A MEAN-VARIANCE PORTFOLIO OPTIMIZATION OF CALIFORNIA'S GENERATION MIX TO 2020:

ACHIEVING CALIFORNIA'S 33 PERCENT RENEWABLE PORTFOLIO STANDARD GOAL

DRAFT CONSULTANT REPORT

Prepared For:
California Energy Commission

Prepared By:
Bates White, LLC.

July 2007
CEC-300-2007-009D

Prepared By:
Bates White, LLC
Jonathan Lesser
Paul Lowengrub
Spencer Yang
Washington, DC
Contract No. 500-04-027

Prepared For:

California Energy Commission

Rachel Salazar
Contract Manager

Bill Knox
Project Manager

Mark Hutchison
Office Manager
Renewable Energy Office

Valerie Hall
Deputy Director
Efficiency and Renewables Division

B. B. Blevins
Executive Director

ABSTRACT

Keystones of California's energy policy include strategies to ensure adequate energy resources, reduce energy demand, develop alternative energy sources, keep ratepayer costs reasonble, and improve the state's infrastructure. With the passage in 2006 of the California's Global Warming Solutions Act, reducing California's greenhouse gas emissions has become a critical policy driver. Increasing the use of renewable energy to 33 percent in 2020 is a significant step toward reducing emissions. Although California's electric utility resource planning guidelines incorporate risk assessment and scenario analyses, they do not capture important cost/risk inter-relationships that dramatically affect estimated overall costs and risks associated with alternate portfolios of generating resources. To remedy this limitation, a apply mean-variance portfolio theory is applied to create low risk, high return portfolios under various economic conditions. The results of the analysis indicate that compared to the projected 2020 California "business as usual" generating portfolio, there are other potential portfolios that have lower expected costs, less cost risk, and substantially reduced CO_2 emissions and energy import dependency. The analysis suggests that an optimal generating portfolio for California includes greater shares of renewable resource technologies, which may cost more on a stand-alone basis but reduce overall portfolio costs and risks because of their diversification effects.

KEYWORDS

Portfolio analysis, generation mix, renewable energy, electricity planning, fuel prices, energy risks

TABLE OF CONTENTS

INDEX OF FIGURES

INDEX OF TABLES

EXECUTIVE SUMMARY

Keystones of California's energy policy include strategies to ensure adequate energy resources, reduce energy demand, develop alternative energy sources, keep ratepayer costs reasonable, and improve the state's infrastructure. With the passage in 2006 of the Global Warming Solutions Act[1], reducing California's greenhouse gas emissions has become a critical policy driver. Increasing the use of renewable energy to 33 percent in 2020 is a significant step toward reducing emissions. There is little debate on the use of renewable generating technologies as an effective means for climate change mitigation. Policy makers, consumers, and companies, however, are wary because of the widespread perception that these technologies cost more than conventional alternatives so that increasing their deployment will raise overall electricity generating costs.

Although California's electric utility resource planning guidelines incorporate risk assessment and scenario analyses, they do not incorporate portfolio risk. Sensitivity analysis cannot replicate the important cost/risk inter-relationships that dramatically affect estimated portfolio costs and risks, and thus it is no substitute for portfolio-based approaches described in this report. For example, despite significant fuel price volatility, gas-fired resources continue to be added at levels that do not meaningfully reduce California's reliance on natural gas. This results in greater exposure to future electricity price risk and CO_2 risk for California electricity consumers. Renewable resources represent lower risk alternatives to gas-fired resources. However, because portfolio risk has not been incorporated into electricity generation long-term resource planning, the value of this risk reduction is not being fully considered in either the state's procurement or long-term planning processes.

Given this uncertain environment, it makes sense to shift electricity planning from its current emphasis on evaluating alternative technologies to evaluating alternative electricity generating portfolios and strategies. The techniques for doing this are rooted in modern finance theory – in particular mean-variance portfolio theory. Portfolio analysis is widely used by financial investors to create low risk, high return portfolios under various economic conditions. In essence, investors have learned that an efficient portfolio takes no unnecessary risk to its expected return. In short, these investors define efficient portfolios as those that maximize the expected return for any given level of risk, while minimizing risk for every level of expected return.

By applying these concepts, the expected cost and, more importantly, the potential cost risk of California's projected 2020 "business-as-usual" electric generating mix[2], can be evaluated in an environment of uncertain CO_2 prices. These concepts are also applied to identify additional generation portfolios that had lower expected costs and less cost risk than the business-as-usual mix. The resulting optimal portfolios represent various least-cost and risk combinations that can be used as a benchmark to evaluate other alternative generating strategies that will achieve the state's renewable energy goal of 33 percent in 2020 while simultaneously reducing CO_2 emissions.

Findings

A key finding of this report is that, compared to the projected 2020 California business-as-ususal electricity generating portfolio, there exist portfolios that are less risky, less expensive, and that substantially reduce CO_2 emissions and energy import dependency. The analysis suggests that an optimal generating portfolio for California includes greater shares of renewables technologies that may cost more on a stand-alone basis, but overall portfolio costs and risks are reduced because of the effect of portfolio diversification. Though counter-intuitive, the idea that adding more costly renewables can actually reduce portfolio-generating cost is consistent with the basic finance theory. Optimal generating portfolio mixes also enhance California's energy security. The analysis further suggests that the optimal 2020 generating portfolios not only achieve California's 33 percent Renewable Portfolio Standard (RPS) goal but also reduce overall electricity generating cost, market risks and CO_2 emissions relative to the projected 2020 California BAU mix.

Perhaps the single most important lesson of the portfolio optimization analysis is that adding a non-fossil fuel, fixed-cost technology (such as wind energy) to a risky generating portfolio lowers expected costs at any level of risk, even if the non-fossil technology costs more when assessed on a stand-alone basis. This underscores the importance of policy-making approaches grounded in portfolio concepts as opposed to stand-alone engineering concepts. In addition, adding "too much" renewables counter-intuitively increases (not decreases) resulting portfolio risk because it replaces less risky existing technology with more risky new technology and it reduces overall portfolio diversification.

It is important, however, to recognize that the mean-variance portfolio approach has several important limitations with respect to generation planning. The portfolio optimization presented in this paper does not define any specific capacity-expansion plan. Such a plan would require far more detailed modelling and analysis. The results presented here are largely expositional, but demonstrate the value of portfolio optimization approaches and suggest that capacity planning made on the basis of stand-alone technology costs will likely lead to economically inefficient outcomes.

CHAPTER 1: INTRODUCTION

Objective

This report applies portfolio-theory concepts from the field of finance to long-term electric generation planning. By applying these concepts, it is possible to evaluate the expected cost and, more importantly, the potential cost risk of a "business-as-usual" (BAU) electric generating mix, in an environment of uncertain CO_2 prices. For this report, BAU is defined as a mix that incorporates 20 percent renewable energy, with the expectation of achieving all predicted energy efficiency from currently funded programs.

These concepts also allow identification of additional generation portfolios with lower expected costs and less cost risk than the BAU mix. The resulting optimal portfolios represent various least-cost and risk combinations that can be used as a benchmark to evaluate other alternative generating strategies that will achieve the state's 33 percent RPS goal in 2020 while simultaneously reducing CO_2 emissions.

Although California's electric utility resource planning incorporate risk assessment and scenario analyses, they do not incorporate portfolio risk. Sensitivity analysis cannot replicate the important cost/risk inter-relationships that dramatically affect estimated portfolio costs and risks, and thus is no substitute for portfolio-based approaches described in this report. For example, despite significant fuel price volatility, gas-fired resources continue to be added at levels that do not meaningfully reduce California's reliance on natural gas. This results in greater exposure to future electricity price and CO_2 risk for California electricity consumers. Renewable resources represent lower risk alternatives to gas-fired resources. The value of this risk reduction is not captured in the state's current procurement or long-term planning processes.

Another potential problem is a failure to fully account for the benefits of generation portfolio diversification and renewables technology deployment. In deregulated markets, individual power producers evaluate only their own direct costs and risks in making investment decisions. These decisions do not reflect the overall market impacts of the individual generation technology investment decisions. Renewables investors, for example, may be unable to fully capture the risk-mitigation benefits they produce for the overall portfolio, which leads to under-investment in renewables technology relative to levels that are optimal from society's perspective. By contrast, some investors may prefer the risk menu offered by fuel-intensive technologies such as combined-cycle gas turbines (CCGT), which have low initial costs. Regulated utilities are able to transfer fuel risks onto customers using fuel adjustment clauses. Thus, these investors do not bear the full risk effects they impose onto the generating mix, which may lead to over-investment in gas relative to what is optimal from a total portfolio perspective. All this suggests a rationale for economic policies, such as California's 33 percent RPS goal,[3] that favor technologies that bring diversification benefits

The mean-variance portfolio analysis proposed in this report exemplifies how cost risk can be examined and incorporated into state policy decisions about future generating resources. Portfolio analysis may also enable California decision makers to assess potential changes to a portfolio's risks and costs brought about by adding specific renewable resources that have their own individual risk and cost profiles. The resulting risks and costs of alternative combinations of assets can then be quantified, allowing those portfolios that provide the best combinations of costs and risk to be identified along a curve. That curve is called the "efficient frontier." It represents portfolios that, for any given level of risk, are the least expensive. Conversely, for any given level of cost, there is an associated least-risk portfolio. Portfolio analysis allows for considering risk preferences in choosing among portfolios, as well as for examining different tradeoffs among various risks and costs.

Background

The Energy Commission's 2005 Integrated Energy Policy Report (2005 IEPR),[4] and other state energy policy documents reinforce policies to ensure adequate energy resources, reduce energy demand, development of alternative energy sources, and improve the state's infrastructure. An essential component of California's energy policy is to reduce greenhouse gas emissions in part by increasing renewable generation to 33 percent of retail sales in 2020.

There is little debate on the use of renewable generating technologies as an effective means for climate change mitigation. Policy makers, consumers, and companies, however, are wary because of the widespread perception that these technologies cost more than conventional alternatives so that increasing their deployment will raise overall electricity generating costs. However, since the beginning of the Renewables Portfolio Standard Program, nearly all new renewable contracts have been below market prices for natural gas generation. And their relatively low risk makes it essential to increase the proportions of renewables in California's portfolio.

The 2006 Integrated Energy Policy Report Update (2006 IEPR Update)[5] shows that California does not appear to be on course to achieve the short-term goal of 20 percent renewable generation by 2010. The 2006 IEPR Update identifies five primary barriers to achieving this policy that include a common theme, risk and costs:

1. Inadequate transmission infrastructure to connect remotely located renewable resources.

2. Uncertainty regarding whether projects with supplemental energy payment awards will be able to obtain project financing.

3. Complexity and lack of transparency in the Renewable Portfolio Standard program implementation for investor owned utilities (IOUs).

4. Insufficient attention to the possibility for contract failure and delay.

5. Lack of progress in re-powering aging wind facilities.

From the utility's perspective, managing portfolio risk is of strategic importance. But when utilities pass-through fuel costs, there is a potential conflict between minimizing shareholder risk and minimizing ratepayer risk.

The role of renewable energy resources in utility portfolio risk reduction has been cited to support the claim that the fixed cost nature of renewable energy resources, as opposed to fuel or variable cost, should earn these projects a premium over traditional resources such as natural gas fired power plants. In order to install a renewable generation power plant, the power generator must outlay a significant capital expenditure in the short-term to launch the facility; the fixed costs are front-loaded and constitute a significant capital outlay in the current period.[6]

In the longer term, however, the cost to operate the facility is considerably less than the that of a fossil fuel facility. The renewable power generator must only concern themselves with the operations and maintenance of the facility, because the fuel is "free."

Although there has been a substantial amount of economic analyses on the cost side, little has been done to incorporate risk into analysis. California regulators and utilities, however, face numerous challenges to achieve renewable energy targets Some of these issues include:

- Will renewable technologies continue to develop?

- How will politics, pressure from the insurance industry, and fuel prices affect climate change regulation? How will "early credit" programs be treated?

- Will consumer interest in "clean power" increase or wane?

- Will the United States continue to be bifurcated into regional markets and territorial markets?

- Will capacity expansion be driven regionally and, if so, by what mechanisms?

- Will renewable energy development satisfy state targets?

- Will fuel prices and environmental constraints strand some assets and speed development of new technologies?

This report builds on the previous and ongoing research by treating energy planning as an investment-decision problem. Investors commonly evaluate such problems using portfolio theory to manage risk and maximize portfolio performance under a variety of unpredictable economic outcomes. Treating energy planning as an investment-decision problem, this report uses mean-variance portfolio theory to examine the risk and cost effects of achieving the California's renewable energy goals as discussed in the 2005 IEPR and 2006 IEPR Update.

Use of portfolio theory involves quantifying risk. In this case, construction, investment, operations and maintenance, and fuel risks are quantified using data provided by the California Energy Commission, Energy Information Administration (EIA), Federal Energy Regulatory Commission (FERC), and if necessary, European data from TECHPOLE, an energy database operated and maintained at LEPII, University of Grenoble.

This report applies portfolio-theory optimization to produce an expository evaluation of the 2020 projected California BAU electricity generating mix with the following objectives:

- Highlight the benefits of applying portfolio optimization to assessing the costs and risks of future generating portfolios by measuring the risk of achieving the penetration of preferred resources;
- Demonstrate a new rationale for renewable energy technologies that goes beyond the least-cost planning arguments that have dominated the debate on this subject to date; and
- Create a vehicle for constructive dialogue among the state's energy agencies and electric utilities.

