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Accounting for the Upper Limit in Returns to Conservation Investments in Risk Diversification Strategies

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Applications for risk diversification strategies in addressing conservation problems commonly ignore upper limits in returns, which may not reflect the fact that these economic returns are often beyond the scope of what conservation assets can produce given constraints on species, sites, or activities. This research identifies the consequences of failing to account for upper limits on returns from conservation in a modern portfolio theory (MPT) framework. We find that the amount of risk reduction conservation organizations can achieve with the same level of compromise in the expected return on investment is higher when returns are constrained.

Key words: biodiversity, climate and market uncertainty, conservation assets, constrained returns, modern portfolio theory

Introduction

Given the persistent uncertainty related to their effectiveness, the design and planning of conservation investments based purely on historical data may yield misleading results (Cho et al., 2018; Newbold, 2018; Snäll et al., 2021). Modern portfolio theory (MPT), a quantified version of the adage "Do not put all your eggs in one basket," was developed by Markowitz (1952) and published in the financial literature; this theory has been applied in recent years to help diversify risk in conservation investments (Shipway, 2009). This tool accounts for heterogeneities in climate and market uncertainty to minimize risk associated with investment portfolios that focus on conservation-related assets such as species, sites, and activities (Ando and Mallory, 2012; Eaton et al., 2019).

Despite the merits of MPT, applications to conservation investment have not accounted for upper limits in returns that arise from physical limitations. In a species conservation context, return on conservation investment is clearly bounded by the total amount of species habitat available (e.g., the forested area that can be protected for a given site). A conservation organization will also face an

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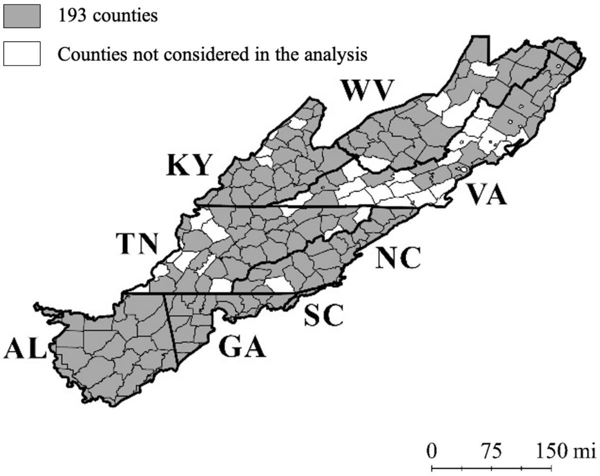

Figure 1. Map of Counties Used for Naïve and Constrained Modern Portfolio Therapy (MPT)

Notes: 53 counties are not considered for analysis since they are consolidated city-counties or counties with negative relative opportunity costs that do not face urban development concerns.

upper limit in return to conservation if individual values for species conservation do not scale with the number of species protected. For example, surrogate bidding in nonmarket valuation studies may indicate that the willingness to pay to protect 100 animals is no different than the willingness to pay to protect 1,000 animals (Kahneman and Knetsch, 1992). Economic returns generated from ignoring such upper limits do not reflect what the conservation assets can actually produce given constraints on species, sites, or activities and can lead conservation organizations to inefficiently focus investment toward certain high-return assets. In other words, conservation organizations may not be able to "put all their eggs in one basket" if the basket is not large enough to hold every egg.

This limitation of MPT comes from its original application to financial investments, where the asset market is perfectly competitive and no single investor is capable of influencing the returns of an asset and thus does not face an upper limit constraint. Early applications of MPT to conservation problems did not consider potential constraints to each asset, and most subsequent studies continue to overlook this issue (e.g., Figge, 2004; Ando and Mallory, 2012). None of the 26 species-habitat MPT case studies summarized by Ando et al. (2018) considered an upper limit constraint in returns.

A limited number of recent studies have sought to improve conservation-related MPT applications by indirectly limiting returns due to physical constraints (Jin, DePiper, and Hoagland, 2016; Runting et al., 2018). For example, Jin, DePiper, and Hoagland applied MPT to the implementation of an ecosystem-based fishery management approach in different geographic regions. The authors considered the limited stock of each fish species available to harvest in their MPT application by constraining the maximum weight applied to each species' harvest. Similarly, Runting et al. (2018) reformulated an integer quadratic programming MPT approach with a binary decision variable representing whether each site is selected for wetland protection. By using a binary decision variable, the authors indirectly accounted for limited returns based on each site's limited availability, along with other physical considerations such as connectivity necessary for the landward migration of wetlands. However, it remains unclear how the benefits of risk diversification are impacted by physical constraints.

The objective of this research is to identify the impacts of failing to account for upper limits on returns from conservation investment in an MPT framework and to understand the implications of accounting for these limits. To achieve this objective, we develop an MPT framework with and without upper limit constraints (referred to as "constrained MPT" and "naïve MPT," respectively) using county-level return on investments (ROIs) for conservation of forest biodiversity in the central and southern Appalachian region of the United States (see Figure 1). Then, we conceptually illustrate the impacts of upper limits on MPT outcomes using two hypothetical counties with different expected ROIs and associated risk levels. Next, we compare MPT outcomes between the two approaches using two metrics measuring the effectiveness of risk diversification: the slope of the efficient frontier representing risk–reward trade-offs and the vertical distance between the simple diversification point and the efficient frontier representing the difference in potential expected ROIs gained by the different MPT frameworks given the same risk level.

We choose to frame the models at the county level since counties (i) provide a relevant spatial grain when deciding how to allocate conservation budgets, (ii) are a relevant administrative and political unit for regional and local land-use planning in the United States, and (iii) are the level of units for which our socioeconomic variables are available (Le Bouille, Fargione, and Armsworth, 2023).

Because of the covariance in returns between counties, reducing risk implies forgoing expected return (i.e., spreading one's bets on conservation). The extent of risk reduction that conservation organizations can attain with the same level of compromise in expected return is hypothesized to be different for the two MPT approaches. Restrictions on portfolio weights with constrained MPT impose a degree of "bet spreading," while naïve MPT does not. Therefore, the constrained MPT is useful for conservation investment when a regulatory cap on budget allocation for each site is present. Many conservation partnership programs are limited by regulatory constraints imposed by partnership funds. These kinds of regulatory constraints would imply that upper limits on returns diminish the value added from using MPT. However, if the constraints force conservation organizations to bet spread anyway, then it is wise to use MPT to allocate the bet spread in the best way possible. Our constrained MPT approach is designed to serve this purpose.

Methods

Naïve MPT Framework

Suppose a conservation organization wishes to allocate optimal portfolio weights across the counties. By modifying the framework developed by Runting et al. (2018), where risk minimization and expected return maximization are combined in a single framework, we develop a naïve MPT approach formatted as a quadratic programming problem without upper limit constraints as follows:

$$(1) \qquad \text{Min}_W \ \lambda \boldsymbol{W^T \Sigma W} - \boldsymbol{W^T M},$$

subject to

$$(2) \qquad \boldsymbol{0} \leq \boldsymbol{W} \leq \boldsymbol{I}$$

and

$$(3) \qquad \boldsymbol{W^T I} = \boldsymbol{1},$$

where λ is a weight for risk minimization that represents relative emphasis on risk mitigation from 0 to infinity, $\boldsymbol{W^T \Sigma W}$ is the weighted sum of the variance of counties representing the portfolio's variance (or risk), where $\boldsymbol{W^T}$ is a vector transpose of $\boldsymbol{W}$, an $n \times 1$ vector of efficient portfolio weights across n counties as the decision variable, and $\boldsymbol{\Sigma}$ is an $n \times n$ variance–covariance matrix of ROIs across n counties. The variance–covariance matrix between county i and county j is calculated as $E[(ROI_i - E[ROI_i])(ROI_j - E(ROI_j))]$, where ROI_i (or ROI_j) is the ROI for county i (or j) under s uncertainty scenarios. $\boldsymbol{M}$ is an $n \times 1$ vector of expected ROIs, which are calculated as expected values of ROIs for n counties: $E[ROI_i] = \sum_s p \times ROI_{is}$, where p is the probability of uncertainty scenario s occurring, which is equal to $1/s$ by assuming a uniform probability distribution among s scenarios, and ROI_{is} is the ROI for county i under specific uncertainty scenario s. $\boldsymbol{W^T M}$ is the expected ROI of the portfolio calculated by the weighted average of $\boldsymbol{M}$ with efficient portfolio weight $\boldsymbol{W}$.

The objective function in equation (1) maximizes expected ROI (i.e., $\boldsymbol{W^T M}$) or minimizes the portfolio's variance (i.e., $\boldsymbol{W^T \Sigma W}$) at a certain weight for risk minimization (λ). Equation (2) represents the minimum and maximum constraint on portfolio weights, and $\mathbf{0}$ and $\boldsymbol{1}$ are $n \times 1$ vectors whose elements are equal to 0 and 1, respectively. The sum of all portfolio weights is always equal to 1 for any given risk level.

Constrained MPT Framework

For constrained MPT, we consider two layers of constraints—physical limitations and total budget constraints—under the assumption that a conservation organization wishes to allocate optimal portfolio weights across the counties. To account for both constraints, we replace the decision variable of efficient portfolio weights shown in equation (1) with a decision variable for efficient budget allocation across counties X shown in equation (4):

$$\text{Min}_X \, \lambda \boldsymbol{X^T \Sigma X} - \boldsymbol{X^T M}, \tag{4}$$

subject to

$$0 \leq \boldsymbol{X} \leq \boldsymbol{C} \tag{5}$$

and

$$\boldsymbol{X^T I} = \text{B}, \tag{6}$$

where $\boldsymbol{X^T}$ is a vector transpose of $\boldsymbol{X}$, an $n \times 1$ vector of efficient budget allocation in dollars across n counties as the decision variable, $\boldsymbol{C}$ is an $n \times 1$ vector of county-level physical constraints whose elements are specified as the product of the size of eligible forestland (i.e., unprotected private forestland) as a physical constraint and unit opportunity cost for conservation as a cost constraint across n counties, and B is a hypothetical total budget amount for the entire region.

