On the economic impacts, returns and risks of timberland investments

by

WEIYI ZHANG

(Under the Direction of Bin Mei)

ABSTRACT

Over the past three decades, timberland has become an increasingly popular alternative investment vehicle for institutional investors, because of their unique features, such as high risk-adjusted returns, inflation hedging capabilities and diversification potentials. The first part of this dissertation aims to assess the risks and returns of optimal portfolios comprised of timberland and farmland assets in the United States. The results show that diversification potentials of natural resource investments decline, when investment sizes increase and portfolios become more constrained. The second part investigates the impacts of forest-related conservation easements (CEs) on values of properties in the surrounding area. The results show CE' positive effect on property values in the vicinity after CE' establishment, and this effect diminishes with distance. The third part examines the roles of timberland assets in mixed-asset portfolios using both short- and long-period investment returns. The results demonstrate assets' varying diversification potentials as investment horizons lengthen, and show private-equity timberland's superior diversification benefits over public-equity timberland in long-horizon investments.

INDEX WORDS: Agriculture, Forestry, Linear Programming, Real Estate, REITs, TIMOs

ON THE ECONOMIC IMPACTS, RETURNS AND RISKS OF TIMBERLAND INVESTMENTS

by

WEIYI ZHANG

B.S.A., the University of Georgia, 2013

M.F.R., the University of Georgia, 2015

A Dissertation Submitted to the Graduate Faculty of The University of Georgia in Partial Fulfillment of the Requirements for the Degree

DOCTOR OF PHILOSOPHY

ATHENS, GEORGIA

2018

ON THE ECONOMIC IMPACTS, RETURNS AND RISKS OF TIMBERLAND INVESTMENTS

by

WEIYI ZHANG

Major Professor: Bin Mei
Committee: Jon P. Caulfield
Yanshu Li
Cheolwoo Park

Electronic Version Approved:

Suzanne Barbour
Dean of the Graduate School
The University of Georgia
August 2018

DEDICATION

To my loving and supporting family.

ACKNOWLEDGEMENTS

First of all, my most sincere gratitude goes to my major advisor, Dr. Richard Bin Mei. Thank you for your guidance, help and support, especially in the time of need. I could not complete this program without them. Your meticulousness and drive will inspire me for many years to come.

In addition, I would like to thank my committee members, Drs. Jon Caulfield, Yanshu Li and Cheolwoo Park. Thank you for taking time out of your busy schedules to attend my meetings, provide suggestions to my research, ask questions and give support. I learnt a great deal from each and every one of you.

I am very grateful to the amount of support that I have received during my graduate programs from Timber Mart-South and the Harley Langdale Jr. Center for Forest Business, as well as the Warnell School. Bob Izlar, Sara Baldwin, Tom Harris, Jacek Siry and Jonathan Smith are among the many who gave me valuable advices and encouragements along the way. I am equally thankful for the support and guidance from Mary Ellen, Bill and Keith in HNRG. It is also a privilege to have been around a group of young and aspiring professional MFR students, such as Cade, Devon, Andrew, Skeet, Remy and Nick.

Thanks to my parents, whom I have not always been around since I was fifteen and pursuing education abroad. Your support from afar is the only anchor so that I could make it this far. Finally, Ivy, without you, this would not happen. Thanks for your love and patience, and being there with me till the end.

TABLE OF CONTENTS

LIST OF TABLES

Page

LIST OF FIGURES

CHAPTER 1

INTRODUCTION AND LITERATURE REVIEW

Timberland Investments in the United States

Timberland assets have attracted increasing popularity as an alternative investment vehicle among institutional investors since the 1980s in the United States (Waggle and Johnson 2009), because of unique characteristics, such as inflation hedging capabilities (Wan et al. 2013; Washburn and Binkley 1993), high risk-adjusted returns (Cascio and Clutter 2008; Mei 2017) and low correlation with other financial assets (Caulfield and Newman 1999; Mei and Clutter 2010; Sun and Zhang 2001). Traditionally, investments in timberland have been in the forms of buying large tracts of timberlands and holding them for long periods of time. However, through ownership structure changes in the past twenty years, currently there exist two options for timberland investors, namely private- and public-equity timberland investments. Institutional investors and wealthy families invest in timberland in private ownership through closed- or open-end funds. These private assets are managed by timberland investment management organizations (TIMOs). Individual and institutional investors can also access timberland investment through buying stocks of publicly traded timber firms or real estate investment trusts (REITs), which are liquid and tax efficient (Mendell, Mishra and Sydor 2008).

Economic Impacts of Forests

The United States has abundant forest resources with over 750 million acres covered by forestland. Of the total forestland, 57% is privately owned timberland (Smith et al. 2009). Forestry-related businesses support over 2.7 million jobs nation-wide (Jefferies 2016). In the state of Georgia alone, private forests create $37 billion in annual ecosystem services (GFA 2017), $32 billion direct revenue and 133,000 jobs (Hafer 2017). In addition to direct economic and ecosystem benefits, forests bring about environmental benefits and amenities that are valued by people who live close or have access to these open spaces, reflected by changes in property values (Chamblee et al. 2011).

Previous Studies on Financial Performance of Timberland Investments

A rich array of studies has been done on the financial returns and risks of timberland investments. Various models have been applied to model timberland returns, including capital asset pricing model, arbitrage pricing theory, Fama-French three-factor model and intertemporal capital asset pricing model (Mei and Clutter 2010; Sun and Zhang 2001; Yao and Mei 2015; Yao, Mei and Clutter 2014). In addition, a variety of studies have employed portfolio analysis under the modern portfolio theory of Markowitz (1952) to evaluate the financial performance and diversification benefits of timberland assets (Caulfield 1998; Mills and Hoover 1982; Newell and Eves 2009; Thomson 1997).

Finding appropriate return benchmarks is key to efficient portfolio analysis. The National Council of Real Estate Investment Fiduciaries (NCREIF) timberland indices (NTI) are used as representatives of returns on private-equity timberland. While most prevalent works rely on NTI, alternative indices are proposed or modified based on NTI (Caulfield 1994; Mei 2016; Scholtens and Spierdijk 2010). The identification of risk measures is another key to portfolio optimizations.

The prevalent optimization framework is the mean-variance framework (M-V), where variance or standard deviation (SD) of asset returns reflects asset risk, assuming multivariate normal distributions of asset returns. However, financial asset and timberland returns are usually not normally distributed (Petrasek et al. 2011; Sheikh and Qiao 2009; Wan et al. 2015). To account for this issue, Petrasek et al. (2012) and Wan et al. (2015) propose alternative mean-conditional value-at-risk (M-CVaR) framework to perform similar portfolio analysis to study timberland's role in mixed-asset portfolios.

Motivations of the Dissertation

NTI has been used as the primary timberland investment return proxy to represent private-equity timberland investments on a broad scale, e.g., national or regional. To conduct portfolio analysis on a finer level, there is a need for alternative return series. Chapter 2 aims to develop such an index at finer geographical levels and conduct portfolio analysis of natural resource portfolios comprised of timberland assets and farmland crop types in the United States.

Forests and other open spaces provide comprehensive environmental benefits to surrounding areas. The protection of forests is essential to maintain a viable forest industry and a healthy natural environment for future generations to enjoy. Conservation Easement (CE) is a widely used tool to keep land forested while maintaining timber harvests. Chapter 3 intends to examine and quantify the impacts of forest-related CEs on the values of surrounding properties in the metro Atlanta area in the state of Georgia, where urban developments are thriving and forestry is an economic pillar.

Timberland plays an important role in mixed-asset portfolios (Caulfield and Zinkhan 1998; Wan et al. 2015). Most portfolio studies use single-period optimization frameworks to assess performance metrics, i.e., return, risk and correlations of timberland assets. However, timberland investment should be considered with a long-term perspective. Therefore, the long-term assessment of timberland performance metrics is essential. Chapter 4 aims to fill this void by conducting portfolio analysis based on both single-period and long-horizon performance metrics, and compares the roles of private- and public-equity timberland investments in mixed-asset portfolios.

Objectives of the Dissertation

The overall purpose of this dissertation is to examine the economic impacts, returns and risks of timberland investment in the United States. The objectives are: (1) to evaluate the risks and returns of investments in US timberland and farmland assets; (2) to investigate factors that contribute to the valuation of properties near CE-protected forests and open spaces; (3) to examine the role of timberland investment in mixed-asset portfolios.

Chapters 2 – 4 achieve the three objectives, and are formatted as three independent journal articles, each with its own sections of introduction, literature review, data description, methodologies, results and conclusions. Chapter 5 summarizes the key findings for this dissertation and overlay potential topics for future studies.

CHAPTER 2

Assessing the risk and return of optimal portfolios of us timberland and farmland[1]

[1] Zhang, W. and B. Mei. 2018. Submitted to *Journal of Real Estate Portfolio Management*, 2/12/2018.

Abstract

We apply the modern portfolio theory to optimally construct portfolios of US timberland and farmland, and evaluate risks and returns under different investment scenarios. First, we develop a set of synthetic timberland return series for 22 sub-regions in the US South over a 17-year time horizon (2000-2016) and use the NCREIF data to represent returns of various farm crops. A mix of timberland and farmland assets is used to conduct portfolio optimizations under the mean-conditional value-at-risk (CVaR) framework. Recognizing the limited and discontinuous nature of the investable universe of natural resource assets at any given time, we incorporate constraining factors and evaluate their impacts, under two investment sizes and find lowered diversification effects as investment size increases. The optimal tangency portfolios yield risks of 0.16% and 0.55%, and returns of 1.42% and 1.38% respectively. Finally, we use Monte Carlo simulation to estimate the VaR and CVaR of the optimal portfolios for a 10-year time span for each scenario and find increasing risk levels associated with investment of larger scales.

Introduction

Natural resource assets, such as timberland and farmland, are gaining increasing popularity among institutional investors in the last three decades in the United States (Waggle and Johnson 2009). The use of these natural resource assets is relatively new, first experimented by institutional investors in 1980s. Institutional timberland investment came into existence in early 1980s and expanded more rapidly in early 1990s (Washburn, Binkley and Raper 1996), while institutional farmland investment came into spotlight following the farm crisis after land prices stabilized around 1985 (Koeninger and HighQuest Partners 2017). Currently, institutions own $77 billion worth of timberland and $10 billion worth of farmland in the US (Campbell Global 2017; Gillam 2014). Diversification benefits exist in timberland and farmland investments due to their common characteristics, including high risk-adjusted returns (Hennings, Sherrick and Barry 2015; Mei 2017), low correlation with traditional financial assets (Caulfield and Newman 1999; Lins, Sherrick and Venigalla 1992; Mei and Clutter 2010; Wan et al. 2015), and protection against inflation (Dahl 2013; Wan et al. 2013; Washburn and Binkley 1993).

The National Council of Real Estate Investment Fiduciaries (NCREIF) compiles return data for institutionally managed timberland and farmland, i.e., the NCREIF Timberland Index (NTI) and the NCREIF Farmland Index (NFI). Most previous studies examining diversification benefits of timberland and farmland use these indices. Although NCREIF indices are functional in terms of performing asset allocations within mixed-asset portfolios, they are subject to smoothing bias (Mei 2016). Furthermore, the NTI and NFI are comprised of broad regional returns, with each region encompassing one or more states. Current portfolio analyses tend to treat timberland and farmland as homogeneous asset classes and do not make further differentiation within each class. Finally, although farmland return data of individual crop types can be queried from the NCREIF, there lack timberland return data at a finer geographical level.

The purpose of this study is to investigate the risk and return features of diversified optimal portfolios of timberland and farmland assets. Two frameworks, mean-variance (M-V) and mean-conditional value at risk (M-CVaR), are proposed for the investigation, in which standard deviation (SD) and CVaR are two risk measures. To achieve this goal, we need to find suitable data to represent asset returns and examine their characteristics. We first develop synthetic timberland return series for 22 geographic sub-regions within the southern US, in which forests are important contributors to local and national economies (Oswalt and Smith 2014). In addition, this study only focuses on pine stumpage price data because of the significant economic and ecological values of southern pine species in the region (Coyle et al. 2015). We then use these synthetic series and return indices of six major farmland crop types from the NFI to perform portfolio allocation analysis. Results show that the CVaR better estimates downside risks and the M-CVaR is a more efficient optimization framework. Building on that, two different hypothetical investment scenarios are proposed to impose physical constraints associated with natural resource investment. Finally, we extend the single-period optimization results to a ten-year horizon using the VaR and CVaR measures to reflect the increasing risk exposure associated with larger investment sizes.

Literature Review

Performance benchmarks are needed to represent asset returns. While most studies on private natural resource assets rely on NCREIF indices, a number of different indices exist in the field of timberland investment research (Mei 2017). Caulfield (1994) introduces the timberland performance index based on existing timberland funds managed by a group of investment management companies. He uses the index to study timberland investment and identify biological growth as the primary return driver. Thomson (1997) builds a theoretical timber return series of Douglas fir and southern pine based on historical price data and derived land values, and finds timberland return's negative correlation with other financial assets over the long run. Addressing the smoothing bias, Scholtens and Spierdijk (2010) construct an unsmoothed version of the NTI by using the unsmoothing approach outlined by Fisher, Geltner and Webb (1994). In a more recent study, Mei (2016) devises a transaction-based timberland index using property level transaction data and compares it with the appraisal-based NTI.

The modern portfolio theory establishes the M-V optimization framework to evaluate roles of financial assets in portfolios (Markowitz 1952). Applying the M-V framework in mixed-asset portfolios, many studies have examined the roles of natural resource assets. Mills and Hoover (1982) first study the performance of natural resource assets. They find that timberland assets provide diversification benefits to portfolios whose components also include farm options, common stocks and bonds. Newell and Eves (2007) use total NFI, regional NFI and sub-indices of two farmland types from 1984Q2 to 2006Q4 to benchmark farmland returns, and confirm the portfolio diversification benefits added by farmland. However, they claim that farmland contributes less significantly if real estate is already in the portfolio. In a later study, they use the NTI and its regional indices from 1987Q1 to 2007Q4 to represent timberland returns (Newell and Eves 2009). They find that timberland adds significant values to the portfolios, albeit the benefits diminish in the more recent ten-year sub-period. Waggle and Johnson (2009) investigate the roles of both timberland and farmland combined with other commercial real estates and financial assets. They conclude that timberland bears lower risk compared with other assets. In the unconstrained scenario of their study, timberland is heavily weighted in certain scenarios, while farmland is consistently excluded. Scholtens and Spierdijk (2010) use the NTI to represent private-equity timberland investment, timber real estate investment trust index to represent public-equity timberland investment, and exchange traded securities to represent other forestry-related sector indices. They conclude that public-equity timberland investment hardly adds diversification benefits, while private-equity timberland assets' diversification benefits diminish when the NTI is unsmoothed. Martinez-Oviedo and Medda (2017) create a portfolio with a sovereign wealth fund that invests in a broad spectrum of industries in various geographical regions across the world. They use the NTI and NFI as return proxies of natural resource assets and find that adding timberland and farmland supplants equity investments.

The normality of asset returns affects the efficient estimation of downside risk of portfolios built under the M-V framework. Nonetheless, this assumption is often violated in the real world (Petrasek et al. 2011; Sheikh and Qiao 2009). Therefore, alternative frameworks are needed. Bacmann and Gawron (2004) examine the normality assumptions of hedge funds and find that assets with fat-tailed and asymmetric returns are better modelled using the M-CVaR framework. In the field of natural resource investment, Petrasek et al. (2012) first employ CVaR as a risk measure and evaluate the allocation of regional timberland assets in a mixed-asset portfolio. Wan et al. (2015) build mixed-asset portfolios with traditional financial assets and timberland using both M-V and M-CVaR frameworks. They find that timberland assets are generally risk diversifiers and conclude that portfolios built under the M-CVaR framework are more efficient than those under the M-V framework.

In summary, most works rely on NCREIF indices to represent returns of timberland and farmland assets. These indices are subject to the "4th quarter" seasonality effect because appraisals are typically conducted in the 4th quarter (Mei 2017; Newell and Eves 2007). In addition, most studies perceive timberland and farmland as homogeneous assets, neglecting the correlation of timber product prices in different regions and farmland returns from different crop types. We aim to address these missing pieces in the previous literature by first focusing on sub-regional levels in the US South for timberland returns and individual crop types for farmland returns, and then incorporating both the M-V and M-CVaR frameworks to conduct portfolio analysis.

Methodology and Data

Modern portfolio theory

The idea of modern portfolio allocation comes largely from the M-V efficient portfolio theory of Markowitz (1952). All else being equal, investors prefer greater financial returns while being exposed to a given risk level. One of the most prevalent ways to achieve this goal is through diversification, which spreads the capital allocation among several assets in order to have a lower risk than investing in a single asset. Investors build portfolios by changing the weights of assets, $w = (w_1, w_2, \dots, w_n)^T$, each generating individual returns, $r = (r_1, r_2, \dots, r_n)^T$. The mean returns are denoted as $\bar{r} = (\overline{r_1}, \overline{r_2}, \dots, \overline{r_n})^T$. The portfolio return is the weighted sum of individual asset returns, $w^T\bar{r} = \sum_{i=1}^{n} w_i\,\overline{r_i}$. The risk of a portfolio is a function of asset weights and covariance matrix, and can be generically expressed as $\Re(w, cov(r))$. The portfolio then can be optimized by solving the following risk minimization problem:

$$\operatorname*{Min}_{w} \Re(w, cov(r))$$

$$\text{s.t. } w^T\bar{r} = u \text{ and } \sum_{i=1}^{n} w_i = 1 \tag{1}$$

Risk measures

SD

While the overall portfolio return is simply the weighted sum of individual asset returns, the overall portfolio SD is less than the weighted sum of individual asset return SDs. Markowitz's theory proposes that the interactions between assets within a portfolio, represented by the covariance, play an important role in determining the variance, σ_p^2, of a diversified portfolio (Rubinstein 2002):

$$\sigma_p^2 = \sum_{i=1}^{n} \sum_{j=1}^{n} w_i w_j \rho_{ij} \sigma_i \sigma_j \tag{2}$$

where σ_i and σ_j are standard deviations of assets *i* and *j*, ρ_{ij} is the correlation between the returns of assets *i* and *j*. In other words, $\rho_{ij}\sigma_i\sigma_j$ is the covariance of between assets *i* and *j*. This shows that correlations among assets determine the overall portfolio variance. When there is less-than-perfect correlation, i.e., when $\rho_{ij} < 1$, overall portfolio risk is reduced. The portfolio can then be optimized, under the M-V framework, by estimating portfolio σ_p^2 by s_p^2 solving the problem:

$$\min_{w} s_p^2$$

$$\text{s.t. } w^T \bar{r} = u \text{ and } \sum_{i=1}^{n} w_i = 1 \tag{3}$$

The portfolio SD estimator, s_p, is simply the square-root of the portfolio variance.

CVaR

CVaR is a relatively recent risk measure (Rockafellar and Uryasev 2000). First, the loss function of a portfolio is denoted as a function of asset weights and returns, $f(w, r)$, where r follows a probability density function, $p(r)$. Following that, the cumulative distribution function of the loss associated with the weights, w, and maximum loss level, Υ, can be formulated as:

$$\Psi(w, \Upsilon) = \int_{f(w,r) \leq \Upsilon} p(r)\, dr \tag{4}$$

The VaR at a confidence level, $1-\alpha$, VaR_α is:

$$\mathrm{VaR}_\alpha(w) = min\{\Upsilon \in \Re : \Psi(w,\Upsilon) \geq \alpha\} \tag{5}$$

and the CVaR_α is:

$$\mathrm{CVaR}_\alpha(w) = \frac{1}{1-\alpha}\int_{f(w,r)\leq \mathrm{VaR}_\alpha(w)} f(w,r)\, p(r)dr \tag{6}$$

The portfolio can then be optimized, under the M-CVaR framework, by solving the problem:

$$\underset{w}{\mathrm{Min}}\, \mathrm{CVaR}_\alpha(w)$$

$$\text{s.t. } w^T\bar{r} = u \text{ and } \sum_{i=1}^{n} w_i = 1 \tag{7}$$

All through our analysis, VaR and CVaR are calculated at the 5% quantile of the return distributions.

CVaR-deviation (CVaR^{Δ})

The portfolio SD and CVaR value cannot be directly compared. SD measures the width of a return distribution, whereas the CVaR of a portfolio is the value of the portfolio's loss at the "worst-case" scenario. To better compare the two risk measures, we translate the CVaR of a portfolio to the corresponding CVaR^{Δ}, which measures the distance between the CVaR and the mean return. Under a normal distribution, CVaR^{Δ} =2.06×SD at the 5% level (Xiong and Idzorek 2010).

Return data

Timberland return

For timberland investment returns, we devise a synthetic return series for 22 sub-regional areas within the US South from 2000Q1 to 2016Q4 with price data from TimberMart-South (TMS 2017). This definition of areas divides each of the 11 Southern states into two sub-regions (Figure 1). This return series includes income and capital appreciation components. The cash flow from harvesting is the income component in calculating returns, while the difference in timberland values is the capital appreciation component. The return formula for timberland is:

$$R_t = \frac{CV_t + NI_t}{CV_{t-1}} - 1 \tag{8}$$

where:

R_t = total return per acre during period t;

CV_t = capital value per acre during period t;

NI_t= net income received per acre during period t.