Summary

A key finding of this report is that, compared to the projected 2020 CA-BAU electricity generating portfolio, there exist portfolios that are less risky, less expensive, and that substantially reduce CO_2 emissions and energy import dependency. This analysis suggests that an optimal generating portfolio for California includes greater shares of renewables technologies that may cost more on a stand-alone basis, but overall portfolio costs and risks are reduced because of the effect of portfolio diversification. Though counter-intuitive, the idea that adding more costly renewables can actually reduce portfolio-generating cost is consistent with basic finance theory. Optimal generating portfolio mixes also enhance California's energy security. This analysis further suggests that the optimal 2020 generating portfolios not only achieve California's 33 percent RPS goal but also reduce overall electricity generating costs and market risks as well as CO_2 emissions relative to the projected 2020 CA-BAU mix.

Organization

The remainder of the report is organized as follows: Chapter 2 sets out the main principles of a portfolio-based approach to electricity resource planning. Chapter 3 describes the data needed for such an approach and specifies the data sources used in this report. Using these data, Chapter 4 identifies optimal CA electricity generating portfolios for 2020 and it presents key features of these *expository* portfolios. Chapter 5 provides a preliminary assessment of nuclear acceleration and promotion policies, and the effects of carbon pricing on generating portfolio mixes and CO_2 emissions for optimal mixes. Chapter 6 summarizes, concludes, and recommends future steps to further support California electricity planners' decision making processes.

CHAPTER 2: PORTFOLIO-BASED APPROACH TO ELECTRICITY RESOURCE PLANNING

Least-Cost Versus Portfolio Based Approach

Financial investors commonly apply portfolio theory to manage risk and maximize portfolio performance under a variety of unpredictable economic outcomes. By contrast, traditional energy planning focuses on finding the least-cost generating alternative. This approach worked sufficiently well in a technological era marked by relative cost certainty, low rates of technological progress, and technologically homogenous generating alternatives and stable energy prices. However, today's electricity planner faces a diverse range of resource options and a dynamic, complex, and uncertain future. Attempting to identify least-cost alternatives in this uncertain environment is virtually impossible. As a result, more appropriate techniques are required to find strategies that remain economical under a variety of uncertain future outcomes.

Given this uncertain environment, it makes sense to shift electricity planning from its current emphasis on evaluating alternative technologies to evaluating alternative electricity generating portfolios and strategies. The techniques for doing this are rooted in modern finance theory – in particular mean-variance portfolio theory. Portfolio analysis is widely used by financial investors to create low risk, high return portfolios under various economic conditions. In essence, investors have learned that an efficient portfolio takes no unnecessary risk to its expected return. In short, these investors define efficient portfolios as those that maximise the expected return for any given level of risk, while minimizing risk for every level of expected return.

Portfolio theory is highly suited to the problem of planning and evaluating electricity portfolios and strategies because energy planning is not unlike investing in financial securities. Similarly, it is important to conceive of electricity generation not in terms of the cost of a particular technology today, but in terms of its expected portfolio cost. At any given time, some alternatives in the portfolio may have high costs while others have lower costs, yet over time, an astute combination of alternatives can serve to minimize overall generation cost relative to the risk. In sum, when portfolio theory is applied to electricity generation planning, conventional and renewable alternatives are not evaluated on the basis of their stand-alone cost, but on the basis of their contribution to overall portfolio generating cost relative to their contribution to overall portfolio risk. Portfolio-based electricity planning techniques thus suggest ways to develop diversified generating portfolios with known risk levels that are commensurate with their overall electricity generating costs. Simply put, these techniques help identify generating portfolios that can minimize California's energy price cost and risk.

This also has important implications for energy security. Although energy security considerations are generally focused on the threat of abrupt supply disruptions, a case can also be made for the inclusion of a second aspect: the risk of unexpected electricity cost increases. This is a subtler, but equally crucial, aspect of energy security. Energy security is reduced when ratepayers hold inefficient portfolios that are needlessly exposed to the volatile fossil fuel cost risk. Displacing California's coal and gas dependency by adding renewables technologies enhances California's energy security. The reason is that renewables costs are generally uncorrelated to fossil prices; this enables these technologies to diversify California's generating mix and enhance its cost-risk performance while simultaneously reducing CO_2 emissions.

Portfolio Optimization Basics

Portfolio theory was developed for financial analysis, where it locates portfolios with maximum expected return at every level of expected portfolio risk. In the case of electricity generating portfolios, it is more convenient to optimize portfolio generating *cost* as opposed to *return*. This choice does not affect results and conclusions presented in this report.

How Adding More Costly Renewable Resources Reduces Overall Cost

Efficient generating portfolios are defined by twin properties: they minimize expected cost for any given level of risk while minimizing expected risk for every level of expected cost. The idea that adding a more costly technology raises average generating cost seems obvious and compelling. Nonetheless, it is flawed. Estimating overall generating costs for a given mix involves assessments of long-term future cost *expectations* for highly uncertain fossil fuel and other outlays that have fluctuated significantly and unpredictably in the past. In other words, generating cost estimates reflect an assessment of how cost will behave in the distant future, 10 or 20 years from now. Highly uncertain long-term generation costs cannot be directly observed or calculated in a manner that – for example – fruit salad costs for dinner can be calculated at the market. Here the arithmetic is simple and intuitive: adding expensive strawberries to the mix, for example, raises the cost of making fruit salad.

The simple salad making cost formula does not work for fuel and operating outlays or any other uncertain future cost stream. Nonetheless, this is more or less how electricity planning models estimate costs for given generating mixes. According to traditional electricity planning models, when you add (say) 10¢/kWh geothermal energy to a 8¢/kWh fossil-fuel generating mix, overall costs must increase. However, contrary to what these models say, adding an appropriate share of renewable-based electricity, even if it costs more on a stand-alone basis, does not raise expected generating costs. The key for understanding this counter-intuitive result is "risk."

Box 1. Portfolio optimization basics

Portfolio theory was initially conceived in the context of financial portfolios, where it relates expected portfolio return to expected portfolio risk, defined as the year-to-year variation of portfolio returns. This box illustrates portfolio theory as it applies to a two-asset generating portfolio, where the generating cost is the relevant measure. Generating cost (cent/kWh) is the inverse of a return (kWh/cent), that is, a return in terms of physical output per unit of monetary input.

Expected portfolio cost

Expected portfolio cost is the weighted average of the individual expected generating costs for the two technologies:

(1) Expected Portfolio Cost = $X_1 E(C_1) + X_2 E(C_2)$,

Where X_1 and X_2 are the fractional shares of the two technologies in the mix, and $E(C_1)$ and $E(C_2)$ are their expected levelized generating costs per kWh.

Expected portfolio risk

Expected Portfolio risk, $E(\sigma_p)$, is the expected year-to-year variation in generating cost. It is also a weighted average of the individual technology cost variances, as tempered by their covariances:

(2) Expected Portfolio risk = $E(\sigma_p) = \sqrt{X_1^2 \sigma_1^2 + X_2^2 \sigma_2^2 + 2 X_1 X_2 \rho_{12} \sigma_1 \sigma_2}$,

Where: X_1 and X_2 are the fractional shares of the two technologies in the mix; σ_1 and σ_2 are the standard deviations of the holding period returns of the annual costs of technologies *1* and *2* as further discussed below; and ρ_{12} is their correlation coefficient.

Portfolio risk is always estimated as the standard deviation of the holding period returns (HPRs) of future generating cost streams. The HPR is defined as: *HPR = (EV–BV)/BV*, where *EV* is the ending value and *BV* the beginning value (see Brealey and Myers 2004 for a discussion on HPRs). For fuel and other cost streams with annual reported values, *EV* can be taken as the cost in year $t+1$ and *BV* as the cost in year t. HPRs measure the rate of change in the cost stream from one year to the next. A detailed discussion of its relevance to portfolios is given in Awerbuch and Yang (2007).

Each individual technology actually consists of a portfolio of cost streams (capital, operating and maintenance, fuel, CO_2 costs, and so on). Total risk for an individual technology – that is, the portfolio risk for those cost streams – is σ_T. In this case, the weights, X_1, X_2, and so on, are the fractional share of total levelized cost represented by each individual cost stream. For example, total levelized generating costs for a coal plant might consist of ¼ capital, ¼ fuel, ¼ operating costs, and ¼ CO_2 costs, in which case each weight X_i = 0.25.

Correlation, diversity, and risk

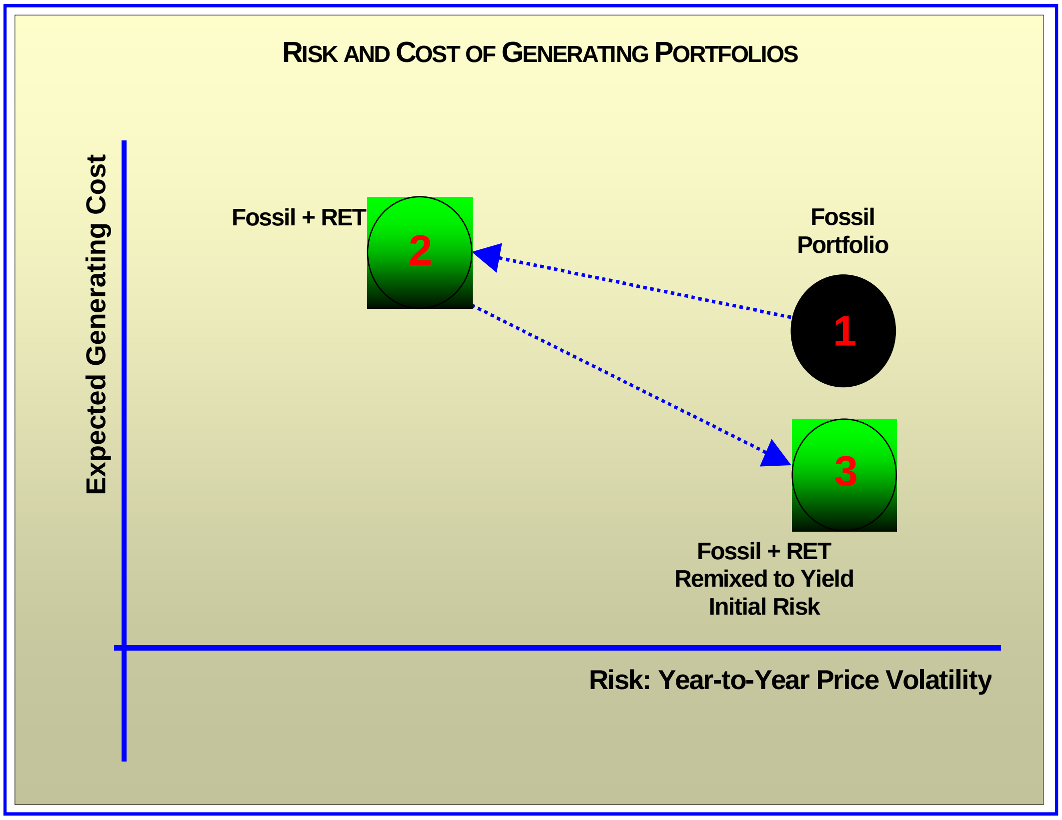
The correlation coefficient, ρ, is a measure of diversity. Lower ρ among portfolio components creates greater diversity, which reduces portfolio risk σ_p. More generally, portfolio risk falls with increasing diversity, as measured by an absence of correlation between portfolio components. Adding renewables to a risky fossil fuel generating mix lowers expected portfolio cost at any level of risk, even if the renewable technologies have higher direct costs. A pure fuel-less, fixed-cost technology, has $\sigma_i = 0$ or nearly so. This lowers, σ_p, since two of the three terms in equation (2) reduce to zero. This, in turn, allows higher-risk/lower-cost technologies into the optimal mix. Finally, it is easy to see that σ_p declines as $\rho_{i,j}$ falls below 1.0. In the case of fuel-less renewable technologies, fuel risk is zero and its correlation with fossil fuel costs is zero too.

When the element of risk is included, the portfolio equation produces important results that are part of the so-called *portfolio effect* discussed in any finance textbook. The portfolio effect of adding a fixed-cost asset, such as wind, to the risky fossil generation mix is powerful and counter-intuitive. Modern finance theory tells us that a fixed-cost asset can have the remarkable effect of *lowering* expected portfolio cost, adjusted for risk, even if its stand-alone cost is *higher* than the remaining portfolio components. For example, adding riskless government bonds yielding 5 percent to an existing stock portfolio producing 10 percent raises (not reduces) the expected return of the resulting portfolio that contains both risky stocks and riskless government bonds. This outcome is based on statistics: by definition, a fixed-cost asset is uncorrelated with the costs of all of the other assets. Statistical correlation affects the degree of diversification and hence overall portfolio risk.

This idea applies directly to generating portfolios. Passive, capital-intensive, and fuel-less renewables technologies such as wind and solar photovoltaic (PV) have cost structures that are nearly fixed or riskless over time, once construction is complete. Viewed over a sufficiently diversified geographic area, for example, the "production" costs of a generating portfolio with 20 percent wind varies a lot less than one with no wind.

Figure 1 illustrates how adding a more costly renewable generating resource reduces overall portfolio costs. Beginning with a 100 percent fossil portfolio (circle 1), when wind generation is added, portfolio costs increase, but portfolio risk decreases. This is shown as a move up and to the left to circle 2. Next, suppose that after adding wind generation, the overall resource portfolio is adjusted to increase portfolio risk back to the initial level before the wind generation was added. The result is that the wind generation lowers the *expected* or average cost of the portfolio at the original level of risk (circle 3). This is how portfolio optimization minimizes portfolio costs and risk when higher cost, but less risky, renewable resources are added to a lower cost, but higher risk, portfolio of fossil-fuel resources. Without considering "risk" this counter-intuitive result is not possible. Thus, traditional generation planning efforts that fail to incorporate portfolio risk are incomplete: they focus on overall cost and ignore useful information about risk.

