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Abstract

Presence of the energy trilemma implies the need for policymakers to make choices among its components. One method to determine the trade-offs among the various components is calculating the optimal energy mix using portfolio theory. In the standard model, the various generating technologies are each associated with two important parameters: the expected rate of return and the risk measured by the variance in the return. Two extensions are made in this paper. First, a third dimension is added to the framework by incorporating the amount of carbon emissions for each type of generating technology. Second, a methodology to select a point (or line) in the optimal frontier is proposed. A welfare function is introduced whose components are the three relevant variables: risk, return, and carbon emissions. The weights of each of these variables reflect the preferences of a hypothetical Department of Energy Secretary. Different combinations of weights will yield different choices which are defined in terms of the shares of the various generation technologies.

Key words: Energy Trilemma, Portfolio Optimization, Generation Mix, Energy Planning, Renewable Energy

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1. Introduction

Renewable energy is leading the transition from a carbon-reliant energy sector to a sustainable energy system (World Energy Council, 2019). The success of the transition relies on policies to manage the three dimensions of the energy trilemma namely, energy security, energy equity and environmental sustainability. The World Energy Council (2019) formally defines the three dimensions of the energy trilemma as follows: (1) energy security reflects a nation's capacity to meet current and future energy demand reliably, withstand and bounce back swiftly from system shocks with minimal disruption to supplies; (2) energy equity assesses a country's ability to provide universal access to affordable, fairly priced and abundant energy for domestic and commercial use; and (3) environmental sustainability represents the transition of a country's energy system towards mitigating and avoiding potential environmental harm and climate change impacts. The challenge for policymakers is how to balance the trade-offs involved in the interplay of these three dimensions.

The Philippines represents a particularly interesting case in the study of the energy trilemma due to its increasing energy demand and dependence on fossil fuel, the high electricity prices, energy access and its greenhouse gases (GHG) emission targets. According to the World Energy Trilemma Report, the Philippines ranked 94th out of 128 countries based on the WEC Trilemma Index with a score of 58.6.[1] The country was given a grade of BCC for the three components of the trilemma and was ranked unfavorably compared with its ASEAN neighbors. The cost of electricity as well as the increasing carbon emissions due to electricity generation are among the factors that explain the low score.

[1] WEC Trilemma Index ranks the countries in their ability to provide sustainable energy based on three dimensions: energy security, energy equity, and environmental sustainability. The ranking measures overall performance in achieving sustainable mix of policies. (Source: https://trilemma.worldenergy.org/)

Using data from the Wholesale Electricity Spot Market (WESM), the research aims to develop a diversified optimal energy mix in the Philippines using portfolio theory. The research considers the interplay between risk, total carbon emissions and expected rate of return of each energy portfolio. It also proposes a methodology which policymakers can adopt in energy systems planning. The methodology considers the different trade-offs of the three dimensions of energy trilemma and identifies which energy portfolios provide the highest welfare.

Review of Related Literature

The energy planning literature proposes two methodologies in selecting power generation assets. The most common methodology, known as the least-cost approach, chooses technology with the lowest cost and evaluates energy generation assets based on the levelized cost of electricity (LCOE[2]). However, the focus on a single criterion in evaluating power generating technologies has been criticized because it gives preference to fossil fuels compared to renewables (deLlano-Paz, Calvo-Silvosa, Antelo and Soares, 2017).

The second methodology addresses the shortcomings of the least-cost approach and frames energy planning as an investment selection problem. The methodology is based on modern portfolio theory. Developed by Nobel laureate Harry Markowitz, the Mean-Variance Theory (MVT) or the Modern Portfolio Theory (MPT) is a mathematical framework used in finance for portfolio selection under uncertainty (Royal Swedish Academy of Sciences, 1990). Unlike traditional portfolio theory, MPT emphasizes diversification, evaluating the portfolios on a risk-return perspective, and selecting the most efficient allocation of assets.

[2] The National Renewable Energy Laboratory (NREL) describes the Levelized Cost of Electricity (LCOE) as the lifetime cost of the energy system including initial investment, operations and maintenance, cost of fuel, cost of capital.

Bar Lev and Katz (1976) pioneered the use of MPT in energy planning. Using 1969 U.S. regional data, they generated an efficient portfolio of fuel mixes and compared it with actual data from electric utilities. They found that although the portfolios are diversified they are characterized by a relatively high rate of risk and return.

Humpreys and McClaim (1998) proposed the use of GARCH models to generate an efficient portfolio frontier that allows time-varying covariance matrix that can generate more realistic and efficient estimates. This addressed the shortcomings of the Bar-Lev and Katz's methodology. The study focused on finding an energy mix that can reduce the risk of energy price shocks in the U.S. economy. In contrast to the findings of Bar-Lev and Katz, they noted that the U.S. is not operating efficiently and are following a risk aversion strategy due to their position close to the minimum variance. To reduce price volatility, they suggested increasing coal generation in the energy mix.

Awerbuch and Berger (2003) applied the MPT on current and projected European Union (EU) data to develop energy portfolios that exhibit lower cost and risk. They found that current and projected EU generation mixes are inefficient from a risk-return perspective and a more diversified energy generation portfolio with renewables is more cost-effective compared to a fuel-dominated mix.

