ASSESSING THE ROLE OF U.S. TIMBERLAND ASSETS IN A MIXED PORTFOLIO UNDER THE MEAN-CONDITIONAL VALUE AT RISK FRAMEWORK

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ABSTRACT

This study examines the role of U.S. timberland assets in a mixed portfolio from the risk perspective. Using the mean-conditional value at risk (M-CVaR) optimization approach, the efficient frontier of the mixed portfolio is dramatically improved by adding timberland assets compared with the traditional mean-variance (M-V) optimization approach. Our study uses three risk metrics including standard deviation (SD), value at risk (VaR), and CVaR to measure and compare the portfolio risk. The results indicate that SD underestimates downside risk VaR and CVaR. Both static and dynamic risk decomposition of portfolios are used to identify the risk sources under four different scenarios. The empirical results reveal that large-cap stocks and small-cap stocks are generally risk intensifiers, whereas treasury bonds, treasury bills, and timberland assets are risk diversifiers in the mixed portfolio. The asset allocation strategies formulated by the M-CVaR approach indicate that timberland assets maintain a significant allocation in the mixed portfolio over static and dynamic optimizations.

Keywords: asset allocation, efficient frontier, mean-conditional value at risk (M-CVaR), risk decomposition, timberland assets

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Introduction

Timberland assets have attracted institutional investors in recent decades because of its distinct features, including high risk-adjusted returns (Cascio and Clutter, 2008), risk diversification potentials (Caulfield, 1998b), and inflation hedging abilities (Washburn and Binkley, 1993). To better understand the timberland assets, previous studies employed the modern portfolio theory to evaluate its performance and analyze its diversification effects. Mills and Hoover (1982) introduced the mean-variance (M-V) optimization approach to examine the relationship between returns and risks in forest investments and proved that forest investment could provide diversification benefits. Zinkhan et al. (1992) and Caulfield (1998a) demonstrated that adding timberland assets to a portfolio could improve the portfolio performance and provided asset allocation suggestions for institutional investors. Newell and Eves (2009) analyzed the risk-adjusted performance of U.S. timberland in real estate portfolios and concluded that the timberland assets strongly performed over 1987 – 2007.

Under the M-V framework, variance or standard deviation (SD) of asset returns is used to measure the portfolio risk under the assumption of multivariate normal distribution. When asset returns follow a normal distribution, SD can help us understand how much the asset returns vary around the mean value. However, investors are more concerned about the significant losses from the extreme events such as financial crisis, and therefore, more attention have been paid to downside risks in practice. Meanwhile, value at risk (VaR) has become a popular tool among portfolio managers to measure the downside risk since it is easy to calculate and interpret. VaR gives the maximum loss that will not be exceeded with a given probability over a period of time, whereas conditional VaR (CVaR) measures the loss greater than VaR.

It is well observed that the returns of financial assets such as stocks and bonds are not normally distributed. They generally exhibit non-normality properties such as skewness and kurtosis in the real world (Sheikh and Qiao, 2010). For instance, negatively skewed asset returns suggest that the left tail is longer than the right tail, implying that the probability of the occurrence of negative returns is higher than positive returns. Asset returns with fat tails imply that both of the extreme negative and positive returns occur more frequently than those normally distributed ones. It is obvious that the mean and variance alone fail to describe the true distribution. Therefore, the M-V approach may not fully reveal the relationship between returns and risks, and therefore, may not correctly construct the efficient frontier for a portfolio. To address the risk measure and non-normality issues, the Mean-CVaR (M-CVaR) optimization approach is introduced in this study. The M-CVaR approach minimizes downside risk measured by CVaR with a given level of target return and does not assume a multivariate normal distribution.

The overall purpose of this study is to examine the role of U.S. timberland assets in a mixed portfolio from the risk perspective. First, the efficient frontier is
constructed by the M-CVaR optimization approach, which minimizes downside risk CVaR and accounts for the non-normality of asset returns. The empirical results indicate that the M-CVaR approach leads to a more efficient frontier than the M-V approach. Second, three risk metrics including SD, VaR, and CVaR are used to evaluate and compare portfolio risks. It is found that SD underestimates the portfolio risk compared with VaR and CVaR, which should reflect the true downside risk. Finally, the portfolio risk is decomposed to identify how the aggregate risk is contributed by individual assets under four different scenarios through backtesting. The results reveal that both large-cap and small-cap stocks are risk intensifier, whereas treasury bills, bonds, and timberland assets are risk diversifiers.