Precise knowledge of $\boldsymbol{C}$ in the future by the conservation organization is not possible because the size of eligible forestland and unit opportunity cost vary under s uncertainty scenarios. Given the unknown probability distribution of uncertainty scenarios, we use its average value across the scenarios for each county for the model. By doing so, we implicitly assume that $\boldsymbol{C}$ is normally distributed; thus, its mean value is a meaningful representation of $\boldsymbol{C}$. For the sensitivity analysis, we estimate the model using the upper limits on both (high and low) ends of the 95% confidence interval of their probability density distributions since upper limits at the mean may not encompass the entire spectrum of potential outcomes of constrained MPT. By performing the sensitivity analysis, we partially encompass infrequent occurrences that can exert significant influence on the size of eligible forestland and unit opportunity cost.

The objective function in equation (4) maximizes the weighted sum of expected ROIs ($\boldsymbol{X^T M}$) and minimizes the portfolio's variance (i.e., $\boldsymbol{X^T \Sigma X}$). Equation (5) specifies the county's physical constraint, $\boldsymbol{C}$, across n counties, and equation (6) constrains the hypothetical total budget, B. The physical constraints are fixed for counties by uncertainty scenario, while hypothetical total budget constraints may change depending on the budget available for the entire region. The physical and budget constraints are specified by equations (5) and (6), respectively, as the total budget is spread from one county to another after meeting each county's physical constraint $\boldsymbol{C}$ as each county's expected ROI goes to 0 (represented as a step function) until exhausting total budget B.

We calculate efficient portfolio weight $\boldsymbol{W}$ for constrained MPT by dividing efficient budget allocation $\boldsymbol{X}$ by total budget B to derive the efficient portfolio's expected ROI and corresponding variance as the weighted sum of expected ROIs ($\boldsymbol{W^T M}$) and the variance of counties ($\boldsymbol{W^T \Sigma W}$) for the risk measure. In doing so, we derive efficient frontiers for naïve and constrained MPT under various levels of risk minimization weight λ by connecting points of expected ROIs and corresponding standard deviations for both MPT approaches. Because the ideal funding amount for forest conservation for biodiversity in the study area is unknown, we compare outcomes of the hypothesis found in the conceptual framework related to the impact of hypothetical total budget amounts on the degree of deviation between the naïve and constrained MPT. Specifically, we compare outcomes based on the two approaches under three hypothetical total budget constraints: low, moderate, and high total budget (i.e., \$3 million, \$50 million, and \$1 billion, respectively).

Given the various ranges of expected ROIs and standard deviation for each approach that are reflected in the various lengths of the frontiers, we normalize the risk level as the percentage above minimum risk (referred to as "risk tolerance level") to compare outcomes based on naïve and constrained MPT at the same degree of risk that conservation organizations can tolerate. If the feasible risk levels were different between the approaches, our comparisons would be limited. For example, if the minimum risk levels were 0 and 3 for naive and constrained MPT, respectively, we could not compare the efficient portfolios at a risk level of 3, which is not the minimum risk level associated with naïve MPT. By drawing the efficient frontiers where the x-axis represents risk tolerance level normalized as stated above, efficient frontiers are comparable at every risk tolerance level and show expected ROIs attainable at any risk tolerance level across different MPT specifications.

Conceptual Illustration

Suppose a conservation organization wishes to allocate optimal portfolio weights between counties A and B based on naïve and constrained MPT. County A has a higher expected ROI with higher risk than county B ($ROI_A > ROI_B$). The positively sloping diagonal line in Figure 2a shows the allocation of efficient portfolio weights between the two counties at different risk levels based on naïve and constrained MPT. The lines indicated by w^M and $1 - w^{M\prime}$ represent the upper limits on weights assigned to counties A and B, as the total weight between the two cannot exceed the full capacity of available resources. Figure 2b illustrates different areas portrayed by changes in expected ROI, $wROI_A + (1 - w)ROI_B$, corresponding to portfolio weights between the two counties based on naïve and constrained MPT shown in Figure 2a.

Based on the naïve MPT outcome, a conservation organization with maximum risk level r_1 protects all conservation assets in county A ($w = 1$ in Figure 2a), with the corresponding expected ROI being area *afho* in Figure 2b. By comparison, consider the case where the constraint is binding in county A. Constrained MPT allocates weight w^M to county A with the remaining weight, $1 - w^M$, distributed to county B at the maximum risk level of r_2, corresponding to $w = w^M$. The resulting expected ROI is shown by area $af'h'o$ for county A and area $g'ghh'$ for county B. These results suggest that constrained MPT mitigates maximum risk relative to naïve MPT by $r_1 - r_2$ but corrects expected ROI by area $f'fgg'$ compared to naïve MPT.

Conservation investment would be divided between the two counties at lower risk than risk level r_1 based on naïve MPT. With weight assignments of w_Q and $1 - w_Q$ for counties A and B, respectively, the minimum risk level of 0 is reached. As a result, the expected ROI at the minimum risk level for naïve MPT is shown as the sum of area *aceo* for county A and area *dghe* for county B. In comparison, consider the case in which the constraint is binding in county B, where $w^{M\prime}$ and $1 - w^{M\prime}$ represent upper limits on weights assigned to counties A and B, respectively. Constrained MPT would allocate weight, $1 - w^{M\prime}$, to county B and the remaining weight, $w^{M\prime}$, would be distributed to county A at the minimum risk level of r_3. Expected ROIs are shown by area $ac'e'o$ for county A and area $d'ghe'$ for county B. These results suggest that constrained MPT sacrifices the minimum risk level by r_3 but increases expected ROI by area $cc'd'd$ relative to naïve MPT because of the added weight to the higher ROI county (i.e., county A) based on constrained MPT. Other

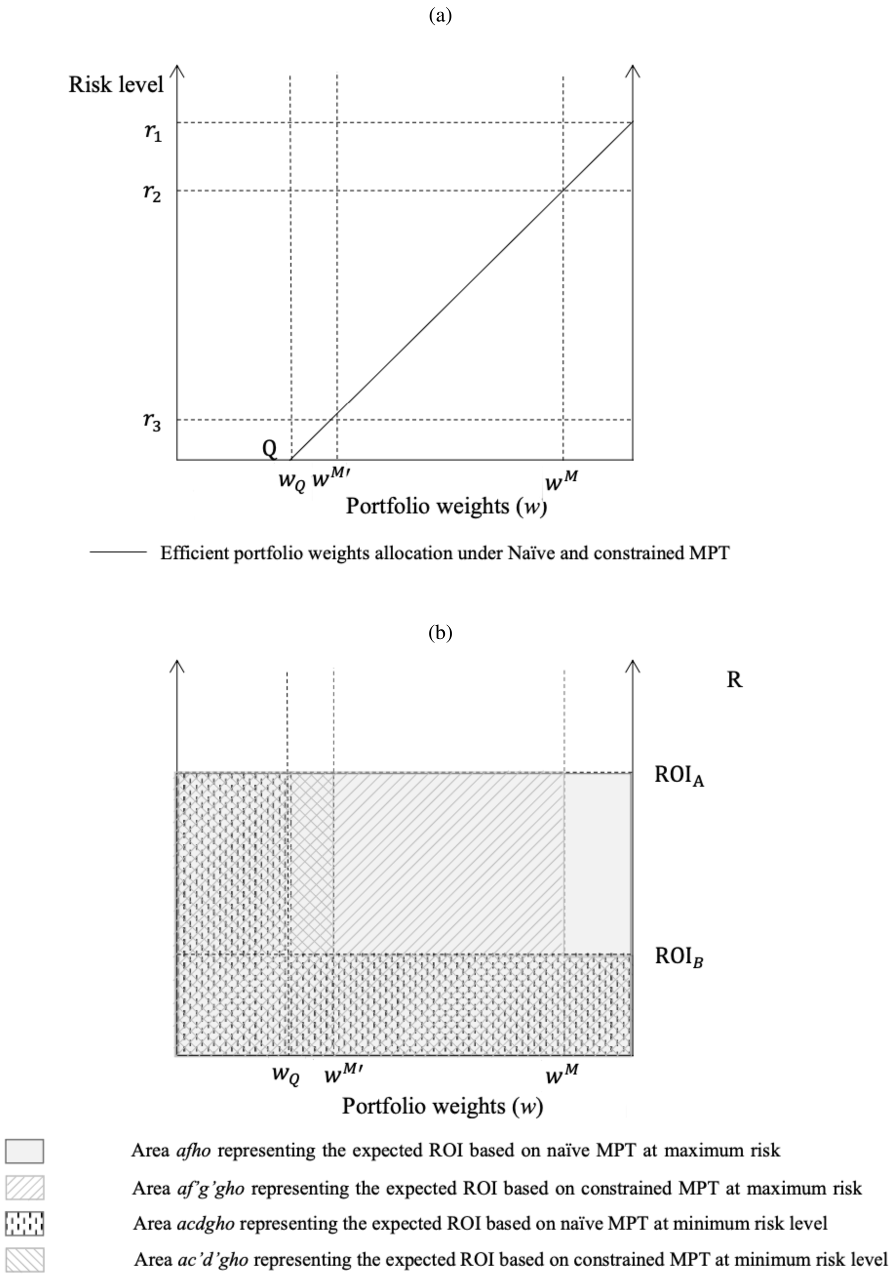

Figure 2. Consequences of Failing to Account for an Upper Limit Constraint in Modern Portfolio Theory (MPT)

Notes: Figure 2a shows allocations of efficient portfolio weights between two counties (w^M and $1 - w^{M'}$ represent upper limits on weights for counties A and B, and w^Q and $1 - w^Q$ represent weights at the minimum risk level for counties A and B) at different risk levels (0 and r_1 for minimum and maximum risk level based on naïve MPT and r_2 and r_3 for minimum and maximum risk levels based on constrained MPT) based on MPTs. Figure 2b illustrates changes in expected ROI (ROI_A is expected ROI for county A and ROI_B is expected ROI for county B), corresponding to efficient portfolio weights between the two counties ($w^{M'}$ and $1 - w^{M'}$ represent weights assigned to counties A and B for the case where the constraint is binding in county B at minimum risk level, and w^M and $1 - w^M$ represent weights for counties A and B where the constraint is binding in county A at maximum risk) based on naïve and constrained MPT shown in Figure 2a.

cases could include a situation where county B provides both lower expected ROI and higher risk. In this case, budget constraints on county A could both lower the expected ROI and increase the risk of investing.