Capital values are assumed to be correlated with stumpage prices. When calculating the capital values, the last 12 quarters of stumpage prices are used to reduce volatility of the return series. Another assumption is made that the weights of the three major pine product classes are equal so that:

$$CV_{rt} = 1/78 \sum_{n=0}^{11} (12 - n) P_{r(t-n)} \tag{9}$$

where:

$$P_{rt} = \frac{1}{3} ppwd\$_{rt} + \frac{1}{3} cns\$_{rt} + \frac{1}{3} pst\$_{rt} \tag{10}$$

and $ppwd\$_{rt}, cns\$_{rt}$ and $pst\$_{rt}$ are the prices reported in TimberMart-South for pine pulpwood, chip-n-saw and sawtimber for region r in period t, and P_{rt} is therefore the average timber price in region r during period t.

To find net income, a key term *Income Rate* is needed, which represents the ratio of periodic income to capital value of an investment-grade forest, such that:

$$NI_{rt} = P_{rt} \times Income\ Rate \tag{11}$$

The *Income Rate* is estimated as follows. First, a south-wide return series is generated by aggregating the 22 sub-regions' returns series using a subjective *Income Rate*. Then, this south-wide series is compared with the NTI-South series. A recursive algorithm is used to change the *Income Rate* until it finds the smallest sum of squared differences.

Farmland return

For farmland investment, we use data queried from the NCREIF and focus on six major crop types: Almonds, Apples, Grapes, Corn, Other Annual Crops (OAC) and Other Permanent Crops (OPC). OAC includes vegetables such as potatoes. OPC includes walnuts and pecans. These are either historically popular farm commodities or attractive crops among investors (Retkwa 2014). We choose to diversify farmland investment based on crop types instead of regions because of data availability. The NCREIF does not publish data for regions with fewer than three data contributors due to confidentiality concerns (NCREIF 2017). These six crop types are chosen because only their return data go back to as far as 2000Q1.

Assumptions, constraints and scenarios

Building on the unconstrained optimization framework, we attempt to add a few assumptions to perform a more sensible portfolio analysis. In practice, investment-grade timberland is scarce on the market at any given time in a given area. Institutional investors may require capital to be spent acquiring timberland assets in a timely manner, implying that high transaction costs, illiquidity and lack of available assets to purchase could render such unconstrained allocation impractical (Caulfield and Newman 1999). Therefore, we consider the availability of timberland (Table 1) based on USDA Forest Service sampling of corporate private timberland in southern states (Miles 2017). With an average timberland transaction price of $2,000/acre (Industry Intelligence 2017), total values of investable timberland in each of the sub-regions can be estimated. Secondly, we approximate farmland price based on regional or state averages (NASS 2017). Land prices are $5,370/acre for Almonds, Grapes and OPC, which is the average in California; $3,000 for Apples, which is the average in Washington; and $6,260/acre for Corn and $2,910/acre for OAC, which are the average in Corn Belt and Delta regions.

Mimicking the size of mid- and large-size institutional natural resource investment managers, we establish two portfolios worth of US$2 billion and US$10 billion each (Zhang, Nagubadi and Butler 2012). Considering their respective market sizes, we constrain the ratio of timberland and farmland allocation to be 6:1. Furthermore, we stipulate that farmland allocation must be evenly divided between annual crops (Corns and OAC) and permanent crops (Almonds, Apples, OPC and Grapes).

Optimal portfolios

To compare portfolio performance under different scenarios, we use the Sharpe Ratio (Sharpe 1994):

$$Sharpe\ Ratio = \frac{E[r_p]-r_f}{\sigma_p} \tag{12}$$

where $E[r_p]$ is expected portfolio return and r_f is the risk-free return.[2] For the M-CVaR metric, the Conditional Sharpe Ratio (CSR) is devised to measure the risk-adjusted performance (Chow and Lai 2015):

$$CSR = \frac{E[r_p]-r_f}{CVaR} \tag{13}$$

Long-term investment simulation

The simulation provides a long-term outlook of the expected portfolio values and losses in the worst scenarios. Using the parametric estimation method (Manfredo and Leuthold 1999), we first fit the probability distributions of each asset returns. From the fitted distributions, returns are randomly drawn for each asset and then aggregated using the optimal allocation to get the

[2] The 90-day Treasury bill rate, 0.26% per quarter, is used in this study.

portfolio return for a quarter. This step is repeated for 40 quarters and compounded to generate a return series over a 10-year horizon. Returns are multiplied by the initial portfolio value to yield a random portfolio value each quarter. This entire process is iterated for 1,000 times, and the mean portfolio value, VaR and CVaR are calculated for each of the 10 years based on the simulation.

Results and Discussion

Descriptive statistics

Synthetic return series are built for 22 sub-regions within the US South. The *Income Rate* is estimated to be 1.8%. Average quarterly return across 22 sub-regions is 2.30% from 1987Q1 to 2016Q4 and 1.30% after 2000Q1. In comparison, average NTI-South quarterly return is 2.25% over the past 30 years and 1.42% from 2000Q1 to 2016Q4. The synthesized return series and NTI-South series have a correlation coefficient of 0.49 from 2000Q1 to 2016Q4 (Figure 2).

The descriptive statistics of the individual timberland regions and farmland crop types are displayed in Table 2. Results show that AR.2 and TN.2 have the highest SD (about 4%) and quarterly return (about 2%) among timberland assets. Almonds bear the highest SD (about 10%) and yield the highest average return among farmland crop types (about 5%). Comparing the two risk measures, we notice that $CVaR^{\Delta}$ is smaller than SD for Almonds and OPC, indicating that these two returns are not normally distributed. Furthermore, while all assets display skewed returns, TN.2, Almonds, Corn, OAC and OPC are highly positively skewed. Returns on Almonds and OAC show highest excess kurtosis, indicating fat-tailed distributions. Almonds have both highly positive skewness and excess kurtosis.

Results of Jarque-Bera tests show that the null hypothesis of normal distribution is rejected at the 5% level for TN.2, VA.1 and all farmland crop types. VA.1 displays heavily left-skewed return distribution, Grapes shows slightly right-skewed return distribution, and the other six assets display heavily right skewed return distributions (Figure 3). Lastly, the Shapiro-Wilk test rejects the null hypothesis of multivariate normality at the 1% level. All these tests suggest that the M-CVaR optimization approach is more appropriate.

Unconstrained portfolio optimization and asset allocations

The M-V framework yields an optimal portfolio with the Sharpe Ratio at 1.72, SD at 0.97% and risk-adjusted return at 1.67%. The $CVaR^{\Delta}$ of the portfolio is calculated to be 1.75%. In comparison, the actual $CVaR^{\Delta}$ is smaller than the theoretical one for a normal distribution, indicating a potential overestimation of portfolio risks under the M-V framework. Therefore, the ensuing discussions will focus on results under the M-CVaR framework.

The unconstrained M-CVaR efficient frontier of the portfolio allocations shows that by altering weights of individual assets, the portfolio risks range from -0.99% to 3.31%, while the span of quarterly returns can reach as low as 2.47% and as high as 4.76% (Figure 4). Asset prominence[3], which is also known as asset persistence, suggests that only eight assets are persistently present in the unconstrained scenario (Table 3). Table 3 also shows that the asset allocation changes along the efficient frontier. Ranking the efficient portfolios by increasing risks in quartiles, we find that the minimum-risk portfolio consists of four timberland assets and four farmland assets, while the maximum-risk portfolio consists of Almonds only. In between extrema, the allocation shifts from timberland assets towards farmland assets, as risk and return increase.

[3] Asset prominence is calculated by dividing the number of positive allocations by the total number of portfolios on the efficient frontier.

Constrained portfolio optimization and optimal portfolio allocations

The increasing investment size makes portfolios more constrained. Only 14 sub-regions have binding allocation constraints in the US$2-billion portfolio, while all 22 sub-regions are constrained by timberland availability in the US$10-billion portfolio. As shown in Figure 5, the M-CVaR efficient frontier shifts downwards and covers a narrower risk range as portfolio size increases from US$2 billion to US$10 billion. Therefore, the ability to diversify becomes more restricted after the investment size increases beyond the US$2 billion threshold. Specifically, the US$2-billion optimal portfolio has a CSR of 9.08, with a corresponding risk of 0.16% and a return of 1.42%, whereas the US$10-billion optimal portfolio has a reduced CSR of 2.50, an increased risk of 0.55% and a lower return of 1.38% (Table 4).

Acreages allocated to timberland regions and farm crop types also change each time the investment requirement is stricter as shown by the changing composition of the portfolios. There are eight timberland sub-regions with positive allocations in the US$2-billion scenario, compared to 15 sub-regions in the US$10-billion scenario. On the farmland side, Corn, OAC and OPC are consistently positively allocated assets, indicating their superior return-risk ratios among farmland assets. For timberland, asset prominence suggests persistent allocations on regions in North Carolina, Tennessee and Virginia, which are outside of highly sought-after timber markets. For farmland, asset prominence suggests persistent allocations on OAC and OPC.

Long-horizon portfolio VaR and CVaR values

The long-term commitment of capital to natural resource investments, especially timberland investments, posts additional risks to investors. The portfolio VaR and CVaR values over the 10-year holding period represent the “worst-case” portfolio values. They are estimated based on fitted distribution parameters and weight allocations of the optimal tangency portfolios for the US$2- and US$10- billion scenarios. The exposure to long-term risks is shown by the widening gaps between mean portfolio values and "worst-case" values (Figure 6). For the portfolio with US$2 billion initial value, the mean portfolio value at the end of the 10-year horizon is US$3.89 billion, while the "worst-case" value is US$1.73 billion, indicating a 14% loss of the original investment. For the US$10 billion portfolio, the mean portfolio value after 10 years is US$20.57 billion, while the "worst-case" scenario suffers a 16% loss.

Correlations of asset returns

The correlation among assets based on historical returns may not hold into the future. To better examine whether correlations of asset returns change over time, we fit a multivariate generalized autoregressive heteroskedasticity (GARCH) model and compare historical correlations with forecasted ones. We use only regional timberland returns considering the completeness and availability of historical data. With TimberMart-South data going back to 1987Q1, we are able to generate 120 quarterly return series in the 22 regions. In addition, the historical correlations in the sub-period of most recent 68 quarters, the sample period of this study, are singled out to be separately compared with the forecast. Two sample *t*-tests determine that, at the 5% level, the predicted correlations are significantly different from the overall historical correlations, but not significantly different from the correlations in the last 68 quarters. Therefore, we deem our portfolio allocation analysis to be valid and robust.

Conclusion

This study aims to examine the risk and return features of diversified portfolios of timberland and farmland assets. To investigate timberland assets at a finer geographical level, synthesized return series are first constructed using regional timber price data. This is preferable than directly using the NTI and regional indices because our synthesized series can be more frequently updated using timber price data than existing indices, which are based on annual appraisals and subject to the smoothing bias (Mei 2017). These series combined with the NFI crop type return indices enable us to build hypothetical portfolios under the M-V and M-CVaR frameworks. Results show that SD in the M-V framework overestimates downside risk, while the CVaR in the M-CVaR framework more precisely estimates the downside risk and thus allows for improved optimization efficiency.

Practicality becomes a restricting factor when portfolio sizes increase. Given the size of institutional portfolios of natural resource assets, optimal portfolios can only be built after considering land availability in each sub-region and imposing practical and sensible portfolio construction constraints. Our hypothetical multi-billion-dollar portfolio optimizations show that as the size of investment increases, the portfolio becomes more constrained, the diversification benefit lowers, the portfolio risk increases, and the portfolio return decreases. The long-term VaR and CVaR simulations also support this conclusion.

This diminishing diversification benefit is in contrast to the finding from conventional real estate portfolio studies (e.g., Byrne and Lee 2003). This might result from the lack of available less-correlated, investment-grade natural resource assets, which makes larger portfolios more constrained. The dominance of timberland allocation to unlikely regions is probably due to favorable historical return-risk ratios in these regions, which makes them more attractive under the purely theoretical optimization framework. Further efforts are needed to find more practical constraints, such as local market conditions and actual business practices. Finally, static correlation pattern in the past may not carry over into the future. An appropriate selection of historical data for valid future inferences becomes an issue. Additional studies are needed in this aspect as natural resources investment often requires long time horizons.

Table 2.1. Available corporate private timberland acreages and values in 22 regions.

Region	Available acreage	Total value
AL.1	1,033,325	2,066.65
AL.2	1,529,535	3,059.07
AR.1	1,681,657	3,363.31
AR.2	6,494	12.99
FL.1	853,960	1,707.92
FL.2	584,400	1,168.80
GA.1	277,046	554.09
GA.2	2,689,902	5,379.80
LA.1	1,424,600	2,849.20
LA.2	153,531	307.06
MS.1	786,219	1,572.44
MS.2	1,375,513	2,751.03
NC.1	47,167	94.33
NC.2	1,543,174	3,086.35
SC.1	1,430	2.86
SC.2	103,031	206.06
TN.1	207,278	414.56
TN.2	56,906	113.81
TX.1	88,621	177.24
TX.2	1,317,037	2,634.07
VA.1	63,195	126.39
VA.2	749,275	1,498.55
Total	16,573,298	33,146.60

Note: Timberland values are in US$ millions.

Table 2.2. Summary statistics of asset returns: quarterly data from 2000 to 2016.

Region or crop type	Average return	SD	CVaR$^{\Delta}$	Skewness	Excess kurtosis	Jarque-Bera test
AL.1	0.81	1.81	3.07	0.01	-0.51	0.69
AL.2	0.86	1.63	3.06	0.01	-0.58	0.62
AR.1	1.06	2.14	3.55	0.41	0.04	0.37
AR.2	2.03	3.93	6.93	0.08	-0.10	0.95
FL.1	1.40	1.73	2.94	0.19	-0.74	0.37
FL.2	1.33	1.80	3.26	0.11	-0.73	0.44
GA.1	0.97	2.19	4.42	-0.35	-0.69	0.25
GA.2	1.09	1.84	2.98	0.28	-0.62	0.36
LA.1	1.31	1.94	3.61	0.04	-0.58	0.61
LA.2	1.18	1.38	2.70	-0.08	-0.52	0.66
MS.1	0.52	1.77	2.77	0.26	-0.55	0.44
MS.2	0.86	1.49	2.58	0.33	0.06	0.52
NC.1	1.64	2.26	4.56	0.02	0.29	0.89
NC.2	1.53	1.68	3.04	0.41	0.36	0.30
SC.1	1.20	1.43	2.35	0.26	-0.77	0.29
SC.2	1.35	1.40	2.27	0.25	-0.97	0.18
TN.1	1.90	5.12	7.61	0.35	-1.00	0.12
TN.2	1.65	4.28	6.18	1.27	2.72	0.00
TX.1	1.19	2.41	4.05	0.39	0.05	0.41
TX.2	1.37	2.34	4.91	-0.09	-0.14	0.92
VA.1	1.80	2.11	4.80	-0.83	2.68	0.00
VA.2	1.55	1.45	2.83	-0.12	-0.69	0.47
Almonds	5.02	10.11	8.06	3.99	20.79	0.00
Apples	1.61	7.30	13.89	0.74	1.42	0.00
Corn	2.81	2.89	3.59	1.37	1.35	0.00
OAC	3.05	3.19	3.28	2.40	6.95	0.00
OPC	3.90	6.11	5.90	1.55	1.39	0.00
Grapes	2.52	4.31	7.09	0.74	0.07	0.04
Shapiro-Wilk test	0.00					

Note: All returns and deviation measures are in percentages. JB test and SW test report p-values from hypothesis tests. OAC stands for other annual crops. OPC stands for other permanent crops.

Table 2.3. Quartile portfolios' allocation under the M-CVaR framework and statistics for the unconstrained scenario.

Region or Crop type	Minimum	1st Quartile	2nd Quartile	3rd Quartile	Maximum	Asset prominence
AL.1	-	-	-	-	-	-
AL.2	-	-	-	-	-	-
AR.1	-	-	-	-	-	-
AR.2	2.82	0.8	-	-	-	26.92
FL.1	6.23	-	-	-	-	11.54
FL.2	-	-	-	-	-	-
GA.1	-	-	-	-	-	-
GA.2	-	-	-	-	-	-
LA.1	-	-	-	-	-	-
LA.2	-	-	-	-	-	-
MS.1	-	-	-	-	-	-
MS.2	-	-	-	-	-	-
NC.1	11.78	4.04	1.10	-	-	46.00
NC.2	-	-	-	-	-	-
SC.1	-	-	-	-	-	-
SC.2	-	-	-	-	-	-
TN.1	-	-	-	-	-	-
TN.2	1.07	-	-	-	-	19.23
TX.1	-	-	-	-	-	-
TX.2	-	-	-	-	-	-
VA.1	-	-	-	-	-	-
VA.2	-	-	-	-	-	-
Almonds	1.46	7.66	30.33	54.03	100.00	100.00
Apples	-	-	-	-	-	-
Corn	35.30	33.77	-	-	-	38.46
OAC	36.46	38.66	56.51	14.99	-	80.77
OPC	4.89	15.06	12.06	30.98	-	100.00
Grapes	-	-	-	-	-	-
Exp. Return	2.47	2.93	3.48	4.12	4.76	
CVaR (5%)	-0.99	-0.70	-0.15	1.05	3.31	

Note: Asset allocation, prominence, portfolio returns and risks are in percentages. OAC stands for other annual crops. OPC stands for other permanent crops.

Table 2.4. Optimal portfolio allocations under the M-CVaR framework and statistics for the US$2-billion and US$ 10-billion portfolios

Region or Crop type	US$ 2 billion		US$ 10 billion	
	Optimal allocation	Asset prominence	Optimal Allocation	Asset Prominence
AL.1	-	-	-	-
AL.2	-	-	-	-
AR.1	-	-	-	-
AR.2	0.65	46.34	0.13	100.00
FL.1	47.16	90.24	17.08	100.00
FL.2	-	21.95	11.69	100.00
GA.1	-	-	-	-
GA.2	-	-	12.10	84.00
LA.1	-	-	11.13	98.67
LA.2	13.60	53.66	3.07	86.67
MS.1	0.30	12.20	-	30.67
MS.2	-	-	6.95	57.33
NC.1	4.72	100.00	0.94	100.00
NC.2	13.46	80.49	2.95	100.00
SC.1	0.14	36.59	0.03	98.67
SC.2	-	9.76	2.06	100.00
TN.1	-	29.27	0.20	69.33
TN.2	5.69	100.00	1.14	100.00
TX.1	-	-	-	-
TX.2	-	-	-	1.33
VA.1	-	80.49	1.26	100.00
VA.2	-	58.54	14.99	100.00
Almonds	-	85.37	-	42.67
Apples	-	-	-	-
Corn	-	-	-	-
OAC	7.15	100.00	7.15	100.00
OPC	4.43	65.85	7.15	84.00
Grapes	2.71	36.59	-	1.33
Exp. Return	1.42		1.38	
CVaR (5%)	0.16		0.55	
CSR	9.08		2.50	

Note: Asset allocation, prominence, portfolio returns and risks are in percentages. OAC stands for other annual crops. OPC stands for other permanent crops. CSR stands for the conditional Sharpe Ratio.

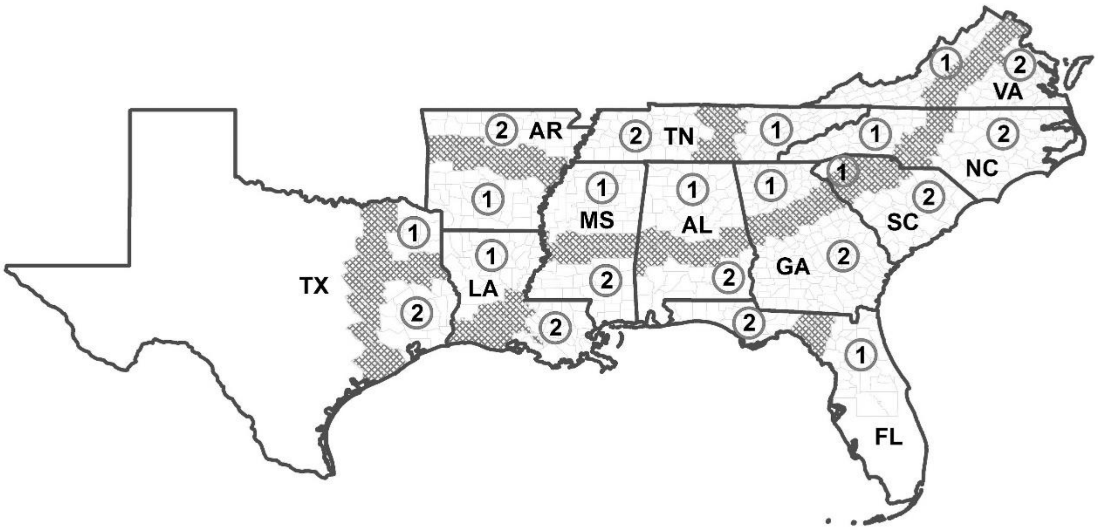

Figure 2.1. TimberMart-South southern states delineation of 22 sub-regions.