Figure 1: How adding a more costly renewables can reduce overall cost



Risk from a Portfolio Perspective

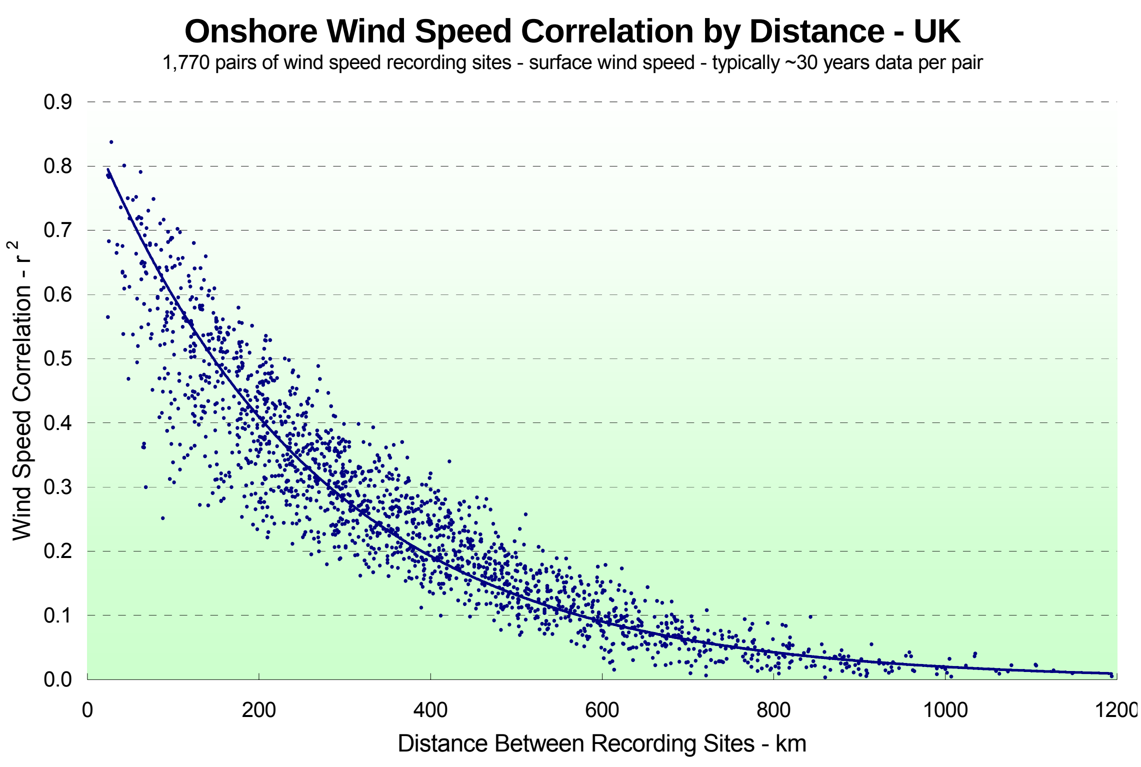
Having sketched the gist of the portfolio approach to electricity generation planning, it is useful to comment on the distinction between unsystematic (or firm-specific) risk, systematic (or market) risk, and risks usually considered in engineering approaches to analysing the pros and cons of alternative generation technologies.

Finance theory divides total risk into two components: unsystematic risk that affects primarily the prices of an asset (these risks can be reduced through diversification) and systematic risk that affects the prices of all assets. Systematic risk refers to the risk common to all securities and cannot be diversified away (within one market). Within an efficient portfolio, unsystematic risk will be diversified away to the extent possible. Systematic risk is therefore equated with the risk (standard deviation) of the market portfolio.

In the case of generating technologies and other real assets, diversification and portfolio risk are frequently misunderstood. Some analysts adopt an engineering approach that strives to enumerate all conceivable risks, include those risks that do not affect overall portfolio risk by virtue of diversification. Ignoring diversification effects in this manner, however, yields a portfolio risk estimate that is systematically biased upwards.

For example, year-to-year fluctuations in electric output from a wind farm is an unsystematic risk that is likely irrelevant for portfolio purposes. The reasons it that wind output is uncorrelated to the risk of other portfolio cost streams – though this unsystematic risk presents a potential risk to the owner of the wind farm and could potentially increased system integration costs. Certainly in the case of a large, geographically dispersed mix, year-to-year wind resource variability can be considered random and uncorrelated to fossil fuel prices or other generating cost components. While it is possible to measure the standard deviation of the yearly wind resource at a given location, its correlation to the output of other distant wind farms, or to many other generating cost components, is arguably zero (that is, $\rho_{12} = 0$ in equation (2) of Box 1). Thus, wind variability at a particular location does not contribute significantly to portfolio risk. Figure 2 shows how wind speed correlations rapidly decrease as distance between wind farms increase.

Figure 2: Onshore wind speed correlation by distance – United Kingdom



From a portfolio perspective, there is another important point to consider. Operating costs for wind, solar, and other passive, capital-intensive renewables are essentially fixed, or riskless, over time.[7] Perhaps more important is that these costs are uncorrelated to fossil fuel prices. This enables these technologies to diversify the generating mix and enhance its cost-risk performance. Given sufficient geographic dispersion in the wind resources, the operating cost of a generating system with 20 percent wind will fluctuate less from year-to-year than a system with no wind.

The idea that enumerating all conceivable unsystematic risks is misleading for purposes of a generating portfolio study holds for other engineering variances such as annual variations in attained fuel conversion efficiency for a particular gas plant. Some analysts choose to include this risk. Although such yearly efficiency fluctuations might change the accountant's estimate of kWh generating costs at a given site,[8] it is reasonable to assume that risk is uncorrelated, making only small contributions to overall portfolio risk.

Summary: How Portfolio Theory Improves Decision-making

As noted above, current least-cost approaches for evaluating and planning electricity generating mixes consistently bias in favor of risky fossil alternatives while understating the value of wind, PV, geothermal, and similar fuel-less fixed-cost, low-risk, passive, capital-intensive technologies. The evidence indicates that such renewables technologies offer a unique cost-risk menu along with other valuable attributes that traditional least-cost utility resource planning models cannot "see." For example, Bolinger, Wiser, and Golove (2004)[9] show that compared to standard financial hedging mechanisms, accelerating and promoting wind technology cost-effectively hedges fossil price risk.

By contrast, portfolio optimization exploits the interrelationships (i.e. correlations) among the various technology generating cost components. For example, because fossil prices are generally correlated with each other, a fossil-dominated portfolio is undiversified and exposed to fuel price risk. Conversely, renewables such as wind and geothermal, along with other non-fossil options, diversify the generation portfolio and reduce its risk because their costs are not correlated with fossil prices.[10] This portfolio effect is illustrated in Figure 3, which shows the costs and risks for various possible two-technology portfolios. Technology A is representative of a generating alternative with higher cost and lower risk such as geothermal. It has an expected (illustrative) cost around $0.10 per kWh with an expected year-to-year risk of approximately 8 percent. Technology B is a lower-cost/higher-risk alternative such as gas-fired generation. Its expected cost is about $0.08 per kWh with an expected risk of 12 percent. The correlation factor between the total cost streams of the two

Box 2: Risk Measurement

There are many ways to measure risk besides variance. All of them rely on the existence of probability distributions that are used to develop analytical estimates of risk. Thus, how such probability distributions are estimated is crucial. Some of the more common measures include:

1. Coefficient of Variation (CV). This measure is the ratio of the distribution's standard deviation to its mean. It is one way to measure risk relative to return, or in this case, variation in price relative to mean price, measured over a defined period. Tolerance bands can be established around CV.

2. Beta. Beta is a measure of the systematic risk of a single instrument or an entire portfolio and describes the sensitivity of an instrument or portfolio to broad market movements. A portfolio with a large beta will tend to benefit or suffer from broad market moves more strongly than the market overall, while one with a small beta will swing less violently than the broad market. It is defined as the ratio of the portfolio's covariance with the market divided by the market's variance or Covariance (portfolio, market) / Variance (market). Beta is used to measure volatility of stock returns relative to an index like S&P 500 returns, and one could consider measuring volatility of a resource portfolio's cost relative to volatility of spot market prices. However, it must be remembered that beta does not capture specific risk (the riskiness of the portfolio itself, irrespective of market risk). A portfolio can have a low beta but still be very volatile if its variations are simply not correlated with those of the market.[11]

3. Extreme Value Measures - This term is used here as a catch-all for a variety of conceptually straightforward measures of portfolio riskiness. In general, this type of measure is the difference in cost between a portfolio's expected cost and some estimate of

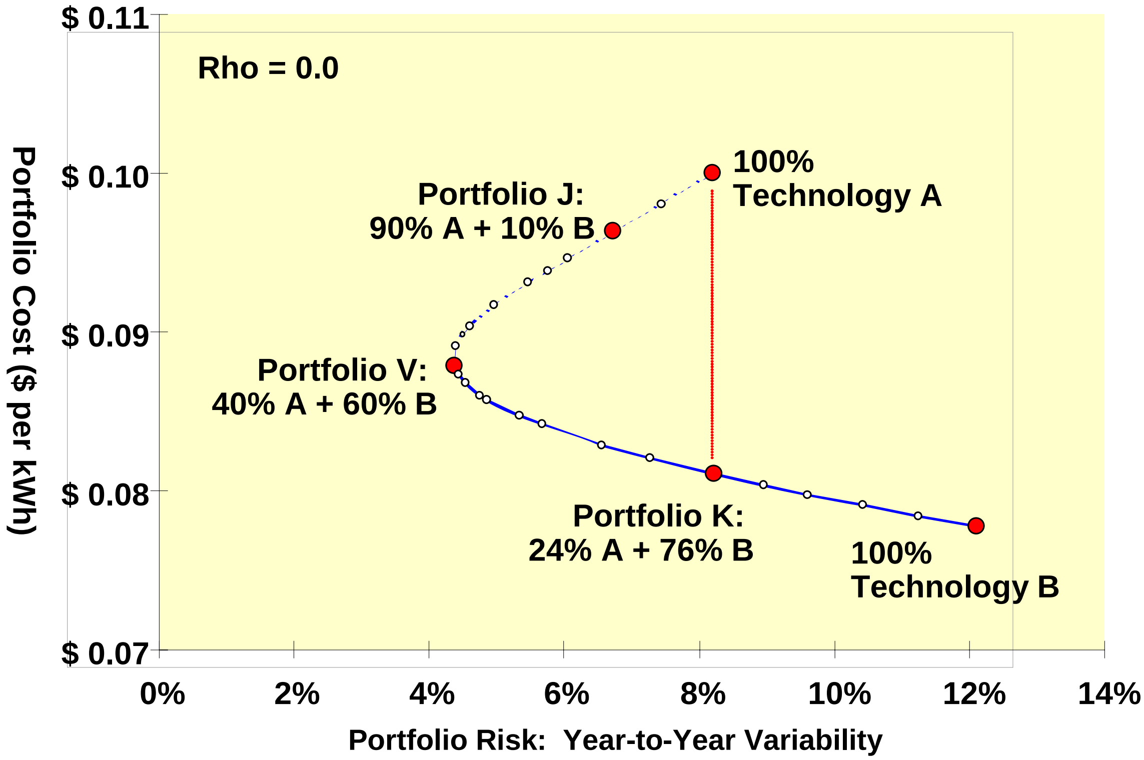
4. Value-at-Risk (VaR) - A traditional approach for quantifying risk of investment portfolios.101 VaR measures the downside risk of a portfolio. It is always calculated in the context of a risk level and a planning horizon. In the case of an electricity resource portfolio, VaR would be a measure of the dollar cost increase that has a certain probability (the selected risk level) of occurring over a certain time period (the selected planning horizon). For example, a regulator might be interested in the VaR of a proposed resource portfolio over a one year planning horizon at the 99 percent risk level. That VaR would tell us the amount of extra cost that would have a 1 percent chance of occurring over the next year. Or, a VaR at the 90 percent risk level for a ten year planning horizon would tell us the amount of extra cost that portfolio has a 10 percent chance of incurring over the next ten years.

5. Cash-flow-at-Risk (CFaR), Earnings-at-Risk (EaR). CFaR and EaR are similar to VaR, except they define “value” in specific terms.

The benefits and drawbacks of using specific risk measurements are application-specific. For example, where risks are asymmetric, especially downside risks, variance alone will not provide an accurate risk measure. Detailed estimates of CFaR or EaR, on the other hand, may be especially sensitive to changes in underlying assumptions.

technologies is assumed to be zero. This is a simplification since in reality the capital and operating cost risks of geothermal will exhibit some non-zero correlation with the capital and operating costs of gas-fired generation.

Figure 3: Portfolio effect for illustrative two-technology portfolio



As a consequence of the portfolio effect, total portfolio risk decreases when the riskier Technology B is added to a portfolio consisting of 100 percent A. For example, Portfolio J, which comprises 90 percent of Technology A plus 10 percent B, exhibits a lower expected risk than a portfolio comprising 100 percent A. This is counter-intuitive since Technology B is riskier than A. Portfolio V, the minimum variance portfolio, has a risk of 4 percent, which is one-half the risk of A and one-third the risk of B. This illustrates the concept of portfolio diversification.

Investors would not hold any mix above Portfolio V, since mixes exhibiting the equivalent risk can be obtained at lower cost on the solid portion of the line, below portfolio V. Portfolio K is therefore superior to 100 percent A. It has the same risk, but lower expected cost. Investors would not hold a portfolio consisting only of Technology A, but rather would hold the mix represented by K. Taken on a stand-alone basis, technology A is more costly, yet properly combined with B, as in Portfolio K, it has attractive cost and risk properties. Not only is Mix K superior to 100 percent A, most investors would also consider it superior to 100 percent Technology

B. Compared to B, Mix K reduces risk by one-third while increasing cost by approximately 10 percent, which gives it a favorable Sharpe ratio.[12]

To summarize, Mix K illustrates that astute portfolio combinations of diversified alternatives produce efficient results, which cannot be measured using stand-alone cost concepts: portfolio optimization locates minimum-cost generating portfolios at every level of portfolio risk, represented by the solid part of the line in Figure 3, that is, the stretch between V and B.