At the maximum risk level, naïve MPT maximizes risk and expected ROI by allocating a weight above the feasibility of county A (w=1 in Figure 2a); at the minimum risk level, naïve MPT minimizes risk by allocating a weight above the feasibility of county B ($w = w_Q$ in Figure 2a). However, constrained MPT prevents the overallocation of weights to counties A and B at maximum and minimum risk levels, respectively. By doing so, the optimal portfolio based on constrained MPT suggests high risk but high expected ROI at the minimum risk level, whereas it compromises expected ROI at the low risk level in comparison with the optimal portfolio generated based on naïve MPT.

Other cases are also possible. For example, in a situation where county B provides both lower expected ROI and higher risk, any upper limit constraint on the weight that can be assigned to county A will both lower the expected ROI and increase the associated risk. More generally, we can then see that adding upper limit constraints on how much investment can be directed to each asset is ambiguous in terms of whether it will increase or decrease expected ROI and associated risk.

The overall budget to be invested in conservation also matters. If the overall budget is small relative to the level of investment each asset can receive, accounting for upper limits on how much investment is possible for each asset is irrelevant. In contrast, when the overall program budget is large enough that the constraints may be binding, accounting for this in the optimization approach becomes more important. Risk and expected ROI corrections made by constrained MPT, relative to naïve MPT, intensify with a greater hypothetical total budget because the share of the budget assigned to each county, constrained by its upper limit, decreases with a higher hypothetical total budget. Thus, we hypothesize that the total budget available to a conservation organization influences the degree of deviation of risk level and corresponding expected ROI between the two approaches.

Before developing a fuller empirical application, we first consider a simple two-county case as an example to illustrate the effects of risk level and expected ROI on naïve and constrained MPT. While these comparisons are sufficient to build intuition for changes in return and risk, the notion of upper limits on return is grounded in the assumption of a linear relationship between risk and return, implying a clear and consistent trade-off between the two. However, real-world dynamics render the risk-return relationship more intricate, subject to fluctuations over time and diverse scenarios. Notably, factors like the physical constraints for conservation could also be influenced by climate and market uncertainties. In addition, we do not consider richer patterns of covariance. Accounting for covariance structure differences is where the strength of MPT reveals itself, and we next examine this with our empirical application. Furthermore, we assume that the two counties are not perfectly correlated with each other; thus, the risk diversification strategy used has a feasible solution for both MPT approaches.

Illustrative Example: Forest Conservation in Central and Southern Appalachia

To illustrate our framework, we apply MPT to forest conservation in a biodiversity hotspot—central and southern Appalachia, which provides critical habitat and a corridor for biodiversity (Zhu et al., 2021). The region is expected to experience further climate change impacts and urban development pressure (Rogers et al., 2016). For both MPT approaches, we use expected ROIs for biodiversity conservation in 2050, which is far enough in the future to observe the impact of climate and market uncertainty on benefits and costs. The benefit component for expected ROI is calculated by estimating future species ranges using species distribution models. The conservation cost component for expected ROI is proxied as urban return minus forestland return (referred to as "relative opportunity cost") under the assumption that urban development is the dominant competing land use for forestland. This assumption is based on evidence that urbanization is the main driver of forest loss in the study region (Wear and Greis, 2013; Keyser et al., 2014).

Estimating Scenario-Specific ROI

Scenario-specific expected ROIs are structured by combining predicted future benefit scenarios and relative opportunity cost scenarios at the county level for 193 of the 246 counties in our study area. Fifty-three counties are not considered in our analysis since they are either consolidated city-counties or counties where urbanization is not a primary concern (see Figure 1). Scenarios for predicting future biodiversity benefits are related only to climate change, and multiple climate scenarios are considered. In comparison, relative opportunity costs are projected under various climate and market scenarios associated with different climate, land use, and market conditions.

Multiple sources of uncertainty associated with benefits and costs derived from climate and market scenarios may have (i) different forms of variability and covariance structures, (ii) different patterns of covariance structure across counties within each type of uncertainty, and (iii) different patterns of covariance structure between each type of benefit and cost uncertainty. Due to these covariance structure differences, efforts to diversify market-induced risk may undermine or complement efforts to diversify climate-induced risk.

The benefit component for biodiversity ROI was taken from Zhu et al. (2021), who estimated species distributions for 258 forest-dependent vertebrates of policy concern as determined by the US Fish & Wildlife Service (1973) and Landscape Conservation Cooperative Network (2020). Future species distributions in 2050 were specified as the benefit component for biodiversity since they are direct representations of areas where species can be found and protected (Fuentes-Castillo et al., 2019). The species distribution model (SDM) Maxent was used to forecast future species distributions under future climate scenarios for two representative concentration pathways (RCPs; RCP4.5 and RCP 8.5) and six general circulation models (GCMs; ACCESS1-0, CanESM2, CCSM4, CNRM-CM5, CSIRO-Mk3, and INM-CM4) (Phillips, 1956; Intergovernmental Panel on Climate Change, 2014) using the ClimateNA database (Wang et al., 2016).

Maxent was used to estimate the probabilities of climatic suitability for species at the 1-km^2 pixel level under 12 future climate scenarios (i.e., 6 GCMs, each associated with RCP 4.5 and 8.5). Then, probabilities were converted into binary variables using a 10% training presence threshold, which allows the top 90% of predicted probabilities to be considered suitable habitat and the remaining 10% to be considered unsuitable habitat (Peterson et al., 2011). Next, pixel areas from the suitability binary variables are aggregated for all 258 species at the county level, and these estimates were specified as the benefit component of species distributions for all species under 12 future climate scenarios. See Zhu et al. (2021) for more details related to the methodology used to project future species distributions.

For the future urban return needed to estimate relative opportunity cost, annualized median assessed land value was determined by broadly emulating Lubowski, Plantinga, and Stavins (2006): First, land value ratios per hectare were estimated by dividing assessed land value per hectare by total assessed value at the parcel level for sample counties for which data were available. Second, land value ratios at the parcel level were converted to the census block group (CBG) level by regressing land value ratio per hectare against socioeconomic and location variables at the CBG level (see Liu et al., 2019, for more details). Third, median housing price in 2050 under three real estate market conditions (upturn, moderate, downturn) was projected based on recent real estate growth cycles to account for the effect of real estate market uncertainty on urban return. Finally, median assessed land value per hectare was estimated by multiplying median housing price under the three real estate market conditions by land value ratio per hectare, which was then annualized (see Mingie and Cho, 2020, for details).

The effect of climate and market uncertainty on forestland return was considered by projecting future harvest volume and timber price to estimate future annualized forest return using the soil expectation value (SEV). County-level harvest volume projections were created for three special report on emission scenarios (SRES; A1B, A2, and B2). State-level timber prices were estimated based on a stochastic modeling approach using regional stumpage price datasets from TimberMart-

South (2015) and other timber price reports. Three timber price scenarios were estimated: high (2050 mean plus standard deviation), moderate (2050 mean), and low (2050 mean minus standard deviation).

Scenarios have been represented slightly differently across climate change assessment reports, and our study draws on products that span different reports. The A1B and A2 scenarios in the SRES correspond better with the RCP8.5 scenario. Meanwhile, the B2 scenario in the SRES corresponds better with RCP4.5. The full set of scenarios we consider in our analyses are generated by cross-factoring an emissions scenario with a GCM for making climate predictions and an assumption about timber volume, timber price, and the real estate market. Under the more intensive emissions situation (RCP 8.5), we include 324 possible futures (2 SRES $\times$ 6 GCMs $\times$ 3 timber volume scenarios $\times$ 3 timber price scenarios $\times$ 3 real estate market scenarios). In addition, under an assumption of more moderate future emissions (RCP4.5), we include a further 162 possible futures (1 SRES $\times$ 6 GCMs $\times$ 3 timber volume projections $\times$ 3 timber price scenarios $\times$ 3 real estate market scenarios).

A shared-based land use model was applied at the county level using historical land use data from the National Land Cover Database (US Geological Survey, 2016) and historical relative opportunity cost data. We forecasted forestland area in each county under diverse scenarios in 2050 using the parameters from the land use model and the forecasts of the relative opportunity costs under different scenarios. While the land use change model predicts the forest area that will remain in the county in 2050 with or without investment, it does not forecast where exactly this forest area will be located within the county. The improvements in the persistence probabilities for species resulting from protecting forestland in different counties do not consider counties' proximity to one another.

We also needed to make an additional assumption to convert changes in forest within climatically suitable areas for a species into a statement about region-wide species persistence in 2050. Following Armsworth et al. (2020), the probability of persistence function was assumed to be a linear, piecewise continuous, hockey-stick function, which allowed the persistence probability to equal 0 when no forest remained but increase linearly when forest area in the county increased until a saturation threshold of 1 was reached. We also considered the difference in ecological quality between protected forest and private forest, treated as intermediate usable habitat, and differentiated the land use types by assigning two weights (i.e., 1 or 0.25) to protected and private forests, respectively (see Armsworth et al., 2020, for more details).

Based on the probability of persistence function and average opportunity cost, we estimated the marginal benefit-to-cost ratio in each county, which was optimized by both naïve and constrained MPT. Finally, expected marginal ROI under each scenario was defined as the change in species richness (i.e., number of species) by aggregating relevant probabilities for 258 species, which was optimized by both naive and constrained MPTs (Kang et al., 2022).

Empirical Results

Figure 3 shows four efficient frontiers indicating the expected ROI-risk tolerance relationship for portfolios generated from naïve MPT and constrained MPT with three hypothetical total budget constraints with upper limits at the mean. The four efficient frontiers are upward sloping, implying higher return (i.e., expected ROI) with higher risk. The four frontiers are also concave-shaped, implying that risk diversification becomes more costly (i.e., more return is sacrificed) as portfolio risk is reduced.