Arnesano et al. (2012) applied the portfolio theory to generate energy portfolios that will reduce cost and risk and promote environmental sustainability in the Italian energy sector. Improving on the model developed by Awerbuch (2003), Awerbuch and Berger(2003), and Awerbuch, Jansen, and Beurskens (2006), they quantified the contributions of renewables in the energy generation mix. Their results showed that increasing the contribution of RE in the portfolio mix will reduce costs.

Similarly, Stempien and Chan (2017) tried to address the energy trilemma in energy planning by extending the model of Awerbuch and Berger (2003). To quantify the environmental sustainability aspect of the trilemma, they introduced the expected return on emissions in their framework. Their objective was to maximize the rate of return(equity) and the return on emission (environmental sustainability) while reducing risk (energy security). Using Singapore as a case study, they found that while the generation mix of Singapore at that time was optimal, it was biased against energy security. They also determined that portfolios with a greater share of solar technology are more sustainable and provided more energy security.

In the Philippines, a recent study by Balanquit and Daway-Ducanes (2018) applied the portfolio optimization theory to generate portfolios and find the optimal generation mix. Their aim was to find an efficient generation mix that will address energy security, price stability and clean energy. The result suggests that the actual energy mix in the Philippines in 2017 (50% from coal, 30% natural gas and 20% RE) was inefficient. A move towards increasing RE and decreasing coal would produce a more efficient generation portfolio with a higher rate of return at the same level of risk. However, Yap, Gabriola, and Herrera (2020) pointed out that the methodology used by Balanquit and Daway-Ducanes only partially addressed the aspects of the energy trilemma as it did not quantify the impacts of carbon emissions in their model.

This study tries to fill the gap by extending the methodology of Balanquit and Daway-Ducanes. The impact of carbon emissions is quantified and enables the analysis of the interplay among risk, return, and total carbon emissions. This paper then develops a tool that allows policymakers to evaluate energy generation portfolios in the framework of the energy trilemma.

Theoretical Framework and Empirical Results

In their study, Balanquit and Daway-Ducanes (2018) consider eight generating technologies, each associated with two important parameters: the expected rate of return r_i and the risk measured by the variance in the return. These parameters are both derived from the technology's daily power price (PP) ratio, defined as the amount of energy sold or discharged over its average price.

$$r_i = E\left[\frac{PP_{it} - PP_{i(t-1)}}{PP_{i(t-1)}}\right], \tag{1}$$

$$\sigma_i^2 = E\left[\left(\frac{PP_{it} - PP_{i(t-1)}}{PP_{i(t-1)}}\right)^2\right] - r_i^2 \tag{2}$$

$$E(r) = \sum_{i=1}^{8} \alpha_i r_i \tag{3}$$

where $\alpha_i \in (0,1)$ is the share of technology i and that $\sum_i \alpha_i = 1$.

On the other hand, the expected portfolio risk is given by:

$$Var(r) = \sum_{i=1}^{8} \alpha_i \sigma_i^2 + 2 \sum_{1 \leq i \leq j \leq 8} \alpha_i \alpha_j \sigma_{ij} \tag{4}$$

where σ_{ij} is the covariance of two distinct technologies i and j. The methodology then adopts the approach of Markowitz (1952) by minimizing a given portfolio's risk for every targeted rate of return r. The problem can be depicted as:

$$\min_{\alpha_i \in [0,1]} Var(r) = \sum_{i=1}^{8} \alpha_i^2 \sigma_i^2 + 2 \sum_{1 \le i \le j \le 8} \alpha_i \alpha_j \sigma_{ij} \tag{5}$$

$$\text{s.t. } \sum_{i=1}^{8} \alpha_i r_i = \bar{r} \tag{6}$$

$$\sum_{i=1}^{8} \alpha_i = 1 \tag{7}$$

The procedure will yield optimal shares of each type of technology. A set of optimal portfolios can be depicted on the return-risk plane (Figure 1). The curve is the optimal portfolio frontier. Any point to the left is infeasible while any point to the right is considered sub-optimal.

Figure 2 shows the equivalent of Figure 1 using hourly generation data from February to May 2020 in Luzon from the Wholesale Electricity Spot Market (WESM). This was constructed using a simulation-based optimization procedure (see Box 1). Following the methodology of Balanquit and Daway-Ducanes (2018) to generate the PP ratio—the amount of energy generated per ₱1 of investment—data including market prices and schedules, marginal plants and market bids and offers were applied. This variable was used to derive the expected rate of return and variance of the portfolio as described in Equations (1) and (2). Applying the Markowitz portfolio theory, a set of efficient mixes were derived to generate an optimal portfolio frontier on the risk-return plane.

The study of Stempien and Chan (2017) incorporates "sustainability" by adding another variable in the model: the expected return on emissions in terms of energy per unit of CO_2, i.e.

kWh per ton of CO_2. Instead of having a two-dimensional optimal portfolio frontier, the efficient plane is as depicted in Figure 3. The three dimensions represent the constraints imposed by the trilemma under which the portfolio is optimized.

To incorporate environmental sustainability in the Balanquit-Daway study, the following equation is added to the optimization problem shown in Equations 5-7:

$$TC = \sum_{i=1}^{n} \propto_i EC_i \tag{8}$$

where TC is the total carbon emissions, $\propto_i$ is the share of technology i in the energy mix, E is the total energy generated and C_i is the carbon emission released per MW of electricity generated by source i. Because there are no standard values for C used in the literature, emissions data from various sources such as the U.S. Energy Information Administration (EIA) and the Intergovernmental Panel on Climate Change (IPCC) were adopted. Table 1 summarizes the amount of carbon released according to generation technology used. Coal emits 1,100 gCO_2 per kWh while renewables such as wind and solar have the lowest emissions during energy generation.