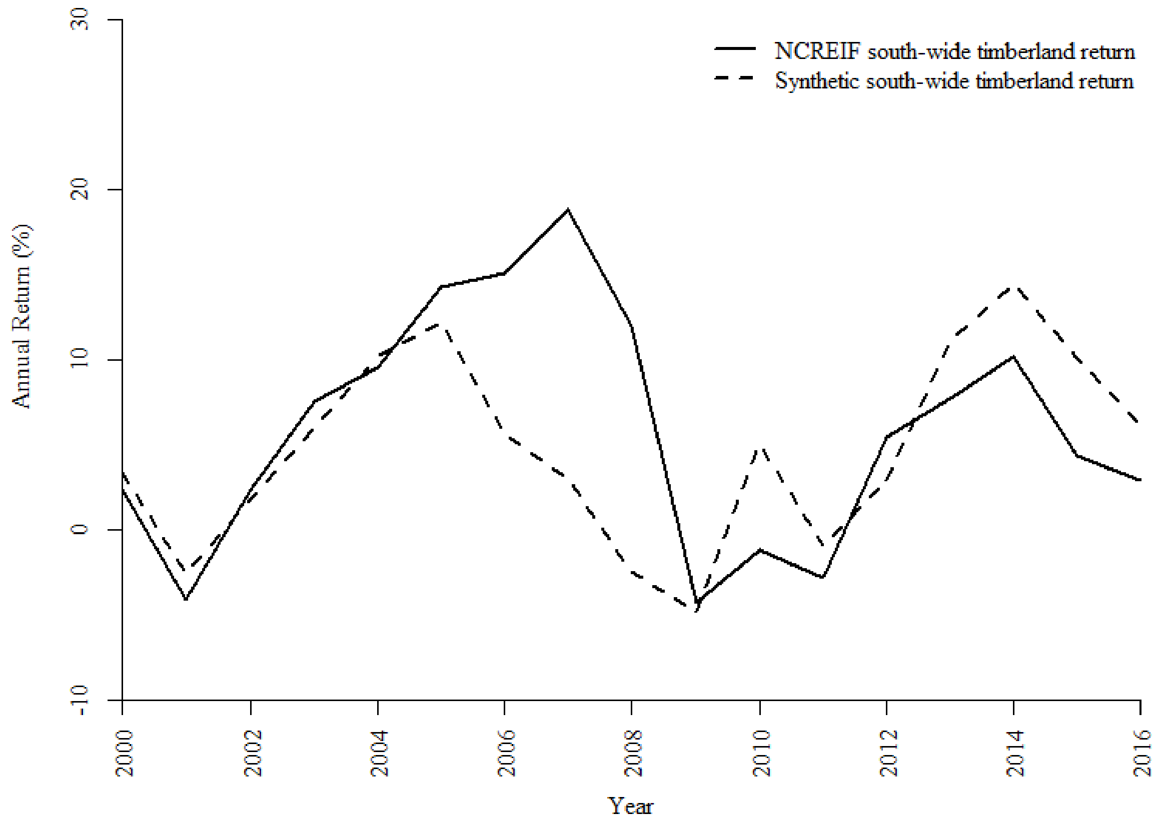

Figure 2.2. Comparison of synthetic, south-wide timberland return series with NCREIF south-wide timberland return series.

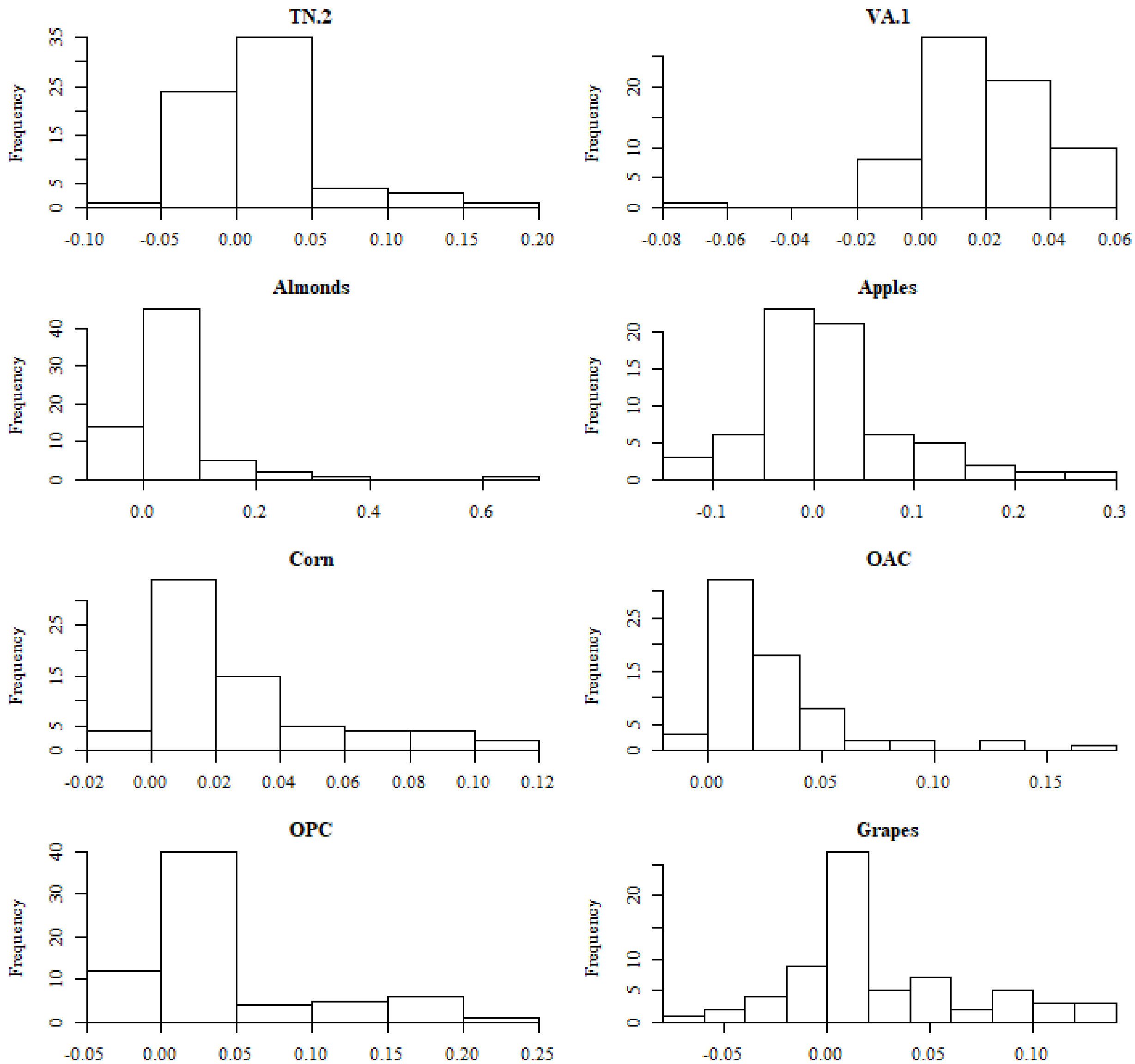

Figure 2.3. Histograms of returns of eight assets with significant Jarque-Bera normality test.

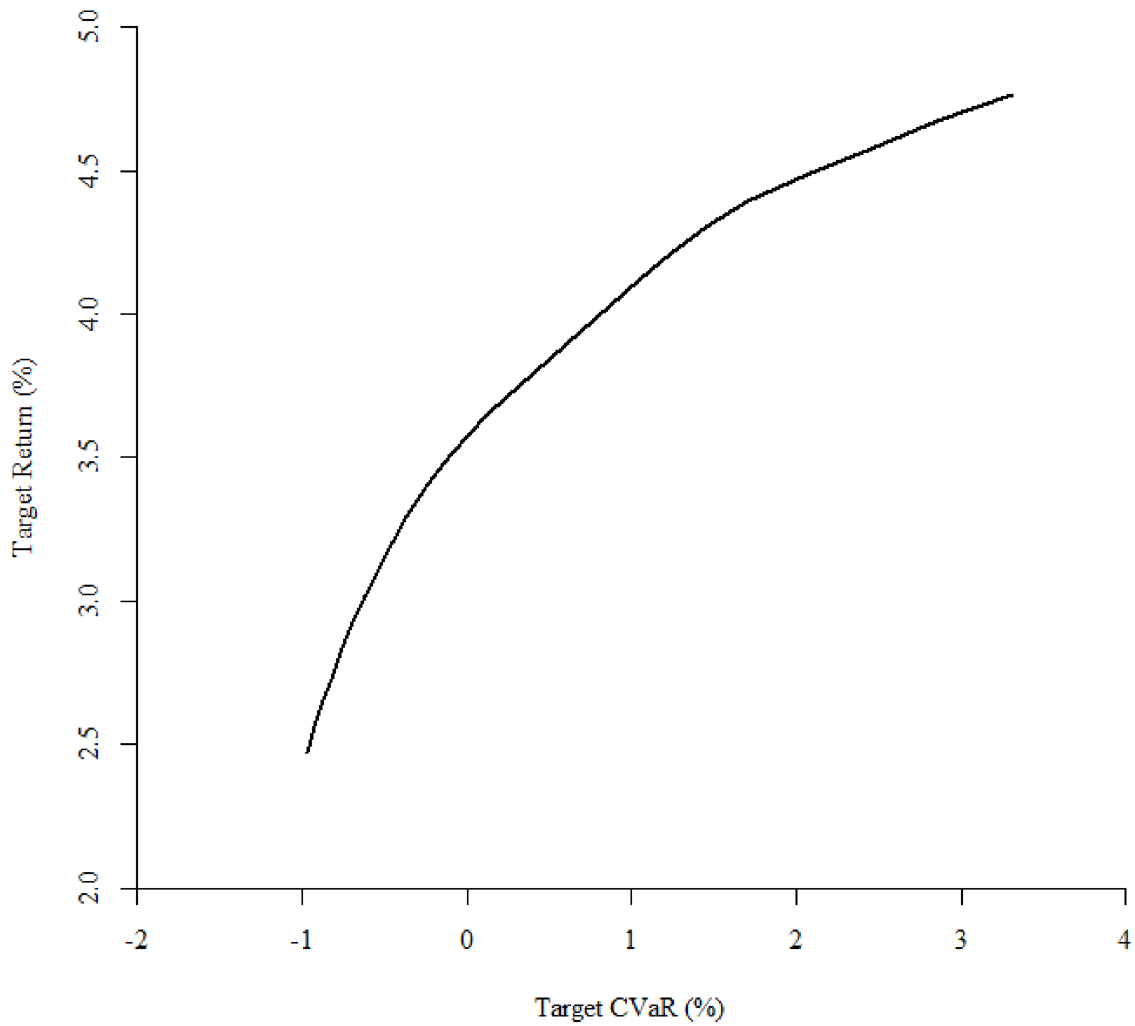

Figure 2.4. M-CVaR efficient frontier based on the unconstrained optimization framework.

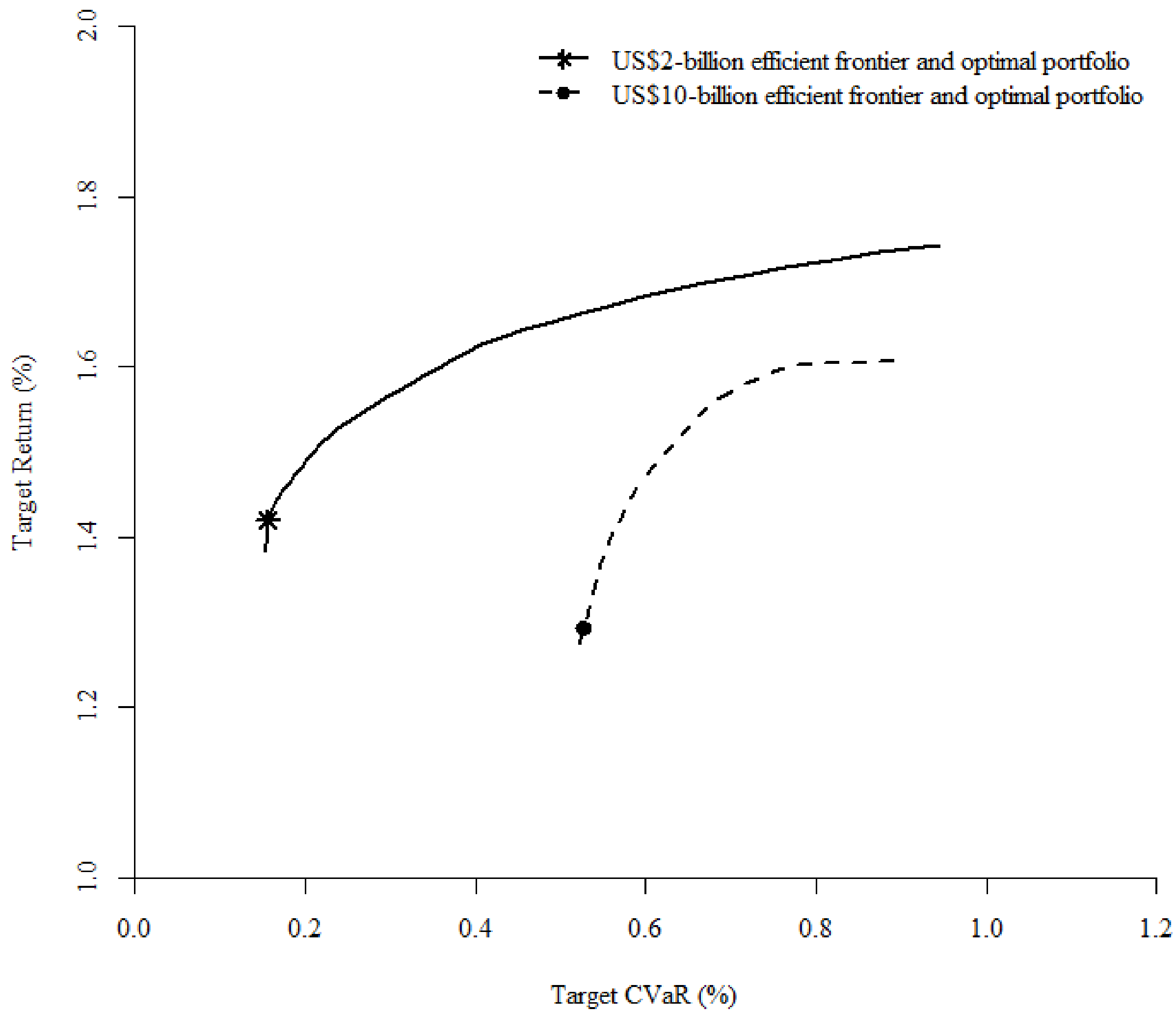

Figure 2.5. Comparison of the M-CVaR efficient frontiers under US$2-billion and US$10-billion scenarios.

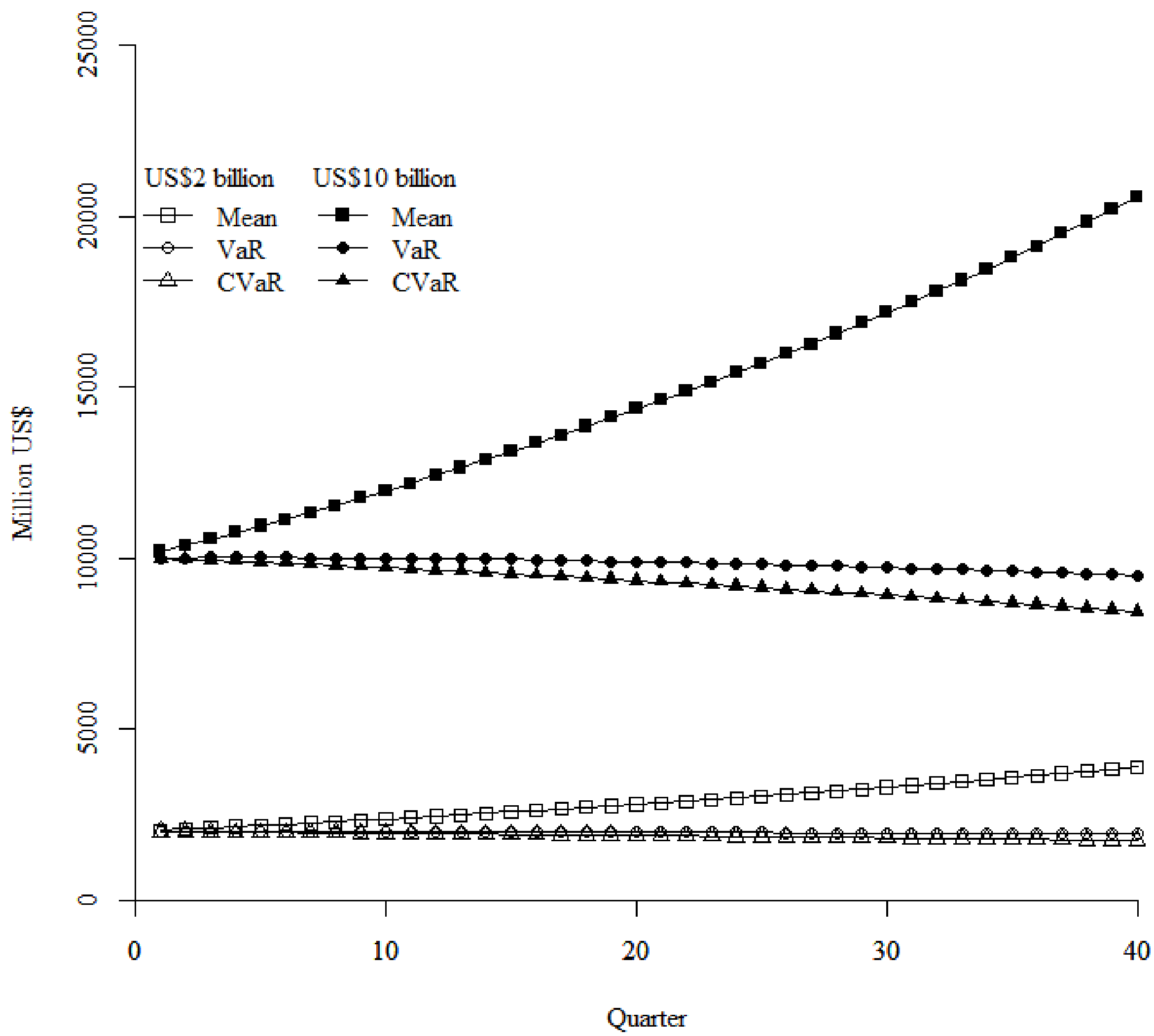

Figure 2.6. Expected portfolio values and their 5% VaR and CVaR over a 10-year horizon, with initial values of US$2 billion and US$10 billion.

CHAPTER 3

Impact of forest-related conservation easements on contiguous and surrounding property values[4]

[4] Zhang, W., B. Mei and R. Izlar. 2017. Accepted by *Forest Policy and Economics*, 05/08/2018. Reprinted here with permission of the publisher, 07/01/2018

Abstract

We apply the hedonic pricing method to analyze the effects of conservation easements (CEs) on surrounding vacant land parcel prices within the Metropolitan Atlanta Statistical Area (MASA). First, we collected data on forest related CEs in 30 counties in MASA and randomly sampled 312 land parcels from these same counties for information related to land parcels. The distance between each property and the nearest CE, and between each pair of properties, are calculated and used to find spatial dependence. Results show that the proximity to CE-protected open space after the CEs are established have positive price effects on the surrounding properties, and this effect diminishes with distance.

Introduction

The United States has abundant forest resources with one third of the country's land area, or 751 million acres, covered by forestland. Of the total, about 57% of forestland is privately owned (Smith et al. 2009). The ongoing development pressure, however, has increased land values and thus property taxes, which makes it more expensive for forest landowners to keep their land intact. Conservation Easement (CE) is a widely used tool to preserve land for conservation purposes by organizations, such as land trusts, whose missions are to protect natural resources (Fisher 2015). Protection of working forests is among the top ten priorities for land trusts in the US (Chang 2016). CEs are a private land conservation mechanism that protects open space from being developed, while helping landowners keep their land (Farmer et al. 2015). A working forest conservation easement is specifically designed to allow operations on forestland, such as harvesting and silvicultural practices, without the risk of losing the forestland due to development pressures (Tesini 2009). Currently, CEs are protecting more than two million acres of private forestland and the total acreage has been increasing over time, according to the Forest Legacy Program, administered by the US Forest Service (USFS 2015). All states in the US have passed statutes enabling working forest CEs (Ebers and Newman 2014).

The impacts of CEs are multi-faceted. CEs' purpose of preserving natural land brings about many environmental and social benefits, including open space for recreational activities and wildlife habitat, that are valued by the public (Geoghegan, Lynch and Bucholtz 2003). These benefits may also help increase property values surrounding the CEs. From a different perspective, in addition to keeping their land, CEs benefit landowners from a tax standpoint. Landowners engaged in CEs are considered to have donated a part of their rights for a charitable cause and thus are entitled to enjoy income tax deductions and lower property taxes, to be compensated for public goods provision (Chamblee et al. 2011; Fava 2013). Legislatively, many states have passed laws that mandate lower tax valuation for properties with conservation restrictions (Stockford 1990).