Figure 3 illustrates how constraints on returns impact the effectiveness of risk mitigation in two ways. First, the constraints reduce how much expected ROI must be forgone to achieve the same level of risk reduction (see Figure 3a). The slope of the frontier is smaller under constrained MPT than under naïve MPT especially at higher budget amounts where constraints are binding for more counties. These findings imply that when a conservation organization will have to spread more investment around due to a larger total budget, it can reduce risk with less loss in expected return with constrained MPT than with naïve MPT.

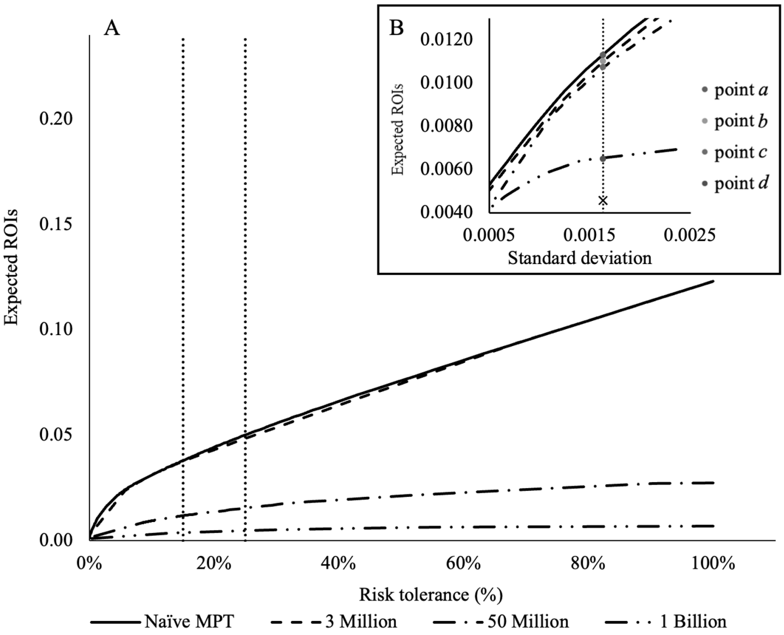

Figure 3. Four Efficient Frontiers of the Expected ROI–Risk Tolerance Relationship

Notes: Frontiers are for portfolios from naïve modern portfolio theory (MPT) and constrained MPT with three budgets ($3 million, $50 million, and $1 billion), with upper limits at the mean. (A) Constraints on asset returns lower the slope of the frontier at many reasonable risk tolerance levels implying less expected ROI must be forfeited to reduce risk. (B) Constraints on asset returns also reduce the increase in expected ROI that can be achieved through risk diversification. Points a, b, c, and d are the points on the efficient frontiers for the naïve MPT and constrained MPT with $3 million, $50 million, and $1 billion, respectively, with the same standard deviation as point X.

Figure 3b also shows how constraints on returns could force land managers in the Appalachian region to spread their bets by spreading the budget to a greater number of counties. This bet-spreading behavior yields an expected ROI closer to what would be achieved if the budget were divided evenly among all counties (i.e., simple diversification; point marked as an X in Figure 3b). Specifically, the difference in expected ROI at the same risk level between the constrained efficient frontiers and the simple diversification point decreases as the budget increases.[1] Points *a*, *b*, *c*, and *d* are points on the efficient frontier for naïve MPT and constrained MPT with $3 million, $50 million, and $1 billion budgets, respectively, at the same standard deviation as point X. The vertical distances from simple diversification portfolio X to points *a*, *b*, *c*, and *d* represent differences in potential expected ROI gained by the different MPT frameworks, given the same risk level. The longer vertical distance from X to *a* compared to distances from X to *b*, *c*, and *d* reinforces the notion that MPT is less efficient with constrained MPT since constraints direct more investment to counties with a smaller ROI.

Table 1 shows optimal portfolio expected ROI for biodiversity conservation and risk, reflected in its standard deviation, at four risk levels from naïve MPT and constrained MPT with three hypothetical total budget scenarios with upper limits at the mean. At the maximum risk level, the results show that constrained MPT compromised expected ROI while improving risk mitigation to a greater extent compared to naïve MPT. At the minimum risk level, constrained MPT gained higher expected ROI by reducing risk mitigation more than naïve MPT. These findings imply that constrained MPT corrects misallocated portfolio weights and, based on this correction, the tradeoff between risk and expected ROI at maximum and minimum risk levels, respectively.

[1] We make comparisons using the expected ROI-standard deviation frontiers, instead of the expected ROI-risk tolerance frontiers because the simple diversification portfolio cannot be normalized.

Table 1. Summary Statistics

		Constrained MPTs		
Risk Level	**Naïve MPT**	**$3 million**	**$50 million**	**$1 billion**
Minimum				
Portfolio's expected ROI	0.00173	0.00119	0.00104	0.00091
Portfolio's standard deviation	0.00005	0.00004	0.00004	0.00004
No. of counties selected	12	12	12	16
No. of counties bound by its upper limit constraint	–	0	1	9
Average cost of selected counties ($)	90,762,849	90,762,849	90,762,849	92,585,968
15%				
Portfolio's expected ROI	0.03792	0.0376	0.01174	0.00372
Portfolio's standard deviation	0.01607	0.01617	0.00185	0.0004
No. of counties selected	3	4	8	35
No. of counties bound by its upper limit constraint	–	1	4	27
Average cost of selected counties ($)	8,386,061	7,200,854	17,481,817	32,823,862
25%				
Portfolio's expected ROI	0.04996	0.04902	0.01534	0.00474
Portfolio's standard deviation	0.02667	0.02735	0.00307	0.00065
No. of counties selected	3	4	9	43
No. of counties bound by its upper limit constraint	–	1	3	38
Average cost of selected counties ($)	3,253,555	7,200,854	10,461,209	24,450,516
Maximum				
Portfolio's expected ROI	0.12324	0.12324	0.02744	0.00691
Portfolio's standard deviation	0.10734	0.10734	0.01234	0.00228
No. of counties selected	1	1	9	59
No. of counties bound by its upper limit constraint	–	0	8	58
Average cost of selected counties ($)	3,645,232	3,645,232	5,588,646	17,942,059

Notes: Portfolio expected ROI for biodiversity conservation, portfolio risk reflected in its standard deviation, number of counties selected, number of counties bound by upper limit constraints, and average costs of selected counties from naïve MPT and constrained MPT with three total budgets under four risk levels with upper limits at the mean.

Deviations in risk level and expected ROI between naïve and constrained MPT depend on how efficiently county portfolio weights are bound by upper limits. For example, portfolio weights for constrained MPT with a $3 million total budget did not deviate much from those for naïve MPT since counties with optimal budgets above county-level physical constraints (e.g., 1 of 16 counties selected at four risk tolerance levels) were rare. No correction of risk or expected ROI is made by constrained MPT with a $3 million budget at the maximum risk level since the efficient portfolios between the two models are the same: All investment is allocated to a single county, Coosa County, Alabama. The upper limit constraint of Coosa County is less than the total budget of $3 million. Thus, the efficient portfolio weight of the county is not bound by its upper limit. Similarly, efficient portfolio weights between the approaches are the same at the minimum risk level (see Table S1 for details on portfolio weight allocations) since all efficient portfolio weights do not reach their upper limits. As a result, the efficient portfolio is the same regardless of whether the upper limit is considered. In contrast, deviation was much more apparent if the total budget for constrained MPT increased to $1 billion since counties with optimal budgets above county-level budget constraints (e.g., 81 of 85 counties selected at four risk tolerance levels) were much more numerous (see Table 1). These findings show that the degree of correction in risk and expected ROI made by constrained MPT is greater with higher total budgets, and greater diversification of counties is achieved regardless of risk mitigation, especially when higher total budgets are considered.

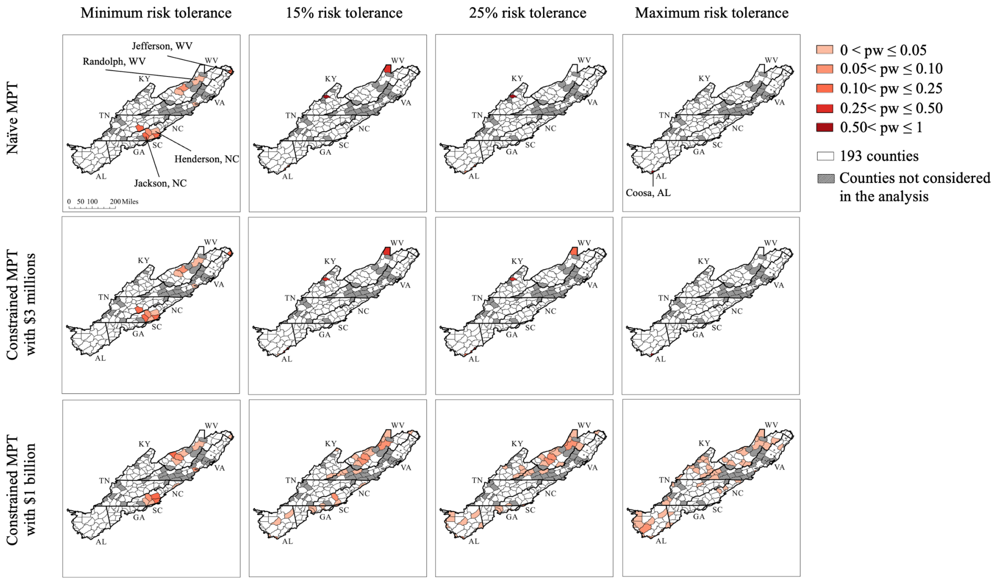

Figure 4. Spatial Distributions of Portfolio Weight Allocations

Notes: Allocations are from naïve modern portfolio theory (MPT) and constrained MPT with $3 million and $1 billion total budgets at four risk tolerance levels (i.e., minimum, 15%, 25%, and maximum risk tolerance levels) with upper limits at the mean.