Figures 4 and 5 present the optimal portfolio frontier of the Philippines in the emissions-risk and emissions-return planes, respectively. The parabolic shape of the frontiers can be explained by the sharp fall of emissions as the share of fossil-fuel based sources declines.

When conducting the simulation-based simulation, additional constraints were imposed on the model. First, a floor was set for the share of coal, i.e. $\propto_{Coal} \geq 0.30$. This reflects the requirement for the system to have a reliable baseload capacity. This constraint can be modified when, for example, solar and wind energy sources become more cheaply dispatchable with lower cost battery storage.

The second constraint is a cap on both hydropower and geothermal sources. Both are not widely available in the Philippines. The relevant constraints are $\propto_{Hydro} \leq 0.30$ and $\propto_{Geothermal} \leq 0.10$. These constraints can readily be modified as technology evolves.

Operationalizing the Framework

Neither the study of Balinquit and Daway-Ducanes nor that of Stempien and Chan provides a mechanism to choose among the options along the optimal portfolio frontier. This can be achieved by specifying a set of indifference curves—or planes in the multi-dimensional case. This is depicted in Figure 6.[3] A similar figure can be constructed for the emissions-risk and emissions-return planes. The indifference curve can be considered as the equivalent of a Welfare Function that is a combination of return (r), risk (σ), and amount of carbon emissions (T*C*) or:

$$W = r^{\delta}\ \sigma^{\beta} TC^{\gamma} \tag{9}$$

The parameters δ, β, and γ can be determined using any of the techniques under Multiple-criteria decision-making (MCDM). Box 2 provides an overview of MCDM. Assuming values of the parameters have been calculated, Point A in Figure 6 gives the maximum value of W assuming TC is constant or given. The optimal values of r and σ are r* and σ* respectively. The maximum value W_A* is:

$$W_A^* = r^{*\delta}\ \sigma^{*\beta}\ TC^{\gamma} \tag{10}$$

[3] This digression is necessary because while it is straightforward to specify the functional form of W, the functional form of the optimal frontier is not readily obtained from the empirical data.

For this paper, a similar simulation-based optimization procedure to obtain the frontier was applied to obtain W* (see Box 1). The results for various combinations of the parameters are presented in Table 2. These results are obtained without the aforementioned constraints. Hence, the share of hydro power reaches 90% in most scenarios. If lower emissions receives a high priority, the share of variable renewable energy, i.e. solar and wind combined, reaches 90%. These results are optimal but not feasible.

The results with constraints on the share of coal, geothermal and hydro power are shown in Table 3. The constraints apparently restrict the solution to a fixed point. A more robust simulation methodology has to be implemented before these results are deemed acceptable.

Similar to the argument of Yap, et al. (2020), the parameters reflect the revealed preference of a hypothetical Secretary of the Department of Energy. The choice of the optimal mix would depend on his preferences.

Conclusion

This paper extends the application of MPT on energy generation planning by adding carbon emissions in the framework. By quantifying the impact of GHG emissions, the environmental sustainability dimension of the energy trilemma is addressed. In addition, a welfare function is introduced which allows the energy planner to select a portfolio based on his/her set of preferences.

The findings from the simulations suggest that under unconstrained optimization, a higher share of hydro power results in a more efficient energy mix. Under a scenario wherein lower carbon emissions is a priority, 52% of solar and 38% of wind energy generates the highest welfare. Allowing constraints on coal, hydro and geothermal fixes the solution for all scenarios to a portfolio with 40% biomass, 30% coal and 30% hydro power.

The use of more complete spot market data which covers several years and a more robust simulation methodology for constrained optimization will likely produce a more realistic scenario for energy planning. The paper achieves the minimal objective of explaining an alternative methodology to manage the energy trilemma.

Box 1: Simulation-based Optimization

Carter, Dare and Elliot (2002) developed a model to solve for the mean-variance efficient portfolio using Microsoft excel. Their procedure aims to address the tedious mathematical computation in applying the Markowitz portfolio theory in optimization. The framework is adapted in this study to generate an efficient portfolio frontier. Following this model, the return for each generation asset i at time t is calculated as follows:

$$R_{i,t} = \frac{PP_{i,t} - PP_{i,t-1}}{PP_{i,t-1}} \quad (11)$$

where $R_{i,t}$ is the return on technology i at time t and PP is the power-price ratio. To generate the return on the portfolio, the sum product (SUMPRODUCT) function is applied as follows:

$$Portfolio\ Return = SUMPRODUCT(w, \mu) \quad (12)$$

where w is a vector of weights and μ is a vector of average returns. The SUMPRODUCT function calculates the sum of the products of the weights of each electricity generation asset and its mean (expected) returns.