Protecting forests and other open space from increasing development and growing population is challenging. About 6,000 acres of open space are lost daily (USFS 2017). In light of the growing development pressure on forestland and the tax implications of CEs, we investigate the price effects of CEs on surrounding land in the Metropolitan Atlanta Statistical Area (MASA) (Figure 1). The reason for choosing the MASA region is because of the relationship among land conversion, forestland conservation and increasing developmental pressure observed in this region. Being one of the fastest growing metropolitan areas in the US, Metro Atlanta has seen its population grow significantly over the past decade. In terms of Gross Domestic Product growth, Atlanta has the second fastest economic growth in the US (BEA 2017). The enormous pressure from the urban sprawl and economic development activities within the region make MASA an appropriate study target. In the state of Georgia, where MASA is located, working forests and private forests are important to the state's economy, as they provide raw materials to the forest industry in the state. Georgia is among the nation's leading forestry states (GFC 2011). Private forests alone create $37 billion in annual ecosystem services in Georgia (GFA 2017). In terms of direct economic impacts, in 2015, a total revenue of $32.2 billion and 133,000 jobs were provided by the forest industry in Georgia (Hafer 2017). CE programs help the industry to protect raw material sources, and more importantly, help private forest landowners keep their forests. The fastest growing metropolitan area coupled with a leading forest industry creates a unique situation and hence makes MASA an interesting target area to study.

This study investigates factors that contribute to the valuation of properties near forests and open spaces encumbered with CEs. We use CE records and property sales data obtained from public sources to examine the price effects of CEs across different counties in MASA. A hedonic pricing model is used to explore the effects of characteristics of properties and CEs in determining property values.

Literature Review

A number studies have been conducted to identify the effects on property values brought by the proximity to open spaces, such as agricultural land and forests. Geoghegan, Lynch and Bucholtz (2003) use parcel-level data of residential properties to construct a pricing model for three counties (Calvert, Carroll and Howard) in Maryland. They find that in two of the three counties, residents living next to preserved open spaces value the environmental benefits, e.g., better air and water quality, brought by open spaces. On top of the environmental benefits, natural amenities such as better views and the access to nature are also factors that help increase surrounding residential property values. It is also noted that residents in Carroll County value open spaces less because they have more of them in the county. Sander and Polasky (2009) estimate the value of views and open space in Ramsey County, Minnesota and similarly conclude that the access to and the view of natural open spaces, such as water and grassy areas, have positive effects on home sale prices in the study area. Other open spaces, such as parks and trails, are also highly valued by home buyers. In a study focusing on undeveloped land, Zygmunt and Gluszak (2015) find similar effects on undeveloped real estate values near Las Wolski Forest in Poland. They collect data from 355 real estate development transactions in this area during 2002-2011, and use three estimation models. Their results indicate positive price effects of the proximity to this forest, with land values decreasing by 3% every one-hundred-meter further away from the forest.

The effects of conservation programs on surrounding land values have also been studied widely, and in most cases, are found to be positive. Geoghegan (2002) studies the relationship between two types of conserved open space and their effects on land prices in Howard County, Maryland. She defines these two types of conservation activities as “permanent open space” and “developable open space”, whose difference primarily lies in the expected future land use. The “permanent open space” category is congruent with the mechanism of CE programs. Results indicate that “permanent open space”, such as CE-protected land, has a statistically significant positive association with land prices, reflected through the higher housing prices in the surrounding area. Anderson and Weinhold (2008) investigate the effects of CEs and attempt to value development rights. They collect sales data and characteristics information on 131 properties with and without CE-restriction in South Central Wisconsin and compare their prices. Their results suggest that there is a significantly negative effect of CE restrictions on prices of undeveloped land, but not on prices of developed land. In addition, they are unable to conclusively establish a significant relationship between CEs and values of surrounding properties. In a later study on the relationship between conservation activities and land prices in North Carolina, Chamblee et al. (2011) collect data on vacant land transactions in a 12-year time span and information on conservation programs in Buncombe County, North Carolina. They distinguish conservation programs into two main mechanisms, namely fee-simple conservations and CE programs. Their study finds that fee-simple conservation programs increase surrounding land values by 46%. CE programs’ positive effects are less substantial, at 11%. They attribute this difference to land trusts’ inclination to use CEs to protect only properties with lower development prospects. In addition, they find that there exist non-capitalized benefits enjoyed by the residents who live close to, but not adjacent to the conserved land. A similar study done in Florida uses data on nine open space projects, called the Florida Forever, sales records of surrounding homes, and the hedonic model to investigate the effects of land conservation on nearby property values (Beal-Hodges 2012). She finds that when land is placed on the conservation acquisition list and considered undevelopable, the surrounding property values increase, in some of the study areas.

On the tax aspect of CE programs, several studies have been conducted to find the impacts of conservation activities on property value assessments, since taxes are assessed based on values. Stockford (1990) slices through laws and court cases on federal, state and local levels, to reveal the challenging factors that complicate the valuation assessment of properties encumbered with CEs. He finds that uncertainties exist in various aspects of the valuation system, and that easements can increase the market values of nearby properties and thus increase tax revenues from the surrounding area accordingly. King and Anderson (2004) sample 29 towns in Vermont using the stratified random sampling plan and study the effects on property taxes brought by CEs in Vermont. They use data on local communities' budgets, demographics and policies to examine the marginal effects of CEs. An interesting finding of their study is that the tax effects on the encumbered properties are positive only in the short-run. Over the long term, CEs have either no impact or a diminishing impact on property tax rates in Vermont towns. They also find increased appraised values of surrounding properties for governments to have sufficient tax revenues to cover essential service expenses. In a study to explore economic models that maximize net social benefits of CEs, Gustanski and Wright (2011) conduct case studies on three CE projects in Montana and New Mexico, facing three different levels of development pressures:

low, moderate and high. They conclude that acquisition costs associated with CEs increase as development pressure heightens. More importantly, they note that having an effective valuation model for CEs is essential to the efficient use of public tax money to subsidize conservation activities. Mittal (2014) conducts a study on the effects on home prices of nearby conservation activities, including both fee-simple conservation and CEs in Worcester, Massachusetts. He collects sales data on single-family detached houses and information on conservation projects. Through an OLS-based hedonic model, he finds that homes surrounding CE-encumbered parcels, especially homes with visual access to these parcels are priced higher. He concludes that CE-protected lands render surrounding homes more attractive to buyers and investors, and therefore drive prices higher. The higher values of homes surrounding CEs in turn provide more tax revenues to the local government and community.

In summary, numerous work has been done to study the relationship among natural open spaces, conservation programs and property values. Most studies find positive price effects of conservation activities and open spaces, but with varying degrees among different regions. Most of the reviewed literature either focuses primarily on values of residential properties, or targets only a few areas with variable development pressure. There lacks a localized study to particularly investigate the effects of CE programs on parcels with a variety of land uses. Especially, there has not been any study in MASA, where the development pressure is among the highest in the nation. We aim to fill that void by examining the price effects of CEs on surrounding properties by including different property types, i.e., vacant agricultural, commercial, industrial and residential parcels. We expect to address the emerging conflicts between environmental conservation and development pressure by sampling property transaction records and conservation program information in the rapidly urbanizing MASA.

Method and Data

This study uses a hedonic pricing model that is similar to a number of recent studies (Chamblee et al. 2011; Geoghegan 2002; Geoghegan, Lynch and Bucholtz 2003; Zygmunt and Gluszak 2015). The hedonic model aims to separate the various price effects related to the properties' physical features and characteristics of CEs in the surrounding area, and the model is defined as follows,

$$P_i = SIZE_i^{\alpha} Exp[\beta \mathbf{X}_i + \delta \mathbf{C}_i + \varepsilon_i] \tag{1}$$

where

P_i is the price of the i^{th} land parcel in dollars;

$SIZE$ is the size of the i^{th} land parcel in acres;

$\mathbf{X}_i$ is a collection of the physical characteristics of the i^{th} land parcel;

$\mathbf{C_i}$ is a collection of the characteristics of the CEs that are related to i^{th} land parcel; and

ε_i is the error term.

Both $\mathbf{X_i}$ and $\mathbf{C_i}$ are in vector forms. The model is transformed into a linear form by taking natural logs so that an ordinary least squares (OLS) regression can be performed to estimate the coefficients α, β and δ:

$$\boldsymbol{y} = \mathbf{A}\alpha + \mathbf{X}\beta + \mathbf{C}\delta + \boldsymbol{\varepsilon} \tag{2}$$

where the dependent variable **y** is a vector of log-transformed land prices, **A** is a vector of log-transformed acreage, **X** and **C** are collections of log-transformed variables related to land and CE characteristics.

The hedonic pricing model is based on spatially distributed property data, so there is a need to investigate the spatial dependences among properties. We investigate the spatial dependence by adding spatial disturbance in the error term, and employ a Spatial Error Model (SEM), built on Maximum Likelihood Estimation, by modifying Eq. (2) to:

$$\boldsymbol{y} = \mathbf{A}\alpha + \mathbf{X}\beta + \mathbf{C}\delta + \xi \tag{3}$$

$$\xi = \boldsymbol{\lambda}\mathbf{W}\xi + \boldsymbol{\epsilon} \tag{4}$$

where $\mathbf{W}\boldsymbol{\xi}$ is a vector of error terms, weighted by spatial distances. $\boldsymbol{\lambda}$ is the error coefficient vector to be estimated, and $\boldsymbol{\epsilon}$ is the error vector that captures uncorrelated variability in prices. The spatial weight matrix $\mathbf{W}$ is a nonnegative $n \times n$ matrix. Binary weights are given based on threshold distance:

$$[w_{ij}] = \begin{cases} \frac{1}{n_i}, & within\ threshold\ distance \\ 0, & otherwise \end{cases} \tag{5}$$

where w_{ij} weighs the Euclidean distance between each pair of sampled properties, and n_i is the number of nearby properties within the threshold of 20 miles. $\mathbf{W}$ is standardized so that the sum of weighted threshold distances from each property is 1.

Based on the proposed pricing model, two main sets of data are needed. They are the information related to both the properties and CEs. In this study, only vacant land parcels are sampled. Information on 312 vacant parcels is sampled from the websites of tax assessor offices of all 30 counties in MASA from 2000 to 2016. Information on CEs is available online and obtained from the National Conservation Easement Database (NCED 2015). Since there is no complete list of all forest CE programs in Georgia, data scrutinizing and cleaning are conducted. Given the purpose is to study the impact of working forest conservation easements, we eliminate CEs that are held by National Parks, National Forests and National Monuments. Other non-forest related CE projects, such as the Atlanta Botanic Garden, are also taken off the list. Nonetheless, it is impossible to completely separate forest-related CE projects from the more encompassing category of agricultural conservation programs. A total of 115 CE projects are found in the dataset and are located in 24 MASA counties.

The explanatory variables are compiled in Table 1, accompanied with descriptions and statistics. *PRICE* lists the actual prices of 312 transactions in 30 counties in MASA. We then describe the explanatory variables that are related to the properties first. *SIZE* is the acreage of land parcels. $\mathbf{X_i}$ contains the variables that describe the physical features of the land, which are property types (*PropertyClass*) and the Euclidean distance from each property to the geographical center of Atlanta (*DistATL*). *PropertyClass* is a categorical variable, where 0, 1, 2 and 3 represent agricultural land, commercial lot, industrial lot and residential lot, respectively.[5] *DistATL* is measured in miles. We expect it to have a negative sign because urban economic theory indicates that property value is positively related to the proximity to a city where employment opportunities are amble (Brigham 1965). *ATLANTA* is a dummy variable that takes the value of one if the property is in one of the three counties in the Atlanta-Sandy Spring-Roswell area, and the value of zero if the property is in other counties within MASA. We expect this variable to have a positive sign, since these parcels come with an easy access to a network of interstate highways and the world's busiest airport.

Variables that are related to the CEs are contained in vector **C**. For every land parcel sold in our sample, we determine the closest CE based on the Euclidean distance, and note this distance as *CEDist*. We expect *CEDist* to have a negative sign because people value being close to open spaces. *CESize* is the area of the closest CE in acres and expected to have a positive sign because the larger the protected area, the greater the environmental benefits and hence the higher the property values. In addition, we measure the number of CEs within a ten-mile radius of each

[5] PropertyClass 0 is omitted in the regression to avoid the dummy trap.

property (*CENearby*). *CENearby* is expected to a have positive sign because the greater total number of CEs leads to more protected area, which should enhance property values. The dummy variable *CEPost* is zero if a parcel is sold before the closest CE is established, and one if a parcel is sold afterwards. We expect *CEPost* to have a positive sign because property buyers see future development to be unlikely if a CE is already in place (Geoghegan 2002). Finally, since we expect the amenity values diminish as a property gets further away from the closest CE, we include an interaction term *CEPostDist*. This variable is expected to be negative, which shows the decreasing price effect per mile further away from the conserved land.

Results and Discussion

Estimation results are shown in Table 2. First, as previously mentioned, the log-transformation is applied on Eq. (1) to account for the skewed distribution. However, the log-transformation alone does not guarantee unbiased and efficient estimation. Hence, we employ five models to estimate the coefficients: standard OLS, OLS with robust standard errors, random effects model, fixed effects model and SEM.

First, a standard OLS estimation is applied. Among other assumptions, homoscedasticity is an important assumption to ensure unbiased OLS estimation. Since properties are dispersed across 30 counties and thus may not share a common error structure with a zero mean, there may exist heteroscedasticity in the error term. To test for heteroscedasticity, the Breusch-Pagan test is performed and returns a statistic of 36.22 with p-value less than 0.01, therefore rejects the homoscedasticity null hypothesis. Variabilities within each county may be correlated. This correlation is unknown but can be explained by different county's budgetary concerns and fiscal practices. Therefore, we relax the homoscedasticity assumption and recognize the correlation within counties. To account for this within-group correlation, the robust standard errors are specified in the second OLS process.

Furthermore, the first two OLS processes do not allow for unobserved heterogeneity, which can be correlated with any of the explanatory variables. Therefore, we include group effects at the county level and control for unobserved county heterogeneity, using both the random effects model and fixed effects model. We compare the two models using the Hausman test. The test statistic is insignificant, suggesting that the random effects model is sufficient. We also compare the OLS and random effects models by the Breusch-Pagan test and find that the random effects model is significantly more superior.

Finally, defining group effects by the county level may still not appropriately capture heterogeneity. It is very likely to have properties that are close to each other, situated in the same neighborhood and but in different counties. Therefore, from that perspective, we define neighborhoods by the distances among properties and use the SEM model to account for spatial effects. The Moran's *I* test presents a *p*-value of 0.042, indicating that there are spatial dependences. So, the following discussion is focused on the SEM model.

The size of parcels is the most significant in determining prices with a positive coefficient of 0.61. This coefficient is the size elasticity of price, and a value between 0 and 1 confirms the concave relationship between parcel size and price (Colwell and Munneke 1997). In addition, the land type variables for commercial and industrial lots show strong statistical significance. These property type variables also have positive coefficients, as expected. If a lot is designated as commercial and industrial land, the parcel respectively enjoys 480% and 400% premiums, over agricultural land. On the other hand, vacant residential lot shows 0.6% discount with insignificant levels. The discount may be due to other features of the lots that are unaccounted for, such as access to utilities, infrastructure and the suitability of the lot to be built on. As expected, the distance from the center of Atlanta (*DistATL*) has a negative impact on prices. One additional mile away from Atlanta city center comes with 2% discount in land price. Lastly, all else equal, parcels within the Atlanta-Sandy Spring-Roswell area enjoy 85% premiums relative to parcels in other MASA counties.

Regarding CE-related variables, not all of them are significant. Opposite to expectation, the sign on *CEDist* is negative, albeit the magnitude of the effect is small. One additional mile closer to a CE-protected open space from a parcel will see 0.2% price reduction. *CESize* also has a negative effect and is statistically significant. Each additional acreage to the closest CE-protected area results in a 0.1% land price discount. This is possibly due to the nature of sampled parcels. Close to 40% of sampled parcels are not residential lots, while environmental benefits are valued more by residents and less by industrial and commercial land owners (Magnan, Seidl and Loomis 2012). We notice that the effect of *CESize* is negligible, and suspect that the size of a nearby CE-protected area does not necessarily affect the perceived value of a nearby industrial property with development prospects. This interpretation resonates with the land-use planning process of local government. Other studies also find that the prevention of development on one lot does not imperatively decrease total development activities in the area (Richardson and Bernard 2011). On the other hand, *CENearby* is positive and significant. This means that each additional CE in the surrounding area can lead to a 1.7% price premium.

Dummy variable *CEPost* is positive and significant at the 10% level. *CEPost* indicates whether the parcel is sold after a CE is established in its surrounding area or not. The coefficient on *CEPost* shows a 57% premium after an open space is perpetually protected by a CE in the neighborhood. In line with our expectation, the interaction term, *CEPostDist*, is negative and significant. The result suggests that if there is a CE-protected land in the surrounding area, one additional mile away from the CE-protected land will see a 6% price reduction, which shows that the post-CE premium diminishes with distance.

Conclusion

In this study, we examine the effects of CE programs on surrounding property values, using information on existing CEs and vacant land sales records in MASA. The estimation models explore the price effects of variables related to characteristics of both land parcels and CEs. Since the primary objective of this study is to investigate the price effects of CEs, we discuss the results on CE-related variables first. These results show that impacts of CEs on property values vary. Different from our expectation, the characteristics of the nearest CE has little impact on the surround values. However, the total number of CEs in the surrounding area positively enhances land values. In addition, the post-CE effects on land values are in line with our expectations, that after a CE is established, vacant land parcels within its vicinity increases in value by 57%. We conclude from these results that conservation activities' positive price effects on land values are comprehensive and diminishing with distance.

The estimation results on variables about physical characteristics of land parcels illustrate the challenges faced by conservation efforts, and shed some light on the necessity of publicly funded conservation programs, such as CEs. Positive variable coefficients on commercial and industrial lots show high price premiums of these land types, and confirms the presence of high development pressure in MASA. Increasing land values make it economically attractive for some land owners to sell the land to developers, who may convert forests to commercial and industrial uses, instead of keeping it for timber production, recreation or wildlife habitat. Moreover, for other owners who have an emotional attachment to their land, high property values in their subdivisions make it unaffordable to keep paying high property taxes (Farmer et al. 2015). In addition, higher land prices make it more difficult for land trusts to purchase property rights and conserve land that are more susceptible to commercial and industrial development (Gustanski and Wright 2011). CEs are used by land trusts to help landowners keep their properties from being developed. CE deals are often funded by public money and CE-related tax benefits to owners are facilitated by federal and state tax laws, essentially making CEs subsidized land conservation. Our study is successful in providing a model to properly value the development rights of commercial and industrial land, and thus helps with the efficient use of public funds. However, our study does not account for a few other questions that are pertinent to the full benefits of CEs.

First, while this study shows positive post-CE price effects on vacant land parcels, the effects have not been studied in full. Our data set does not include sales information on the same land parcels both before and after CEs' establishment. It will require more repeat sales for parcels in the sample to better account for unobserved heterogeneity at the property level.

Secondly, although our model can help value commercial and industrial lots, it may not fully capture values of the development right on residential lots. An optimum method of valuation can have implications in determining the effectiveness of using public funds in conserving private land. Our study touches on the point of land conservation's impacts on taxation on the local levels. While CEs take away development rights from encumbered land, and hence lower taxes collectable from the encumbered land, we argue that the spillover effects of CEs enhance property values in the surrounding areas, and hence offset tax revenues lost due to CEs. Nevertheless, the fair valuation of development rights is still worth more rigorous investigation. Currently, the prevailing appraisal-based CE valuation can be misinforming, subject to appraisal malpractice and may lead to legal challenges, thus creating bigger hurdles for private landowners to pursue CEs.[6]

The benefits of CEs include the protection of natural landscape and the related ecosystem services, as well as steady raw material sources for the forest industry. Nonetheless, it comes with changing the tax structure of the government and possibly limiting development opportunities in the area. On regional levels, the net overall social benefits of having CEs are still up for more investigations. With a more comprehensive list of forest-only conservation programs and a larger pool of sampled properties and repeat sales information across time, the dilemma of allocating scarce natural resources and forest landscape between economic activities and forest conservation can be further examined.

[6] New England Forestry Foundation, Inc. v. Board of Assessors of Hawley, Commonwealth of Massachusetts Appellate Tax Board, 2013

Table 3.1. Variable names and definitions.

	Definitions	Units	Mean	Std. Dev.
PRICE	Transaction prices in nominal dollars	$US	1,354,843	7,582,710
SIZE	Acreage of sample properties	Acres	15.41	32.20
LnSize	Natural log of property acreage	Acres	1.89	1.23
PropertyClass	0: Agricultural land	-	2.08	1.24
	1: Commercial lot	-		
	2: Industrial lot	-		
	3: Residential lot	-		
DistATL	Distance from the property to the city center of Atlanta	Miles	36.64	12.85
ATLANTA	Parcel located within Atlanta-Sandy Spring-Roswell area	-	0.11	0.32
CEDist	The distance from the property to the closest CE protected space	Miles	6.25	3.75
CESize	The area of the closest CE protected space	Acres	122.91	152.26
CENearby	Number of CE protected spaces within a 10-mile radius of the property	-	3.26	3.4
CEPost	Parcel sold after conservation of nearest parcel in CE	-	0.57	0.49
CEPostDist	Distance to the nearest CE-protected land and parcel sold after CE	Miles	3.61	4.08

Table 3.2. Regression results of the Hedonic models.