Table 2 illustrates heterogeneity in different aspects of 16 selected counties from naïve MPT, among which three are chosen twice in different risk levels. Ten of the 16 counties are categorized as rural. The sizes of the counties display considerable variations. For example, Randolph County, West Virginia, the largest county among the 16 counties (402,033 hectares), is almost 5 times the size of Jefferson County, West Virginia, the smallest county among the 16 counties (82,416 hectares). Forestland area generally reflects the size of the county, and the average ratio of public to private forestland over the 486 uncertainty scenarios ranges from 0 to 16 across the 16 counties. The average species ranges for 258 species vary from 10.5 million to 55.4 million hectares across the counties across uncertainty scenarios. The scale and variation of the urban return is greater than those of the forest return. As a result, the discrepancy in relative opportunity costs is determined more by urban return than by forest return. A noticeable disparity is found in the ROIs across the counties. In particular, a $1 million investment would allow for the persistence of 0.1232 additional species in Coosa County, Alabama, more than 300 times greater than the expected ROI in Buncombe County, North Carolina (0.0004) on average across uncertainty scenarios.

Figure 4 shows the spatial distributions of portfolio weight allocations from naïve and constrained MPT with $3 million and $1 billion total budgets at four risk tolerance levels (i.e., minimum, 15%, 25%, and maximum risk tolerance), with upper limits at the mean. At minimum risk tolerance, we observe that a portfolio weight of 0.12 is assigned to Henderson County, North Carolina, based on constrained MPT with a $1 billion total budget, whereas the same county's portfolio weight is 0.24 for naïve MPT. The portfolio weight of 0.24 without an upper limit constraint does not exceed the county-level budget constraint of $120 million if the total budget constraint is $3 million. Consequently, the portfolio weight of 0.24 remains the same between naïve and constrained MPT at minimum risk tolerance when a $3 million total budget is considered. (See S1 and Table S1 in the online supplement at www.jareonline.org for discussion on portfolio weights between the two MPT approaches with three hypothetical total budgets and four risk levels.) These findings suggest that constrained MPT corrects misleading portfolio weights only if the optimal budget assigned to a county without a total budget constraint is above the county's budget constraint.

Table 2. Summary of the 16 Selected Counties from Naïve Modern Portfolio Theory (MPT) under Four Risk Levels

Risk Level	County	Type	Size (hectare)	Size of Forestland (hectare)	Private Forestland (hectare)	Public Forestland (hectare)	Species Ranges of 258 Species (hectare)	Forest Return ($/hectare)	Urban Return ($/hectare)	Relative Opportunity Cost ($/hectare)	ROI (increase in no. of species persistence/$1 million invest)
Minimum	Buncombe, NC	Urban	244,890	162,436	128,962	33,474	33,554,911	87	1,959	1,872	0.0004
	Haywood, NC	Rural	205,647	163,698	55,369	108,329	29,633,914	76	1,057	981	0.0011
	Henderson, NC	Urban	138,699	86,721	70,874	15,847	19,234,632	65	1,824	1,758	0.0006
	Jackson, NC	Rural	182,754	154,343	8,906	145,437	26,604,084	104	901	797	0.0008
	Transylvania, NC	Rural	140,519	119,281	34,785	84,496	19,626,066	91	952	862	0.0010
	Greenville, SC	Urban	292,390	151,886	151,886	–	38,557,472	55	1,731	1,676	0.0009
	Sevier, TN	Rural	222,275	161,512	88,767	72,745	29,947,641	65	1,015	950	0.0005
	Roanoke, VA	Urban	95,201	66,524	61,410	5,115	12,886,994	130	1,438	1,308	0.0005
	Fayette, WV	Rural	255,761	219,338	200,872	18,467	36,137,436	60	390	330	0.0023
	Jefferson, WV	Urban	82,416	23,413	23,167	246	10,526,362	62	1,544	1,482	0.0008
	Nicholas, WV	Rural	251,337	203,827	175,096	28,730	35,744,704	20	226	206	0.0049
	Randolph, WV	Rural	402,033	353,349	156,814	196,535	55,448,499	68	552	484	0.0035
15%	Clay, AL	Rural	218,645	157,964	124,256	33,708	27,414,832	45	85	40	0.0415
	Wolfe, KY	Rural	84,926	67,963	53,030	14,933	11,480,003	47	69	22	0.0463
	Preston, WV	Rural	254,289	193,619	186,693	6,925	36,454,081	17	119	102	0.0185
25%	Clay, AL	Rural	218,645	157,964	124,256	33,708	27,414,832	45	85	40	0.0415
	Coosa, AL	Rural	239,645	171,112	171,112	–	30,449,521	46	68	21	0.1232
	Wolfe, KY	Rural	84,926	67,963	53,030	14,933	11,480,003	47	69	22	0.0463
Maximum	Coosa, AL	Rural	239,645	171,112	171,112	–	30,449,521	6	8	1	0.1232

Notes: Species ranges are average values of 258 species over 486 uncertainty scenarios, and private forestland, forest return, urban return, relatively opportunity cost, and ROI are average values over 486 uncertainty scenarios.

Figures S1 and S2 and Tables S2 and S3 in the online supplement show, respectively, (i) the expected ROI-standard deviation frontiers and (ii) optimal portfolio expected ROI for biodiversity conservation and risk under four risk levels between naïve and constrained MPT with three hypothetical total budget scenarios using upper limits on both ends of 95% confidence interval of their probability density distributions. These consistent findings with different size of upper bound constraints reaffirm the robustness of characteristics discussed in the conceptual illustration. Specifically, these findings reinforce two key points: First, constraints can enhance the efficiency of resource allocation, especially in scenarios with large budgets where the risk of excessive investment in a single county is heightened. Second, within a constrained MPT framework, as the total budget expands, there is a natural inclination to distribute the budget more evenly across a greater number of counties. This consistency holds true irrespective of the specific upper-limit constraints applied in the constrained MPT analysis.

Discussion

The comparison of MPT outputs with and without upper limit constraints shows that the change in portfolio risk that conservation organizations can achieve with the same level of compromise in expected ROI is higher with constrained MPT than with naïve MPT. This finding has implications for conservation strategies with different objectives. Constrained MPT is useful when seeking to protect species that are habitat specialists, such as several highly endemic salamanders in our case study region. It is also useful when prioritizing land that is only occasionally available for conservation acquisition because there may only be a few properties available in a desirable location during a period when the conservation program must allocate its budget.

Another possible circumstance that fits well for constrained MPT is when additional capacity constraints might be limiting (e.g., if the conservation program relies on partners for long-term management of the site). For example, the Critical Ecosystem Partnership Fund (Critical Ecosystem Partnership Fund, 2022) supports the protection of natural areas essential to biodiversity with designated budget amounts. There are also state programs that cap how much any one state can receive. For example, the Co-operative Endangered Species Conservation Fund supports section 6 of the ESA (50th Congress, 1937; US Fish & Wildlife Service, 2024) and provides grants to states and territories for species and habitat conservation actions on nonfederal land. State allocations from this fund are derived from an established formula and specific constraints. The funding proportion given to each state does not change from year to year since these appropriations are based on the program's formula.

Despite our study's contribution, conservation organizations should be mindful of the limitations associated with relying solely on upper limits on returns from conservation using a constrained MPT. Precise projections of the upper limits are not possible given the unknown probability distribution of uncertainty scenarios. Instead, we use average values of upper limits on returns across the scenarios for the main finding and vary their values as a sensitivity analysis. This type of approach offers layers of optimal solutions and allows a comparison of their implications for conservation decisions. However, conservation organizations need to go beyond comparing outcomes using multiple upper limits as they have little reference for which upper limits are most relevant to their conservation decision making. Furthermore, unexpected economic, political, and technological shifts may result in upper limits beyond those covered by the scenario-specific projections. The potential occurrence of such extreme conditions hinders the application of the constrained MPT.

Another aspect of limitation lies in the influences of behavioral and social factors on conservation decisions. Conservation decision making and behavior can deviate from rational expectations because they can be linked to social, psychological, and behavioral factors. For example, emotion, habit, culture, and involvement have been found to be significantly and positively associated with conservation behavior (Singha et al., 2022), resulting in overreactions or underreactions to conservation commitment. As a result of these influences, conservation organizations may deviate from optimal risk-diversification strategies with their decision-making processes. Consequently, their portfolios of conservation practices might exceed the projected upper limits on return, which in turn can shape the dynamics of conservation behaviors. Likewise, we modeled a range of future scenarios, but our models would obviously not perform well if future black-swan-like events fell well outside the range that we considered.

It is also worth mentioning caveats for identifying future research needs. Our constrained MPT models focus on upper limits in returns that arise from physical limitations of conservation investments, while a conservation organization also faces upper limits due to diminishing returns. For example, a conservation organization attempting to protect species habitat for a specific target site faces diminishing returns at each target site since the number of species preserved per unit area will monotonically decrease as each additional unit area is protected if the response of each species to protection is not convex (Popov et al., 2022). In a way, our constrained MPT accounts for marginal returns with a step function in which ROI goes to 0 when the weight crosses a threshold of the physical constraint in equations (5) and (6). The use of a step function reflects the fact that practitioners may only be able to coarsely estimate diminishing returns since data on the marginal effect of conservation investment are limited. Thus, future research could explore developing another modified constrained MPT framework accounting for upper limits in returns that arise from both physical limitations and diminishing returns when data on the marginal effect of conservation investment are viable.

We recognize that there are other limitations to existing applications of MPT (both naïve and constrained) in conservation. As with any approach, assumptions must be made. For example, applications of MPT in conservation typically assume static, one-off decisions that are relevant to some conservation programs (e.g., those needing to allocate funds during fixed windows of time) but not others (e.g., those planning acquisition strategies that are to be implemented gradually over a couple of decades). In reality, conservation agencies typically face scenarios in which building conservation programs at different sites takes time. In the interim, they accumulate new information relevant for final decision making (Pressey et al., 2013). To address this challenge, future research will have to develop a dynamic counterpart to the MPT approach to conservation planning and use it to determine a time series of portfolios of target sites for conservation that accommodates future spatial and temporal uncertainties.