To get the portfolio risk, a variance-covariance matrix (VCM) is constructed using the Data Analysis tool. The matrix contains the variance of each generation asset in the main diagonal together with the pair-wise covariance between technologies. Next, the matrix multiplication (MMULT) function is applied to calculate the portfolio variance:

$$Portfolio\ Variance = MMULT(TRANSPOSE(w), MMULT(VCM, w)) \quad (13)$$

With the computed portfolio return and variance, the excel solver tool can find any point on the efficient frontier and provide the energy mix that minimizes the variance. Setting different target returns will generate other points on the efficient portfolio frontier.

The total emissions generated per portfolio is calculated as follows:

$$TC = PRODUCT\ (\propto_i, E, C_i) \quad (14)$$

where TC is the total carbon emissions, $\propto_i$ is the share of technology i in the energy mix, E is the total energy generated and C is the carbon emission released per MW of electricity generated.

To reflect the negative relationship between welfare-emissions and welfare-risk, the reciprocals of C and σ were incorporated in the welfare function. The data on returns was normalized to convert the values of the dataset to a common scale, without distorting differences in the ranges of values.

$$W = r^{\delta} \left(\frac{1}{\sigma}\right)^{\beta} \left(\frac{1}{C}\right)^{\gamma} \tag{5}$$

For the baseline model, the parameters $\delta, \beta,$ and γ were assigned equal weights and welfare was calculated for each portfolio as follows:

$$W_{BM} = PRODUCT \left(r^{\frac{1}{3}}, \left(\frac{1}{\sigma}\right)^{\frac{1}{3}}, \left(\frac{1}{C}\right)^{\frac{1}{3}} \right) \tag{6}$$

To present the impact of an energy planner's preference, $\delta, \beta,$ and γ were adjusted to different values as shown in Table 2. The values of W is optimized by applying a similar methodology used with the excel solver tool described above.

Box 2: Multiple-criteria decision-making (MCDM)

Multiple-criteria decision-making (MCDM) or multiple-criteria decision analysis (MCDA) is a sub-discipline of operations research that explicitly evaluates multiple conflicting criteria in decision making. The literature identifies many methods to implement MCDM, particularly in giving weights to the criteria involved. Among the methods are: Aggregated Indices Randomization Method (AIRM), Analytic hierarchy process (AHP), Analytic network process (ANP), Balance Beam process, Base-criterion method (BCM), Best worst method (BWM), Brown–Gibson model, etc.

A relatively complicated process is the Stochastic Multi-criteria Acceptability Analysis or SMAA (Lahdelma and Salminen, 2010). This is a family of methods for aiding multi-criteria group decision making in problems with uncertain, imprecise or partially missing information. These methods are based on exploring the weight space in order to describe the preferences that make each alternative the most preferred one, or that would give a certain rank for a specific alternative. The main results of the analysis are rank acceptability indices, central weight vectors and confidence factors for different alternatives. The rank acceptability indices describe the variety of different preferences resulting in a certain rank for an alternative, the central weight vectors represent the typical preferences favoring each alternative, and the confidence factors measure whether the criteria measurements are sufficiently accurate for making an informed decision.

SMAA was applied to the energy trilemma by Song et al. (2017). The different alternatives were evaluated based on three criteria which are the components of the trilemma. As an exercise, the authors used as alternatives the top ten countries based on the 2015 Energy Trilemma Index. Exact weights of the three criteria were not derived but these can be inferred from the reported rank acceptability indices.

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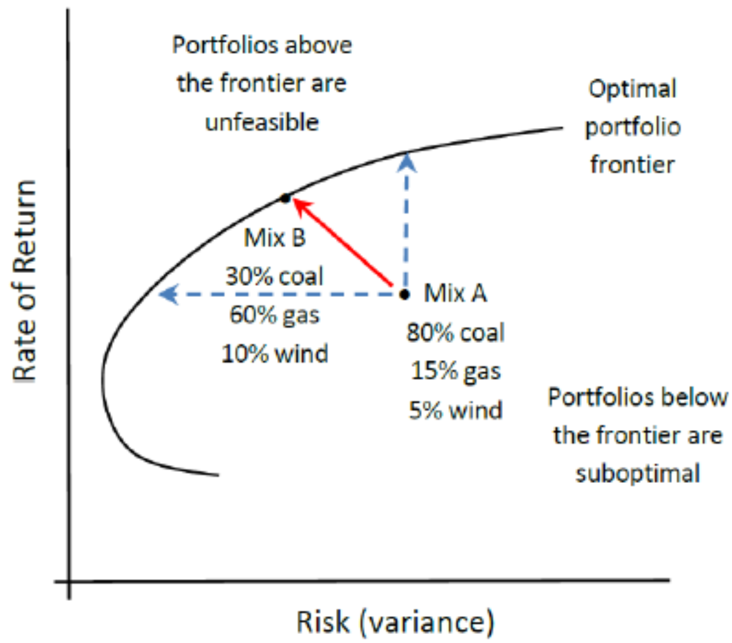
Figure 1: An example of an optimal portfolio frontier



Source: Figure 1 of Balanquit and Daway-Ducanes (2018).