CHAPTER 3: CALIFORNIA PORTFOLIO COST, RISK, AND CORRELATIONS

Applying portfolio optimization to the CA generating mix requires the following inputs:

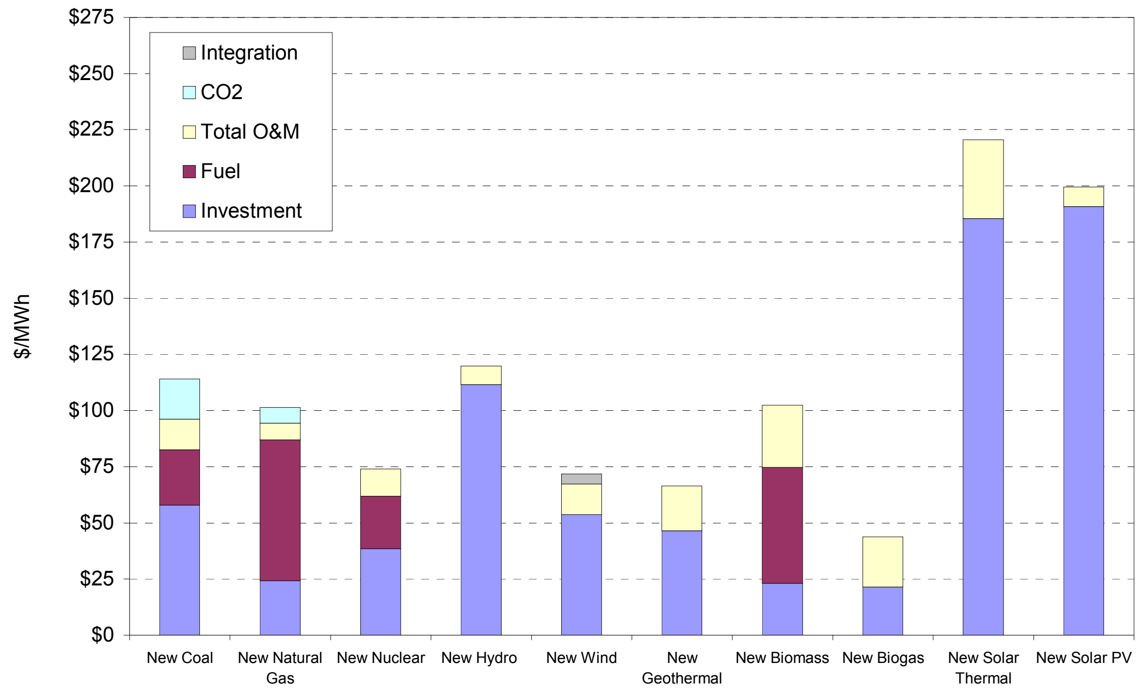
- Capital, fuel, operating, and CO_2 costs per unit of output for each technology;
- The risk (standard deviation) of each cost component; and
- The correlation factors between all cost components.

The following sub-sections will address each input and how they are used to determine optimal portfolios. Detailed presentations are provided in the Appendix.

Technology Generating Cost

Figure 4 shows the levelized 2020 generating cost for various technologies based on the CEC Staff's Cost of Generation (COG) Report.[13] All costs are taken on a post-tax/credit basis. Existing coal and nuclear technology costs are estimated using the TECHPOLE database,[14] because the COG report did not estimate them. New coal and nuclear technology costs are assumed to be equal to the COG estimation of IGCC and advanced nuclear costs, respectively. New solar PV technology costs are assumed to decrease by 50 percent by 2020. The 50 percent decrease for solar PV technology is based on expectations of the California Solar Initiative and is consistent with other Energy Commission analysis.[15] The rest of the technology costs are assumed to be the same as the corresponding levelized 2006 generating costs.[16]

Figure 4: CA 2020 Generating Costs for Various Technologies (CO_2 = $20/tonne)



As for the cost of CO_2, a value of $20/tonne of CO_2 has been used. This can be interpreted as an expected market price of CO_2, assuming that economic policies aimed at internalising the economic cost of CO_2 emissions yield a market price of CO_2 – for example, under the California's proposed ETS (Emissions Trading Scheme).[17] Alternatively, in the absence of such policies, the cost of CO_2 can be interpreted as the shadow price of CO_2, estimated on the basis of the economic cost of CO_2 emissions and of CO_2 abatement cost. For example, recent Synapse study estimates the future cost of CO_2 in 2020 to be between $10/ton and $33/ton and EIA analysis of proposed CO_2 legislation assumes a CO_2 cost of between $14/ton and $36/ ton in 2020.[18]

System integration is a complex issue. As renewable resources continue to increase, it is anticipated that there may be additional integration costs to accommodate renewables, specifically intermittent resources like wind. Typically, an integration cost is added to wind generation to compensate for additional regulation or load following needed to "firm up" wind resources. On top of these costs, the existing electricity network organization and protocols require capacity reserves to ensure system reliability, such as spinning and non-spinning reserves.

This portfolio analysis uses the results of the California Intermittency Analysis Report (IAP), which estimates the aggregate intermittency costs in the range of $0.69 per MWh for a 33% percent total renewable penetration rate.[19] Accounting for these costs as well as other integration costs results in an average system operating cost adder of $4.50/MWh. However, neither possible associated systematic risks that may become more significant for wind penetrations in excess of 20-30 percent nor any additional wind-related transmission infrastructure costs are not included.[20]

Technology Risk Estimates

One of the major benefits of renewables technologies over traditional fossil-fuel technologies is that they are relatively unaffected by upheavals in fossil-fuel prices. However, renewables technologies are not risk-free. There are a number of market and non-market risks that can affect the value of renewables as part of an overall portfolio of resources to meet electricity demand in California. Thus, in determining future generation portfolios having the lowest expected costs, it is crucial to incorporate the key risks that affect those costs and to understand the unique risks associated with for both renewables and fossil-fuel technologies. The following sub-sections will address each risk components.

Investment Cost Risk

Investment cost risks vary by technology types and are generally related to the complexity and length of the construction period. A World Bank analysis covering a large number of projects estimates the standard deviation of construction period outlays for thermal plants and for large hydro plants (Bacon *et al.* 1996).[21] Investment cost risk estimates for wind, gas, geothermal, and solar risk were determined from developer interviews as reported in Awerbuch *et al*. (Sandia Report). Investment cost risks of existing technologies were assumed to be zero percent. This means that 'new' assets are riskier than old ones – for example, the investment cost risks for a new, not yet constructed coal plant are greater than those for an existing coal plant.

Fuel Cost Risk

Fuel cost risks have been estimated on the basis of historical (1980-2005) California (biomass and natural gas), NUEXCO (uranium), and EIA (coal) prices. Annual price observations were used because they eliminate seasonal variations that could potentially bias the results. Since renewable technologies require no fuel costs and thus there is no fuel cost risk, with the exception of biomass.

O&M Cost Risk

The EIA (Energy Information Agency) and FERC (Federal Energy Regulatory Commission) databases maintain O&M costs of units operated by regulated utilities. This data was used to estimate the holding-period-return (HPR) standard deviations (SD) for O&M costs (along with the correlations between these costs discussed in the next subsection).[22]

CO_2 Risk

The last risk cost category is the cost of CO_2 emissions. The future cost of CO_2 emissions is relevant for fossil fuel technologies. The HPR standard deviation for CO_2 has been estimated at 0.26. This estimation was obtained using two principal methodologies – an analytical approach and a Monte Carlo simulation. Various sensitivity analyses were also performed to test the reasonableness and robustness of the estimated CO_2 HPR standard deviation value of 0.26. A more comprehensive presentation of the CO_2 risk can be found in the Appendix.

Summary of Risk Estimates

Table 1 summarizes the technology risk estimates. Investment cost risks of new technologies range from 0.10 for new solar technologies to 0.40 for new nuclear technology. Fuel cost risks for both existing and new technologies range from 0.05 for coal to 0.35 for nuclear. Natural gas fuel cost risk is estimated to be 0.30. For O&M risks, different technologies show different year-to-year fluctuations – ranging from 0.034 percent for solar photovoltaic to 0.153 for hydro technology.[23] This takes us to the risk associated with last cost category, that is, the cost of CO_2 emissions, which is relevant for fossil fuel technologies. As Table 1 indicates, the HPR standard deviation for CO_2 has been estimated at 0.26. The approach that underlies this estimate will be presented next in the context of discussing the correlation between fossil fuel costs, O&M costs for different technologies, and CO_2 costs.

Table 1: Technology Risk Estimates

Generating Resource	Investment	Fuel	Total O&M	CO_2
Coal	0.35	0.049	0.054	0.260
Biomass	0.20	0.133	0.108	-
Natural Gas	0.20	0.291	0.105	0.260
Nuclear	0.40	0.346	0.055	-
Hydro - Large	0.35	0.000	0.153	-
Hydro - Small	0.20	0.000	0.153	-
Wind	0.20	0.000	0.080	-
Solar Thermal	0.10	0.000	0.080	-
Biogas	0.20	0.133	0.108	-
Solar PV	0.10	0.000	0.034	-
Geothermal	0.20	0.000	0.153	-

Correlation Coefficients

The correlation coefficient, *ρ,* is a measure of diversity. Lower (or negative) correlation among portfolio components creates greater resource diversity, which serves to reduce overall portfolio risk. More generally, portfolio risk *falls* with increasing diversity, as measured by an absence of correlation (covariance) between portfolio components. Adding a fixed-cost technology to a risky generating mix serves to *lower* expected portfolio cost at any level of risk, even if the fixed-cost technology costs more. A pure fixed-cost technology has a cost variance (σ_i) of 0.0. This lowers portfolio risk (since two of the terms in Equation (2) of Box 1 reduce to zero), which in turn allows other higher-risk/lower-cost technologies into the optimal mix.[24] In the case of fuel-less renewable technologies, fuel risk is zero, and its correlation with fossil fuel costs is also taken as zero.

In the context of an electric generating portfolio, the expected risk of future CO_2 cost is further affected by the correlation (covariance) of CO_2 prices against future fossil fuel costs and other important generating cost streams. The estimates of the standard deviations and correlations of CO_2 prices are derived using both analytic techniques and Monte Carlo simulation. The analytical approach to estimating CO_2 risk and correlation follows the spirit of Green (2006),[25] who expresses CO_2 price in terms of gas and coal prices. This relationship is used to derive the HPR standard deviation of CO_2 as well as its correlation with fossil fuels. The Monte Carlo approach uses a series of simulations that provide a second set of CO_2 risk and fossil fuel correlation estimates. The Monte Carlo analyses use the volatility and other trends from 18 months of actual European Union Emissions Trading Scheme (EU-ETS)[26] historical data to simulate 20 years of trading. This and its correlation to coal and gas provide an estimate of annual risk factors for CO_2.

The two methods provide a range of estimates of CO_2 risk and correlations. The analytical and Monte Carlo results were compared and subjected to various sensitivity analyses to test the reasonableness and robustness of these estimates. The HPR standard deviation for CO_2 used in the portfolio optimization model (0.26) is shown in the last column of Table 1 above. The CO_2 cost/fuel cost correlation coefficient used in the portfolio optimization is shown in the last column (or row) of Table 2 below.

Table 2: Fuel and CO_2 HPR Correlation Factors

Generating Resource	Coal	Biomass	Natural Gas	Uranium	CO_2
Coal	**1.00**	0.39	0.53	-0.25	-0.49
Biomass	0.39	**1.00**	0.30	-0.27	0.00
Natural Gas	0.53	0.30	**1.00**	-0.16	0.68
Uranium	-0.25	-0.27	-0.16	**1.00**	0.00
CO_2	-0.49	0.00	0.68	0.00	**1.00**

As can be seen from these correlation coefficients, there is a negative correlation between CO_2 and coal prices and a positive correlation between CO_2 and gas. This is the expected result. Intuitively, as gas becomes more expensive, electricity generation shifts to coal, putting upward pressure on CO2 prices – be they market determined or shadow prices. Conversely, rising coal prices shift generation to gas, which emits about half as much CO2. As a result, the price of CO_2 falls with rising coal prices.

Table 2 above also shows the correlation coefficients among the various fuels. In most cases, there is positive correlation between fuels – reflecting the fact that most fuels are substitutes for one another – with the notable exception of nuclear. A number of researchers (e.g., Awerbuch and Berger 2003; Roques, et al. 2006)[27] have found a negative correlation between nuclear and fossil fuels. This suggests a greater diversification potential of nuclear technologies depending on the level of risks for nuclear technologies. The impact of potential nuclear acceleration and promotion policies for California is described in Section 5 of the report.[28]

In addition, O&M correlation coefficients are estimated based upon the historical maintenance costs reported in the EIA and the FERC databases. These are shown in Table 3.