Additionally, applications of MPT (both naïve and constrained) are limited in the number of assets they can consider, which can result in a reliance on relatively coarse units such as the counties used in our empirical analysis. Specifically, the MPT cannot determine optimal solutions when the number of scenarios available is equal to or less than the number of assets considered because the information needed to calculate the variance–covariance matrix for the solution of portfolio weights in such cases would not be sufficient (Mallory and Ando, 2014). We have not yet compared the relative importance of accounting for upper limit constraints on how much investment can be directed to different assets to the relative importance of accounting for other refinements of MPT. We chose to focus here on the role of upper limit constraints on potential targets for investment because these constraints have the potential to induce some degree of risk spreading, which has been touted as a prevailing benefit of MPT. In our empirical application, we find that including these constraints enhanced the benefits of applying MPT. In essence, if a conservation organization must spread investment around anyway, it would be wise to use MPT to maximize the benefits of doing so.

Conclusion

The constrained MPT model is structured to correct potentially misleading portfolio weights from naïve MPT that do not account for upper limits in returns from conservation investments. We find that the amount of reduction in risk conservation that organizations can achieve with the same level of compromise in expected ROI is higher with constrained MPT than with naïve MPT.

However, our findings also suggest that improvement can be made only if the total budget assigned to a conservation organization is large enough so that portfolio weights from naïve MPT allocate beyond physical limitations determined by upper limits of potential target sites or regions that trigger misallocation of portfolio weights for target sites. For this reason, divergences between each approach's outcomes become more evident if the total budget for constrained MPT is higher, and the degree of divergence depends on how physical limitations bind and correct for misleading portfolio weights.

Constrained MPT can help conservation organizations by providing risk-mitigating portfolios of conservation targets that consider each target site's upper limit constraint. Comparing naïve and constrained MPT outcomes under various total budget constraint levels illustrates the vulnerability of naïve MPT and can help conservation organizations evaluate risk-diversifying strategies that are specific to different available total budget levels. Using constrained MPT for a given risk tolerance level and specific total budget can identify a risk- and budget-specific portfolio of target sites for biodiversity conservation. This suggests that the portfolio weights associated with the risk-mitigating allocation of conservation investment can be adjusted by a conservation organization's risk tolerance and the total budget it manages.

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References

50th Congress. 1937. "Pittman-Robertson Wildlife Restoration Act." US Government Publishing Office. Available online at https://www.govinfo.gov/app/details/USCODE-2011-title16/USCODE-2011-title16-chap5B-sec669c.

Ando, A. W., J. Fraterrigo, G. Guntenspergen, A. Howlader, M. Mallory, J. H. Olker, and S. Stickley. 2018. "When Portfolio Theory Can Help Environmental Investment Planning to Reduce Climate Risk to Future Environmental Outcomes—and When It Cannot." *Conservation Letters* 11(6):e12596. doi: 10.1111/conl.12596.

Ando, A. W., and M. L. Mallory. 2012. "Optimal Portfolio Design to Reduce Climate-Related Conservation Uncertainty in the Prairie Pothole Region." *Proceedings of the National Academy of Sciences* 109(17):6484–6489. doi: 10.1073/pnas.1114653109.

Armsworth, P. R., A. E. Benefield, B. Dilkina, R. Fovargue, H. B. Jackson, D. Le Bouille, and C. Nolte. 2020. "Allocating Resources for Land Protection Using Continuous Optimization: Biodiversity Conservation in the United States." *Ecological Applications* 30(6):e02118. doi: 10.1002/eap.2118.

Cho, S.-H., J. Lee, R. Roberts, E. T. Yu, and P. R. Armsworth. 2018. "Impact of Market Conditions on the Effectiveness of Payments for Forest-Based Carbon Sequestration." *Forest Policy and Economics* 92:33–42. doi: 10.1016/j.forpol.2018.03.009.

Critical Ecosystem Partnership Fund. 2022. "CEPF." Available online at https://www.cepf.net/ [Accessed February 24, 2023].

Eaton, M. J., S. Yurek, Z. Haider, J. Martin, F. A. Johnson, B. J. Udell, H. Charkhgard, and C. Kwon. 2019. "Spatial Conservation Planning Under Uncertainty: Adapting to Climate Change Risks Using Modern Portfolio Theory." *Ecological Applications* 29(7):e01962. doi: 10.1002/eap.1962.

Figge, F. 2004. "Bio-Folio: Applying Portfolio Theory to Biodiversity." *Biodiversity and Conservation* 13(4):827–849. doi: 10.1023/B:BIOC.0000011729.93889.34.

Fuentes-Castillo, T., R. A. Scherson, P. A. Marquet, J. Fajardo, D. Corcoran, M. J. Román, and P. Pliscoff. 2019. "Modelling the Current and Future Biodiversity Distribution in the Chilean Mediterranean Hotspot. The Role of Protected Areas Network in a Warmer Future." *Diversity and Distributions* 25(12):1897–1909. doi: 10.1111/ddi.12988.

Intergovernmental Panel on Climate Change. 2014. "Evaluation of Climate Models." In *Climate Change 2013 – The Physical Science Basis,* Cambridge University Press, 1st ed., 741–866. doi: 10.1017/CBO9781107415324.020.

Jin, D., G. DePiper, and P. Hoagland. 2016. "Applying Portfolio Management to Implement Ecosystem-Based Fishery Management (EBFM)." *North American Journal of Fisheries Management* 36(3):652–669. doi: 10.1080/02755947.2016.1146180.

Kahneman, D., and J. L. Knetsch. 1992. "Valuing Public Goods: The Purchase of Moral Satisfaction." *Journal of Environmental Economics and Management* 22(1):57–70. doi: 10.1016/0095-0696(92)90019-S.

Kang, N., C. Sims, P. Armsworth, G. Zhu, J. Mingie, and S.-H. Cho. 2022. "Risk Diversification Strategies for Biodiversity Conservation Investment." doi: 10.17632/6KMCKBX4ZZ.1.

Keyser, T., J. Malone, C. Cotton, and J. Lewis. 2014. *Outlook for Appalachian-Cumberland Forests: A Subregional Report from the Southern Forest Futures Project*. General Technical Report SRS-GTR 188. Asheville, NC: USDA Forest Service, Southern Research Station. doi: 10.2737/SRS-GTR-188.

Landscape Conservation Cooperative Network. 2020. "Appalachian Landscape Conservation Cooperative." Available online at https://lccnetwork.org/lcc/appalachian [Accessed May 24, 2023].

Le Bouille, D., J. Fargione, and P. R. Armsworth. 2023. "The Cost of Buying Land for Protected Areas in the United States." *Biological Conservation* 284:110138. doi: 10.1016/j.biocon.2023.110138.

Liu, X., S.-H. Cho, D. J. Hayes, and P. R. Armsworth. 2019. "Potential Efficiency Gains in Payment Programs from Resolving Spatial and Temporal Heterogeneity in the Cost of Supplying Forest Carbon." *Journal of Environmental Management* 250:109421. doi: 10.1016/j.jenvman.2019.109421.

Lubowski, R. N., A. J. Plantinga, and R. N. Stavins. 2006. "Land-Use Change and Carbon Sinks: Econometric Estimation of the Carbon Sequestration Supply Function." *Journal of Environmental Economics and Management* 51(2):135–152. doi: 10.1016/j.jeem.2005.08.001.

Mallory, M. L., and A. W. Ando. 2014. "Implementing Efficient Conservation Portfolio Design." *Resource and Energy Economics* 38:1–18. doi: 10.1016/j.reseneeco.2014.05.001.

Markowitz, H. 1952. "Portfolio Selection." *Journal of Finance* 7(1):77–91.

Mingie, J. C., and S. Cho. 2020. "Spatial Targeting of Payments for Ecosystem Services under Growth Uncertainties." *Applied Spatial Analysis and Policy* 13(4):805–822. doi: 10.1007/s12061-019-09329-z.

Newbold, T. 2018. "Future Effects of Climate and Land-Use Change on Terrestrial Vertebrate Community Diversity Under Different Scenarios." *Proceedings of the Royal Society B: Biological Sciences* 285(1881):20180792. doi: 10.1098/rspb.2018.0792.

Peterson, A. T., J. Soberón, R. G. Pearson, R. P. Anderson, E. Martínez-Meyer, M. Nakamura, and M. B. Araújo. 2011. *Ecological Niches and Geographic Distributions*. No. 49 in Monographs in Population Biology. Princeton, NJ: Princeton University Press.

Phillips, N. A. 1956. "The General Circulation of the Atmosphere: A Numerical Experiment." *Quarterly Journal of the Royal Meteorological Society* 82(352):123–164. doi: 10.1002/qj.49708235202.

Popov, V., P. Shah, R. K. Runting, and J. R. Rhodes. 2022. "Managing Risk and Uncertainty in Systematic Conservation Planning with Insufficient Information." *Methods in Ecology and Evolution* 13(1):230–242. doi: 10.1111/2041-210X.13725.

Pressey, R. L., M. Mills, R. Weeks, and J. C. Day. 2013. "The Plan of the Day: Managing the Dynamic Transition from Regional Conservation Designs to Local Conservation Actions." *Biological Conservation* 166:155–169. doi: 10.1016/j.biocon.2013.06.025.

Rogers, B. M., P. Jantz, S. J. Goetz, and D. M. Theobald. 2016. “Vulnerability of Tree Species to Climate Change in the Appalachian Landscape Conservation Cooperative.” In A. J. Hansen, W. B. Monahan, D. M. Theobald, and S. T. Olliff, eds., *Climate Change in Wildlands: Pioneering Approaches to Science and Management,* Washington, DC: Island Press/Center for Resource Economics, 212–233. doi: 10.5822/978-1-61091-713-1_11.

Runting, R. K., H. L. Beyer, Y. Dujardin, C. E. Lovelock, B. A. Bryan, and J. R. Rhodes. 2018. “Reducing Risk in Reserve Selection Using Modern Portfolio Theory: Coastal Planning Under Sea-Level Rise.” *Journal of Applied Ecology* 55(5):2193–2203. doi: 10.1111/1365-2664.13190.

Shipway, I. 2009. “Modern Portfolio Theory.” *Trusts & Trustees* 15(2):66–71. doi: 10.1093/tandt/ttn129.

Singha, B., O. Eljamal, S. C. Karmaker, I. Maamoun, and Y. Sugihara. 2022. “Water Conservation Behavior: Exploring the Role of Social, Psychological, and Behavioral Determinants.” *Journal of Environmental Management* 317:115484. doi: 10.1016/j.jenvman.2022.115484.