Figure 2: Risk-return frontier using Philippine data

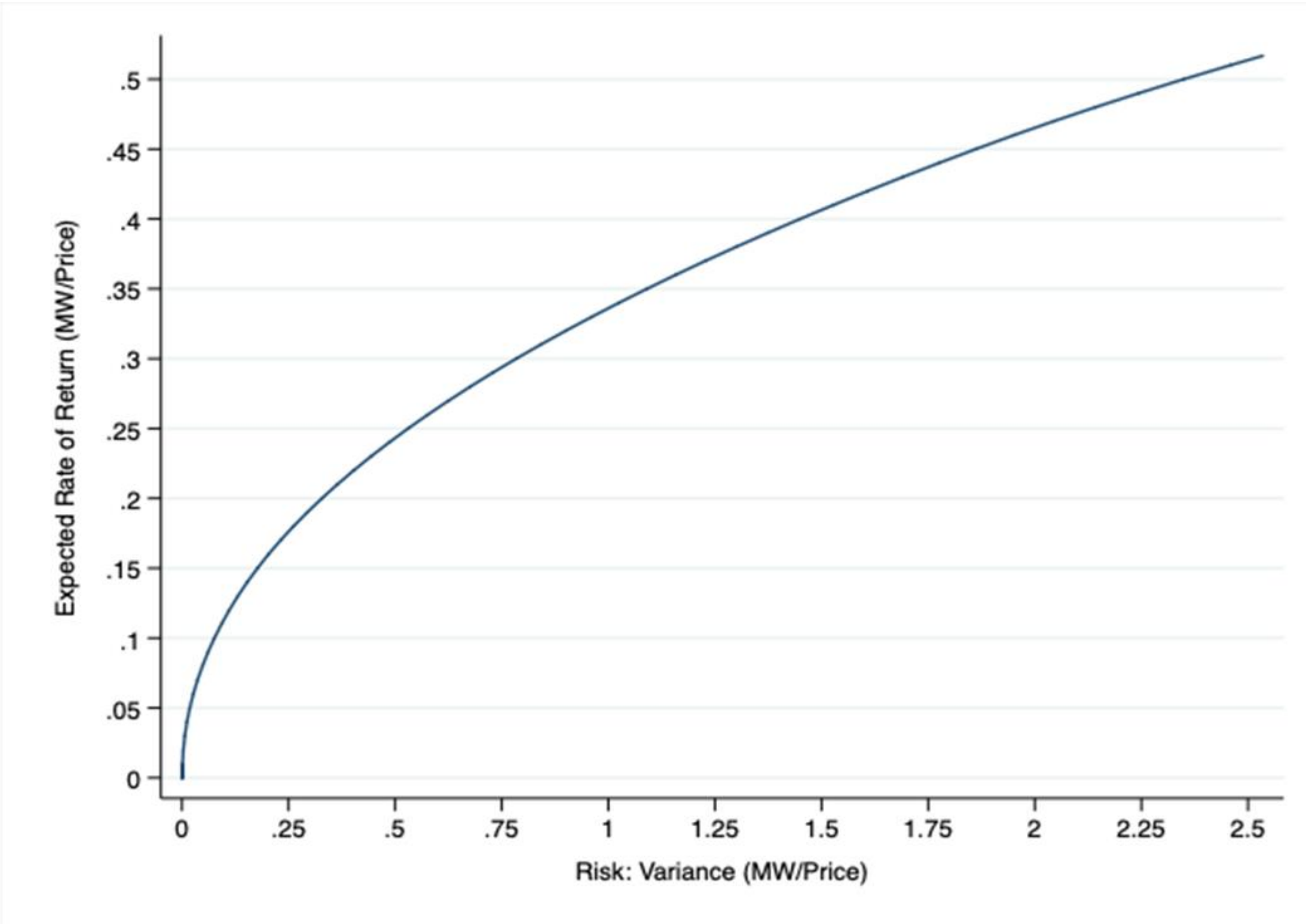
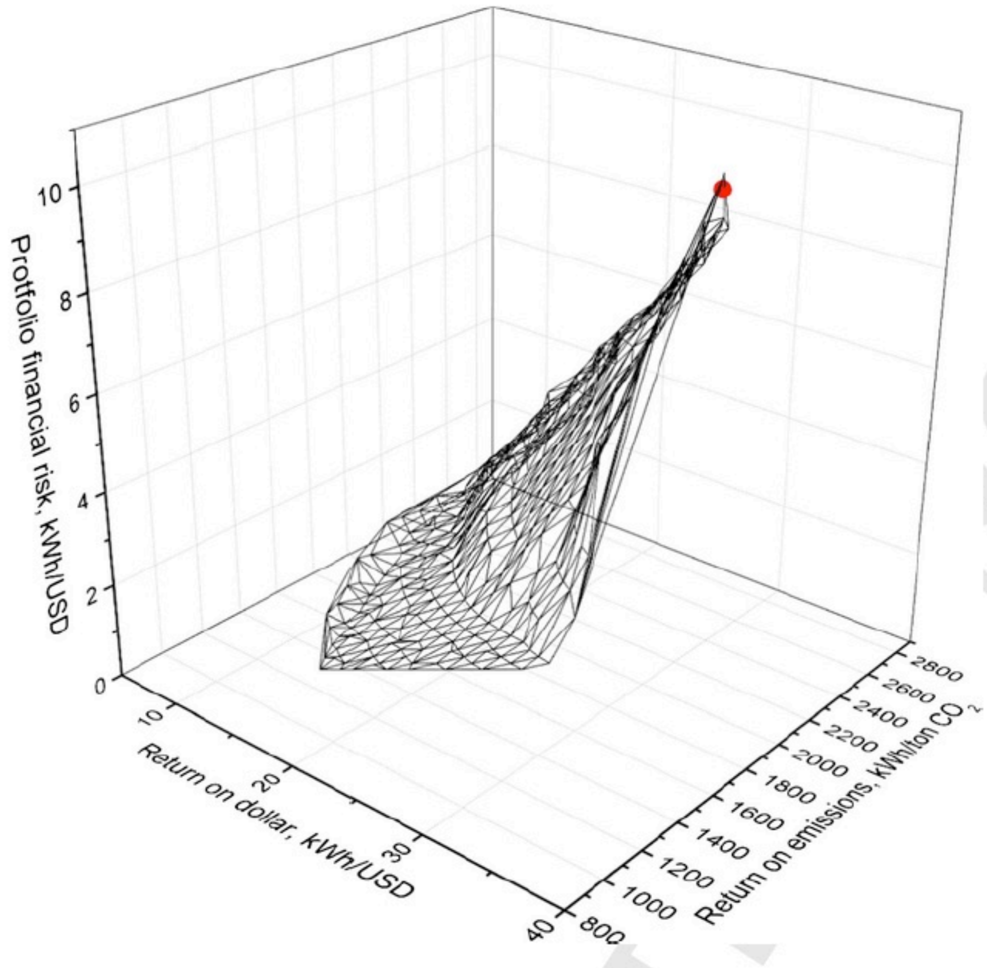