**Methodology**

*Modern Portfolio Theory*

Modern portfolio theory proposed by Markowitz (1952) establishes the foundation of portfolio optimization and asset allocation strategies. This theory constructs a set of optimal portfolios through weighted combinations of assets whose returns are viewed as random variables. The returns of these portfolios are measured by the sample means of the combined assets. Mathematically, a set of assets indexed by \( i (i = 1, 2, \ldots, n) \) generate individual returns \( r_i = (r_{i1}, r_{i2}, \ldots, r_{in})^T \) at the end of the holding period. Their mean values are denoted by \( \bar{r} = \mu(r) = (\bar{r}_1, \bar{r}_2, \ldots, \bar{r}_n)^T \) over the holding period. Investors construct their portfolios by adjusting the weight of individual asset \( w = (w_1, w_2, \ldots, w_n)^T \) constrained by \( \sum_{i=1}^{n} w_i = 1 \) and \( w_i > 0 \) (short-selling is not allowed). Therefore, the portfolio return can be calculated by \( R(w, r) = w^T \bar{r} = \sum_{i=1}^{n} w_i \bar{r}_i \), where \( R \) is a random variable with a cumulative distribution function \( F_R \). Assume the portfolio risk \( \mathfrak{R} \) is a function of asset weights and returns, then the portfolio can be optimized by minimizing the risk subject to a given target return \( u \) as follows.

\[
\begin{align*}
\operatorname{Min} & \quad \mathfrak{R}(w, r) \\
\text{s.t.} & \quad w^T \bar{r} = u \quad \text{and} \quad \sum_{i=1}^{n} w_i = 1
\end{align*}
\]

*Risk Measures*

Risk measure I: standard deviation (SD). The standard deviation defined in equation (2) is commonly used to measure the portfolio risk, where \( \Sigma \) is the variance-covariance matrix of the \( n \) assets. This portfolio optimization is under the multivariate normal distribution assumption and is called the mean-variance (M-V) optimization approach. Solving the problem of \( \operatorname{Min} \sigma^2(w, r) \) with a given set of target returns can generate M-V efficient frontiers, where \( \sigma^2(w, r) = w^T \Sigma w \) is the variance of the portfolio. This portfolio optimization problem can be solved by quadratic programming solvers.
Risk measure II: value at risk (VaR). VaR has become the most widely used industry standard to measure risks. It calculates the downside risk into one number, allowing easy comparisons among individual assets and portfolios (Morgan, 1996). It is defined as the maximum loss that will not be exceeded within a period of time at a confidence level. Given a confidence level \( \alpha \in (0,1) \), a portfolio’s \((1-\alpha)\%\) VaR can be calculated by the following formula.

\[
VaR_\alpha(w,r) = -F^{-1}_\alpha(1-\alpha)
\]  

(3)

Where \( F^{-1}_\alpha \) is the quantile function of the asset or portfolio returns. Although VaR has become a popular risk measure, it lacks of some desirable properties such as subadditivity (Artzner et al., 1999). For example, a portfolio’s VaR may be greater than the sum of the individual VaR. Moreover, it is difficult to minimize a portfolio’s VaR since it is a non-smooth and non-convex function with respect to asset weights.

Risk measure III: Conditional value at risk (CVaR). CVaR overcomes many of the drawbacks of VaR as a downside risk measure. For example, CVaR has the coherent properties, including subadditivity, homogeneity, monotonicity, and translation invariance (Krokhmal et al., 2002). CVaR is defined as the conditional expectation of losses exceeding VaR at a confidence level. A portfolio’s CVaR can be defined in terms of its own VaR with a confidence level \( \alpha \).

\[
CVaR_\alpha(w,r) = -E[R(w,r)|R(w,r) \leq -VaR_\alpha(w,r)] = -\frac{1}{1-\alpha} \int_{-\infty}^{-VaR_\alpha(w,r)} zf(z)dz
\]

(4)

Where \( f(z) \) is the probability density function of portfolio return \( R(w,r) \). Solving the problem of \( \text{Min} CVaR_\alpha(w,r) \) with a given set of target returns can generate M-CVaR efficient frontiers (Rockafellar and Uryasev, 2000).