	(1)			(2)			(3)			(4)			(5)		
	OLS			Robust OLS			Random Effects			Fixed Effects			Spatial Error Model		
LnSize	0.57	(0.07)	***	0.57	(0.08)	***	0.59	(0.06)	***	0.59	(0.06)	***	0.61	(0.06)	***
PropertyClass 1	1.74	(0.28)	***	1.74	(0.46)	***	1.66	(0.26)	***	1.66	(0.26)	***	1.76	(0.27)	***
PropertyClass 2	1.51	(0.46)	**	1.51	(0.30)	***	1.15	(0.40)	**	1.12	(0.41)	**	1.62	(0.45)	**
PropertyClass 3	-0.10	(0.21)		-0.10	(0.22)		-0.18	(0.20)		-0.19	(0.21)		-0.01	(0.21)	
DistATL	-0.01	(0.01)	·	-0.01	(0.01)		-0.01	(0.01)		-0.01	(0.01)		-0.02	(0.01)	·
ATLANTA	0.75	(0.29)	*	0.75	(0.74)		0.46	(0.59)					0.61	(0.29)	*
CEDist	-0.01	(0.03)		-0.01	(0.03)		0.01	(0.03)		0.02	(0.04)		0.00	(0.03)	
CESize	0.00	(0.00)	*	0.00	(0.00)	*	0.00	(0.00)	*	-0.01	(0.00)	*	0.00	(0.00)	*
CENearby	0.02	(0.03)		0.02	(0.02)		0.04	(0.03)	·	0.04	(0.03)	·	0.02	(0.30)	·
CEPost	0.28	(0.29)		0.28	(0.49)		0.54	(0.31)	·	0.66	(0.34)		0.45	(0.04)	·
CEPostDist	-0.04	(0.04)		-0.04	(0.05)		-0.05	(0.04)		-0.05	(0.04)		-0.06	(0.03)	*
CONSTANT	10.90	(0.63)		10.90	(0.63)	***	10.63	(0.59)	***				10.76	(0.49)	***
H_0: Homoscedasticity[a]		0.00	***												
H_0: RE VS OLS[b]								0.00	***						
H_0: RE VS FE[c]										0.99					
H_0: No spatial dependence[d]														0.04	***
Observations		312			312			312			312			312	

Note: Standard errors are presented in parentheses. RE for random effects. FE for fixed effects. [a] Breusch-Pagan test. [b] Breusch-Pagan test. [c] Hausman test. [d] Moran's I test. · Significant at 10%. * Sigficant at 5%. **Significant at 1%. ***Significant at 0.1%.

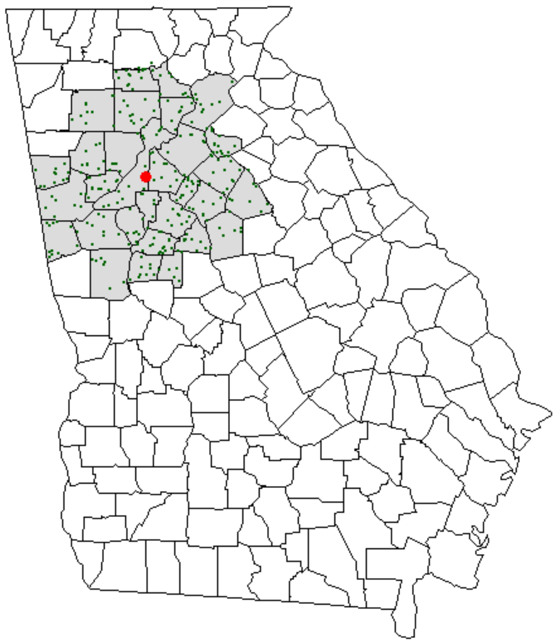

Fig. 3.1. MASA counties and the city of Atlanta.
Note: The red dot indicates the location of Atlanta. Green Dots are the sampled property locations.

CHAPTER 4

ANOTHER TAKE ON THE ROLE OF TIMBERLAND ASSETS IN A MIXED-ASSET PORTFOLIO[7]

[7] Zhang, W. and B. Mei. 2018. Submitted to *Journal of Real Estate Research*, 3/13/2018.

Abstract

We investigate the role of timberland in a mixed-asset portfolio in the United States, especially as investment horizons lengthen. In addition to using conventional single-period returns, this study modifies return, volatility and correlation for multi-period and infinite horizons, to account for features of long-term investments, and builds mixed-asset portfolios including traditional financial assets and timberland, under the mean-variance framework. The constrained optimizations prove the diversification benefits of both private- and public-equity timberland investments using single-period returns. Long-term optimizations show private-equity timberland is a more superior diversifier over public-equity timberland. Infinite-horizon optimizations prove private-equity timberland's persistent roles in mixed-asset portfolios.

Introduction

Timberland assets have received increasing attention from investors over the last three decades in the United States (Waggle and Johnson 2009). As an alternative asset class, investors seek diversification benefits from holding timberland (Mei 2015a) for its desirable financial characteristics, including high risk-adjusted returns (Cascio and Clutter 2008; Mei 2017), low correlation with other financial assets (Caulfield and Newman 1999; Mei and Clutter 2010; Wan et al. 2015), and the ability to protect against inflation (Wan et al. 2013; Washburn and Binkley 1993).

There are generally two options to invest in timberland. First, investors can hold large tracts of timberland in private ownership through closed- or open-end funds managed by timberland investment management organizations (TIMOs). This approach is typical for institutional investors, such as pension funds and university endowments, and high net-worth families, and requires significant capital commitment and long holding periods. The other option is through investing in publicly-traded timber firms or real estate investment trusts (REITs). This option enables an easy access for both institutional and individual retail investors to engage in timberland investment without losing liquidity (Mendell, Mishra and Sydor 2008). Overall, TIMOs manage over US$77 billion worth of timberland (Campbell Global 2017), while public timber firms and REITs own over US$34 billion in market capitalization values (WRDS 2018).

The return and risk are keys to understand financial performance of an asset. Past research uses arithmetic mean and standard deviation (SD) to measure timberland investment return and volatility, and focuses on single-period performance under the mean-variance (M-V) framework to examine its financial performance assuming independent and identically distributed (i.i.d.) returns. However, private real estate returns usually exhibit high autocorrelations, which complicates long-term risk measures (Pagliari 2017). Hence, there is a need to investigate long-term performance metrics of timberland investments.

We aim to examine the three components under the M-V framework, mean, volatility and correlation of timberland returns, as the investment horizon lengthens. Results show that using long-term volatility captures serial correlations in asset returns. In addition, we prove the key roles that timberland assets play in mixed-asset portfolios. Finally, we assess the interplay between private- and public-equity timberland investments in both unconstrained and constrained scenarios of asset allocations.

Literature Review

Numerous work has used the M-V framework to study the financial performance of timberland investments. Mills and Hoover (1982) first introduce the concept of M-V portfolio optimization framework to measure the performance of investment in forest land, and show that timberland assets provide diversification benefits to mixed-asset portfolios that also include farm options, stocks and bonds. Thomson (1997) evaluates investments in Douglas fir and southern pine using a modified M-V method, and shows that investing in timberland in a limited and consistent manner lowers the overall portfolio risk. Caulfield (1998) uses the timberland performance index to represent financial performance of existing timberland investment management companies and constructs efficient frontiers based on the index. He determines that the addition of timberland provides desirable return-enhancing and risk-reduction benefits to institutional portfolios.

A concern of timberland investment under the M-V framework is finding an appropriate return index. Most past studies use periodic returns reported in the National Council of Real Estate Investment Fiduciaries (NCREIF) Timberland Index (NTI) and regional indices to represent private-equity timberland returns in portfolio analysis (Mei 2017). Newell and Eves (2009) use the NTI to prove that private-equity timberland adds significant diversification benefit to a mixed-asset portfolio, which also includes real estate and farmland assets. However, they find diminishing diversification potential in the more recent sub-period, as the correlation between timberland and other assets strengthens.

With regards to the statistical characteristics of private timberland investment returns, Mei (2015a) uses the BDS test to show that the NTI and most of its regional indices violate the i.i.d. assumption under the M-V framework and attributes the non-i.i.d. nature to illiquidity, while public-equity timberland does not violate the assumption. He also extends single-period M-V portfolio analysis into long-term holding periods using simulation methods and concludes that private timberland assets see decreasing return-to-risk ratios as holding periods extend. In a later study, he devises a transaction-based index to proxy returns on private timberland investment and compares the NTI, and concludes that using different return proxies for private timberland results in different portfolio allocations under the M-V framework (Mei 2016).

On the proxies for public-equity timberland returns, in addition to using weighted stock returns of public timber firms, Mei (2015b) proposes a pure-play timberland index to represent investment returns attributed to only timberland business segments within securitized timber firms. By deleveraging public-equity timber firms and sifting out non-timber segments, he argues that the pure-play timberland index better represents returns on securitized timberlands and more effectively compares with private-equity timberland returns.

Different asset pricing methods have been used to model the returns on private- and public-equity timberland investments. Sun and Zhang (2001) use capital asset pricing model and arbitrage pricing model to compare the returns and risks of several hypothetical portfolios, eight of which are forestry-related portfolios, including private institutional timberland investment, timberland limited partnerships[8] and public forest products companies. They conclude that timberland-only investments bear lower risks than investments in forest products companies who own both timberland and timber processing facilities. Using the same two pricing models, Yao, Mei and Clutter (2014) use several indices to represent private- and public-equity timberland investment from 1988 to 2011. Their study finds that at the fund level, private-equity timberland diversifies portfolio risks, while public-equity timberland displays higher-than-expected returns throughout the sample period.

Mei and Clutter (2010) use the capital asset pricing model and Fama-French three-factor model to analyze private- and public-equity timberland investment returns and conclude that while private-equity timberland investment displays higher return with lower systematic risk, public-equity timberland investment performs similarly to the market. Yao and Mei (2015) introduce the intertemporal capital asset pricing model to examine the return-risk relationship between forestry-related assets and innovations in state variables, in two sub-periods. They find excess returns on both private- and public-equity timberland assets only in the first sub-period, and that they respond to shocks in business conditions differently.

In addition to portfolio analysis under the M-V framework, other methods have been employed to study diversification potentials of timberland assets. Sun (2013) assesses the diversification potentials of timber REITs using copula modeling method. By comparing stock returns of timber REITs before and after REIT conversions, he proves a decreasing diversification potential when timberlands are securitized in the form of REITs and show that

[8] Timberland limited partnerships are spin-off companies from several forest products firms in the 1980s. They own and manage timberland for their partners, who usually are forest products firms that had spun them off in the first place.

timber REITs may be attractive to institutional investors who are more prepared for higher volatilities. La and Mei (2015) employ a cointegration analysis to study the diversification potential of investing in timber REITs. They find that there exist imperfect correlations between the overall stock market and timber REIT stock returns and that there is limited cointegrating relation among timber REITs. Thus, they conclude that each timber REIT is a unique candidate for portfolio diversification considerations.

Addressing the potential violation of the multivariate normality assumption of the M-V framework, Wan et al. (2015) build mixed-asset portfolios with timberland and traditional financial assets using both M-V and mean-conditional value-at-risk (M-CVaR) frameworks. They find that timberland assets are generally risk diversifiers and conclude that portfolios built under the M-CVaR framework are more efficient than those under the M-V framework.

Overall, most current work uses arithmetic mean return and SD to represent an asset's expected return and volatility, and conducts portfolio analysis using single-period M-V models. Since timberland investments are intended for long-term, multi-period horizons, it is necessary to distinguish between single- and multi-period analytical models.

Methods

Long-horizon mean returns: Arithmetic versus geometric average

While arithmetic average of periodic returns, $\bar{r}$, is an unbiased measure of the one-period return, it overstates the compounded mean return, or the geometric mean ($\ddot{r}$), over multiple periods. The geometric means can be approximated by the arithmetic mean as:

$$\ddot{r} \approx \bar{r} - \frac{\sigma^2}{2} \tag{1}$$

where $\ddot{r} = \sqrt[T]{\prod_{i=1}^{T}(1 + r_i)} - 1$, $\bar{r} = {\sum_{i=1}^{T} r_i}/{T}$, $\sigma^2 = {\sum_{i=1}^{T}(r_i - \bar{r})^2}/{(T-1)}$, and T is the length of the holding period. The term $\frac{\sigma^2}{2}$ is known as "variance drain" or "cost of risk" (Arnott 2005; Messmore 1995). As T approaches infinity, $\bar{r}$ and $\ddot{r}$ converge (Pagliari 2017), such that

$$\lim_{T\to\infty} \bar{r} = \ddot{r} \tag{2}$$

Long-horizon volatility

Generalizing the variance of long-horizon return, $\sigma^2 = Var[\prod_{i=1}^{T}(1 + r_i)]$, Pagliari (2017) formulates the variance of any T-period horizon as:

$$\sigma_T^2 = T\sigma^2[1 + 2\left[\frac{\varphi}{1-\varphi} - \frac{\varphi(1-\varphi^T)}{T(1-\varphi)^2}\right]] \tag{3}$$

where φ is the autocorrelation coefficient and between 0 and 1. Therefore, the long-horizon variance becomes a function of T, σ^2 and φ. When there is no autocorrelation, or $\varphi = 0$, σ_T^2 is simply $T\sigma^2$, which is the case for independent and identically distributed returns. To produce a periodic long-horizon variance, we can rescale σ_T^2 by T so that

$$\lim_{T\to\infty} \left(\frac{\sigma_T^2}{T}\right) = \sigma^2 (\frac{1+\varphi}{1-\varphi}) \tag{4}$$

Similarly, we can scale long-horizon SD as:

$$\frac{\sigma_T}{T} = \frac{\sigma}{\sqrt{T}} \sqrt{1 + 2\left[\frac{\varphi}{1-\varphi} - \frac{\varphi(1-\varphi^T)}{T(1-\varphi)^2}\right]} \tag{5}$$

Alternatively, we can employ the family of generalized autoregressive conditional heteroskedasticity (GARCH) models to estimate time-varying conditional variances. To guarantee a positive sign of the conditional variance, an exponential GARCH(i,j) model is used,

$$r_t = \mu + \varphi r_{t-1} + \varepsilon_t \tag{6}$$

$$\ln(\sigma_t^2) = \omega + \sum_{i=1}^{p} \gamma_i \frac{\alpha_i \varepsilon_{t-i} + |\varepsilon_{t-i}|}{\sigma_{t-i}} + \sum_{j=1}^{q} \beta_j \ln(\sigma_{t-j}^2) \tag{7}$$

where r_t is asset return at time t $(t = 1, \cdots T)$ and ε_t is the error term. Parameters μ and ω are constants in the conditional mean and variance equations respectively. Parameter α captures the leverage effect of shocks on the conditional variance. The effect of ε_{t-1} is $(\alpha_i + 1)\ \varepsilon_{t-1}$ when ε_{t-1} is positive (i.e., positive market shock), and $(\alpha_i - 1)\ \varepsilon_{t-1}$ when ε_{t-1} is negative (i.e., negative market shock). If $\alpha < 0$, then a negative shock has greater impacts on the volatility than a positive one. Parameter γ represents the magnitude effect of shocks. Parameter β is the GARCH term that measures the volatility persistence. To produce periodic long-horizon variances, averages of conditional variances are taken every T periods.

Long-horizon correlation

Extending the general formula of correlation coefficient ($\rho_{x,y} = \frac{\sigma_{x,y}}{\sigma_x \cdot \sigma_y}$) between two random variables x and y, long-horizon correlation can be calculated as $\rho_{x,y|T} = \frac{\sigma_{x,y|T}}{\sigma_{x|T} \cdot \sigma_{y|T}}$. The infinite-horizon correlation is then expressed as (Pagliari 2017)

$$\lim_{T\to\infty} \rho_{x,y|T} = \rho_{x,y} \frac{1-\varphi_x\varphi_y}{\sqrt{(1-\varphi_x^2)(1-\varphi_y^2)}} \tag{8}$$

The ratio of the infinite-horizon correlation to the single-period correlation is given as

$$\lim_{T\to\infty} \frac{\rho_{x,y|T}}{\rho_{x,y}} = \frac{1-\varphi_x\varphi_y}{\sqrt{(1-\varphi_x^2)(1-\varphi_y^2)}} \tag{9}$$

which reaches its minimum when $\varphi_x = \varphi_y$ and increases as $|\varphi_x - \varphi_y|$ widens. Therefore, assets with significantly different single-period autocorrelations may have a ratio higher than two. As such, their long-term diversification potential may diminish substantially.

Alternatively, just as with conditional variances, conditional correlations can be obtained from a multivariate GARCH model and then averaged every T periods to produce periodic long-horizon correlations.

Portfolio optimization frameworks

The M-V framework

Under the M-V framework, a mixed-asset portfolio can be optimized by minimizing the risk subject to a given target return μ as:

$$\underset{w}{\text{Min}}\, w'\Sigma w \tag{10}$$

$$\text{s.t. } w^T E = \mu, \sum_{i=1}^{n} w_i = 1 \text{ and } w_i > 0$$

where w is the weight vector, Σ is the variance-covariance matrix, and E is the vector of mean returns. The positive weight constraints prohibit short selling. Solving the optimization problem by iteratively changing the weights of assets, the M-V efficient frontier presents the return and risk combinations of all efficient portfolios.

The M-CVaR framework

The M-CVaR framework has been suggested for assets that fail the multivariate normality test (Petrasek et al. 2012; Wan et al. 2015). First, the loss function of a portfolio is denoted as a function of asset weights and returns, $f(w, r)$, where r follows a probability density function, $p(r)$. The cumulative distribution function of the loss can be formulated as $\Psi(w, \Upsilon) = \int_{f(w,r)\leq\Upsilon} p(r)\, dr$, where w is the associated asset weights, and Υ is the maximum loss level. Then we can define VaR and CVaR at a confidence level, α,

$$\text{VaR}_\alpha(w) = min\{\Upsilon \in \Re : \Psi(w, \Upsilon) \geq \alpha\} \tag{12}$$

and

$$\text{CVaR}_\alpha(w) = \frac{1}{1-\alpha} \int_{f(w,r)\leq \text{VaR}_\alpha(w)} f(w, r)\, p(r) dr \tag{13}$$

The portfolio can then be optimized, under the M-CVaR framework, by solving the problem:

$$\underset{w}{\mathrm{Min}}\ \mathrm{CVaR}_{\alpha}(w)$$

$$\text{s.t. } w^T\bar{r} = u \text{ and } \textstyle\sum_{i=1}^{n} w_i = 1 \tag{7}$$

Data

Returns of both private- and public-equity timberland investments from 1987Q4 to 2017Q3 (120 quarters) are analyzed. Private-equity timberland returns are approximated by the NTI, which tracks the gross returns from a large pool of private-equity timberland properties specifically held for investment purposes. As of 2017Q3, the NTI accounts for returns on 457 properties, totaling 14 million acres in size and $25 billion in market value (NCREIF 2017).

Public-equity timberland investment returns (PUBLIC) are proxied by the value-weighted quarterly returns on a dynamic portfolio of publicly traded timber firms in the US that had or have been managing timberlands, a method previously used by Mei and Clutter (2010). Over time, this portfolio has included nine firms, namely Deltic Timber, The Timber Co., IP Timberlands Ltd., Plum Creek, Pope Resources, Potlatch, Rayonier, Weyerhaeuser, and Catchmark. Potlatch, Rayonier, Weyerhaeuser and Catchmark are existing publicly traded timber REITs. Plum Creek was a timber REIT until it merged with Weyerhaeuser in 2016. Deltic Timber and Pope Resources are natural resource companies that focus on the ownership and management of timberland. The Timber Co. and IP Timberlands Ltd. were timberland limited partnerships of Georgia Pacific and International Paper, who sold their timberland holdings to private investors in 2001 and 2006, respectively. As of 2017Q3, PUBLIC consists of value-weighted returns of Potlatch, Rayonier, Weyerhaeuser, Catchmark, Deltic Timber and Pope Resources. Market values of these firms are calculated as the products of average stock prices and total shares outstanding at the end of each quarter. Financial data for these firms are obtained from the Center for Research in Security Prices (CRSP) through WRDS (2018).

In addition to timberland investment returns, another six financial assets' returns are included for the same period. These return data include returns of private- and public-equity real estate, proxied by NCREIF Property Index (NPI) and National Association of Real Estate Investment Trusts (NAREIT) US REITs Index (FTSE 2018), S&P 500 value-weighted returns (SP500), 10-year Treasury bonds yield (LTG) (OECD 2018) and Aaa corporate bonds yield (LTC) (Moody's 2018). Lastly the 1-month Treasury Bills yield (TB) is used for the risk-free rate (WRDS 2018).