Figure 3: Modified Markowitz theory of energy portfolio optimization



Source: Figure 2 of Stempien and Chan (2017).

Figure 4: Emissions-Risk frontier using Philippine data

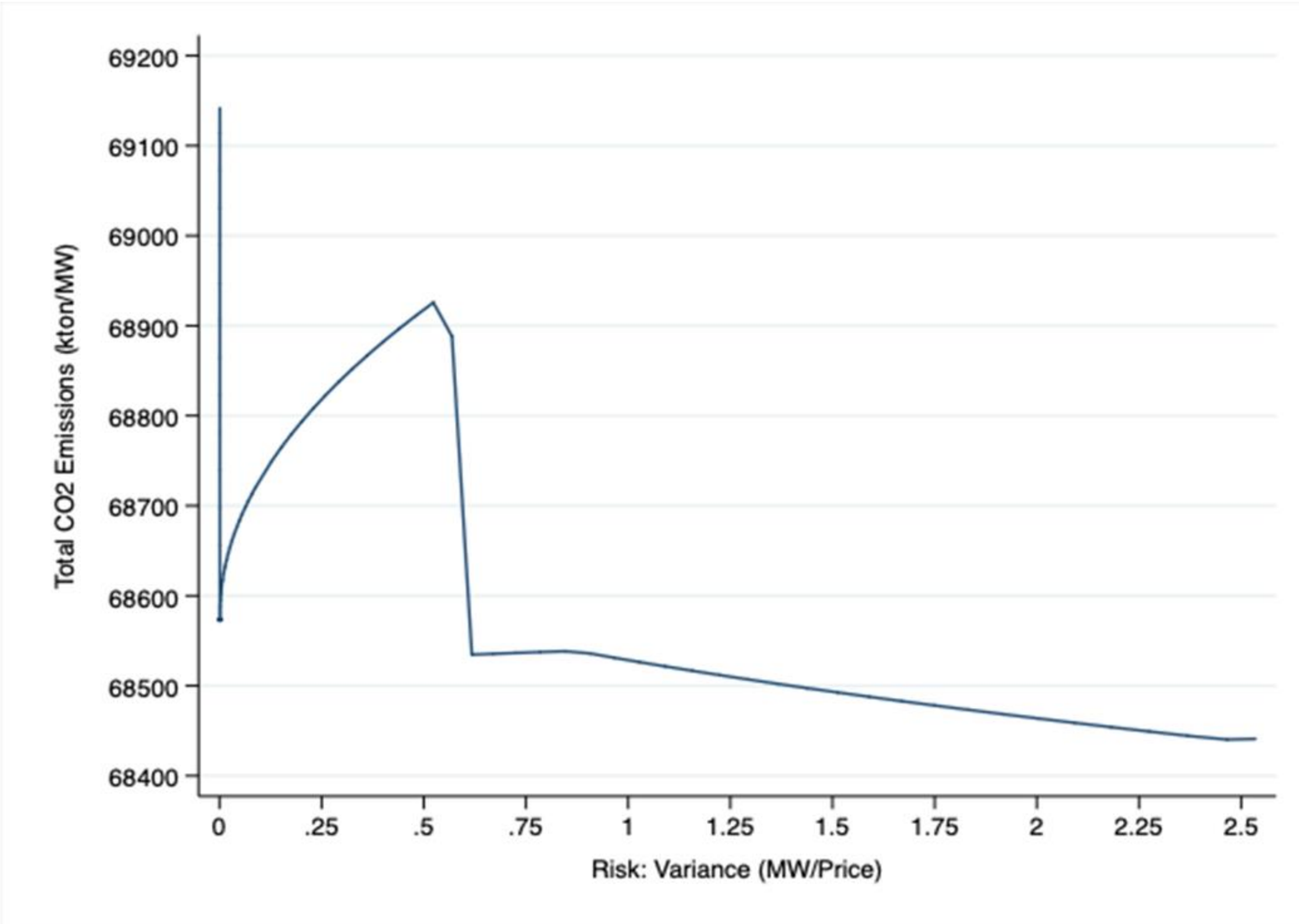