Table 3: O&M Correlation Coefficients

Generating Resource	Coal	Gas	Nuclear	Hydro	Wind	Geo	Solar	Bio
Coal	**1.00**	0.25	0.00	0.03	-0.22	0.14	-0.39	0.18
Gas	0.25	**1.00**	0.24	-0.04	0.00	-0.18	0.05	0.32
Nuclear	0.00	0.24	**1.00**	-0.41	-0.07	0.12	0.35	0.65
Hydro	0.03	-0.04	-0.41	**1.00**	0.29	-0.08	0.30	-0.18
Wind	-0.22	0.00	-0.07	0.29	**1.00**	-0.28	0.05	-0.18
Geo	0.14	-0.18	0.12	-0.08	-0.28	**1.00**	-0.48	-0.70
Solar	-0.39	0.05	0.35	0.30	0.05	-0.48	**1.00**	0.25
Bio	0.18	0.32	0.65	-0.18	-0.18	-0.70	0.25	**1.00**

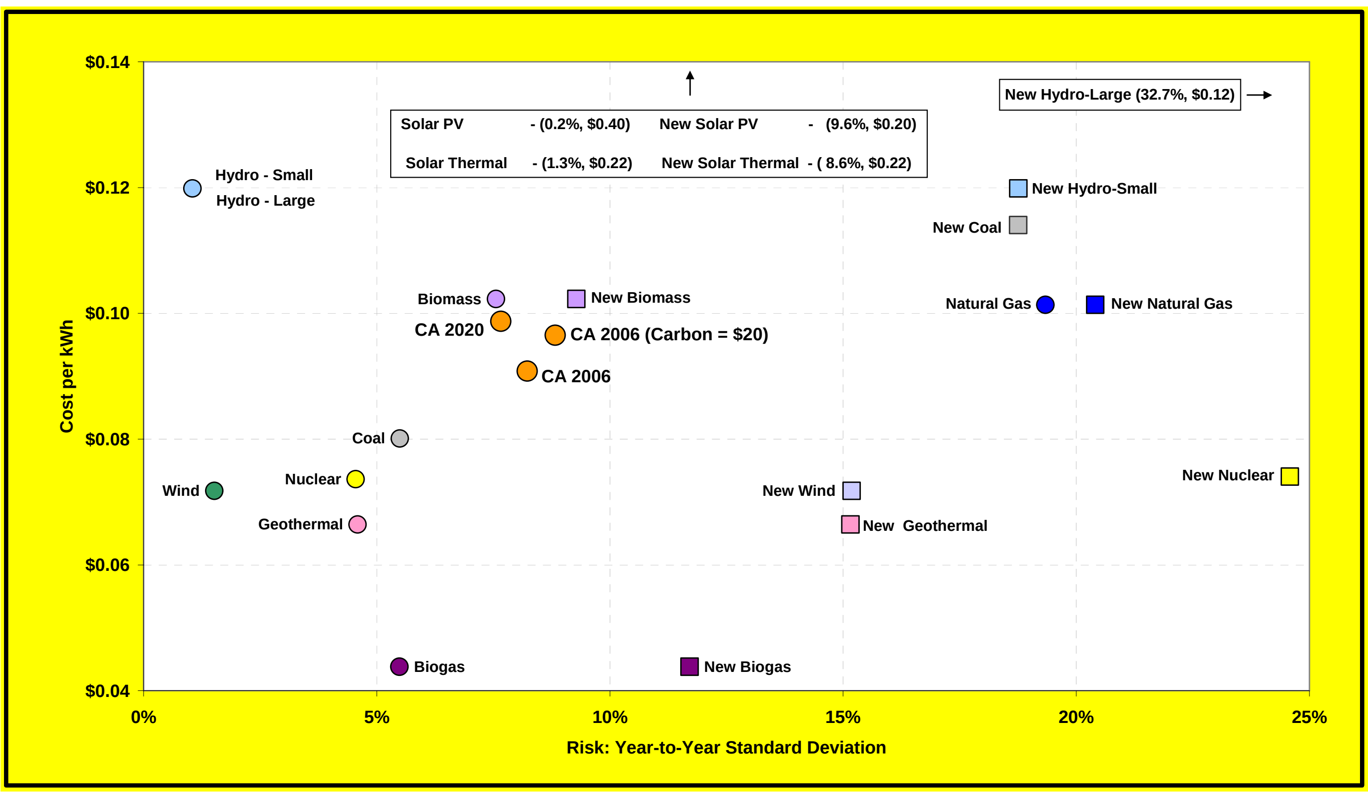
Total Portfolio Cost and Risk

The previous sub-sections described the cost and risk inputs for the various generating technologies. These are combined using equation (2) in Box 1 to produce a total HPR standard deviation for each technology, where the weights (X_1, X_2, …

etc.) are given by the proportional values of the levelized cost components, that is, capital, fuel, O&M, and CO_2 costs.

Figure 5 shows the costs per kWh for each of the generating technologies in 2020 along with its risk, with the added assumption that CO_2 costs $20 per tonne. For comparison, Figure 5 also shows the cost-risk combination of the projected CA 2020 BAU mix and historical CA 2006 mix.[29] The analysis indicates that there exist optimal and efficient portfolios that are less risky, less expensive, and that substantially reduce California's CO_2 emissions and energy import dependency. This optimal generating portfolio mixes include greater shares of renewables technologies: the optimal 2020 generating portfolios not only achieve California's 33 percent RPS goal, but also reduce overall electricity generating costs and market risks as well as CO_2 emissions relative to the projected 2020 CA-BAU mix.

Figure 5: Cost and Risk of Existing and New Generating Alternatives in 2020



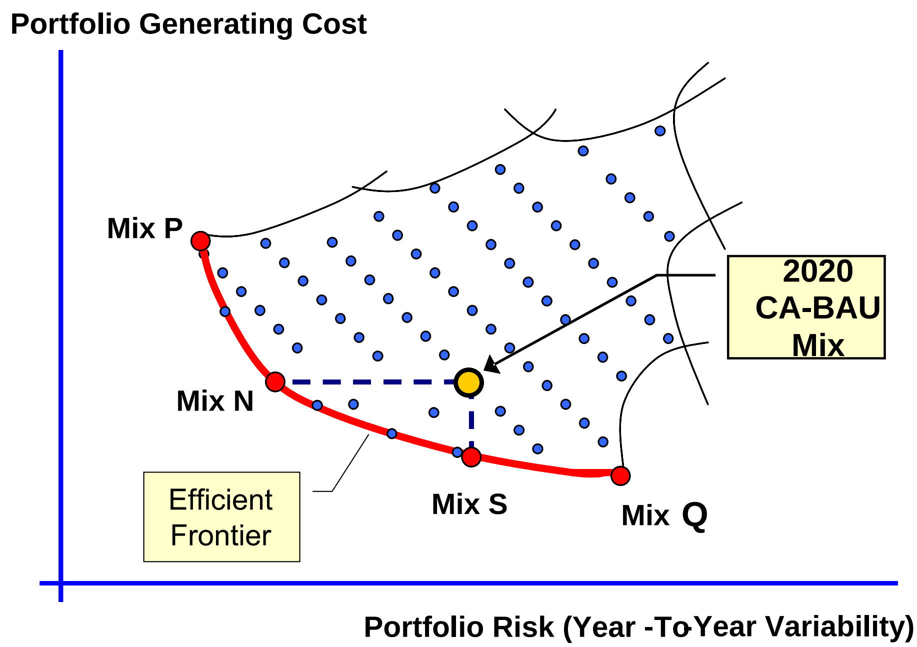
CHAPTER 4: PORTFOLIO OPTIMIZATION OF CA GENERATING MIX

Portfolio Optimization and the Efficient Frontier: an Illustration

As previously stated, the aim in this study is to evaluate whether there exists feasible 2020 generating mixes that are 'superior' to the 2020 CA-BAU mix by virtue of reducing risk or CO_2 emissions or by producing lower-cost electricity. To interpret the results of the portfolio optimization results, it is useful to offer a general illustration of possible results.

Figure 6 illustrates an infinite number of different generating mixes that could meet the 2020 electricity needs with a unique mix of the various technology options. The different portfolios all have different cost-risk as represented by the blue dots. Interestingly, technology shares do not change monotonically in any direction in Figure 6 so that two mixes with virtually identical cost-risk (i.e. two mixes located close to each other in cost-risk space) can have radically different technology generating shares (Awerbuch-Yang 2007). Likewise, radically different mixes can have nearly identical cost-risk, i.e. they could be virtually co-located in risk-cost space. The intuition for this is straightforward: there are many ways to combine ingredients in order to produce a given quantity of salad at a given price.

Figure 6: Feasible region and efficient frontier for multi-technology electricity portfolios



The red curve (PNSQ) is the efficient frontier (EF), the locus of all optimal mixes. There are no feasible mixes below the EF, and along the EF, only accepting greater risk can reduce cost. The Blue-dot mixes in Figure 6 are sub-optimal or *inefficient* because it is still possible to reduce both cost and risk by finding mixes on the EF by moving below or to the left. As shown below, the 2020 CA-BAU mix lies above the efficient frontier.

Although an infinite number of possible generating portfolios lie along the EF, this analysis focuses on four 'typical' optimal mixes P, N, S, Q. Taking the 2020 CA-BAU mix as the benchmark, they are defined as follows:

- Mix P is a high-cost/low-risk portfolio. It is usually the most diverse mix.
- Mix N is an equal-cost/low-risk portfolio, that is, it is the mix with the lowest risk for costs equal to that of the 2020 CA-BAU mix.
- Mix S is an equal-risk/low-cost portfolio, that is, it is the mix with the lowest costs for a risk equal to that of the 2020 CA-BAU mix.
- Mix Q is a low-cost/high-risk portfolio. It is usually the least diverse portfolio.

The portfolio analyses do not advocate for any particular generating mixes, but rather displays the risk-cost trade-offs across many mixes, with a focus on mixes that lie along the efficient frontier (EF). All solutions along the EF are conceded efficient. Although it may turn out that solutions in the region of the 2020 CA-BAU mix, e.g. solutions between portfolios *N* and *S*, may be the most practical, the optimization results cannot provide a roadmap or set of 2020 technology targets. Such results would require considerably more detailed models. The results presented here are largely *expositional*. The results demonstrate the value of portfolio optimization approaches and suggest quite clearly that capacity planning made on the basis of stand-alone technology costs likely leads to highly inefficient mixes (from California customer's perspective). Stand-alone cost approaches ignore important portfolio risk and cost interactions (correlations) among various technologies.

Efficient Electricity Portfolios for 2020 Generation Mix

This portfolio optimization study evaluates the 2020 CA-BAU mix shown in Figure 7 below against the expository realizable case. Its purpose is to help explore practical policy limits and identify policies that may be worth pursuing. For each set of constraints, efficient electricity generation mixes are computed and the level of associated CO_2 emissions are analyzed. The following assumptions were used to develop the expository realizable case lower and upper bounds shown in Table 4:[30]

- The expository realizable case assumes that there will be no *new* investment in coal, nuclear, and large hydro technologies.[31]
- Many realistic constraints on new resources are not included at this time. Proxy assumption include: 10 percent upper bound for new biomass, biogas, small hydro, solar thermal and solar PV technologies; 25 percent upper bound for new geothermal technology; and 30 percent upper bound for new wind and natural gas technologies.
- Lower bounds for new technologies are assumed to be zero.
- Upper bounds for existing technologies are capped by CA-BAU generation share.
- Lower bounds for existing technologies are limited by 50 percent of the CA-BAU generation share except for the following exceptions:
    - Lower bounds for Coal and Gas technologies are 5 percent.
    - Lower bounds for Nuclear and Large Hydro technologies are 80 percent of the CA-BAU generation share.

Figure 7: CA 2006 and 2020 CA-BAU Generation Mix (in TWh)