Results

Testing autocorrelation and normality of returns

Table 1 shows parameter estimates from the GARCH process which are used to determine effects of serial correlations of asset returns. Here we focus the discussion on timberland assets. Specifically, estimates of φ show that both private- and public-equity timberlands have considerable positive serial correlations. Parameter α shows positive leverage effect of shocks on the conditional variance of both timberland asset classes, while estimates on γ show that the magnitude of a shock's impact is negative on private-equity timberland and positive on public-equity timberland. Estimates on β show that both private- and public-equity timberland assets have high volatility persistence. For all assets, estimates of φ are statistically significant at 1% level, except for SP500 whose φ estimate is significant at 10% level, further supporting the need to look at returns from long-term perspectives. Table 1 also lists the p-value of the multivariate Shapiro-Wilk test, which rejects the null hypothesis of returns' multivariate normal distribution, and thus suggests a violation of a key assumption of the M-V framework.

However, closer examinations on return data lead us to believe that M-V is a more practical framework than M-CVaR. The portfolio risk under the M-CVaR framework is the portfolio CVaR, or the "worst-case losses". In the context of this study, quarterly returns for the long-term bonds and treasury bills show almost no negative returns throughout the sample (Figure 1). This means the "worst-case losses" are still positive gains and indicates that some portfolios will have negative risks. While the scenario of negative risks is theoretically possible, it hardly makes practical sense. Therefore, for the remainder of this study, we will focus on the results from M-V portfolio optimizations.

Single- versus multi-period investment horizons

Recognizing the need to examine returns over different horizons, we compare descriptive statistics of single-period and multi-period returns. We assume an investment horizon of five years (20 quarters) to showcase the characteristics associated with long-term horizons. The five-year horizon falls on the low end of the capital requirement for institutional timberland investors, which is usually 5-15 years (Caulfield and Zinkhan 1998). In addition, due to limited length of available return data, twenty quarters fit the dataset nicely to generate six non-overlapping periods.

Table 2 lists the summary statistics and correlation coefficients for the one-quarter and five-year horizons[9]. Comparing mean returns, arithmetic mean returns are negligibly lower, while scaled geometric mean returns stay unchanged as horizon lengthens. The range of multi-period SD changes is considerably wide. For example, the SD of NAREIT is reduced by 7.25% when the five-year horizon is used, while the volatilities of private real estate and long-term bonds decay more slowly. This is consistent with Equation 5, which can be graphically

[9] For summary statistics of multi-period and infinite-horizon returns in this study, all metrics are scaled quarterly, thus making it comparable to single-period statistics.

illustrated by Figure 2. The SD decays as holding periods lengthen, while the rate of decaying (shown by the slopes of curves) depends on assets' serial correlations. In this case, NAREIT shows near-zero serial correlation, so the rate of its long-term volatility decay is a function of time, i.e., $\frac{\sigma_T}{T} = \frac{\sigma}{\sqrt{T}}$. In contrast, both private real estate and long-term bonds have high serial correlations, so their long-horizon volatilities decay more slowly. Also shown in Table 2, the Sharpe Ratios illustrate the interaction of changing mean returns and SD as the holding periods become longer. The general trend is that the average Sharpe Ratio increases, indicating decreasing volatility as the investment horizon lengthens.

The next comparison is on the correlations among assets. As a crude measure of the asset's diversification potential, an asset's average correlation coefficients with other assets are calculated. The average correlations coefficient of private-equity timberland increases from 0.13 to 0.46, as investment horizons lengthen from one to 20 quarters, indicating reduced diversification abilities. For public-equity timberland investments, the average correlation increases by 0.20 as the horizon increases from one to 20 quarters. The correlation between NTI and PUBLIC in the absolute term increases from negative to positive when multi-period returns are used, suggesting that the substitutability between private and public timberland investments increases.

Infinite-horizon investment

A logical extension of long holding periods is to assume an infinite investment horizon, which represents virtual life spans of most institutional funds (Thaler and Williamson 1994). Average returns, volatilities and correlations are approximated from single-period estimations following Equations 2, 4 and 8, with summary statistics presented in Panel C of Table 2. While this exercise is pushing data to the limits, the results show double-digit SD for private-equity timberland, public-equity timberland and common stocks. This observation is not surprising, as these assets have high single-period SD and autocorrelations. Private-equity real estate, which has relatively lower single-period SD, and public-equity real estate, which has near-zero autocorrelation, both see infinite-horizon SD increase less significantly. With respect to correlations, the average correlation coefficients increase from the single-period horizon case for most asset classes, indicating reduced diversification potential across assets when the investment horizon extends to infinity.

Unconstrained portfolio optimization using single- and multi-period horizons

The next step is to incorporate one-quarter, five-year and infinite-horizon returns, volatilities and correlations into the unconstrained portfolio optimization framework. The efficient frontiers show different portfolio return-and-risk combinations when using different holding periods (Figure 3). With the one-quarter horizon, the quarterly portfolio returns range from 1.57% to 2.74%, while SD's span from 0.04% to 3.67%. When the horizon lengthens to five years, the efficient frontier slightly shifts towards the right, showing less efficient allocations. While the range of returns are unchanged, the SD span now indicates roughly a 1% increase as the holding period lengthens. Furthermore, when infinite-horizon returns are used, the frontier shifts lower, indicating further reduced efficiency across all risk preferences. This is consistent with the change in infinite-horizon SD and correlation patterns.

The allocations to various asset classes change when investment horizons lengthen. Here we divide all efficient portfolios along the frontier to five equal segments by SD's to produce five risk levels, namely low-, low-moderate-, moderate-, moderate-high- and high-risk portfolios. Focusing on allocations to timberland assets only. Table 3 illustrates that, when the one-quarter returns are used, in low-risk portfolios, private-equity timberland is allocated 37%, with public-equity timberland at 2.5%. As the portfolio risk increases, private-equity timberland gradually obtains tractions, while public-equity timberland remains low in allocation. In high-risk portfolios, private-equity timberland is allocated nearly 95%, with public-equity timberland at less than 1%.

Using the five-year horizon, private-equity timberland remains significantly allocated, averaging 33% across all risk levels, while public-equity timberland is excluded in all portfolios. In high-risk portfolios, private-equity timberland is allocated over 51% of capital, probably due to its relatively lower long-term SD's (1.03%) among five high-yielding assets[10].

Unconstrained allocations change drastically when investment horizons extend to infinity. Private-equity timberland receives consistent allocations (23% on average), with more allocations in moderate- and high-risk portfolios. Public-equity timberland is excluded in all portfolios. Private-equity timberland's persistence is somewhat intriguing, because as previous pointed out, assets see increased average infinite-horizon correlations, implying lower diversification potentials. Nevertheless, looking closely to NTI's correlations with other high-yielding assets, we find these correlations either become more negative or remain low when switching from one-quarter to infinite-horizon returns. In addition, private-equity timberland's second highest infinite-horizon Sharpe Ratio (0.17) among high-yielding assets makes it more attractive for moderate- and high-risk portfolios.

Constrained portfolio optimization

Prudent researchers would question the heavy allocations on timberland assets in the unconstrained scenario, because timberland investment usually makes up a small proportion of the overall portfolio (Caulfield 1998; Newell and Eves 2009; Wan et al. 2015). Therefore, based

[10] In all ensuing discussions, high-yielding assets refer to the collection of timberland assets, real estate assets and common stocks, i.e., NTI, PUBLIC, NPI, NAREIT and SP500.

on industry practice, we impose a set of maximum allocation constraints, i.e., 2.5%, 5% and 10%, for both private- and public-equity timberland to make practical assessments of timberland's role in mixed-asset portfolios.

Table 4 examines the roles of timberland assets in mixed-asset portfolios, given the impact of changing timberland constraints across investment-horizons. Private-equity timberland is consistently allocated close to the maximum limits across investment-horizons. Public-equity timberland, however, is only consistently allocated near limits when using single-period returns, and excluded when using long-horizon returns. The constrained optimization results support the previous unconstrained results that private-equity timberland is an ideal portfolio diversifier for both short- and long-term portfolios, while public-equity timberland is only attracting consistent allocations in portfolios with short holding periods.

Robustness checks

Robustness check 1: Different investment horizons

As noted earlier, the five-year horizon is chosen because it reflects long capital commitment in practice for private timberland investors, and it fits the length of available dataset well. This section is designated to examine the effects on performance metrics by including alternative hypothetical investment intervals, namely eight quarters (two years), twelve quarters (three years) and twenty-four quarters (six years)[11].

Panel A of Table 5 illustrates the effects of lengthening investment horizons on average returns and volatilities. The general trend follows the analytical framework which states that arithmetic means approach geometric means when investment horizons lengthen, and SD's

[11] The additional long-term intervals do not reflect private-equity timberland holding periods in practice, but rather an exercise to rigorously examine the changes in mean returns, volatilities and correlations associated with changing horizons. The alternative intervals of two-, three- and six-year are only used in robustness checks.

decay as a function of both autocorrelations and the length of holding periods as previously shown in Figure 2. Moving on to correlation patterns, Panel B of Table 5 lists the average correlation coefficients of each asset with others and shows no consistent trend when the horizon increases from one quarter to infinity. Nevertheless, it confirms that correlation patterns change when investment horizons lengthen, and thus necessitates the use long term measures of returns, volatilities and correlations.

Robustness check 2: Varying allocation constraints

Previous works find that strict applications of portfolio optimizations bear potential shortfalls, such that a slight change in the return-risk relationship of one asset may drastically change the weights of optimal allocations of all assets (e.g., Green and Hollifield 1992). To explore this potential impact and test the robustness of the constrained portfolio analysis, instead of placing timberland-only constraints, we extend allocation limits to all asset classes. Starting from 40% for each asset, we gradually tighten the limit to 20% in 5% increments[12]. Moreover, we also include other hypothetical long-term returns as in the first robustness check, i.e., two-year, three-year and six-year returns. Allocations are again categorized into five risk levels.

Table 6 reports the results of this robustness exercise. First focusing on private-equity timberland, NTI consistently reaches full allocation limits in most high-risk portfolios, regardless of investment horizons used. In the low- and low-moderate risk portfolios, NTI's allocations from long-term optimizations are lower than allocations from the one-quarter optimization. However, the decline is not monotonic as investment horizons lengthen. Nevertheless, this indicates private-equity timberland's reducing diversification benefits to low-risk investors as

[12] Different from the constraints on timberland assets in the previous section, the equal allocation limits in this robustness exercise do not reflect industry practice, but rather attempts to rigorously examine the changes in portfolio compositions in response to changing horizons, varying limits on assets and different risk levels.

holding periods lengthen. Overall, private-equity timberland is a suitable risk diversifier when viewed with all short-term and long-term holding perspectives, albeit it has lower diversification potentials when holding periods lengthen.

Moving on to public-equity timberland, PUBLIC is only allocated in portfolios using one-quarter returns, negligibly allocated using two-year returns, and completely absent using all other horizons. PUBLIC's one-quarter allocation is mostly in moderate-high- and high-risk portfolios, averaging over 21% and 25%. In other risk levels, PUBLIC falls way short of maximum allocation limits. When investment horizons lengthen over two years, public-equity timberland becomes too risky, even when other assets are tightly constrained. Therefore, public-equity timberland is only considered as a suitable candidate in a short-term perceptive for investors comfortable with higher risks.

Robustness check 3: Net-of-fee returns

Institutional private-equity timberland assets are managed by TIMOs, who generate income through a set of management and performance related fees which amount to nearly 1% of total assets under management (Mendell 2011). NCREIF releases a sub-index to measure returns of a portfolio of timber funds and separate accounts (TFSAI). Here we use the net-of-fee returns of TFSAI to substitute gross returns as a proxy of private-equity timberland return in portfolio analysis. Table 7 compares private-equity timberland allocations, between the use of gross return and net return. Private-equity timberland still maintains significant allocations across portfolio risk levels, albeit slightly lower allocations when net returns are used. Hence, using returns both before- and after-fees generates similar portfolio analysis results.

Conclusions

The increasing popularity of timberland assets among institutional investors calls for more scrupulous examinations on the diversification characteristics of these assets. While it has been widely established that timberland investment exhibits high risk-adjusted historical returns and low correlations with other financial assets, it is necessary to recognize and investigate the implications of its long-term nature. Past works using single-period returns often do not address this issue. In our study, we use long horizons to allow data to reveal their long-term behaviors.

Stretching from a one-quarter view, to a five-year holding period, and eventually to an infinite horizon, we examine the three factors of the M-V framework, i.e., return, volatility and correlation. First, when the horizon extends from a quarter to five years, the reductions in volatilities for most assets are sizeable, hence presenting a different view of return-risk characteristics of these assets over long horizons. Besides, the infinite-horizon exercise sheds interesting lights on long-term risks, especially that infinite-horizon volatilities of highly-autocorrelated assets considerably increase.

We also assess the roles of timberland assets in mixed-asset portfolios. Private-equity timberland is more consistently and heavily allocated over public-equity timberland. In a more realistic and constrained framework, both private- and public-equity timberland assets are allocated when using single-period returns. However, the long-horizon optimizations show that, while private-equity timberland is persistent in all portfolios, public-equity timberland is completely excluded. Hence, our results reveal that, private-equity timberland maintains its superior diversification roles with both short- and long-term holding periods, while public-equity timberland becomes too risky for portfolios with long holding periods. Infinite-horizon results suggest that, despite strengthening average correlation, private-equity timberland becomes less correlated with other high-yielding assets, supporting its stable presence in open-end fund portfolios as a risk diversifier.

In this study, we present scenarios where private-equity timberland is allocated considerable capital within mixed-asset portfolios. The analyses are limited to the available data of timberland returns. In addition, due to high transaction costs, the lack of available timberland and long turnover times, the actual allocations to private-equity timberland investment may be significantly lower than the results from *ex post* optimization results. In addition, investors may not purely rely on historical results to make forward-looking investments in practice. Future studies can again employ the family of GARCH models to explore *ex ante* portfolio analysis and incorporate more robust analysis with various bootstrapping models to extend beyond data samples. Nevertheless, this study intends to provide yet another perspective to assess returns and risks when it comes to investing in timberland.

Table 4.1. Parameter estimations from the exponential GARCH (1,1) process and test statistic from the multivariate Shapiro-Wilk normality test.

Asset	φ	α	β	γ
NTI	0.80	0.34	0.95	-0.41
PUBLIC	0.82	0.03	0.81	0.24
NPI	0.82	0.09	0.78	1.22
NAREIT	-0.02	-0.18	0.71	0.35
SP500	0.54	-0.51	0.61	0.25
LTG	0.91	0.26	0.83	-0.47
LTC	0.92	0.06	0.41	0.20
TB	0.95	0.49	0.96	0.96
Shapiro-Wilk	0.00			

Note: LTG stands for long-term government bonds. LTC stands for long-term corporate bonds. TB stands for Treasury Bills. Shapiro-Wilk test statistic is the p-value of multivariate normality test, indicating significant evidence exists to reject the null hypothesis of multivariate normal distribution at 1% level.

Table 4.2. Summary statistics of selected asset classes using holding periods of one-quarter, five-year and infinite horizons.

Panel A: Using One-Quarter Returns

Asset	Arithmetic Mean	Geometric Mean	SD	Sharpe Ratio	Correlation Coefficients	NTI	PUBLIC	NPI	NAREIT	SP500	LTG	LTC	TB
NTI	2.82	2.75	3.83	0.55	NTI	1.00							
PUBLIC	3.07	2.43	11.16	0.21	PUBLIC	-0.10	1.00						
NPI	1.94	1.92	2.20	0.55	NPI	-0.05	0.08	1.00					
NAREIT	2.93	2.48	9.29	0.24	NAREIT	-0.08	0.55	0.16	1.00				
SP500	2.04	1.73	7.76	0.17	SP500	0.02	0.68	0.12	0.59	1.00			
LTG	1.21	1.21	0.51	0.94	LTG	0.40	-0.02	-0.11	-0.01	0.02	1.00		
LTC	1.54	1.54	0.43	1.88	LTC	0.36	-0.05	-0.20	-0.05	-0.04	0.98	1.00	
TB	0.73	0.73	0.60		TB	0.36	-0.03	0.10	-0.04	0.06	0.89	0.85	1.00
					Average Coefficient	0.13	0.16	0.04	0.16	0.21	0.31	0.26	0.31

Panel B: Using Five-Year Returns

Asset	Arithmetic Mean	Geometric Mean	SD	Sharpe Ratio	Correlation Coefficients	NTI	PUBLIC	NPI	NAREIT	SP500	LTG	LTC	TB
NTI	2.76	2.75	1.03	1.97	NTI	1.00							
PUBLIC	2.44	2.43	6.93	0.25	PUBLIC	0.36	1.00						
NPI	1.92	1.92	1.34	0.89	NPI	-0.34	0.26	1.00					
NAREIT	2.50	2.48	2.04	0.87	NAREIT	0.32	0.95	0.52	1.00				
SP500	1.75	1.73	3.05	0.33	SP500	0.41	0.86	0.26	0.87	1.00			
LTG	1.21	1.21	0.39	1.23	LTG	0.87	0.08	-0.33	0.09	0.07	1.00		
LTC	1.54	1.54	0.34	2.38	LTC	0.82	-0.02	-0.37	-0.01	-0.03	0.99	1.00	
TB	0.73	0.73	0.51		TB	0.79	0.04	-0.15	0.11	0.04	0.98	0.98	1.00
					Average Coefficient	0.46	0.36	-0.02	0.41	0.36	0.39	0.34	0.40

Table 4.2. Continued.

Panel C: Using Infinite-Horizon Returns					Correlation Coefficients								
Asset	Arithmetic Mean	Geometric Mean	SD	Sharpe Ratio		NTI	PUBLIC	NPI	NAREIT	SP500	LTG	LTC	TB
NTI	2.75	2.75	11.49	0.18	NTI	1.00							
PUBLIC	2.43	2.43	35.77	0.05	PUBLIC	-0.10	1.00						
NPI	1.92	1.92	6.90	0.17	NPI	-0.05	0.08	1.00					
NAREIT	2.48	2.48	9.13	0.19	NAREIT	-0.14	0.99	0.27	1.00				
SP500	1.73	1.73	14.22	0.07	SP500	0.02	0.78	0.14	0.71	1.00			
LTG	1.21	1.21	2.35	0.21	LTG	0.44	-0.03	-0.12	-0.04	0.03	1.00		
LTC	1.54	1.54	2.10	0.39	LTC	0.41	-0.06	-0.22	-0.13	-0.07	0.99	1.00	
TB	0.73	0.73	3.72		TB	0.46	-0.03	0.12	-0.15	0.10	0.93	0.87	1.00
					Average Coefficient	0.14	0.23	0.04	0.22	0.25	0.32	0.26	0.33

Note: LTG stands for long-term government bonds. LTC stands for long-term corporate bonds. TB stands for Treasury Bills. Mean, and SD are in percentages. Average coefficients are calculated as the average of correlation coefficients of the target assets with other assets, excluding themselves.

Table 4.3. Comparison of average allocations to timberland assets on different risk levels with varying investment horizons under unconstrained optimizations.

	Using One-Quarter Returns			Using Five-Year Returns			Using Infinite-Horizon Returns		
Portfolio Risk Levels	NTI	PUBLIC	Total	NTI	PUBLIC	Total	NTI	PUBLIC	Total
Low	37.37	2.46	39.83	2.61	-	2.61	2.82	-	2.82
Low-Moderate	81.98	4.50	71.39	24.40	-	24.40	14.63	-	14.63
Moderate	89.01	3.50	92.51	43.26	-	43.26	27.04	-	27.04
Moderate-High	91.85	2.18	94.03	48.33	-	48.33	37.74	-	37.74
High	94.69	0.86	95.55	51.14	-	51.14	42.37	-	42.37

Note: All allocations are in percentages. The five portfolio risk levels are obtained by equally dividing the portfolios into five segments, along the efficient frontiers ranked by portfolio SD's.

Table 4.4. Comparison of average allocations to timberland assets with different investment horizons, when timberland assets are constrained.

Maximum Weight to Any Timberland Asset	Using One-Quarter Returns			Using Five-Year Returns			Using Infinite-Horizon Returns		
	NTI	PUBLIC	Total	NTI	PUBLIC	Total	NTI	PUBLIC	Total
2.5%	2.47	2.42	4.89	2.19	-	2.19	2.29	-	2.29
5.0%	4.92	4.66	9.58	4.34	-	4.34	4.48	-	4.48
10.0%	9.80	8.61	18.41	8.52	-	8.52	8.55	-	8.55

Note: All allocations are in percentages. The five portfolio risk levels are obtained by equally dividing the portfolios into five segments, along the efficient frontiers ranked by portfolio SD's.

Table 4.5. Summary statistics for the 1-quarter, 2-, 3-, 5- and 6-year holding periods.