Snäll, T., M. Triviño, L. Mair, J. Bengtsson, and J. Moen. 2021. “High Rates of Short-Term Dynamics of Forest Ecosystem Services.” *Nature Sustainability* 4(11):951–957. doi: 10.1038/s41893-021-00764-w.

TimberMart-South. 2015. “Product and Services.” Available online at http://www.timbermart-south.com/products.html [Accessed May 24, 2023].

US Fish & Wildlife Service. 1973. *Endangered Species Act of 1973 as Amended through the 108th Congress*. Washington, DC: US Department of the Interior, US Fish & Wildlife Service. Available online at https://www.fws.gov/law/endangered-species-act.

———. 2024. “ECOS Environmental Conservation Online System.” Available online at https://ecos.fws.gov/ecp/species-reports.

US Geological Survey. 2016. “National Land Cover Database (NLCD).” Available online at https://www.usgs.gov/node/279743 [Accessed October 11, 2023].

Wang, T., A. Hamann, D. Spittlehouse, and C. Carroll. 2016. “Locally Downscaled and Spatially Customizable Climate Data for Historical and Future Periods for North America.” *PLoS One* 11(6):e0156720. doi: 10.1371/journal.pone.0156720.

Wear, D. N., and J. G. Greis. 2013. *The Southern Forest Futures Project: Technical Report*. SRS-GTR-178. Asheville, NC: U.S. Department of Agriculture, Forest Service, Southern Research Station. doi: 10.2737/SRS-GTR-178.

Zhu, G., M. Papeş, X. Giam, S.-H. Cho, and P. R. Armsworth. 2021. “Are Protected Areas Well-Sited to Support Species in the Future in a Major Climate Refuge and Corridor in the United States?” *Biological Conservation* 255:108982. doi: 10.1016/j.biocon.2021.108982.

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Online Supplement: Accounting for the Upper Limit in Returns to Conservation Investments in Risk Diversification Strategies

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The Pattern of Portfolio Weight Distribution

Figure 4 also shows that portfolio weights from naïve MPT spread out among counties at minimum risk tolerance level and gradually concentrate to fewer counties as risk tolerance level increases. For example, portfolio weights from naïve MPT are assigned to 10 counties at minimum risk tolerance level, while the entire portfolio weight is concentrated in a single county at maximum risk tolerance (see Table S1 in Supplementary material for the entire list of portfolio weights across four risk tolerance levels). A similar pattern of more diverse target counties with lower risk tolerance levels or vice versa is found for constrained MPT with a $3 million total budget (see Table 1 for details).

In contrast to naïve MPT and constrained MPT with a $3 million total budget, Table 1 shows that the number of counties with positive portfolio weights from constrained MPT with a $1 billion increases with increasing risk tolerance level. For example, portfolio weights are assigned to 16, 35, 43, and 59 counties, respectively, at minimum, 15%, 25%, and maximum risk tolerance levels for constrained MPT with a $1 billion total budget. This pattern of results is interesting in a sense that it contradicts the conventional wisdom of greater diversification for lower risk tolerance levels and vice versa which coincide with outputs of naïve MPT and constrained MPT with a $3 million total budget as well. While deviating from conventional wisdom, expected ROIs and their standard deviations for the portfolio of counties for constrained MPT with a $1 billion total budget still fulfill the condition of higher return with higher risk or lower risk with lower return. For example, the expected ROI of portfolios from constrained MPT with a $1 billion total budget are 0.00091, 0.00372, 0.00474, and 0.00691, and their corresponding standard deviations are 0.00004, 0.00040, 0.00065 and 0.00228 respectively, at minimum, 15%, 25%, and maximum risk tolerance levels.

We examine the underlying reason for greater diversification at greater risk tolerance level for constrained MPT with a $1 billion total budget by comparing the mechanisms of constrained MPT and naïve MPT. Naïve MPT selects a portfolio of minimum standard deviations and covariances across expected ROIs under different climate and market scenarios with diverse counties at minimum risk tolerance level, while it selects a portfolio of maximum expected ROIs by focusing on a single county with the highest expected ROI at maximum risk tolerance level, both regardless of total budget constraints. As a result, a greater number of counties are selected at lower risk tolerance levels or vice versa using naïve MPT. In contrast, the portfolio of maximum expected ROIs for constrained MPT exhausts the total budget by selecting a greater number of counties because of their lower average cost than the counties selected for a portfolio of minimum

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standard deviations and covariances with lower expected ROI and higher average cost. This pattern of greater number of counties for the portfolio of maximum expected ROI compared to the portfolio of minimum standard deviations and covariances from constrained MPT becomes more evident with a higher total budget constraint.

Table S1. Portfolio Weights from Naïve MPT and Constrained Mpts with $3 Million, $50 Million, and $1 Billion Budgets at Minimum, 15%, 25%, and Maximum Risk Tolerance Levels with Upper Limits at the Mean

	Minimum risk				15%				25%				Maximum risk			
Counties	Naïve MPT	3 millions	50 millions	1 billion	Naïve MPT	3 millions	50 millions	1 billion	Naïve MPT	3 millions	50 millions	1 billion	Naïve MPT	3 millions	50 millions	1 billion
Bibb, AL							0.1167	0.0366			0.1256	0.0366				0.0366
Blount, AL								0.0278				0.0088				0.0349
Chilton, AL							0.1058	0.0518				0.0518				0.0518
Clay, AL					0.2108	0.2852	0.0029		0.1408	0.2889	0.0360				0.0994	0.0050
Cleburne, AL							0.1446		0.0000	0.0000	0.1263	0.0078			0.1570	0.0078
Coosa, AL						0.0183			0.0567	0.1265			1.0000	1.0000	0.0729	0.0036
DeKalb, AL								0.0038				0.0237				0.0237
Fayette, AL												0.0133				0.0181
Jackson, AL																0.0576
Lawrence, AL												0.0075				0.0075
Marion, AL																0.0304
Walker, AL																0.0387
Winston, AL												0.0104				0.0104
Chattooga, GA																0.0111
Fannin, GA								0.0107				0.0107				
Gilmer, GA								0.0151				0.0151				
Habersham, GA								0.0279				0.0388				
Haralson, GA								0.0000								0.0233
Rabun, GA								0.0003				0.0003				
Towns, GA												0.0008				
White, GA								0.0212				0.0212				
Clay, KY																0.0008
Clinton, KY																0.0063
Estill, KY																0.0075
Greenup, KY								0.0347								
Harlan, KY								0.0069				0.0183				0.0183
Jackson, KY							0.0467				0.0467				0.0467	0.0023
Knott, KY												0.0109				0.0109
Letcher, KY												0.0095				0.0095
McCreary, KY				0.0001												0.0001
Magoffin, KY																0.0119
Martin, KY																0.0096
Morgan, KY																0.0148
Rockcastle, KY															0.0699	0.0038
Wayne, KY																0.0321
Wolfe, KY					0.5244	0.3825			0.8025	0.3825	0.0225				0.0229	0.0011
Alleghany, NC																0.0132
Avery, NC																0.0065
Buncombe, NC	0.0490	0.0490	0.0419	0.2414												
Clay, NC								0.0035				0.0035				
Haywood, NC	0.0541	0.0541	0.0550	0.0543				0.0543								
Henderson, NC	0.2448	0.2448	0.2522	0.1246												
Jackson, NC	0.1521	0.1521	0.1419	0.0071				0.0027								
Rutherford, NC								0.0363				0.0363				0.0363
Transylvania, NC	0.0240	0.0240	0.0229	0.0256				0.0300				0.0300				
Wilkes, NC				0.0368				0.0436								
Yancey, NC																0.0153
Greenville, SC	0.0250	0.0250	0.0254	0.1087												
Pickens, SC								0.0946				0.0946				
Grainger, TN				0.0050												0.0138
Lincoln, TN																0.0221
Marion, TN																0.0126
Overton, TN																0.0125
Pickett, TN				0.0039												0.0039
Sequatchie, TN																0.0099
Sevier, TN	0.1574	0.1574	0.1668													
Dickenson, VA								0.0125				0.0125				0.0125
Franklin, VA																0.0796
Page, VA																0.0135
Roanoke, VA	0.0468	0.0468	0.0474	0.0803												
Scott, VA															0.1502	0.0075
Tazewell, VA								0.0370				0.0370				
Wise, VA								0.0057				0.0104				0.0104
Barbour, WV							0.2903	0.0145			0.1881	0.0145				0.0145
Boone, WV								0.0344				0.0344				
Braxton, WV								0.0217				0.0217				0.0217
Clay, WV							0.1542	0.0077			0.1542	0.0077				0.0077
Fayette, WV	0.0309	0.0309	0.0319	0.0663				0.0663				0.0663				
Hardy, WV																0.0221
Jefferson, WV	0.1281	0.1281	0.1296	0.0343												
Kanawha, WV				0.1910												
Lincoln, WV												0.0122				0.0122
Logan, WV																0.0235
Monroe, WV												0.0095				0.0095
Morgan, WV								0.0294				0.0294				
Nicholas, WV	0.0615	0.0615	0.0603	0.0195				0.0360				0.0360				0.0360
Pendleton, WV												0.0038				0.0102
Preston, WV					0.2648	0.3141	0.1385	0.0190		0.2021	0.3004	0.0190			0.3809	0.0190
Raleigh, WV				0.0093				0.0692				0.0692				
Randolph, WV	0.0263	0.0263	0.0248	0.0008				0.0759				0.0759				0.0173
Summers, WV																0.0166
Taylor, WV								0.0097				0.0097				0.0097
Upshur, WV								0.0582				0.0582				
Wyoming, WV												0.0208				0.0208

Table S2. Portfolio Expected ROI for Biodiversity Conservation, Portfolio Risk Reflected in Its Standard Deviation, Number of Counties Selected, Number of Counties Bound by Upper Bound Constraints, and Average Costs of Selected Counties from Naïve MPT and Constrained MPT with Three Total Budgets under Four Risk Levels Using Upper Limits at the Low End of 95% Confidence Interval of Their Probability Density Distributions

