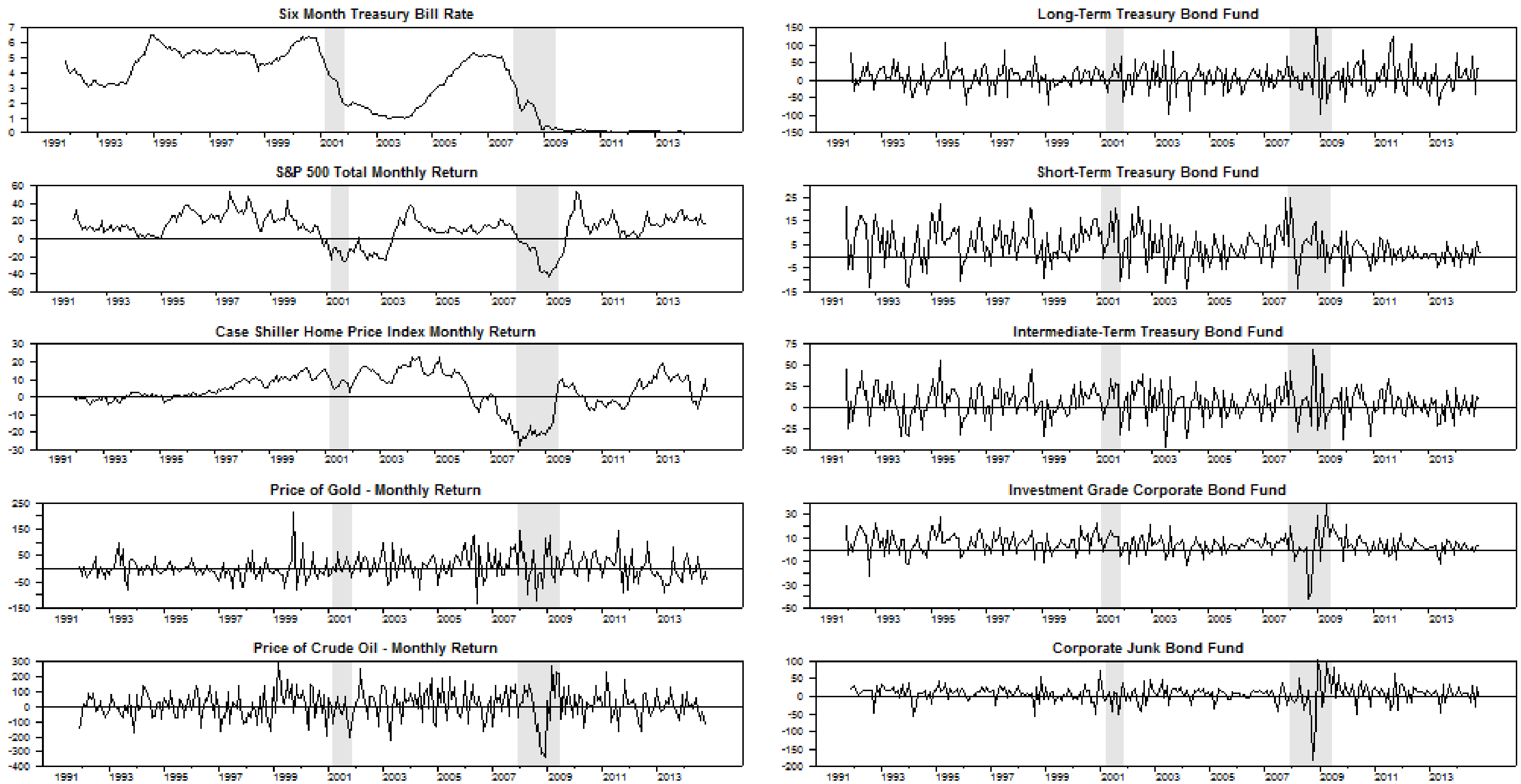

Figure 1. Time Series Plot of Asset Class Percentage Returns

Notes: The variables, except the S&P 500 total monthly return and the six-month Treasury bill rate, are defined as 1200*$(y_t - y_{t-1})/y_{t-1}$. The six-month Treasury bill rate (i.e., the risk free rate) is defined as the yield on the six-month Treasury bill, and the S&P 500 is the total monthly return. Shaded portions of the figures are NBER recession dates.