Panel A –Mean and SD

	Arithmetic Means					SD				
Asset	1-Quarter	2-Year	3-Year	5-Year	6-Year	1-Quarter	2-Year	3-Year	5-Year	6-Year
NTI	2.82	2.77	2.77	2.76	2.76	3.83	1.61	1.32	1.03	0.94
PUBLIC	3.07	2.47	2.47	2.44	2.44	11.16	8.92	8.11	6.93	6.49
NPI	1.94	1.93	1.93	1.92	1.92	2.20	1.74	1.58	1.34	1.26
NAREIT	2.93	2.53	2.51	2.5	2.49	9.29	3.24	2.64	2.04	1.87
SP500	2.04	1.76	1.77	1.75	1.75	7.76	4.52	3.83	3.05	2.81
LTG	1.21	1.21	1.21	1.21	1.21	0.51	0.45	0.43	0.39	0.37
LTC	1.54	1.54	1.54	1.54	1.54	0.43	0.39	0.37	0.34	0.32
TB	0.73	0.73	0.73	0.73	0.73	0.60	0.56	0.54	0.51	0.49

Panel B – Average Correlation Coefficients

	NTI	PUBLIC	NPI	NAREIT	SP500	LTG	LTC	TB
1-Quarter	0.13	0.16	0.01	0.16	0.21	0.31	0.26	0.31
2-Year	0.26	0.14	0.04	0.20	0.22	0.31	0.27	0.31
3-Year	0.34	0.18	-0.10	0.12	0.12	0.31	0.29	0.29
5-Year	0.46	0.36	-0.02	0.41	0.36	0.39	0.34	0.40
6-Year	0.21	0.21	-0.15	0.05	0.12	0.31	0.31	0.31

Note: LTG stands for long-term government bonds. LTC stands for long-term corporate bonds. TB stands for Treasury Bills. Mean, and SD are in percentages. Average coefficients are calculated as average of correlation coefficients of the target assets with other assets excluding themselves.

Table 4.6. Changing constrained allocations to timberland assets under different investment horizons and different risk levels, when all assets are constrained.

Using One-Quarter Returns

Maximum Weight to Any Asset	NTI					PUBLIC				
	Low	Low-Moderate	Moderate	Moderate-High	High	Low	Low-Moderate	Moderate	Moderate-High	High
40%	30.93	40.00	40.00	40.00	40.00	4.39	10.38	15.71	21.04	25.19
35%	28.30	35.00	35.00	35.00	35.00	4.33	11.13	15.67	21.00	27.29
30%	25.47	30.00	30.00	30.00	30.00	4.37	11.43	16.63	21.27	28.69
25%	22.19	25.00	25.00	25.00	25.00	4.78	11.61	19.96	25.00	25.00
20%	19.44	20.00	20.00	20.00	20.00	5.27	14.22	20.00	20.00	20.00

Using Two-Year Returns

Maximum Weight to Any Asset	NTI					PUBLIC				
	Low	Low-Moderate	Moderate	Moderate-High	High	Low	Low-Moderate	Moderate	Moderate-High	High
40%	10.65	31.49	40.00	40.00	40.00	0.20	-	-	-	-
35%	11.51	30.22	35.00	35.00	35.00	0.19	-	-	-	-
30%	11.83	29.11	30.00	30.00	30.00	0.20	-	-	-	-
25%	12.73	24.97	25.00	25.00	25.00	0.18	-	-	-	-
20%	15.37	20.00	20.00	20.00	20.00	0.00	-	0.03	1.04	2.51

Using Three-Year Returns

Maximum Weight to Any Asset	NTI					PUBLIC				
	Low	Low-Moderate	Moderate	Moderate-High	High	Low	Low-Moderate	Moderate	Moderate-High	High
40%	6.37	23.75	36.32	39.80	40.00	-	-	-	-	-
35%	6.78	23.56	34.80	35.00	35.00	-	-	-	-	-
30%	7.22	23.94	30.00	30.00	30.00	-	-	-	-	-
25%	7.59	23.65	25.00	25.00	25.00	-	-	-	-	-
20%	10.56	20.00	20.00	20.00	20.00	-	-	-	-	-

Table 4.6. Continued.

Maximum Weight to Any Asset	NTI					PUBLIC				
Using Five-Year Returns										
	Low	Low-Moderate	Moderate	Moderate-High	High	Low	Low-Moderate	Moderate	Moderate-High	High
40%	6.83	25.03	37.77	40.00	40.00	-	-	-	-	-
35%	7.29	25.55	34.02	35.00	35.00	-	-	-	-	-
30%	7.75	25.37	30.00	30.00	30.00	-	-	-	-	-
25%	8.36	22.20	25.00	25.00	25.00	-	-	-	-	-
20%	11.55	19.93	20.00	20.00	20.00	-	-	-	-	-
Using Six-Year Returns										
	Low	Low-Moderate	Moderate	Moderate-High	High	Low	Low-Moderate	Moderate	Moderate-High	High
40%	19.40	38.05	40.00	40.00	40.00	-	-	-	-	-
35%	18.49	33.77	35.00	35.00	35.00	-	-	-	-	-
30%	17.35	29.56	30.00	30.00	30.00	-	-	-	-	-
25%	15.82	25.00	25.00	25.00	25.00	-	-	-	-	-
20%	15.65	20.00	20.00	20.00	20.00	-	-	-	-	-
Using Infinite-Horizon Returns										
	Low	Low-Moderate	Moderate	Moderate-High	High	Low	Low-Moderate	Moderate	Moderate-High	High
40%	4.48	17.52	27.04	37.82	40.00	-	-	-	-	-
35%	5.47	18.53	27.01	34.76	35.00	-	-	-	-	-
30%	6.44	19.40	26.75	30.00	30.00	-	-	-	-	-
25%	7.72	20.29	25.00	25.00	25.00	-	-	-	-	-
20%	10.44	19.99	20.00	20.00	20.00	-	-	-	-	-

Note: Allocation constraints indicate the maximum weights that can be assigned to any one asset class. Starting from 40% allowed to each asset, the constraints tightens to 20% in five increments, such that the maximum allocation allowed to each asset declines by 5% each time. All allocations and averages are in percentages.

Table 4.7. Comparison of allocations to private-equity timberland using gross and net returns.

Using One-Quarter Returns

Maximum Weight to Any Asset	NTI Low	NTI Low-Moderate	NTI Moderate	NTI Moderate-High	NTI High	TFSAI Low	TFSAI Low-Moderate	TFSAI Moderate	TFSAI Moderate-High	TFSAI High
40%	30.93	40.00	40.00	40.00	40.00	30.12	40.00	40.00	40.00	40.00
35%	28.30	35.00	35.00	35.00	35.00	27.83	35.00	35.00	35.00	35.00
30%	25.47	30.00	30.00	30.00	30.00	25.41	30.00	30.00	30.00	30.00
25%	22.19	25.00	25.00	25.00	25.00	22.31	25.00	25.00	25.00	25.00
20%	19.44	20.00	20.00	20.00	20.00	19.52	20.00	20.00	20.00	20.00
Average	25.26	30.00	30.00	30.00	30.00	25.04	30.00	30.00	30.00	30.00

Using Two-Year Returns

Maximum Weight to Any Asset	NTI Low	NTI Low-Moderate	NTI Moderate	NTI Moderate-High	NTI High	TFSAI Low	TFSAI Low-Moderate	TFSAI Moderate	TFSAI Moderate-High	TFSAI High
40%	10.65	31.49	40.00	40.00	40.00	9.79	27.23	39.84	40.00	40.00
35%	11.51	30.22	35.00	35.00	35.00	10.72	27.42	35.00	35.00	35.00
30%	11.83	29.11	30.00	30.00	30.00	11.30	27.82	30.00	30.00	30.00
25%	12.73	24.97	25.00	25.00	25.00	12.60	24.91	25.00	25.00	25.00
20%	15.37	20.00	20.00	20.00	20.00	15.78	20.00	20.00	20.00	20.00
Average	12.42	27.16	30.00	30.00	30.00	12.04	25.47	29.97	30.00	30.00

Using Three-Year Returns

Maximum Weight to Any Asset	NTI Low	NTI Low-Moderate	NTI Moderate	NTI Moderate-High	NTI High	TFSAI Low	TFSAI Low-Moderate	TFSAI Moderate	TFSAI Moderate-High	TFSAI High
40%	6.37	23.75	36.32	39.80	40.00	3.69	15.86	28.79	31.50	33.57
35%	6.78	23.56	34.80	35.00	35.00	3.70	16.65	29.08	32.59	33.85
30%	7.22	23.94	30.00	30.00	30.00	4.26	18.33	27.43	30.00	30.00
25%	7.59	23.65	25.00	25.00	25.00	5.32	21.01	25.00	25.00	25.00
20%	10.56	20.00	20.00	20.00	20.00	8.80	20.00	20.00	20.00	20.00
Average	7.70	22.98	29.22	29.96	30.00	5.15	18.37	26.06	27.82	28.48

Table 4.7. Continued.

Maximum Weight to Any Asset	Using Five-Year Returns: NTI Low	NTI Low-Moderate	NTI Moderate	NTI Moderate-High	NTI High	TFSAI Low	TFSAI Low-Moderate	TFSAI Moderate	TFSAI Moderate-High	TFSAI High
40%	6.83	25.03	37.77	40.00	40.00	3.11	19.69	27.08	37.51	40.00
35%	7.29	25.55	34.02	35.00	35.00	4.19	20.93	25.69	33.93	35.00
30%	7.75	25.37	30.00	30.00	30.00	5.68	19.80	26.03	29.76	30.00
25%	8.36	22.20	25.00	25.00	25.00	6.06	18.32	25.00	25.00	25.00
20%	11.55	19.93	20.00	20.00	20.00	10.44	19.28	20.00	20.00	20.00
Average	8.36	23.62	29.36	30.00	30.00	5.90	19.61	24.76	29.24	30.00

Maximum Weight to Any Asset	Using Six-Year Returns: NTI Low	NTI Low-Moderate	NTI Moderate	NTI Moderate-High	NTI High	TFSAI Low	TFSAI Low-Moderate	TFSAI Moderate	TFSAI Moderate-High	TFSAI High
40%	19.40	38.05	40.00	40.00	40.00	16.74	36.13	40.00	40.00	40.00
35%	18.49	33.77	35.00	35.00	35.00	16.60	32.06	35.00	35.00	35.00
30%	17.35	29.56	30.00	30.00	30.00	15.70	28.93	30.00	30.00	30.00
25%	15.82	25.00	25.00	25.00	25.00	14.44	25.00	25.00	25.00	25.00
20%	15.65	20.00	20.00	20.00	20.00	15.30	20.00	20.00	20.00	20.00
Average	17.34	29.28	30.00	30.00	30.00	15.76	28.42	30.00	30.00	30.00

Maximum Weight to Any Asset	Using Infinite-Horizon Returns: NTI Low	NTI Low-Moderate	NTI Moderate	NTI Moderate-High	NTI High	TFSAI Low	TFSAI Low-Moderate	TFSAI Moderate	TFSAI Moderate-High	TFSAI High
40%	4.48	17.52	27.04	37.82	40.00	5.23	17.01	23.61	39.07	37.64
35%	5.47	18.53	27.01	34.76	35.00	6.07	18.23	23.85	35.00	34.87
30%	6.44	19.40	26.75	30.00	30.00	7.31	19.14	24.26	30.00	30.00
25%	7.72	20.29	25.00	25.00	25.00	8.96	20.08	25.00	25.00	25.00
20%	10.44	19.99	20.00	20.00	20.00	12.03	20.00	20.00	20.00	20.00
Average	7.78	19.14	25.16	29.52	30.00	7.92	18.89	23.34	28.27	28.29

Table 4.7. Continued.

Note: The purpose of this comparison is to show decreasing allocations to private-equity timberland, switching from gross return (NTI) to net return (TFSAI). Allocation constraints indicate the maximum weights that can be assigned to any one asset class. Starting from 40% allowed to each asset, the constraints tightens to 20% in five increments, such that the maximum allocation allowed to each asset declines by 5% each time. All allocations and averages are in percentages.

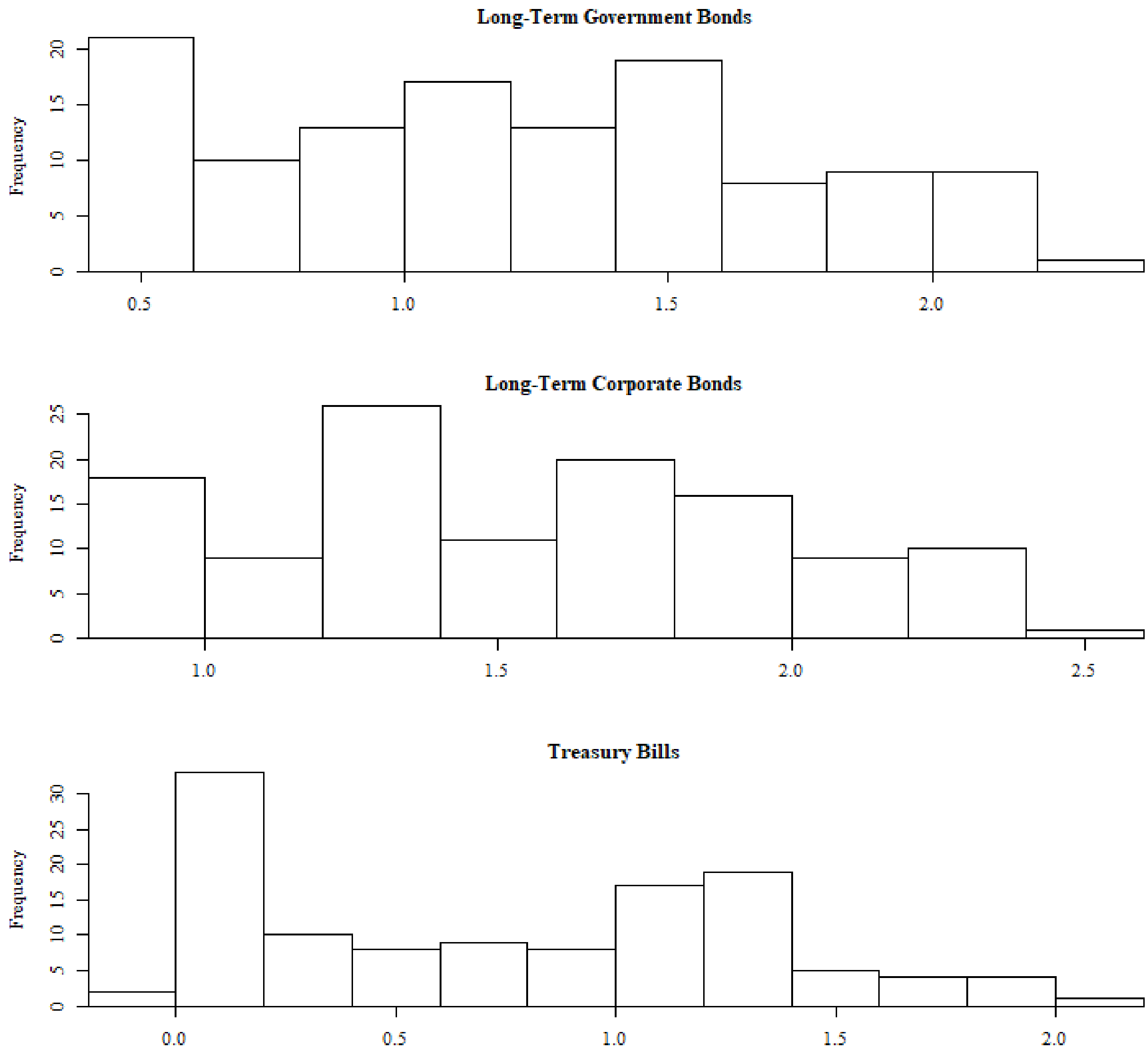

Figure 4.1. Histograms of selected asset return distributions
Note: The histograms show that returns of two long-term bonds and treasury bills are almost exclusively positive, meaning no negative losses even in the worst case for these assets, resulting in potential “negative risks” for a mixed-asset portfolio built under the M-CVaR framework.

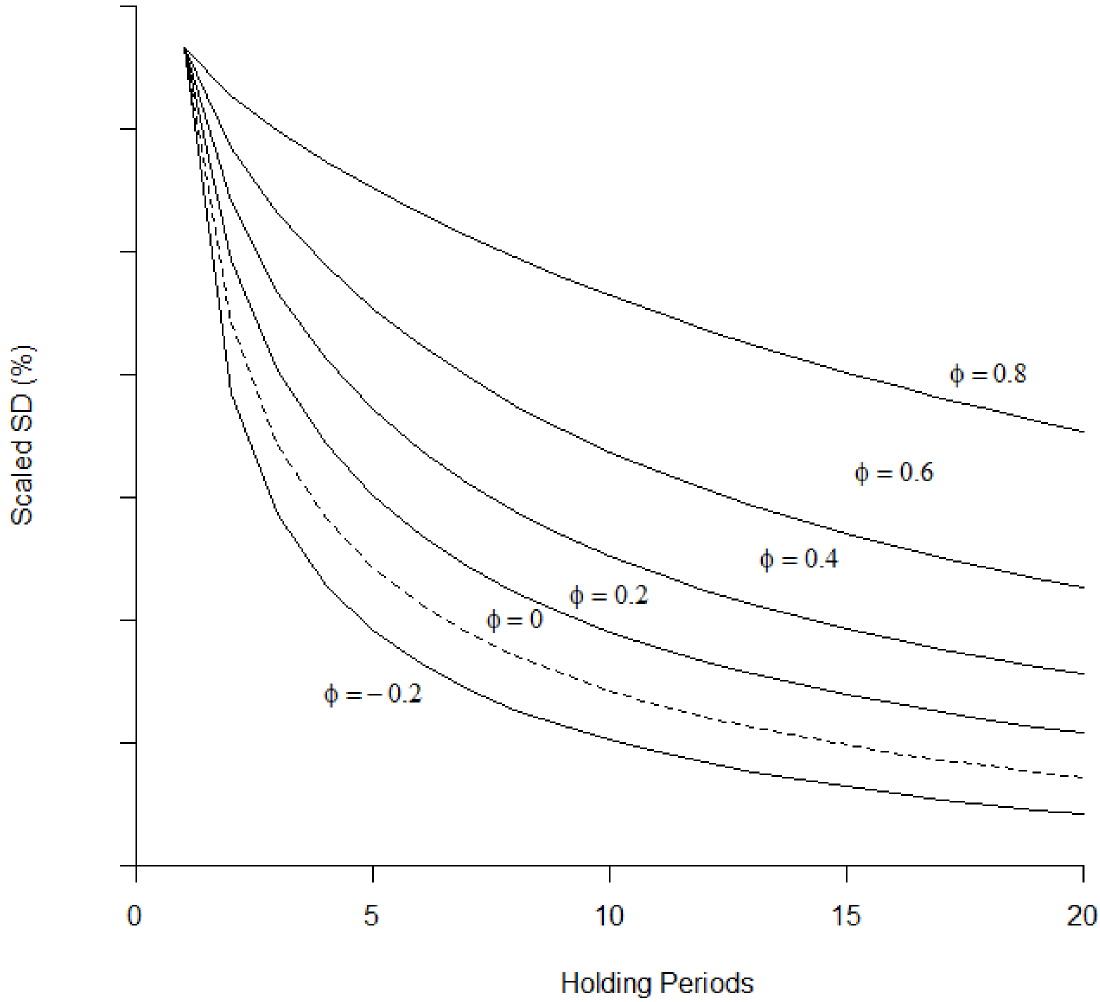

Figure 4.2. Generic illustration of (scaled) long-term SD decay.
Note: The dotted line shows the SD decay of an asset with i.i.d. returns (i.e., ϕ=0). Lines above and below the dotted line aim to illustrate that higher serial correlation slows down decay process, and negative serial correlation accelerates decaying. Long-term SD is quarterly scaled to be comparable with single-period SD.