			Constrained MPTs		
Risk Level		**Naïve MPT**	**$3 million**	**$50 million**	**$1 billion**
Minimum	Portfolio's expected ROI	0.00173	0.00105	0.00102	0.00089
	Portfolio's standard deviation	0.00005	0.00004	0.00004	0.00006
	No. of counties selected	12	12	12	18
	No. of counties bound by its upper bound constraint	-	0	1	8
	Average upper bound costs of selected counties ($)	90,762,849	72,390,768	4,166,667	86,882,407
15%	Portfolio's expected ROI	0.03792	0.02531	0.00701	0.00263
	Portfolio's standard deviation	0.01607	0.00704	0.00082	0.00022
	No. of counties selected	3	4	10	33
	No. of counties bound by its upper bound constraint	-	0	2	27
	Average upper bound costs of selected counties ($)	8,386,061	4,192,334	21,013,319	33,814,580
25%	Portfolio's expected ROI	0.04996	0.03117	0.00965	0.00330
	Portfolio's standard deviation	0.02667	0.01144	0.00133	0.00034
	No. of counties selected	3	4	8	37
	No. of counties bound by its upper bound constraint	-	1	2	32
	Average upper bound costs of selected counties ($)	3,253,555	4,005,203	14,768,104	28,810,805
Maximum	Portfolio's expected ROI	0.12324	0.06547	0.01713	0.00545
	Portfolio's standard deviation	0.10734	0.046129	0.00518	0.00118
	No. of counties selected	1	3	13	54
	No. of counties bound by its upper bound constraint	-	2	12	53
	Average upper bound costs of selected counties ($)	3,645,232	1,140,425	17,640,064	17,798,087

Table S3. Portfolio Expected ROI for Biodiversity Conservation, Portfolio Risk Reflected in Its Standard Deviation, Number of Counties Selected, Number of Counties Bound by Upper Bound Constraints, and Average Costs of Selected Counties from Naïve MPT and Constrained MPT with Three Total Budgets under Different Risk Levels Using Upper Limits at the High End of 95% Confidence Interval of Their Probability Density Distributions

			Constrained MPTs		
Risk Level		**Naïve MPT**	**$3 million**	**$50 million**	**$1 billion**
Minimum	Portfolio's expected ROI	0.00173	0.00105	0.00104	0.00090
	Portfolio's standard deviation	0.00005	0.00004	0.00004	0.00005
	No. of counties selected	12	12	12	14
	No. of counties bound by its upper bound constraint	-	0	1	5
	Average upper bound costs of selected counties ($)	90,762,849	104,059,636	104,059,636	115,679,468
15%	Portfolio's expected ROI	0.03792	0.03744	0.01389	0.00448
	Portfolio's standard deviation	0.01607	0.01569	0.00253	0.00055
	No. of counties selected	3	3	8	31
	No. of counties bound by its upper bound constraint	-	0	2	24
	Average cost of selected counties ($)	8,386,061	10,610,179	13,991,629	34,307,889
25%	Portfolio's expected ROI	0.04996	0.05055	0.01861	0.00565
	Portfolio's standard deviation	0.02667	0.02779	0.00425	0.00091
	No. of counties selected	3	3	8	40
	No. of counties bound by its upper bound constraint	-	1	4	35
	Average cost of selected counties ($)	3,253,555	4,768,006	13,991,629	28,089,152
Maximum	Portfolio's expected ROI	0.12324	0.12324	0.03403	0.00792
	Portfolio's standard deviation	0.10734	0.10734	0.01655	0.00335
	No. of counties selected	1	1	6	47
	No. of counties bound by its upper bound constraint	-	0	5	46
	Average cost of selected counties ($)	3,645,232…	5,749,264	8,367,672	21,408,323

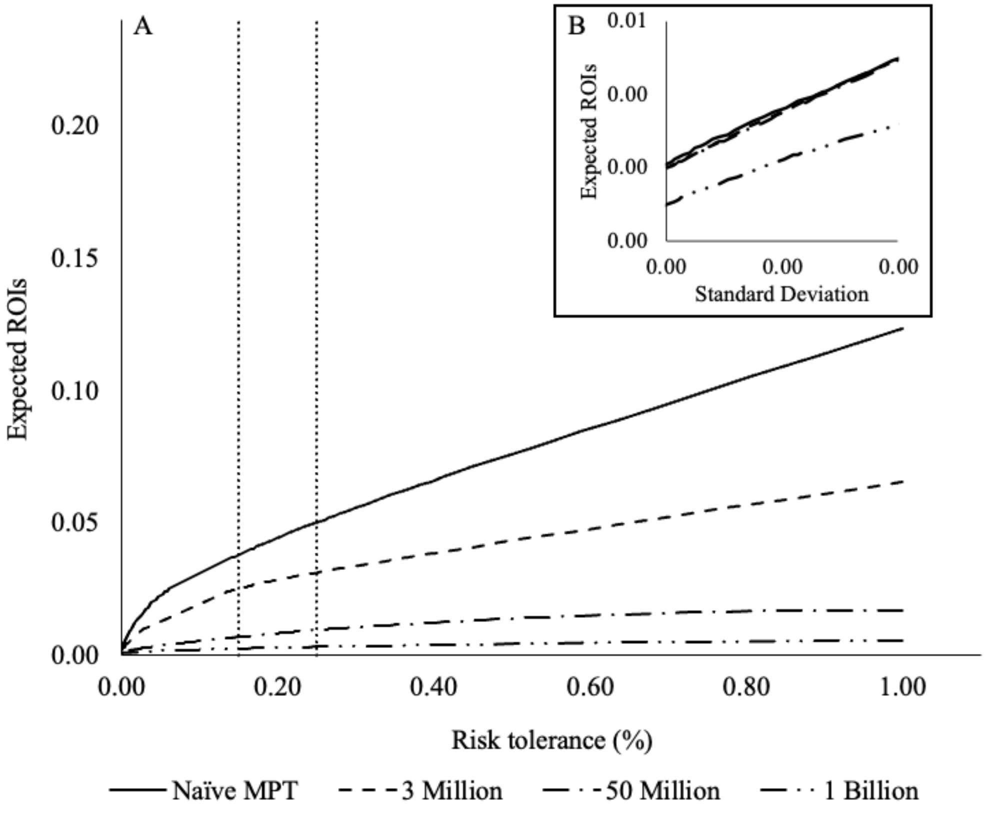

Figure S1. Four Efficient Frontiers of the Expected ROI-Risk Tolerance Relationship for Portfolios from Naïve MPT and Constrained MPT with Three Budgets ($3 million, $50 million, and $1 billion) Using Upper Limits at the Low End of 95% Confidence Interval of Their Probability Density Distributions. (A) Constraints on Asset Returns Lower the Slope of the Frontier at Many Reasonable Risk Tolerance Levels Implying Less Expected ROI Must Be Forfeited to Reduce Risk. (B) Constraints on Asset Returns Also Reduce the Increase in Expected ROI That Can Be Achieved through Risk Diversification

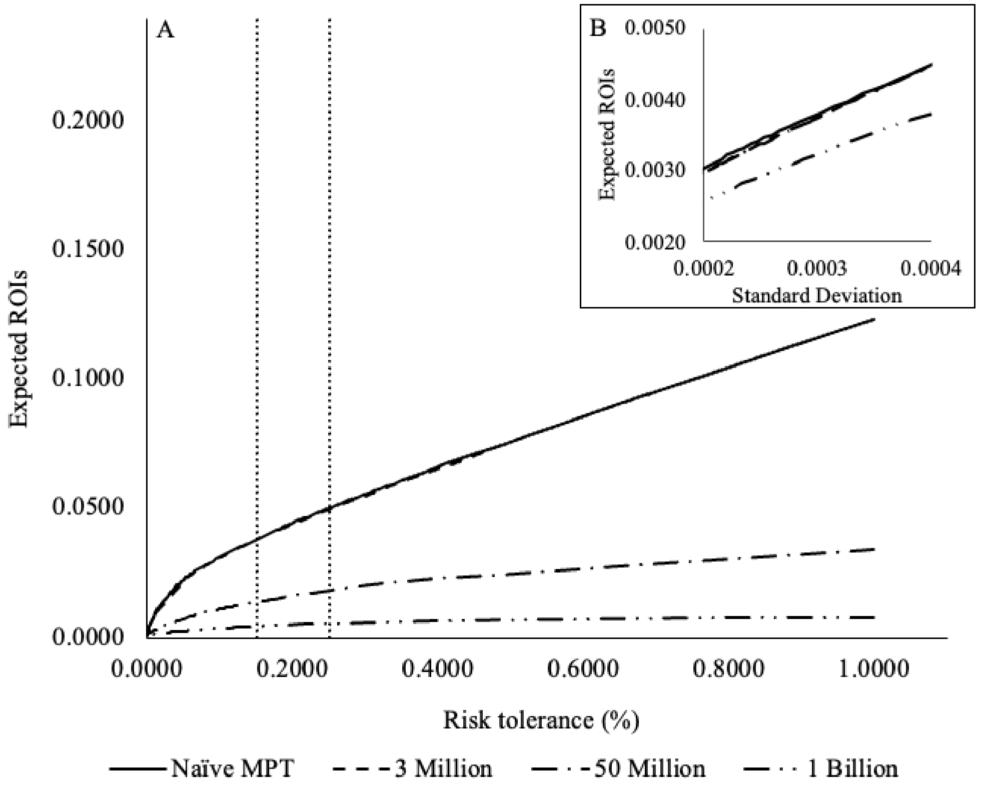

Figure S2. Four Efficient Frontiers of the Expected ROI-Risk Tolerance Relationship for Portfolios from Naïve MPT and Constrained MPT with Three Budgets ($3 million, $50 million, and $1 billion) Using Upper Limits at the High End of 95% Confidence Interval of Their Probability Density Distributions. (A) Constraints on Asset Returns Lower the Slope of the Frontier at Many Reasonable Risk Tolerance Levels Implying Less Expected ROI Must Be Forfeited to Reduce Risk. (B) Constraints on Asset Returns Also Reduce the Increase in Expected ROI That Can Be Achieved through Risk Diversification