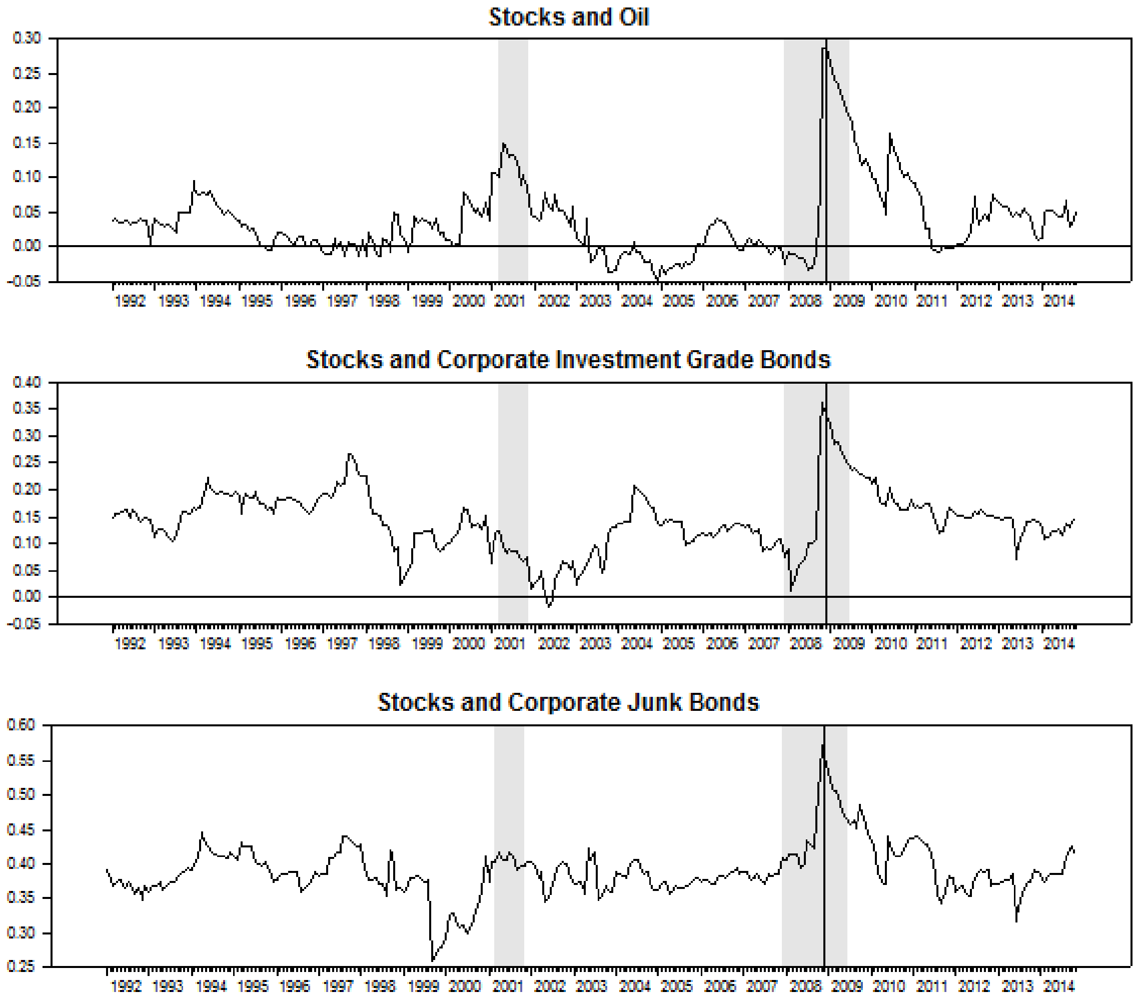

Figure 2. Time-Varying Correlations for Stocks

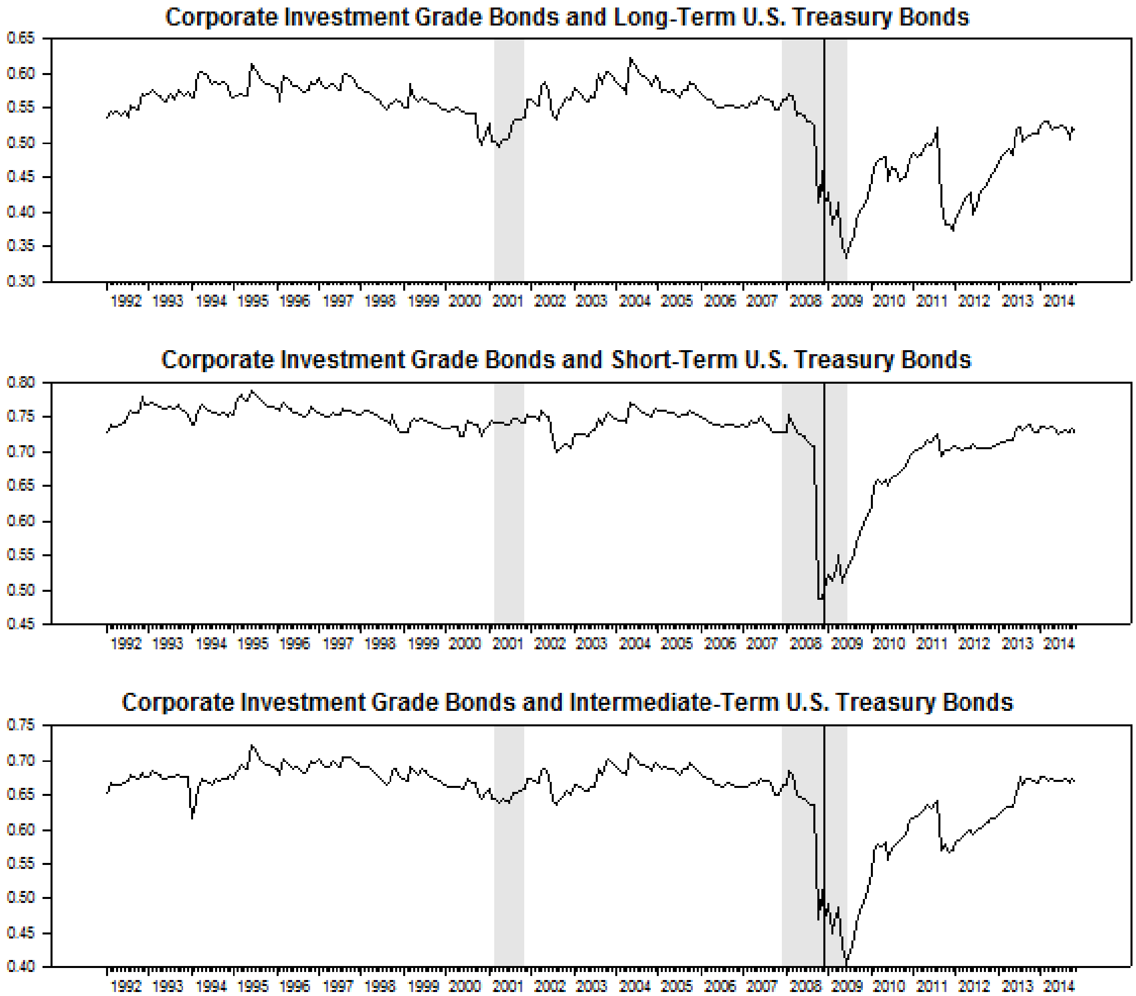

Figure 3. Time-Varying Correlations for Corporate Investment Grade Bonds