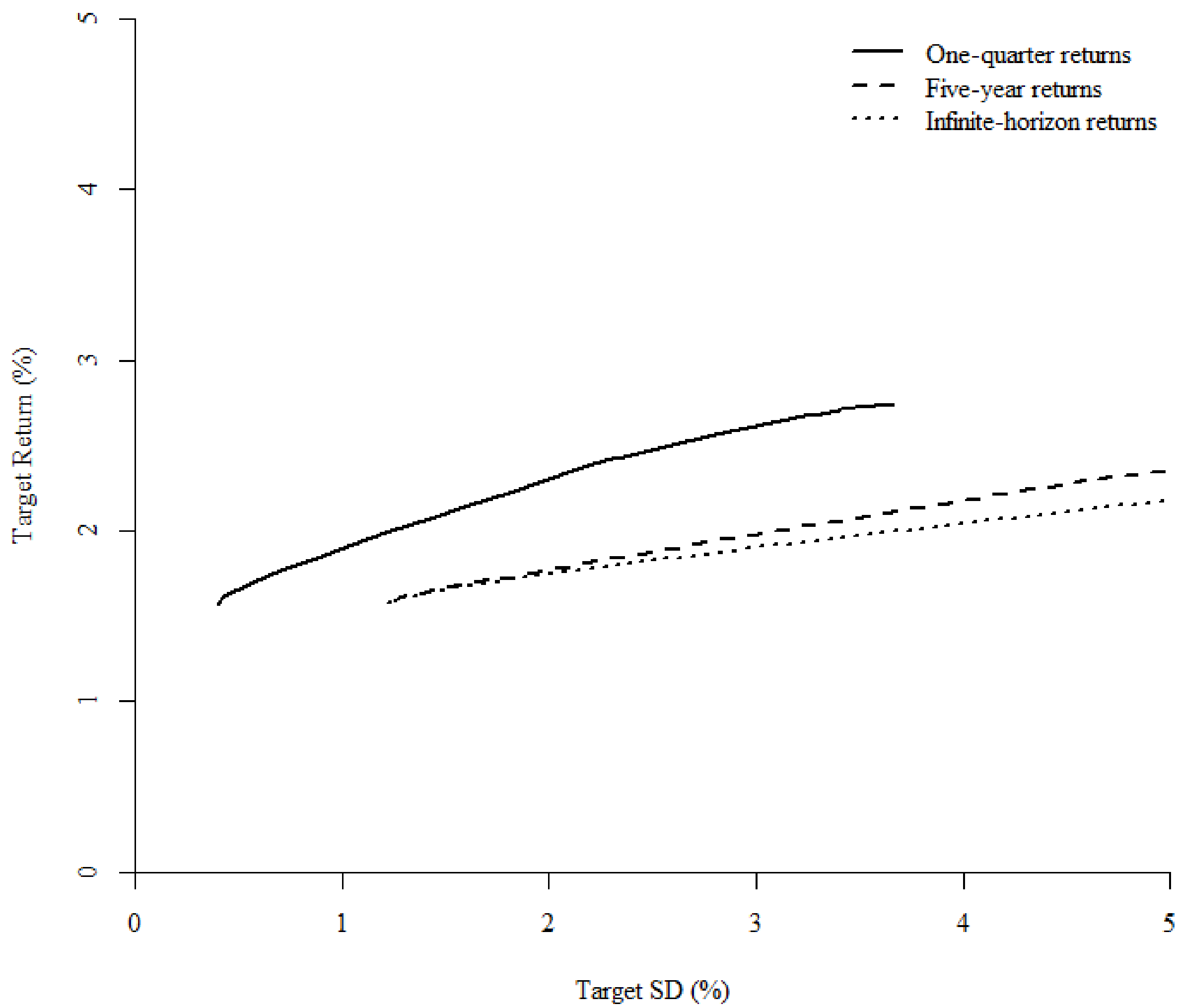

Figure 4.3. Comparisons of efficient frontiers of mixed-asset portfolio with one-quarter, five-year and infinite-horizon returns

CHAPTER 5

DISCUSSIONS AND CONCLUSIONS

Three issues related to the economic impacts, returns and risks of timberland investments are examined: (1) the risks and returns of optimal natural resource portfolios comprised of US timberland and farmland assets; (2) the impacts of forest-related CEs on surrounding property values; (3) the roles of private- and public-equity timberland investments in mixed-asset portfolios.

Chapter 2 examines the risks and returns of optimal portfolios of US timberland and farmland. Using pine product prices in 22 US southern timber regions, synthetic timberland return series provide possibilities for portfolio optimization at finer geographical levels and another alternative timberland return proxy. Results show that M-CVaR is a more efficient framework for portfolio optimizations. US$2 billion and US$10 billion hypothetical portfolios are constructed with allocation constraints. The optimal portfolios show that as investment sizes increase, natural resource assets become more constrained and thus have reduced diversification potentials, with increasing portfolio risk and lower portfolio return. The larger and more constrained portfolio also bears the greater risk over the long term, shown by VaR and CVaR simulations.

Overall, this study provides another perspective to assess risks and returns of natural resource investments using portfolio analysis. Potential future studies can be oriented towards finding the appropriate allocation constraints to improve the quality of portfolio analysis. In addition, to rigorously examine risks in timberland and farmland assets, other measures of risks can be explored and compared with SD and CVaR.

Chapter 3 takes an in-depth look at the impacts of CEs on the values of properties surrounding CE-encumbered forests and open spaces in Metro Atlanta. The results from the hedonic pricing model regression show that CE's impacts on land values are comprehensive and diminishing with distance. The total number of CEs in the vicinity of properties positively enhances land values. In addition, vacant land parcels see increased values after CEs are established in their neighborhoods. Furthermore, estimation results on physical characteristics of properties reflect the challenges faced by conservation activities. High development pressure is shown by positive estimates on commercial and industrial land type variables. Increasing values consequently makes it more expensive to purchase and conserve forests for timber production, natural recreation and wildlife protection. Inflating property valuations also negatively affect owner's ability to pay property taxes on forests.

While this study illustrates the economic benefits of CEs on surrounding vacant land parcels, the quality of results can be improved by collecting more repeat sales information on the same properties to better assess heterogeneity at the property level. Furthermore, the scope of future studies can be zoomed in to examine CE's impacts at smaller geographic scales to arrive at more precise conclusions regarding the relationship between CE and local taxation. In addition, it would be interesting to examine appraisal values' trends before and after CEs' establishments, to rigorously investigate the fairness of appraisal-based CE valuation process.

In Chapter 4, the role of timberland assets is examined within a mixed-asset portfolio, from both single-period and long-horizon perspectives. The study also compares the roles of private-equity and public-equity timberland assets to address the common misnomer that TIMO-management timberlands and REITs have similar diversification potentials.

Exponential GARCH process results show that both timberland assets are positively serially correlated, and therefore, their performance can be misrepresented using only single-period return and volatility. Comparisons of portfolio analysis results using 1-quarter, 5-year and infinite-horizon returns show that both timberland assets are private-equity timberland investment dominates mixed-asset portfolios, and are popular among high-risk portfolios. On the other hand, public-equity timberland is only present when single-period returns are used. Constrained portfolio optimizations support these results. When constrained by maximum weight limits, both private- and public-equity timberland assets are allocated to their limits in short-term portfolios, while long-term portfolios only invest in private-equity timberland assets.

Chapter 4 provides another look on the role of timberland assets in mixed-asset portfolios, by accounting for the serial correlations of asset returns. The results suggest timberland's varying diversification potential as investment horizons lengthen. This is particularly applicable for private-equity timberland, since most such investments require lengthy capital commitment, which suggests long holding periods. Nevertheless, the comparison of allocations to NTI and PUBLIC shows the superior diversification benefits of private-equity timberland over long holding periods. Future studies can use various bootstrapping methods to expand the long-term analysis beyond the available data sample. In addition, the use of GARCH models can improve the analysis to provide important evidence for *ex ante* portfolio allocations.

REFERENCES

Anderson, K., and D. Weinhold 2008. Valuing Future Development Rights: The Costs of Conservation Easements. Ecological Economics 68, 437-446.

Arnott, R. D. 2005. What Cost Noise? Financial Analysts Journal 61:2, 10-14.

Bacmann, J., and G. Gawron 2004. Fat Tail Risk in Portfolios of Hedge Funds and Traditional Investments. Paper presented at the EFMA 2004 Meeting.

BEA 2017. Gross Domestic Product by Metropolitan Area, 2016. Bureau of Economic Analysis, U.S. Department of Commerce: Washington, DC.

Beal-Hodges, M. 2012. Conservation Land Acquisition Lists and Nearby Property Values: Evidence from the Florida Forever Programme. Studies in Agricultural Economics 114:1, 16-23.

Brigham, E. F. 1965. The Determinants of Residential Land Values. Land Economics 41:4, 325-334.

Byrne, P., and S. Lee 2003. An Exploration of the Relationship between Size, Diversification and Risk in Uk Real Estate Portfolios: 1989-1999. Journal of Property Research 20:2, 191-206.

Campbell Global 2017. Timber Primer: Timberland Asset Class Overview. Campbell Global, LLC: Portland, OR.

Cascio, A. J., and M. L. Clutter 2008. Risk and Required Return Assessments of Equity Timberland Investments in the United States. Forest Products Journal 58:10, 61-70.

Caulfield, J. P. 1994. Assessing Timberland Investment Performance. Real Estate Review 24, 76-81.

Caulfield, J. P. 1998. Timberland in Institutional Portfolios and the Question of Persistence. Forest Products Journal 48:4, 23-28.

Caulfield, J. P., and D. H. Newman 1999. Dealing with Timberland Investment Risk: Theory Versus Practice for Institutional Owners. Journal of Forest Economics 5:2, 253-268.

Caulfield, J. P., and F. C. Zinkhan 1998. Timberland Allocation in Institutional Portfolios: Short- and Long-Term Persistence. Paper presented at the Southern Forest Economics Workshop 1998.

Chamblee, J. F., P. F. Colwell, C. A. Dehring, and C. A. Depken 2011. The Effect of Conservation Activity on Surrounding Land Prices. Land Economics 87:3, 453-472.

Chang, K. 2016. 2015 National Land Trust Census Report: Our Common Ground and Collective Impact. Land Trust Alliance: Washington DC.

Chow, V., and C. W. Lai 2015. Conditional Sharpe Ratios. Finance Research Letters 12, 117-133.

Colwell, P. F., and H. J. Munneke 1997. The Structure of Urban Land Prices. Journal of Urban Economics 41:3, 321-336.

Coyle, D. R., K. D. Klepzig, F. H. Koch, L. A. Morris, J. T. Nowak, S. W. Oak, W. J. Otrosina, W. D. Smith, and K. J. K. Gandhi 2015. Review: A Review of Southern Pine Decline in North America. Forest Ecology and Management 349, 134-148.

Dahl, C. 2013. The Rise of Farmland as an Institutional Asset Class. Hancock Agricultural Investment Group: Boston, MA.

Ebers, A., and D. Newman 2014. Economics of Conservation Easements. S Kant and J Alavalapati, editors. Handbook of Forest Resource Economics, Earthscan: Oxford UK.

Farmer, J. R., V. Meretsky, D. Knapp, C. Chancellor, and B. C. Fischer 2015. Why Agree to a Conservation Easement? Understanding the Decision of Conservation Easement Granting. Landscape and Urban Planning 138, 11-19.

Fava, K. L. 2013. Conservation Easement: Tax Donation Update. Journal of Accountancy 215:5, 56-61.

Fisher, J. D., D. M. Geltner, and R. B. Webb 1994. Value Indices of Commercial Real Estate: A Comparison of Index Construction Methods. Journal of Real Estate Finance & Economics 9:2, 137-164.

Fisher, T. M. 2015. The Productivity Problem: An Analysis of Conservation Easement Taxation Issues Following South Dakota's Implementation of a Productivity-Based Land Valuation System. South Dakota Law Review 2, 353.

FTSE 2018. Ftse Nareit U.S. Real Estate Index Series. National Association of Real Estate Investment Trusts: Washington D.C.

Geoghegan, J. 2002. The Value of Open Spaces in Residential Land Use. Land Use Policy 19:1, 91-98.

Geoghegan, J., L. Lynch, and S. Bucholtz 2003. Capitalization of Open Spaces into Housing Values and the Residential Property Tax Revenue Impacts of Agricultural Easement Programs. Agricultural and Resource Economics Review 32:1, 33-45.

GFA 2017. Impact of the Forestry Community. 2017 Georgia Forestry Association.

GFC 2011. Georgia Forest Facts. Georgia Forestry Commission.

Gillam, C. 2014. Institutional Investors Grow Influence on U.S. Farmland - Report. Thomson Reuters.

Green, R. C., and B. Hollifield 1992. When Will Mean-Variance Efficient Portfolios Be Well Diversified? The Journal of Finance 47:5, 1785-1809.

Gustanski, J. A., and J. B. Wright 2011. Exploring Net Benefit Maximization: Conservation Easements and the Public-Private Interface. Law and Contemporary Problems 74:4, 109-143.

Hafer, J. 2017. Deep Roots. Georgia Trend: Atlanta, GA.

Hennings, E., B. J. Sherrick, and P. J. Barry 2015. Portfolio Diversification Using Farmland Investments. Paper presented at the American Agricultural Economics Association Annual Meeting.

Industry Intelligence 2017. Industry Intelligence Report. Industry Intelligence Inc.: Los Angeles, CA.

Jefferies, H. M. 2016. The Economic Impact of Privately-Owned Forests in the United States. Forest2Market, Inc.: Charlotte, NC.

King, J. R., and C. M. Anderson 2004. Marginal Property Tax Effects of Conservation Easements: A Vermont Case Study. American Journal of Agricultural Economics 86:4, 919-932.

Koeninger, J., and HighQuest Partners 2017. History of Institutional Farmland Investment. Boston, MA.

La, L., and B. Mei 2015. Portfolio Diversification through Timber Real Estate Investment Trusts: A Cointegration Analysis. Forest Policy and Economics 50, 269-274.

Lins, D. A., B. J. Sherrick, and A. Venigalla 1992. Institutional Portfolios: Diversification through Farmland Investment. Real Estate Economics 20:4, 549-571.

Magnan, N., A. F. Seidl, and J. B. Loomis 2012. Is Resident Valuation of Ranch Open Space Robust in a Growing Rural Community? Evidence from the Rocky Mountains. Society & Natural Resources 25:9, 852-867.

Manfredo, M. R., and R. M. Leuthold 1999. Value-at-Risk Analysis: A Review and the Potential for Agricultural Applications. Review of Agricultural Economics 21:1, 99-112.

Markowitz, H. 1952. Portfolio Selection. the Journal of Finance 7:1, 77-91.

Martinez-Oviedo, R., and F. Medda 2017. Assessing the Effects of Adding Timberland and Farmland into Resource-Based Sovereign Wealth Fund Portfolios. Journal of Economics and Business 91, 24-40.

Mei, B. 2015a. Illiquidity and Risk of Commercial Timberland Assets in the United States. Journal of Forest Economics 21, 67-78.

Mei, B. 2015b. A Pure-Play Timberland Return Index Based on Securitized Timber Firms. Journal of Real Estate Portfolio Management 21:1, 61.

Mei, B. 2016. Transaction-Based Timberland Investment Returns. Land Economics 92:1, 187-201.

Mei, B. 2017. Investment Returns of Us Commercial Timberland: Insights into Index Construction Methods and Results. Canadian Journal of Forest Research 47:2, 226-233.

Mei, B., and M. L. Clutter 2010. Evaluating the Financial Performance of Timberland Investments in the United States. Forest Science 56:5, 421-428.

Mendell, B. C. 2011. How Do Timberland Investment Managers (Timos) Make Money? Forisk Blog.

Mendell, B. C., N. Mishra, and T. Sydor 2008. Investor Responses to Timberlands Structured as Real Estate Investment Trusts. 106:5, 277-280.

Messmore, T. 1995. Variance Drain. Journal of Portfolio Management 21:4, 104-110.

Miles, P. D. 2017. Forest Inventory Evalidator Web-Application Version 1.6.0.03. USDA Forest Service Northern Research Station: St. Paul, MN.

Mills, W. L. J., and W. L. Hoover 1982. Investment in Forest Land: Aspects of Risk and Diversification. Land Economics 58:1, 33-51.

Mittal, J. 2014. Value Capitalization Effect of Protected Properties : A Comparison of Conservation Easement with Mixed-Bag Open Spaces. The Journal of Sustainable Real Estate 6:1, 23-46.

Moody's 2018. Moody's Seasoned Aaa Corporate Bond Yield [Aaa]. Federal Reserve Bank of St. Louis: St. Louis, MO.

NASS 2017. Land Values 2017 Summary. National Agricultural Statistics Service, USDA: Washington, D.C.

NCED 2015. National Conservation Easement Database.

NCREIF 2017. Data, Index and Products Guide National Council of Real Estate Investment Fiduciaries: Chicago, IL.

Newell, G., and C. Eves 2007. The Role of U.S. Farmland in Real Estate Portfolios. Journal of Real Estate Portfolio Management 13:4, 317-327.

Newell, G., and C. Eves 2009. The Role of U.S. Timberland in Real Estate Portfolios. Journal of Real Estate Portfolio Management 15:1, 95-106.

OECD 2018. Long-Term Government Bond Yields: 10-Year: Main (Including Benchmark) for the United States [Irltlt01usm156n]. Federal Reserve Bank of St. Louis: St. Louis, MO.

Oswalt, S. N., and W. B. Smith 2014. Timber Land and Other Forest. U.S. Department of Agriculture Forest Service: Washington, DC.

Pagliari, J. L. 2017. Another Take on Real Estate's Role in Mixed-Asset Portfolio Allocations. Real Estate Economics 45:1, 75-132.

Petrasek, S., M. E. Aronow, B. Keefer, and C. L. Washburn 2011. Statistical Distributions of Timberland Returns. Hancock Timber Resource Group: Boston, MA.

Petrasek, S., M. E. Aronow, B. Keefer, and C. L. Washburn 2012. Timberland Portfolio Allocation and the Mean-Conditional Value at Risk. Hancock Timber Resource Group: Boston, MA.

Retkwa, R. 2014. Agriculture Investors Develop a Taste for Permanent Crops. Institutional Investor.

Richardson, J. J., and A. C. Bernard 2011. Zoning for Conservation Easements. Law and Contemporary Problems 75:4, 83-108.

Rockafellar, R. T., and S. Uryasev 2000. Optimization of Conditional Value-at-Risk. The Journal of Risk 2:3, 21-41.

Rubinstein, M. 2002. Markowitz's "Portfolio Selection": A Fifty-Year Retrospective. the Journal of Finance 57:3, 1041-1045.

Sander, H. A., and S. Polasky 2009. The Value of Views and Open Space: Estimates from a Hedonic Pricing Model for Ramsey County, Minnesota, USA. Land Use Policy 26:3, 837-845.

Scholtens, B., and L. Spierdijk 2010. Does Money Grow on Trees? The Diversification Properties of Us Timberland Investments. Land Economics 86:3, 514-529.

Sharpe, W. F. 1994. The Sharpe Ratio. Journal of Portfolio Management 21:1, 49-58.

Sheikh, A. Z., and H. Qiao 2009. Non-Normality of Market Returns: A Framework for Asset Allocation Decision Making. Journal of Alternative Investments 12:3, 8-35.

Smith, W. B., P. D. Miles, C. H. Perry, and S. A. Pugh 2009. Forest Resources of the United States: A Technical Document Supporting the Forest Service 2010 Rpa Assessment. US For. Serv.: Washington, DC.

Stockford, D. C. 1990. Property Tax Assessment of Conservation Easements. Boston College Environmental Affairs Law Review 17:4, 829-861.

Sun, C. 2013. On the Market Risk of Securitized Timberlands. Journal of Forest Economics 19, 110-127.

Sun, C., and D. Zhang 2001. Assessing the Financial Performance of Forestry-Related Investment Vehicles: Capital Asset Pricing Model Vs. Arbitrage Pricing Theory. American Journal of Agricultural Economics 83:3, 617-628.

Tesini, D. 2009. Working Forest Conservation Easements. The Urban Lawyer 2, 359.

Thaler, R. H., and J. P. Williamson 1994. College and University Endowment Funds: Why Not 100% Equities? Journal of Portfolio Management 21:1, 27.

Thomson, T. A. 1997. Long-Term Portfolio Returns from Timber and Financial Assets. Journal of Real Estate Portfolio Management 3:1, 57-73.

TMS 2017. Timbermart-South Region Map. TimberMart-South: Athens, GA.

USFS 2015. Forest Legacy Program. 2016.

USFS 2017. Open Space Conservation.

Waggle, D., and D. T. Johnson 2009. An Analysis of the Impact of Timberland, Farmland and Commercial Real Estate in the Asset Allocation Decisions of Institutional Investors. Review Of Financial Economics 18:2, 90-96.

Wan, Y., M. L. Clutter, B. Mei, and J. P. Siry 2015. Assessing the Role of U.S. Timberland Assets in a Mixed Portfolio under the Mean-Conditional Value at Risk Framework. Forest Policy & Economics 50, 118-126.

Wan, Y., B. Mei, M. L. Clutter, and J. P. Siry 2013. Assessing the Inflation Hedging Ability of Timberland Assets in the United States. Forest Science 59:1, 93-104.

Washburn, C. L., and C. S. Binkley 1993. Do Forest Assets Hedge Inflation? Land Economics 3, 215-224.

Washburn, C. L., C. S. Binkley, and C. F. Raper 1996. Institutional Ownership of Us Timberland: History, Rationale, and Implications for Forest Management. Journal of Forestry 94:9, 21-28.

WRDS 2018. Center for Research in Security Prices Files on Stocks, Indexes and Treasury. Wharton Research Data Services: wrds.wharton.upenn.edu.

Xiong, X., and T. Idzorek 2010. Mean-Variance Versus Mean-Conditional Value-at-Risk Optimization: The Impact of Incorporating Fat Tails and Skewness into the Asset Allocation Decision. Ibbotson Associates: Chicago, IL.

Yao, W., and B. Mei 2015. Assessing Forestry-Related Assets with the Intertemporal Capital Asset Pricing Model. Forest Policy and Economics 50, 192-199.

Yao, W., B. Mei, and M. Clutter 2014. Pricing Timberland Assets in the United States by the Arbitrage Pricing Theory. Forest Science 60:5, 943-952.

Zhang, D., R. V. Nagubadi, and B. J. Butler 2012. Institutional Timberland Ownership in the Us South: Magnitude, Location, Dynamics, and Management. Journal of Forestry 110:7, 355-361.

Zygmunt, R., and M. Gluszak 2015. Forest Proximity Impact on Undeveloped Land Values: A Spatial Hedonic Study. Forest Policy and Economics 50, 82-89.