Risk Decomposition

Risk decomposition can help portfolio managers to identify the sources of risk in a portfolio, and therefore, provide important implications for risk management. The contribution by each asset in a portfolio is easily calculated by the Euler’s theorem since all these three risk measures (SD, VaR, and CVaR) are homogenous of degree one. The risk contribution of the \( i^{th} \) asset to the portfolio’s SD, VaR, and CVaR can be calculated by equations (5) – (7) and can be interpreted as the change of the portfolio risk with respect to the percentage change in weight \( w_i \) (Martin et al., 2001; Pearson, 2002; Boudt et al., 2008).
\[ D_i \frac{\partial SD(w, r)}{\partial w_i} = w_i \frac{\partial SD(w, r)}{\partial w_i} \] (5)

\[ D_i \frac{\partial VaR_{\alpha}(w, r)}{\partial w_i} = w_i \frac{\partial VaR_{\alpha}(w, r)}{\partial w_i} \] (6)

\[ D_i \frac{\partial CVaR_{\alpha}(w, r)}{\partial w_i} = w_i \frac{\partial CVaR_{\alpha}(w, r)}{\partial w_i} \] (7)

If the risk contribution is greater than the weight, the asset is a risk intensifier, and otherwise, the asset serves as a risk diversifier. If they are equal, the asset is a neutral. In addition, the individual risk contribution satisfies

\[ \sum_{i=1}^n D_i \frac{\partial SD(w, r)}{\partial w_i} = \sum_{i=1}^n D_i \frac{\partial VaR_{\alpha}(w, r)}{\partial w_i} = \sum_{i=1}^n D_i \frac{\partial CVaR_{\alpha}(w, r)}{\partial w_i} = 1. \]

**Backtesting**

Backtesting is a common method to evaluate the performance of a portfolio using historical data with given strategies. It can provide crucial implications for asset allocation and portfolio management. In this study, backtesting is employed to formulate the asset allocation strategies and analyze the asset risk contributions under the M-CVaR framework. Asset allocations with a given target return are formulated and compared across different scenarios. The corresponding risk contribution is calculated to evaluate the role of timberland assets.

**Data and Scenarios**

Four assets including large-cap stocks, small-cap stocks, treasury bonds, and treasury bills are considered in this study. Among them, returns on large-cap stocks are proxied by the S&P 500 Index collected from the Center for Research in Security Prices (CRSP). Returns on small-cap stocks are approximated by Russell 2000 Index collected from Russell Investments. Returns on treasury bonds are proxied by Barclays Capital U.S. Government/Credit Index collected from Barclays Capital. Returns on treasury bills are approximated by the 3-month treasury bills collected from CRSP. The NCREIF Timberland Index is used to proxy the returns for U.S. timberland investments. Quarterly data from 1987Q1 to 2001Q4 are used in this study.

Institutional investors primarily invest in traditional assets such as stocks and bonds in their portfolios. In practice, individual assets are constrained by allowable allocations. In order to better understand the role of timberland assets in a mixed portfolio, two scenarios are assumed. Scenario 1 places the minimum asset allocation on the large-cap stocks by 20%, small-cap stocks by 15%, treasury bonds by 10%, and treasury bills by 5%. Scenario 2 adds the restriction of a maximum 10% weight on timberland assets to Scenario 1.
Empirical Results

Descriptive Statistics

The descriptive statistics of the individual assets from 1987 to 2011 are reported in Panel A of Table 1. The results show that timberland assets have the highest quarterly return (3.2%) and treasury bills have the lowest standard deviation (0.6%). Returns on large-cap stocks, small-cap stocks, and treasury bills are negatively skewed, whereas returns on treasury bonds are slightly positively skewed and timberland assets are highly positively skewed. Returns on timberland assets have the highest excess kurtosis, indicating fat tails of their distribution. Additionally, results of the Jarque-Bera normality test reveal that the null hypothesis of normal distributions of large-cap stocks, small-cap stocks, and timberland assets are rejected at the 10% confidence level. The Shapiro-Wilk multivariate normality test is rejected at the 1% level.

Three risk measures are applied to individual assets first and the results are reported in Panel B of Table 1. The VaR and CVaR of large-cap stocks and small-cap stocks are much higher than the SD of them, indicating the SD underestimate individual downside risks. Regarding timberland assets, the VaR are lower than the SD but the CVaR is higher than the SD, suggesting that their skewness and kurtosis affect the evaluation of risks. Panel C of Table 1 presents the correlations between each pair of the assets in the mixed portfolio. Large-cap stocks are highly correlated with small-cap stocks but slightly correlated with treasury bills and timberland assets, and negatively correlated with treasury bonds. The low and negative correlations between these assets provide a potential for portfolio diversification.