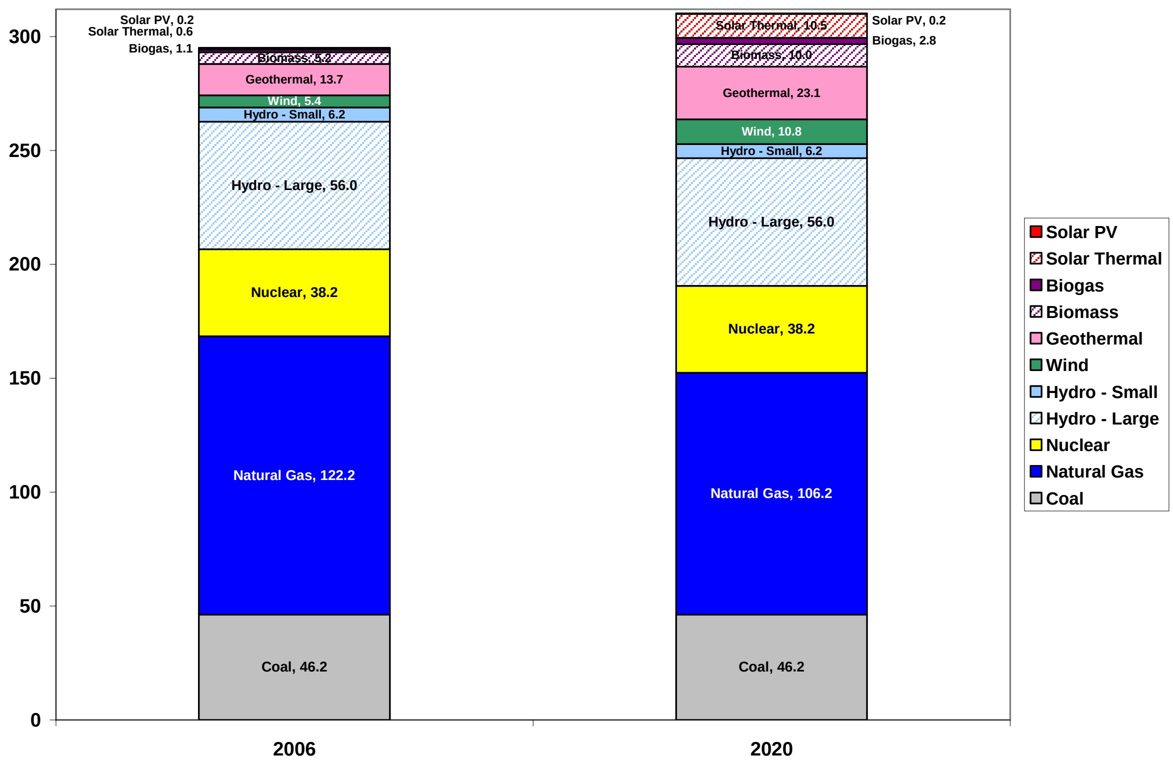


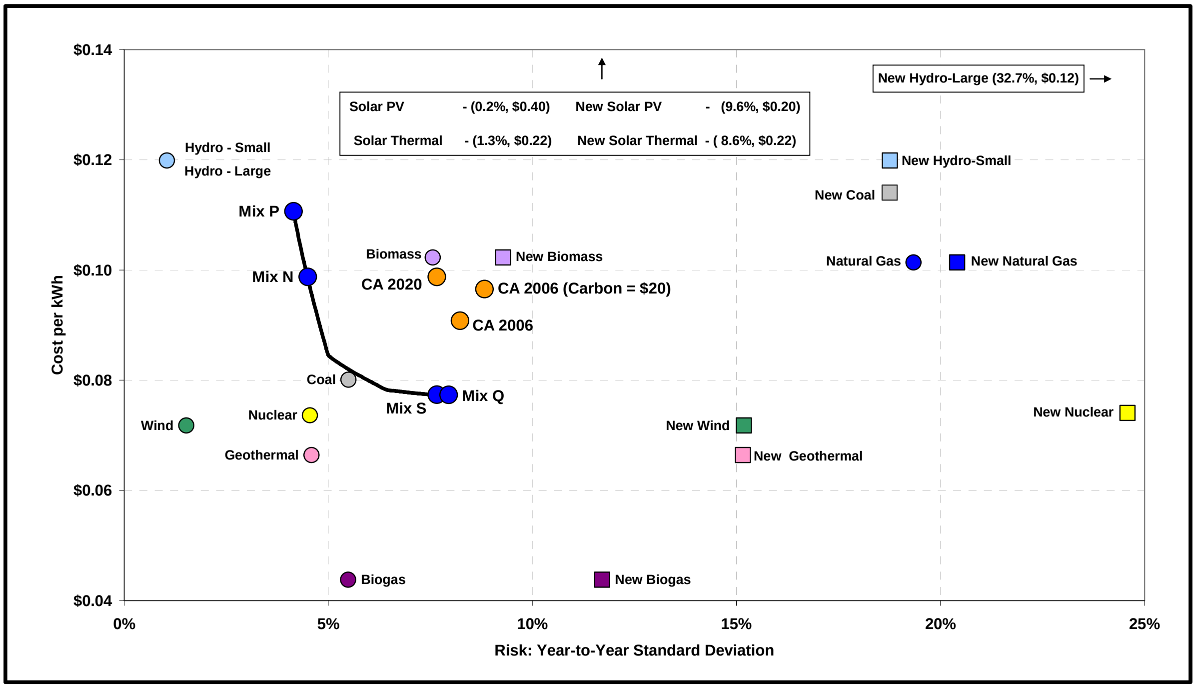
Table 4: Expository realizable case lower and upper limits

	Realizable	
Technology	**Lower bound**	**Upper bound**
Coal	**5.0%**	14.9%
Biomass	0.8%	1.7%
Natural Gas	**5.0%**	34.2%
Nuclear	**9.8%**	12.3%
Hydro - Large	**14.5%**	18.1%
Hydro - Small	1.0%	2.0%
Wind	0.9%	1.7%
Geothermal	2.2%	4.4%
Solar Thermal	0.1%	0.2%
Biogas	0.2%	0.4%
Solar PV	0.0%	0.1%
New Coal	0.0%	**0.0%**
New Biomass	0.0%	10.0%
New Natural Gas	0.0%	30.0%
New Nuclear	0.0%	**0.0%**
New Hydro-Large	0.0%	**0.0%**
New Hydro-Small	0.0%	10.0%
New Wind	0.0%	30.0%
New Solar Thermal	0.0%	10.0%
New Biogas	0.0%	10.0%
New Solar PV	0.0%	10.0%
New Geothermal	0.0%	25.0%

Efficient Portfolios: Results

This section discusses the 2020 expository realizable case optimization results and compares their risk-return characteristics and CO_2 emissions to those of the projected 2020 CA-BAU mix. The results indicate that the optimal realizable portfolios minimize cost and risk and reduce CO_2 emissions. This is shown in Figure 8, which illustrates the risk and return for the projected 2020 CA-BAU and for several optimized mixes under the realizable case. The efficient frontier PNSQ illustrates the location of all optimal portfolios. In other words, the efficient frontier represents portfolios with optimized combinations of risk and cost.

Figure 8: Efficient Frontier for 2020 Electricity Generation Mix – Realizable Case



As Figure 8 shows, the 2020 CA-BAU portfolio lies above and to the right of the efficient frontier, meaning that alternative portfolios can be selected that have both lower expected costs and less risk. The CA-BAU portfolio has an overall generating cost of 9.9 cents per kWh and a risk of 7.7 percent. By comparison, mix *N*, the equal-cost/low-risk portfolio, reduces risk nearly in 42 percent, to 4.5 percent. Alternatively, mix *S,* has the same risk as the 2020 CA-BAU but reduces generating costs by 2.2 cents per kWh, which equates to an CA-wide reduction in annual electricity costs of approximately $6.8 billion.[32]

Mix *P*, is the minimum-risk portfolio, reduces risk slightly relative to mix *N*, but comes with a significant increase in cost: this indicates an unattractive cost-risk trade-off over mix *N*. Similarly, mix *Q*, the minimum-cost portfolio, virtually did not reduce cost relative to mix *S*, but comes with a noticeable increase in risk. Thus, it appears that in cost-risk terms, the practical range of policy interest may be in the range between mix *N* and mix *S*.

Table 5 summarizes the generation components of portfolios P, N, S, Q, with respect to CA-BAU portfolio.

Table 5: Portfolio Mix Details – Realizable Case

	CA-2020 BAU	Portfolio P	Portfolio N	Portfolio S	Portfolio Q
RISK	7.7%	4.2%	4.5%	7.7%	8.0%
COST: cents/KWh	9.9	11.1	9.9	7.7	7.7
CO2: Mil-tonnes/Yr	78	47	47	19	19
Generating Resource			**Generating Shares**		
Coal	15%	15%	15%	5%	5%
Natural Gas	34%	5%	5%	5%	5%
Nuclear	12%	12%	12%	12%	11%
Hydro	20%	20%	20%	15%	15%
Wind	4%	2%	5%	22%	23%
Geothermal	7%	5%	11%	29%	29%
Biomass	3%	12%	12%	1%	1%
Biogas	1%	10%	10%	10%	10%
Solar Thermal	3%	10%	6%	0%	0%
Solar PV	0%	8%	4%	0%	0%
Renewables Share	20%	41%	45%	64%	64%

One finding of the analysis is that the share of renewables could be increased from 20 percent to 45 percent without an increase in expected portfolio costs (i.e., transition from the CA-BAU portfolio to portfolio N). In addition, Mix N reduces CO2 emissions by 31 million tonnes per year relative to projected 2020 BAU portfolio without increasing expected costs.

Perhaps more importantly, another finding of the analysis shows that the share of renewables could be increased from 20 percent to 64 percent with a decrease in expected portfolio costs of 2.2 cents per kWh (i.e., transition from the CA-BAU portfolio to portfolio S). In addition, Mix S reduces CO2 emissions by 59 million tonnes per year relative to projected 2020 BAU portfolio without increasing expected portfolio risks.

In addition, Policy makers tend to view climate change mitigation as an objective that necessarily competes with cost. Indeed, it is widely believed that low-carbon electricity generation will increase overall costs relative to higher-carbon portfolios. However, such beliefs are typically based on stand-alone cost concepts. The expository portfolio results show that, in addition to reducing cost and/or risk relative to the CA-BAU portfolio, the portfolios identified along the efficient frontier can also reduce CO_2 emissions relative to the CA-BAU portfolio.[33] This is shown in Figure 9.

Figure 9: Technology Shares and CO_2 emissions – Realizable Case

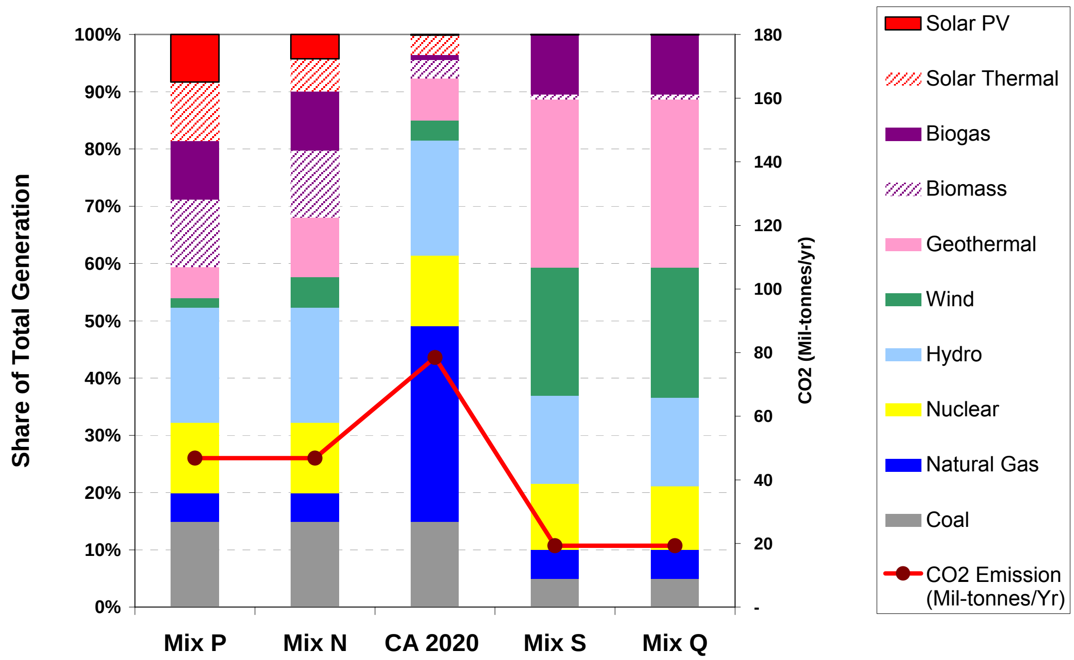
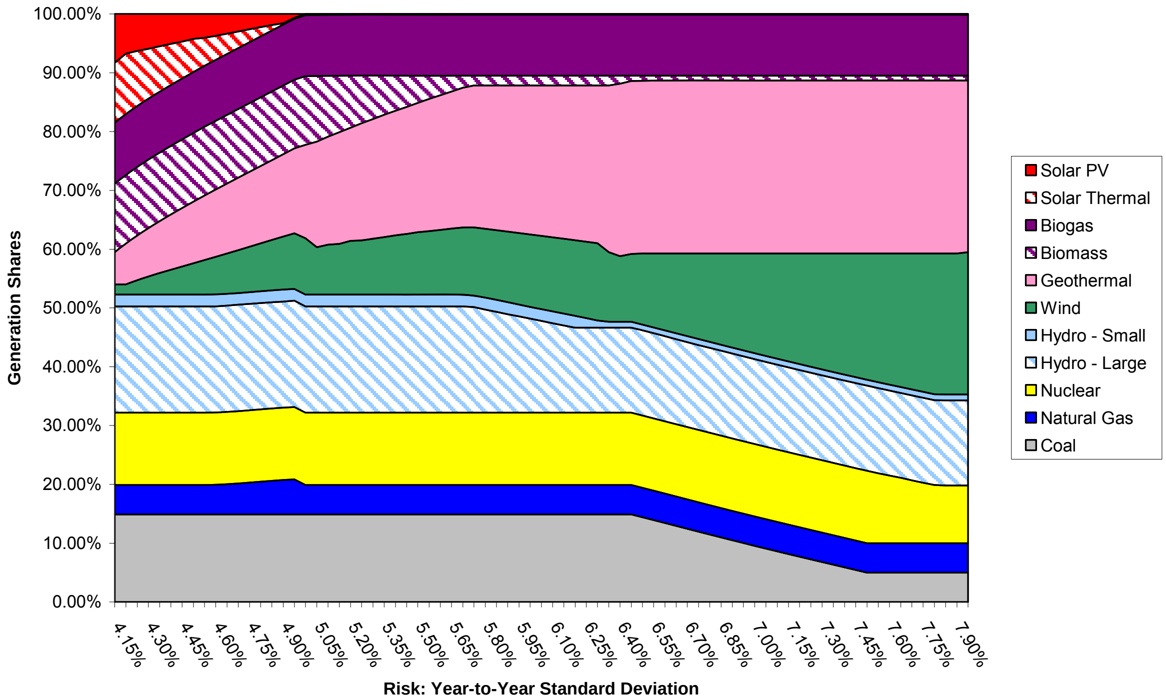


Figure 9 above shows technology shares on the left vertical axis, and CO_2 emissions on the right axis. The lower-risk and more diversified portfolios, P and N, reduce annual CO_2 to approximately 47 million tonnes, which is about 40 percent lower than emissions in the CA-BAU portfolio (78 million tonnes of CO_2). They accomplish this primarily by displacing natural gas-fired generation with renewables, including wind, biomass, and solar. Portfolio P, which is the most diverse resource portfolio, includes about 8 percent of solar PV.[34] The portfolios S and Q, the higher-risk and less diversified portfolios further reduce CO_2 emissions to 19 million tonnes, because they incorporate smaller shares of coal compared to CA-BAU mix. Figure 10 shows how shares of optimal generation mix changes as portfolio risk increases. As noted above, mixes are less diversified as portfolio risk increases.

Figure 10: Efficient Frontier Generation Mix Vs. Portfolio Risk: Realizable Case



To summarize, the preliminary results suggest that larger shares of renewables can help reduce both the expected cost and risk of the CA generating portfolio as well as its CO_2 emissions. Against this background, 33 percent RPS policies designed to accelerate the deployment of renewables technologies appear to be highly cost-effective. Perhaps the single most important lesson of the portfolio optimization analysis is that combining renewables having no fuel risk, with fossil-fuel generating technologies (such as gas and coal) may reduce expected portfolio costs for any level of risk, even if the renewables cost more when assessed on a stand-alone, levelized cost basis. In addition, the analysis also indicates that adding “too much” renewables would increase the resulting portfolio risk (see Mixes S and Q).