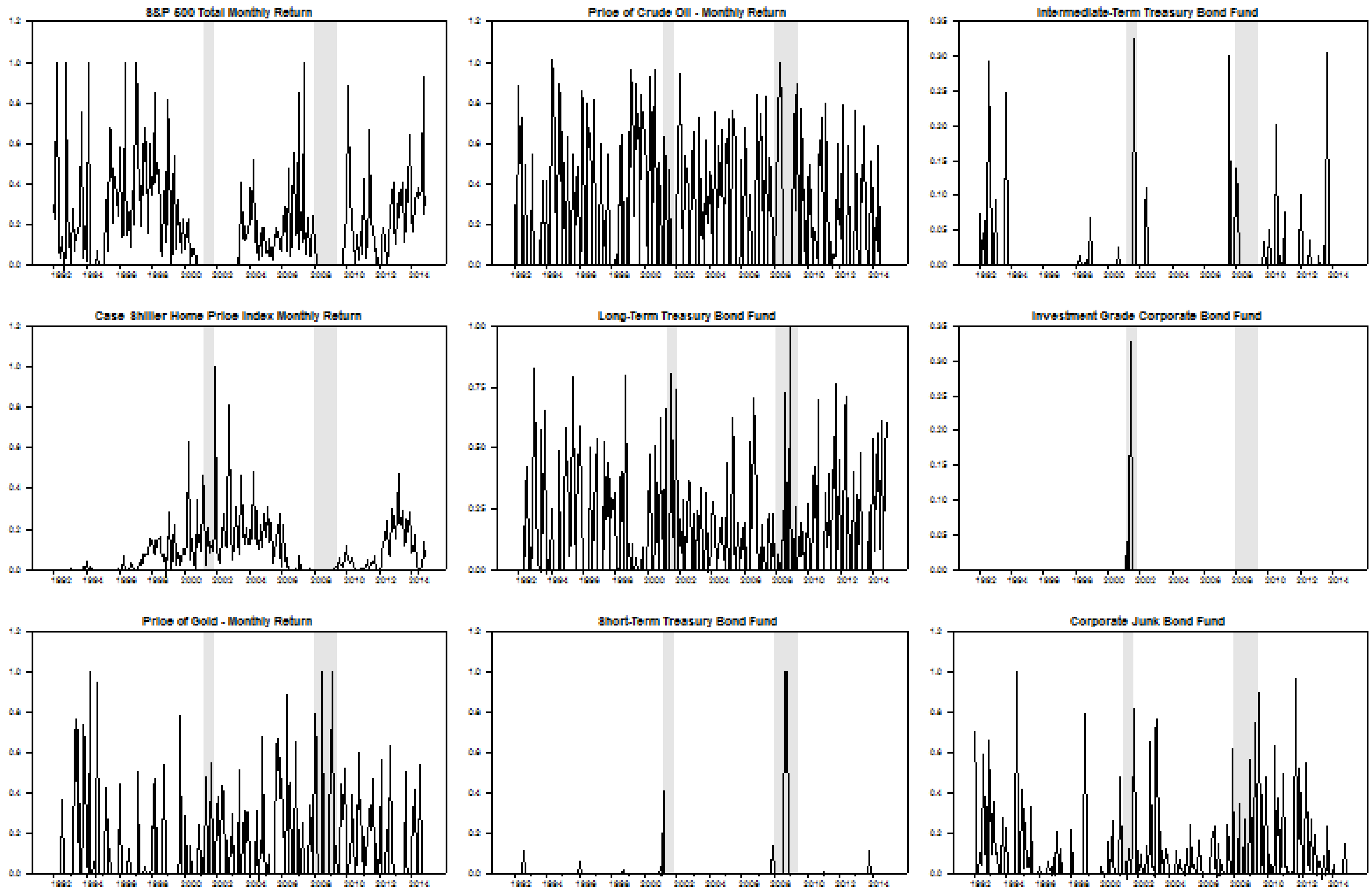

Figure 4. Time-Varying Optimal Weights with No Shorting

Notes: The time-varying optimal weights are estimated by Markowitz mean-variance minimization after estimating conditional correlations, variances, and returns from Cappiello, Engle, and Sheppard (2006). Shaded portions of the figures are NBER recession dates.