### Table 1 Descriptive Statistics, Risks, and Correlations (1987Q1 – 2011Q4)

<table>
<thead>
<tr>
<th></th>
<th>Large-cap Stocks</th>
<th>Small-cap Stocks</th>
<th>Treasury Bonds</th>
<th>Treasury Bills</th>
<th>Timberland Assets</th>
</tr>
</thead>
<tbody>
<tr>
<td>Panel A: Descriptive Statistics</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>Minimum</td>
<td>-0.232</td>
<td>-0.291</td>
<td>-0.032</td>
<td>0.000</td>
<td>-0.065</td>
</tr>
<tr>
<td>Mean</td>
<td>0.020</td>
<td>0.027</td>
<td>0.018</td>
<td>0.010</td>
<td>0.032</td>
</tr>
<tr>
<td>Maximum</td>
<td>0.209</td>
<td>0.297</td>
<td>0.080</td>
<td>0.024</td>
<td>0.223</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>0.083</td>
<td>0.111</td>
<td>0.024</td>
<td>0.006</td>
<td>0.042</td>
</tr>
<tr>
<td>Skewness</td>
<td>-0.609</td>
<td>-0.452</td>
<td>0.081</td>
<td>-0.124</td>
<td>1.797</td>
</tr>
<tr>
<td>Excess Kurtosis</td>
<td>0.789</td>
<td>0.565</td>
<td>-0.700</td>
<td>-0.882</td>
<td>4.810</td>
</tr>
<tr>
<td>JB Normality Test</td>
<td>0.009</td>
<td>0.074</td>
<td>0.389</td>
<td>0.202</td>
<td>0.000</td>
</tr>
<tr>
<td>SW Multivariate Normality Test</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Panel B: Risks</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SD</td>
<td>0.083</td>
<td>0.111</td>
<td>0.024</td>
<td>0.006</td>
<td>0.042</td>
</tr>
<tr>
<td>VaR (95%)</td>
<td>0.129</td>
<td>0.167</td>
<td>0.022</td>
<td>0.000</td>
<td>0.036</td>
</tr>
<tr>
<td>CVaR (95%)</td>
<td>0.185</td>
<td>0.237</td>
<td>0.029</td>
<td>0.002</td>
<td>0.076</td>
</tr>
<tr>
<td>Panel C: Correlations</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Efficient Frontiers

The comparison of the M-V and M-CVaR efficient frontiers is shown in Figure 1. The M-CVaR efficient frontier is dramatically improved with timberland assets compared with the M-V one. For example, with a target return of 2%, the SD and CVaR of the portfolios without timberlands are 2.8% and 3%, respectively. After adding timberland assets in the mixed portfolio, the SD of the portfolio with the same target return is 1.6%, whereas the CVaR of that portfolio is 0.8%. These results indicate that the M-CVaR approach can reduce more risk than the M-V approach. This is because the M-CVaR approach considers the non-normality of the asset returns.

Figure 1 Comparison of the M-V and M-CVaR Efficient Frontiers with Timberland Assets

Static Asset Allocations

Figure 2 shows the static M-CVaR asset allocations under two different scenarios. In Scenario 1, the allocation on treasury bills is more than that on treasury bonds in lower target returns. The weight of timberland assets increases up to 48.5% as investors require higher level of target returns. In Scenario 2, the asset allocations are similar to Scenario 1 in low target returns. Timberland assets are substituted by treasury bonds and small-cap stocks for higher target returns. Overall, timberland assets have a significant allocation in the mixed portfolio.
Based on the asset allocation strategies in Figure 2, the optimal portfolio with a target return of 2% is selected and the its corresponding risks measured by SD, VaR, and CVaR are reported in Table 2. Under both scenarios, the portfolio’s SD is less than its VaR, which is less than its CVaR. This indicates that the portfolio’s SD underestimates the portfolio downside risk. Next, the portfolio’s SD, VaR, and CVaR are further decomposed by equations (5) – (7) to understand the risk contribution of individual assets. The risk contributions of large-cap stocks and small-cap stocks are much higher than their own weights, indicating that stocks are risk intensifiers. In contrast, the risk contribution of treasury bonds is much lower than its own weight, suggesting it is a strong risk diversifier. As for treasury bills and timberland assets, their decomposition percentages are low and less than their own weights. This implies that they are slight risk diversifiers in the mixed portfolio. Therefore, adding treasury bonds, treasury bills, and timberland assets into a mixed portfolio can significantly reduce the portfolio downside risk.