Specifically, the principal conclusions of the analysis are:

1. Generating-technology costs provide highly misleading signals when taken on a stand-alone basis, especially without reference to their market risks. The correlation of costs and risks among technologies yields portfolio outcomes that are generally not easy to predict.

2. Compared to the projected 2020 CA-BAU portfolio, and given a CO_2 price of $20 per tonne, there exist optimal generating portfolios that reduce generating cost by

as much as 22 percent without increasing risk (CA-BAU to Mix S transition). These cost improvements represent approximately $6.8 billion annual electricity cost savings.

3. Policies designed to accelerate the deployment of renewables technologies appear to be cost-effective, subject to the reliability issues mentioned previously. As a matter of policy, current investments to achieve California's 33 percent RPS goal, cost, risk and benefits are best estimated using portfolio-based approaches, rather than stand-alone methods.

4. Adding "too much" renewables increases (not decreases) resulting portfolio risk.

5. The imposition of CO2 charges raises both the cost and the risk of the optimal 2020 generating portfolios.

6. High CO_2 prices increase the cost of fossil-fuel generating resources, although their effects on risk are more complex. High CO_2 prices substantially increase the market risk of existing fossil assets, whose risk is dominated by fossil-fuel volatility and other operating risks. Chapter 5 provides more detailed analysis of the effect of CO_2 prices on California optimal generating portfolios.

7. Except in the general terms presented, the precise relationship between technology shares, CO2 emissions, and cost-risk seems complex and non-linear.

8. The single-most overriding lesson of the portfolio optimization analysis is that stand-alone technology costs and other characteristics interact within portfolios of generating resources in ways that are not always easily predictable. This underscores the importance of policy-based approaches grounded in portfolio concepts as opposed to stand-alone engineering concepts.

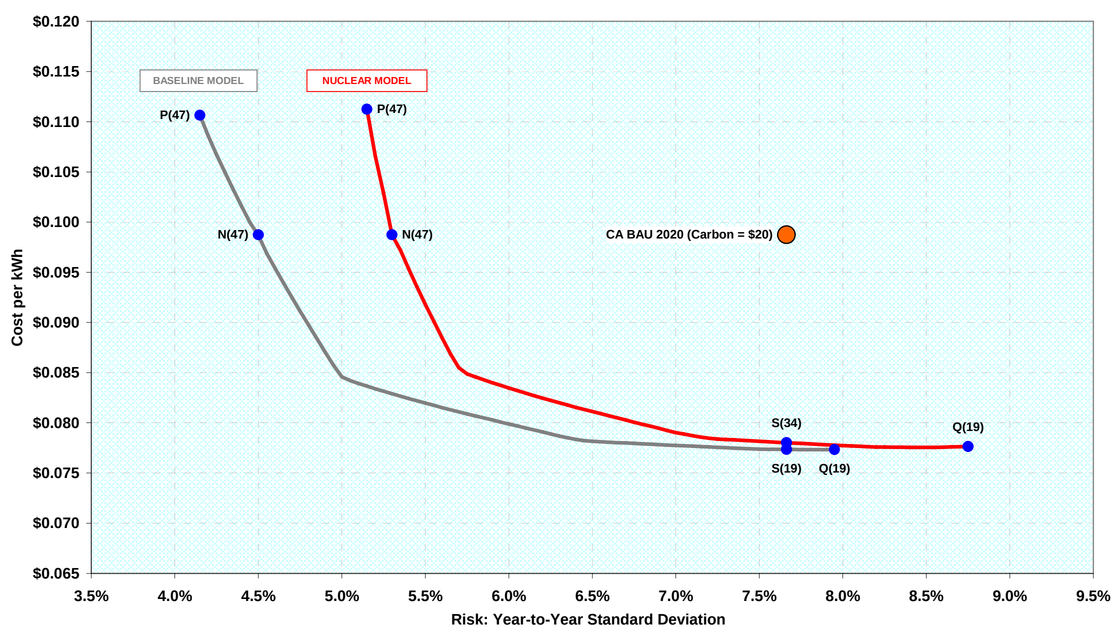
CHAPTER 5: NUCLEAR POLICY AND CO2 PRICE IMPACT OF CA EFFICIENT FRONTIER

The Effects of a Nuclear Acceleration and Promotion Policy

The nuclear cost estimates used for identifying efficient electricity portfolios do not account for the costs and risks of storing nuclear waste. CORWM (2006) recommends a lengthy, potentially decades-long process, involving interim waste storage in preparation for ultimate geological disposal.[35] For example, Germany will not consider new nuclear capacity to meet future electric demand. California has had a similar policy since 1976.[36] Against this background, a policy of a nuclear acceleration and promotion was tested – that is, a generating portfolio that contains 10 percent new nuclear by 2020 – to evaluate its effects on cost and risk of generating resource portfolios.

Figure 11 compares the nuclear promotion policy to the baseline realizable scenario at the CO_2 price of $20 per tonne. (The parenthetical numbers next to the typical portfolios represent annual CO_2 emission levels.)

Figure 11: Comparison of realizable and nuclear promotion policy



As Figure 11 shows, the nuclear promotion scenario shifts California's optimal efficient frontier to the right (i.e., higher risk) without commensurate cost reductions.

In addition, a nuclear promotion policy does not reduce the CO_2 emission levels in a material way compared to the no nuclear promotion policy. In fact, it increases the CO_2 emission levels in Mix S. Therefore, the analysis indicates that nuclear promotion policy for California is not an efficient move. Specifically, for portfolio N, cost stays the same, but risk significantly increases, that is from 4.5 percent to 5.3 percent. For portfolio S, risk stays the same, but cost slightly increases, i.e., from 7.7 cents/kWh to 7.8 cents/kWh.

Table 6 summarizes the details of portfolios P, N, S, Q, with respect to CA-BAU portfolio.

Table 6: Portfolio Mix Details – Nuclear Promotion Policy Case

	CA-2020 BAU	Portfolio P	Portfolio N	Portfolio S	Portfolio Q
RISK	7.7%	5.1%	5.3%	7.7%	8.8%
COST: $-cents/KWh	9.9	11.1	9.9	7.8	7.8
CO2: Mil-tonnes/Yr	78	47	47	34	19
Generating Resource			**Generating Shares**		
Coal	15%	15%	15%	10%	5%
Natural Gas	34%	5%	5%	5%	5%
Nuclear	12%	22%	22%	22%	20%
Hydro	20%	20%	20%	15%	15%
Wind	4%	2%	2%	6%	16%
Geothermal	7%	4%	4%	29%	28%
Biomass	3%	12%	12%	1%	1%
Biogas	1%	3%	10%	10%	10%
Solar Thermal	3%	10%	9%	0%	0%
Solar PV	0%	7%	1%	0%	0%
Renewable Share	20%	33%	39%	48%	56%

Compared to the expository realizable case, the nuclear case is characterized by significantly lower shares of wind and geothermal in portfolio N. This is primarily driven by the requirement to build 10 percent new nuclear by 2020.

Figure 12 shows technology shares on the left vertical axis, and the CO2 emissions on the right axis for the nuclear case.

Figure 12: Technology Shares and CO_2 Emissions – Nuclear Case

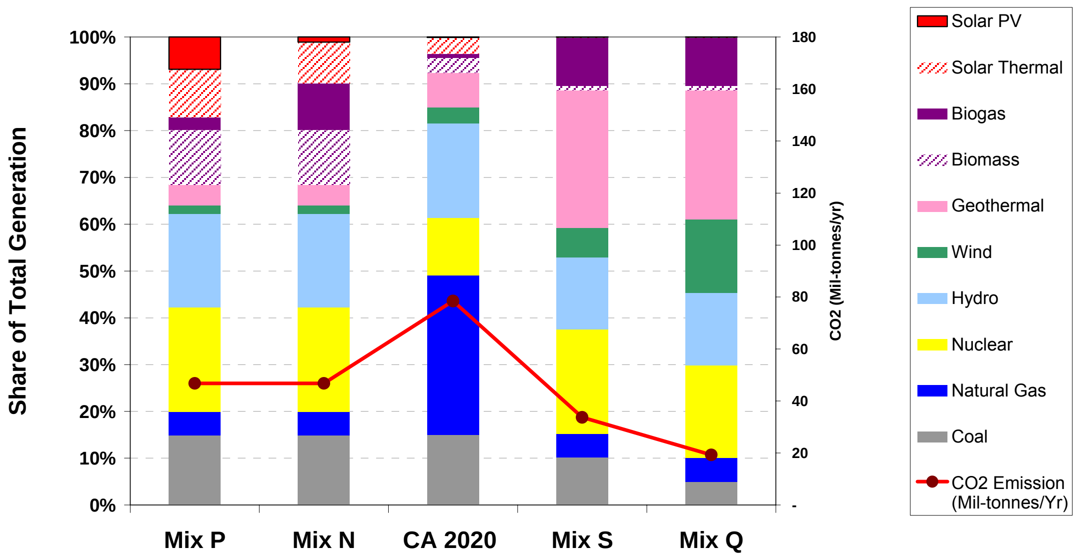
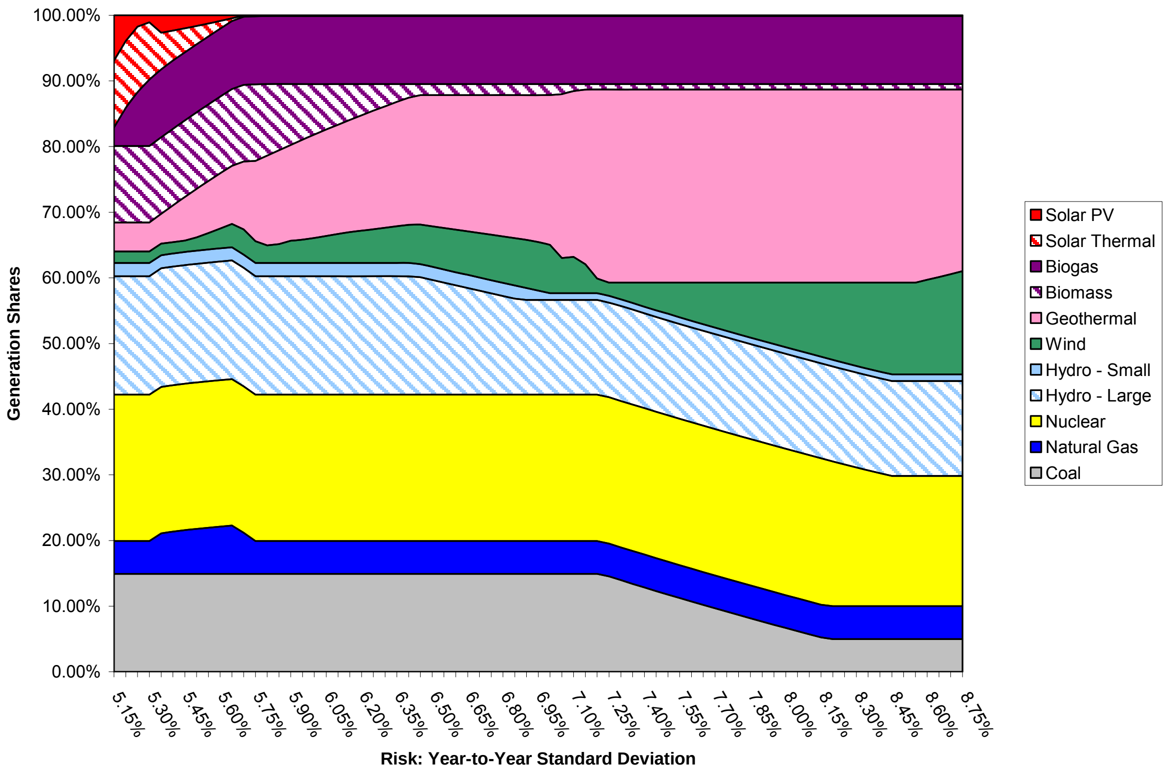


Figure 13 shows how shares of optimal generation portfolio changes as risk increases for the nuclear case. Similar to expository realizable case, the portfolios in the nuclear case are less diversified as portfolio risk increases. Also, Adding "too much" renewables counter-intuitively increases (not decreases) resulting portfolio risk because (a) it reduces portfolio diversification; and (b) it replaces less risky existing technology with more risky new technology.

Figure 13: Efficient Frontier Generation Mix Vs. Portfolio Risk – Nuclear Case

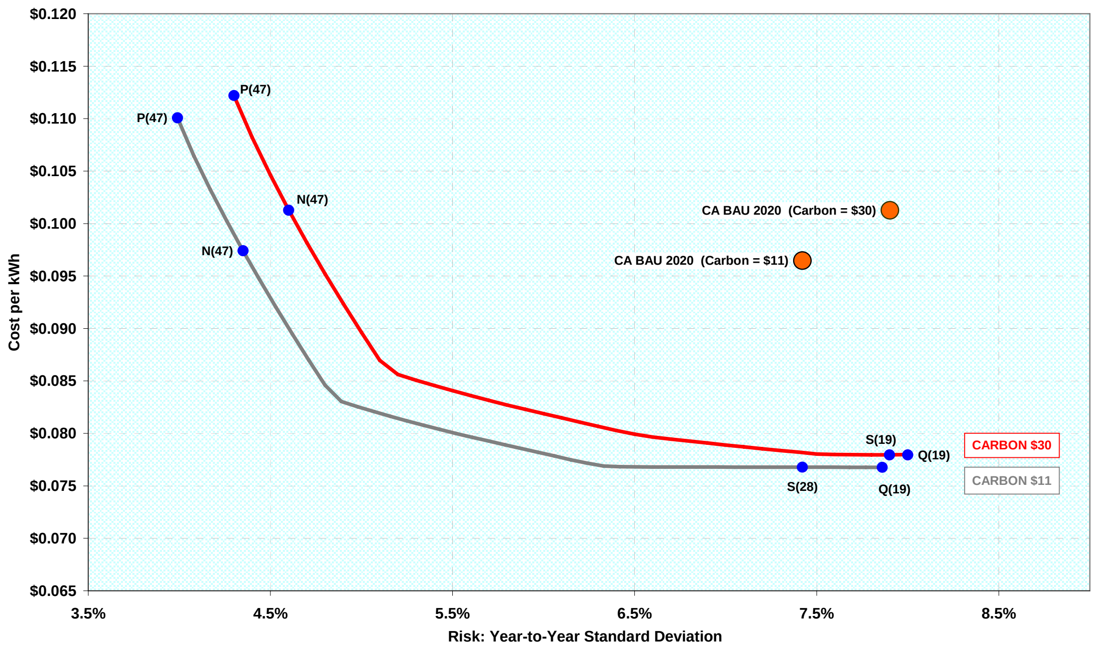


The Effect of CO_2 Pricing

So far, the analysis assumed a charge of \$20 per tonne of CO_2 emitted, interpreted here as either a market price or a marginal abatement cost for carbon emissions. We will now investigate the effect of pricing CO_2 emissions on the cost-risk characteristics of the 2020 CA-BAU mix and of efficient generating portfolios.