Figure 5: Emissions-Return frontier using Philippine data

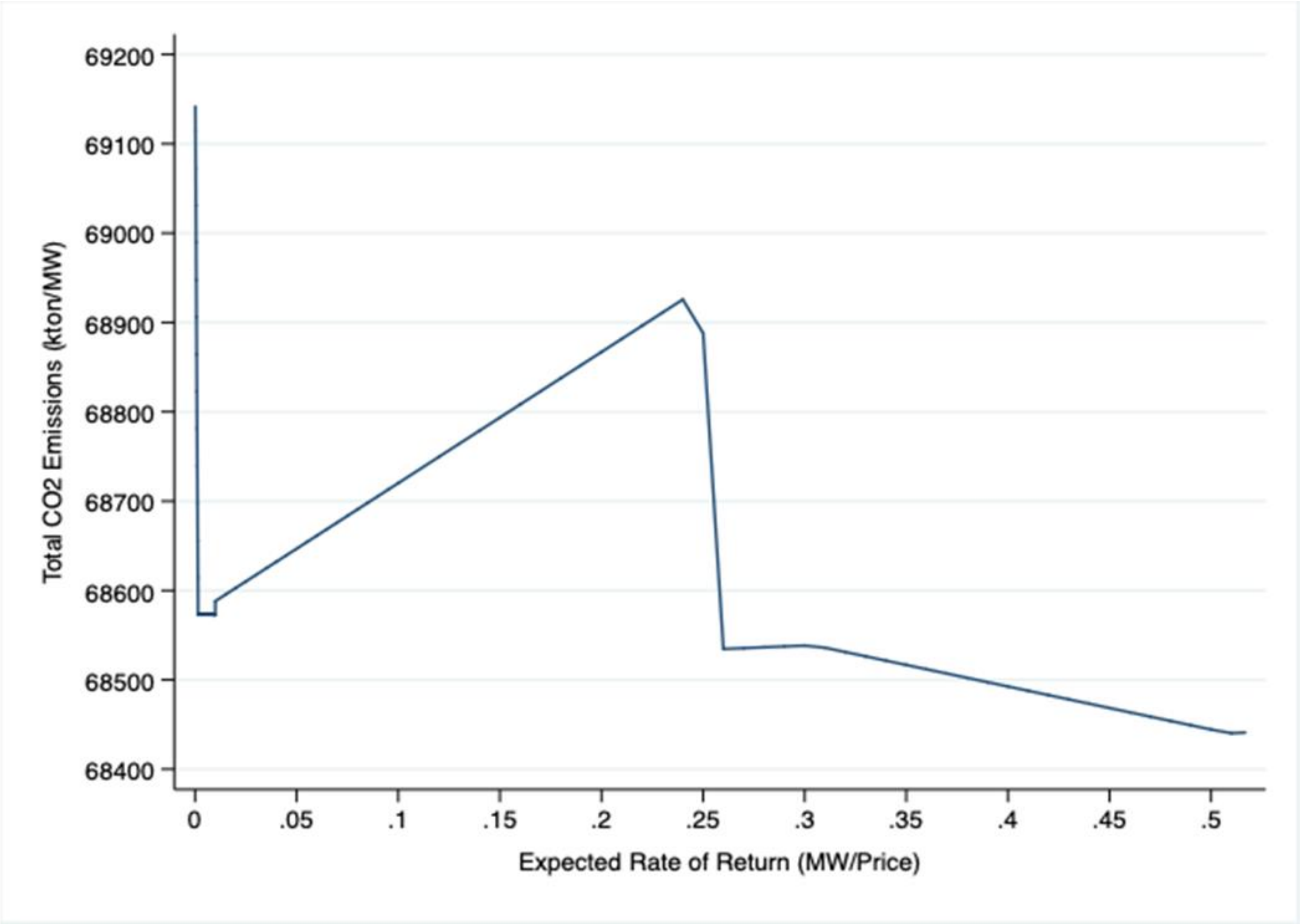


Figure 6: Equilibrium (point A) between optimal portfolio frontier and the indifference curves of the hypothetical DOE Secretary