Table 2 Risk Decomposition of the M-CVaR Portfolios with a Target Return of 2%

<table>
<thead>
<tr>
<th>Scenario</th>
<th>MU</th>
<th>D iSD</th>
<th>D iVaR</th>
<th>D iCVaR</th>
<th>MU</th>
<th>D iSD</th>
<th>D iVaR</th>
<th>D iCVaR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Portfolio</td>
<td>2.0</td>
<td>3.3</td>
<td>3.5</td>
<td>4.8</td>
<td>2.0</td>
<td>3.3</td>
<td>3.5</td>
<td>4.8</td>
</tr>
<tr>
<td>Large-cap Stocks</td>
<td>20.0</td>
<td>45.4</td>
<td>65.0</td>
<td>65.4</td>
<td>20.0</td>
<td>45.4</td>
<td>65.0</td>
<td>65.4</td>
</tr>
<tr>
<td>Small-cap Stocks</td>
<td>15.0</td>
<td>44.1</td>
<td>61.8</td>
<td>63.7</td>
<td>15.0</td>
<td>44.1</td>
<td>61.8</td>
<td>63.7</td>
</tr>
<tr>
<td>Treasury Bonds</td>
<td>55.1</td>
<td>9.8</td>
<td>-22.7</td>
<td>-26.0</td>
<td>55.1</td>
<td>9.8</td>
<td>-22.7</td>
<td>-26.0</td>
</tr>
<tr>
<td>Treasury Bills</td>
<td>5.0</td>
<td>0.1</td>
<td>-1.3</td>
<td>-1.0</td>
<td>5.0</td>
<td>0.1</td>
<td>-1.3</td>
<td>-1.0</td>
</tr>
<tr>
<td>Timberlands</td>
<td>4.9</td>
<td>0.6</td>
<td>-2.8</td>
<td>-2.1</td>
<td>4.9</td>
<td>0.6</td>
<td>-2.8</td>
<td>-2.1</td>
</tr>
<tr>
<td>Sum</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
</tr>
</tbody>
</table>

Note: The bold numbers are MU, SD, VaR, and CVaR for the portfolio with a given target return. MU denotes the target return. SD denotes the standard deviation. All the numbers are interpreted in percentage.
Table 3 provides a comparison of risk decomposition between the low target return of 1.6% and the high target return of 2.4% under Scenario 2. At the low level of target returns, treasury bills as the lowest risk asset dominate in the mixed portfolio because it has low or negative risk contribution to the portfolio. Moreover, it is noted that the allocation to timberland assets is zero at low target returns. Although the allocations to large-cap stocks and small-cap stocks are at their minimum levels, their risk contributions to the portfolio are more than 50%. At high level of target returns, treasury bills are replaced by small-cap stocks and timberland assets. The risk contribution of small-cap stocks to the portfolio’s SD, VaR, and CVaR are 78%, 82.8%, and 82.9%, respectively.

Table 3 Comparison of Risk Decomposition between the Low and High Target Returns

<table>
<thead>
<tr>
<th>Scenario 2</th>
<th>Weight</th>
<th>$D_{SD}$</th>
<th>$D_{VaR}$</th>
<th>$D_{CVaR}$</th>
<th>Weight</th>
<th>$D_{SD}$</th>
<th>$D_{VaR}$</th>
<th>$D_{CVaR}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Portfolio</td>
<td>1.6</td>
<td>3.2</td>
<td>4.1</td>
<td>5.9</td>
<td>2.4</td>
<td>6.9</td>
<td>9.9</td>
<td>14.0</td>
</tr>
<tr>
<td>Large-cap</td>
<td>20.0</td>
<td>50.2</td>
<td>61.8</td>
<td>60.7</td>
<td>20.0</td>
<td>22.4</td>
<td>24.8</td>
<td>24.7</td>
</tr>
<tr>
<td>Small-cap</td>
<td>15.0</td>
<td>49.2</td>
<td>59.2</td>
<td>58.5</td>
<td>49.2</td>
<td>78.0</td>
<td>82.8</td>
<td>82.9</td>
</tr>
<tr>
<td>T-Bonds</td>
<td>15.0</td>
<td>-0.5</td>
<td>-10.0</td>
<td>-11.4</td>
<td>15.8</td>
<td>-0.7</td>
<td>-4.8</td>
<td>-5.0</td>
</tr>
<tr>
<td>T-Bills</td>
<td>50.0</td>
<td>1.2</td>
<td>-11.0</td>
<td>-7.8</td>
<td>5.0</td>
<td>0.0</td>
<td>-0.5</td>
<td>-0.4</td>
</tr>
<tr>
<td>Timberlands</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>10.0</td>
<td>0.2</td>
<td>-2.3</td>
<td>-2.2</td>
</tr>
<tr>
<td>Sum</td>
<td>100</td>
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<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
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</tr>
</tbody>
</table>