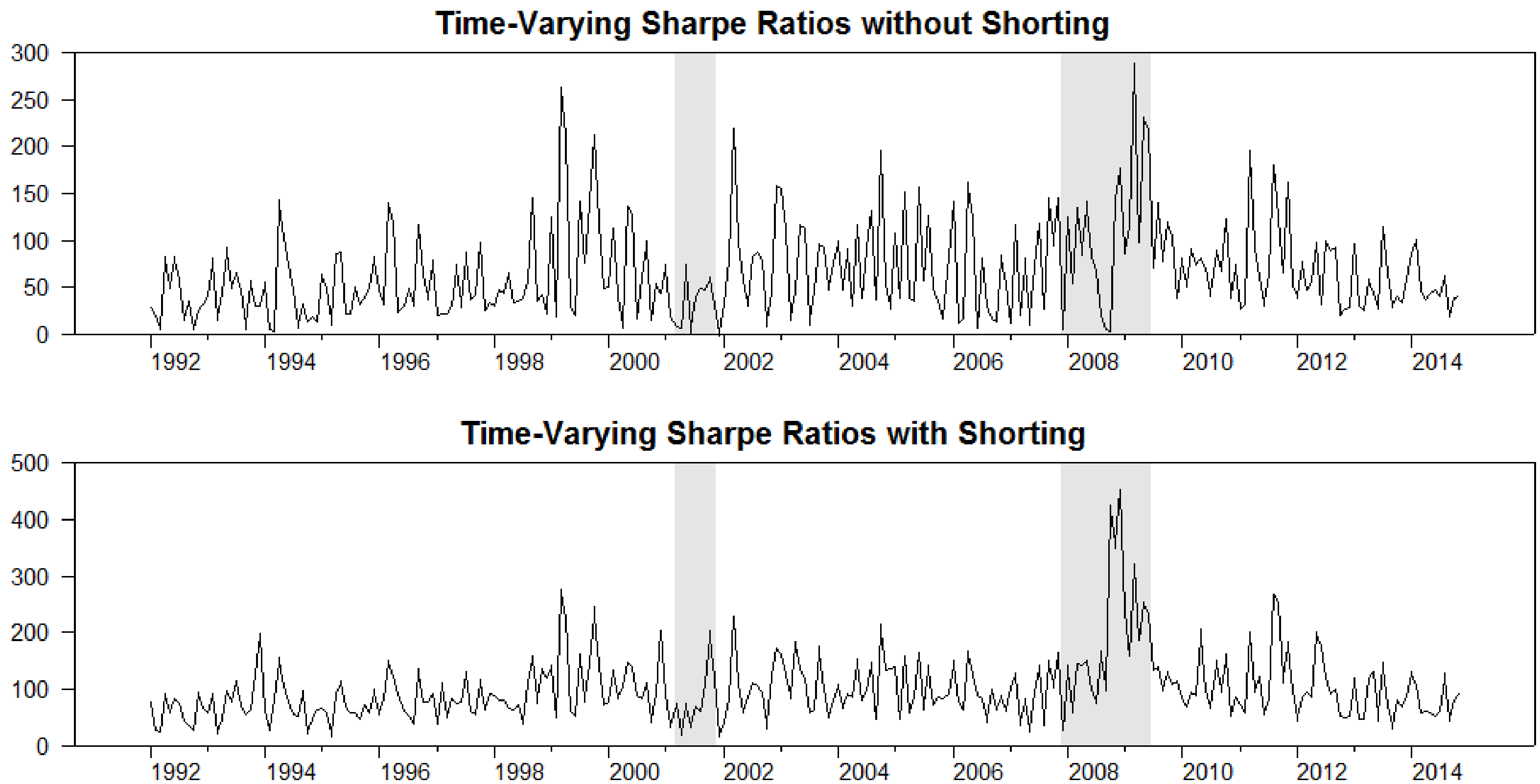

Figure 5. Time-Varying Sharpe Ratios

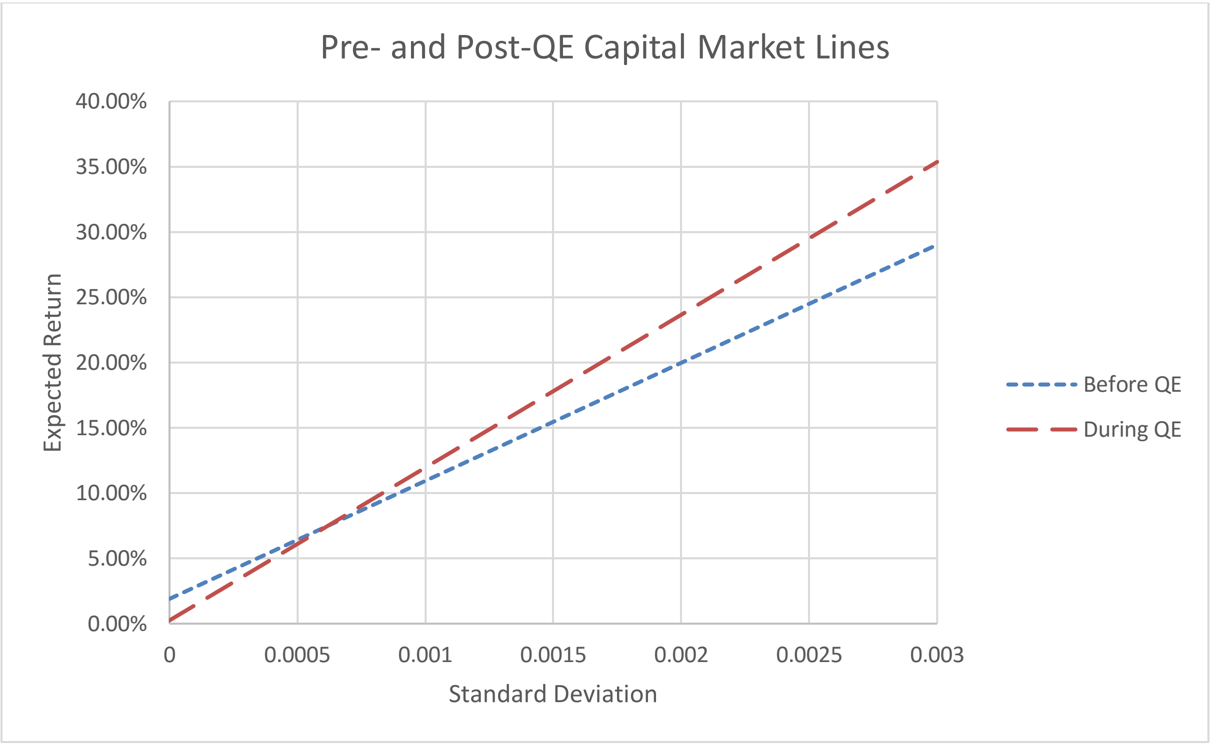

Figure 6. Average CML Before and During QE