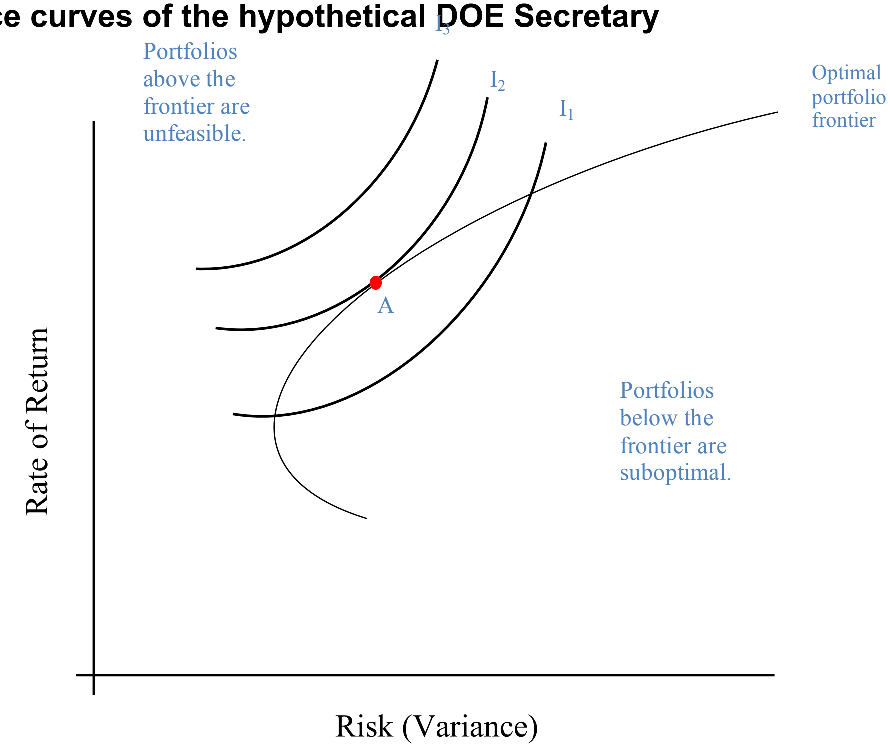


Table 1: Carbon Emissions per kWh of Electricity Generated

Technology	Emissions (gCO2 per kWh)
Solar[a]	42
Wind[a]	23
Coal[a]	1100
CCPP[d]	150
Hydro[a]	31
Bioenergy[b]	67
Natural Gas[c]	450
Geothermal[a]	250
Diesel[e]	278

Sources:

[a] *From Natural Gas and Power Production Presentation by Timothy J. Skone at the 2015 EIA Energy Conference (https://www.eia.gov/conference/2015/pdf/presentations/skone.pdf)*

[b] *Weisser, D. (2007). A guide to life-cycle greenhouse gas (GHG) emissions from electric supply technologies. Energy, 32(9), 1543-1559.*

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[d] *Bruckner T., I.A. Bashmakov, Y. Mulugetta, H. Chum, A. de la Vega Navarro, J. Edmonds, A. Faaij, B. Fungtammasan, A. Garg, E. Hertwich, D. Honnery, D. Infield, M. Kainuma, S. Khennas, S. Kim, H.B. Nimir, K. Riahi, N. Strachan, R. Wiser, and X. Zhang, 2014: Energy Systems. In: Climate Change 2014: Mitigation of Climate Change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Edenhofer, O., R. Pichs-Madruga, Y. Sokona, E. Farahani, S. Kadner, K. Seyboth, A. Adler, I. Baum, S. Brunner, P. Eickemeier, B. Kriemann, J. Savolainen, S. Schlömer, C. von Stechow, T. Zwickel and J.C. Minx (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.*

[e] *Guidelines for Estimating Greenhouse Gas Emissions of Asian Development Bank Projects (https://www.adb.org/sites/default/files/institutional-document/296466/guidelines-estimating-ghg.pdf)*

Table 2: Shares of Each Generation Asset with the Highest Welfare per Scenario (unconstrained)

	Biomass	CCPP	Coal	Diesel	Geothermal	Hydro	Natural Gas	Solar	Wind
Baseline Model $\boldsymbol{\delta = \frac{1}{3}, \beta = \frac{1}{3}, \gamma = \frac{1}{3}}$	3.9	1.0	0.0	0.1	3.1	90.0	1.9	0.02	0.0
Scenario 1: Preference for Lower Risk $\boldsymbol{\delta = \frac{6}{10}, \beta = \frac{1}{10}, \gamma = \frac{3}{10}}$	3.9	1.0	0.0	0.1	3.1	90.0	1.9	0.02	0.0
Scenario 2: Preference for Lower Emissions $\boldsymbol{\delta = \frac{1}{10}, \beta = \frac{1}{10}, \gamma = \frac{8}{10}}$	0.0	0.0	0.0	10.0	0.0	0.0	0.0	51.5	38.4
Scenario 3: Preference for Higher Return $\boldsymbol{\delta = \frac{1}{10}, \beta = \frac{6}{10}, \gamma = \frac{3}{10}}$	3.9	1.0	0.0	0.1	3.1	90.0	1.9	0.02	0.0

Source: Authors's calculations.

Table 3: Shares of Each Generation Asset with the Highest Welfare per Scenario (constrained)

	Biomass	CCPP	Coal	Diesel	Geothermal	Hydro	Natural Gas	Solar	Wind
Baseline Model $\boldsymbol{\delta = \frac{1}{3}, \beta = \frac{1}{3}, \gamma = \frac{1}{3}}$	39.67	0.01	30.0	0.04	0.0	30.0	0.0	0.26	.01
Scenario 1: Preference for Lower Risk $\boldsymbol{\delta = \frac{6}{10}, \beta = \frac{1}{10}, \gamma = \frac{3}{10}}$	39.67	0.01	30.0	0.04	0.0	30.0	0.0	0.26	.01
Scenario 2: Preference for Lower Emissions $\boldsymbol{\delta = \frac{1}{10}, \beta = \frac{1}{10}, \gamma = \frac{8}{10}}$	39.65	0.012	30.0	0.042	0.0	30.0	0.0	0.27	.01
Scenario 3: Preference for Higher Return $\boldsymbol{\delta = \frac{1}{10}, \beta = \frac{6}{10}, \gamma = \frac{3}{10}}$	39.64	0.012	30.0	0.044	0.0	30.0	0.0	0.29	.01

Source: Authors's calculations.

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