Dynamic Asset Allocations

The dynamic efficient frontiers are constructed over a 10-year rolling window from 1987 to 2011. As the rolling portfolio is annually rebalanced, there are 16 efficient frontiers constructed in total. Figure 3 illustrates the dynamic asset allocations for a 2% target return with a 10-year rolling window over 1996 – 2011. Scenario 1 shows that large-cap stocks and small-cap stocks are allocated by the constraint conditions of 20% and 15%. The weight on timberland assets is more than 30% in most of the times except the time period around 2001. Scenario 2 is similar to the scenario 1 except that timberland assets are allocated to the maximum level of 10%.
Conclusions

Timberland assets have become a popular alternative investment for institutional investors in the United States since 1980s. This study employs the M-CVaR optimization approach to formulate asset allocation strategies and to examine the role of timberland assets in a mixed portfolio from the risk perspective. Both static and dynamic backtesting are used to assess the stability of asset allocations and the persistence of asset performance. Several conclusions are reached.

The choice of risk measures is an important decision for portfolio management. First, the commonly used standard deviation may not fully reflect the nature of risk. As investors are particularly concerned with the downside risk in reality, risk measures such as VaR and CVaR are more appropriate than SD. Second, asset allocations under a minimized downside risk framework provide optimal investment strategies for the downside risk averse investors. This is because the M-CVaR method fully reflects the tradeoff between downside risks and returns for investors. Furthermore, the risk decomposition helps us to identify risk sources and manager risks in a mixed portfolio. Overall, risk measures play an important role in portfolio construction and risk management.

Whether the M-V frontiers are efficient or not has been a debatable topic ever since asset returns exhibit non-normality such as skewness and kurtosis in reality. This study provides empirical evidence that the M-CVaR approach constructs more efficient frontiers than the M-V approach through adding timberland assets in a mixed portfolio. This is because the M-V approach underestimates the tail loss under the assumption of multivariate normal distribution. In contrast, the M-CVaR approach fairly captures the asymmetry and fat tail properties and selects asset returns with positive skewness and low kurtosis to reduce the portfolio risk. Thus, the M-CVaR method is more attractive since it not only incorporates the portfolio downside risk into optimization but also considers the non-normality of assets returns.
The asset allocations are conducted over both static and dynamic optimizations. If there is no restriction on timberland assets, both treasury bonds and timberland assets dominate in the portfolio because of their positive skewness. Moreover, timberland assets are preferred in the high level of target returns, indicating its ability to generate high returns. The 10-year rolling optimization offers consistent strategies with static allocations and reveals that the allocations were affected around 2001–2003. It was probably due to the weak performance of the NCREIF Timberland Index over that period of time (Mei and Clutter, 2010). Based on the backtesting, this study also provides some empirical evidence that stocks intensify a portfolio risk, whereas treasury bills, bonds, and timberland assets diversify a portfolio risk. Overall, timberland assets maintain a significant allocation in the mixed portfolio and behave as a persistent risk diversifier.

This study first introduces the M-CVaR approach to analyze the role of timberland assets in a mixed portfolio from the risk perspective. The methodology and findings provide practical implications for investors with different risk preferences and investment purposes. It should help institutional investors to better manage their portfolios and reduce the downside risk. Nevertheless, it should be noted that this ex post analysis does not necessarily guarantee future performance, especially in the current changing markets. Moreover, it may be not easy to frequently rebalance the portfolio from a practical perspective since timberland investment is a long term investment. However, investors can adjust their portfolios through the liquid financial assets such as stocks and bonds to rebalance their portfolios.
References