As Figure 14 illustrates for expository realizable case, portfolio risks and costs rise with rising CO_2 prices. This is true for the BAU portfolio and the efficient electricity generating portfolios. The parenthetical numbers next to the typical mixes represent annual CO_2 emission levels.

Figure 14: Efficient Frontier as a Function of CO_2 price – Realizable Case



As an illustration, the cost of the BAU portfolio increases by nine percent or 0.5 cents per kWh (from 9.6 cents to 10.1 cents per kWh) as CO_2 price increase from $11 to $20 per tonne. The risk of that portfolio correspondingly rises from 7.4 percent to 7.9 percent, illustrating its sensitivity to changing CO_2 prices. By definition, the share of each technology in the BAU portfolio and, thus, CO_2 emissions do not change with a rise in CO_2 prices. Clearly, it makes little sense to keep technology shares constant when CO_2 prices rise.

By contrast, with rising CO_2 prices it is optimal to reduce the share of fossil fuels in electricity generation – as indicated by the amount of CO_2 emissions, which is shown by parenthetical values next to the portfolios in Figure 14. For example, at CO_2 price of $11 per tonne, the portfolio *S* emits 28 million tonnes of CO_2 per year. As the CO_2 price increases, optimal portfolios are re-shuffled to minimize portfolios costs and risks. For a carbon price of $30/tonne CO_2, emissions fall by almost 32 percent to 19 million tonnes per year.

Figures 15 and 16 shows technology shares on the left vertical axis, and the CO2 emissions on the right axis for a $11/tonne and a $30/tonne CO_2 price case, respectively.

Figure 15: Technology Shares and CO_2 Emissions – CO_2 = $11/tonne case

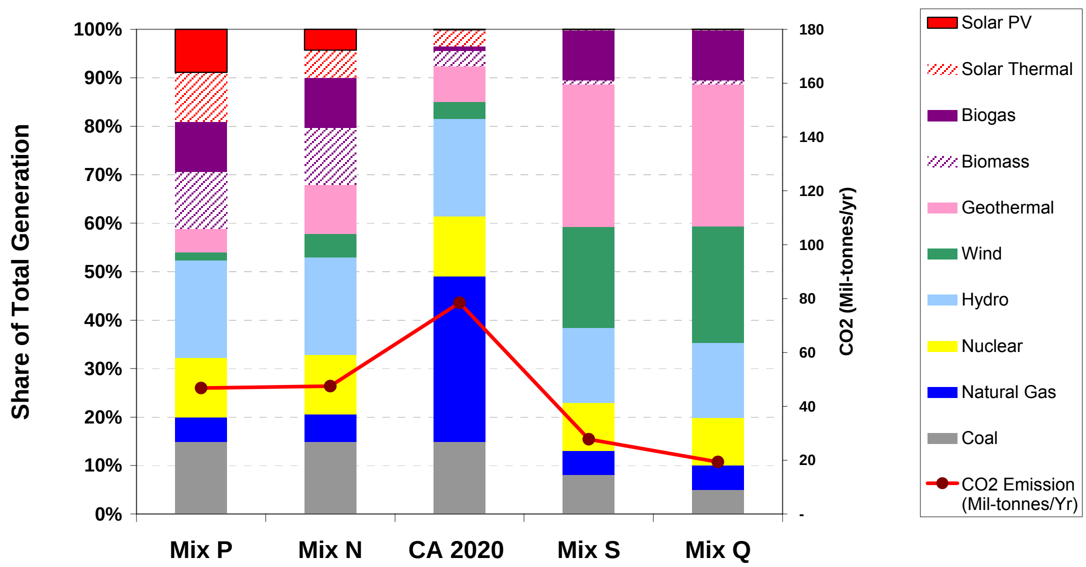
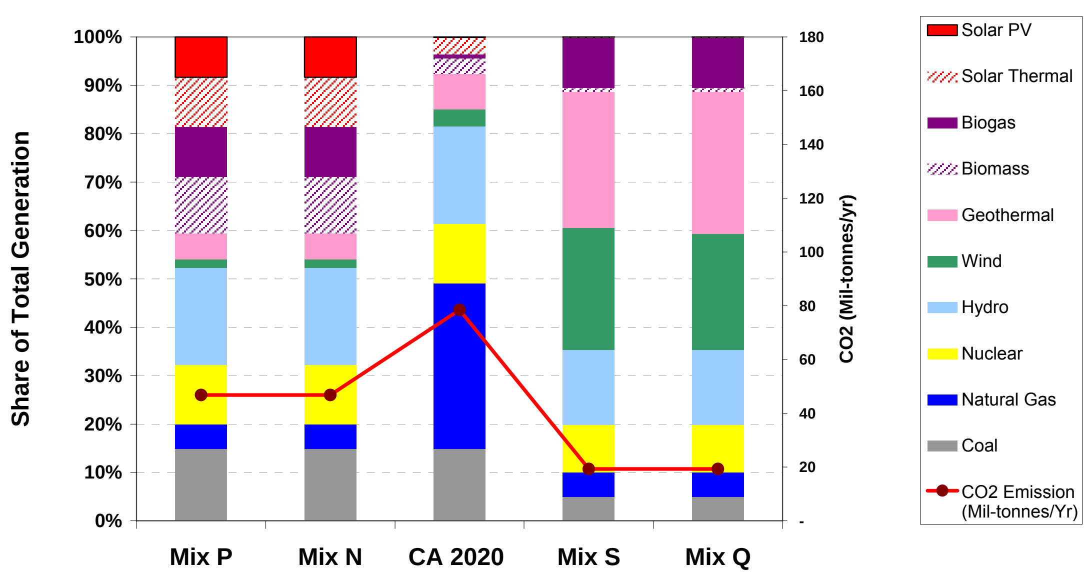


Figure 16: Technology Shares and CO_2 Emissions – CO_2 = $30/tonne case



CHAPTER 6: SUMMARY, CONCLUSIONS, AND FUTURE IMPROVEMENTS

This report has presented a mean-variance portfolio optimization analysis that develops and evaluates optimal (that is, efficient) CA electricity generating mixes for 2020. The results suggest that greater shares of non-fossil technologies can help reduce the cost and risk of the CA generating portfolio as well as its CO_2 emissions. To illustrate, an efficient generating mix that may be achievable by 2020 is estimated to cut annual CA electricity generating cost by $6.8 billion and achieves 33 percent RPS requirements. This portfolio thus produces perpetual annual benefits sufficient to justify current investments in renewable technologies. Against this background, policies designed to accelerate the deployment of key non-fossil technologies appear to be cost-effective.

Our analysis also indicates that nuclear acceleration and promotion policies may not be efficient and optimal portfolios re-shuffles to lower CO_2 emissions in response to increase in CO_2 prices.

Perhaps the single most important lesson of the portfolio optimization analysis is that adding a non-fossil fuel, fixed-cost technologies (such as wind energy) to a risky generating portfolio lowers expected costs at any level of risk, even if the non-fossil technology costs more when assessed on a stand-alone basis. This underscores the importance of policy-making approaches grounded in portfolio concepts as opposed to stand-alone engineering concepts. In addition, adding “too much” renewables counter-intuitively increases (not decreases) resulting portfolio risk because (a) it replaces less risky existing technology with more risky new technology; and (b) it reduces overall portfolio diversification.

Today’s dynamic and uncertain energy environment requires portfolio-based planning procedures that reflect market risk and de-emphasize stand-alone generating costs. Portfolio theory is well tested and ideally suited to evaluating electricity expansion strategies.[37] It identifies solutions that enhance energy diversity and security and are therefore considerably more robust than arbitrarily mixing technology alternatives. Portfolio analysis reflects the cost-risk relationship (covariances) among generating alternatives. Though crucial for correctly estimating overall cost, electricity-planning models universally ignore this fundamental statistical relationship and instead resort to sensitivity analysis and other ill-suited techniques to deal with risk. Sensitivity analysis cannot replicate the important cost inter-relationships that dramatically affect estimated portfolio costs and risks, and it is no substitute for portfolio-based approaches. The mean-variance portfolio framework offers solutions that enhance energy diversity and security and are therefore considerably more robust than arbitrarily mixing technology alternatives.

That said, it is important to recognize that the mean-variance portfolio approach has several important limitations with respect to generation planning. The portfolio optimization presented in this paper does not define any specific capacity-expansion plan. Such a plan would require far more detailed modelling and analysis. The results presented here are largely expositional, but they demonstrate the value of portfolio optimization approaches and suggest that capacity planning made on the basis of stand-alone technology costs will likely lead to economically inefficient outcomes.

Moreover, in deregulated markets, individual power producers evaluate only their own direct costs and risks when making investment decisions. These decisions do not reflect the effects the producers' technologies may have on overall generating portfolio performance. Wind investors, for example, cannot capture the risk-mitigation benefits they produce for the overall portfolio, which leads to under-investment in wind relative to levels that are optimal from society's perspective. Similarly, some investors may prefer the risk menu offered by fuel-intensive technologies such as combined-cycle gas turbines, which have low initial costs. Through existing regulatory mechanisms and strong correlation between electricity market price and gas price, gas generators may be able to transfer fuel risks onto customers. In effect, these investors may not bear the full risk effects they impose onto the generating mix, which may lead to over-investment in gas relative to what is optimal from a total portfolio perspective. All this suggests a rationale for economic policies in favor of technologies that capture diversification benefits.

Lastly, there are many assumptions and limitations affecting the application of mean-variance portfolio analysis techniques to generating assets. For instance, this analysis used exogenously prescribed fossil and nuclear fuel prices that do not vary with demand. As a result, generating mixes containing 35 percent gas-fired generation use the same natural gas price as mixes with 5 percent gas share. In reality, it is likely that gas prices across California would decline with reduced gas demand. For example, Sieminski (2007)[38] estimates that the current 10 percent warmer US winter is causing 17 percent drop in natural gas prices and a 21 percent drop in oil prices. If such feedback between price and demand were included in the analysis, it might make gas more attractive as their portfolio share move toward their lower limits, and less attractive as they move towards their upper bounds. In addition, assuming normal distribution of holding period returns and using past volatility as a guide to the future need to be refined and tested. Future improvement of the portfolio analysis will address such issues to provide better decision-making tools for California's energy planners.

ENDNOTES

[1] Assembly Bill 32, (Nuñez), Chapter 488, Statutes of 2006.

[2] For purposes of this report, “business-as-usual” includes 20 percent renewable energy (the 2010 goal) and predicted results from all funded energy efficiency.

[3] It is interesting to note that In California, over 90% of the RPS contracted energy so far is below MPR (market price reference).

[4] 2005 Integrated Energy Policy Report. Publication # CEC-100-2005-007-CMF.

[5] 2006 Integrated Energy Policy Report Update. Publication # CEC-100-2006-001-CMF.

[6] The one renewable generation exception is biomass, whose cost structure is similar to gas-fired generation.

[7] Strictly speaking, in the case of capital costs, this statement holds only *ex post,* although, given the short lead times of renewables projects and the large proportion of manufactured components, construction-period risks for these technologies is low even *ex ante*. O&M costs for renewables arguably have the same portfolio risks as O&M costs of conventional technologies. However, because they represent a small share of total cost of renewable generation, their risk contribution is also small.

[8] On an accounting basis, kWh generating cost is calculated by dividing annual capital charges plus operating costs by the year’s kWh output. Given a fixed capital charge and relatively fixed maintenance costs, therefore, annual wind output variability would cause year-to-year kWh costs to vary. Sunk capital costs are irrelevant in an economic sense, but fluctuations in periodic wind output might change the economic kWh cost estimate on the basis of avoided costs: i.e. to the extent that periodic wind shortfalls will require replacement purchases from alternative sources which may have to be kept in reserve for such purposes.

[9] Bolinger, M., R. Wiser, and W. Golove, (2006) “Accounting for Fuel Price Risk

When Comparing Renewable to Gas-Fired Generation: The Role of Forward Natural Gas

Prices,” *Energy Policy* 34(6), pp. 706-720.

[10] One notable exception is biomass fuel costs. They are correlated to diesel oil and thus to other fuels, because biomass fuel costs are highly dependent on transportation.

[11] There are also different “flavors” of betas, based on a firm’s leverage.

[12] Developed by Nobel Laureate William F. Sharpe, this ratio relates changes in risk to changes in reward.

[13] Comparative Costs of California Central Station Electricity Generation Technologies. Draft Staff Report. June 2007. CEC-200-2007-011-SD.

[14] TECHPOLE database, LEPII, University of Grenoble, CNRS.

[15] This assumption is also consistent with Energy Commission’s Scenario Analysis Project (CEC-200-2007-010-SD-AP). In this analysis, as in the Scenario Analysis Project, costs born by customers are included for solar PV.

[16] The same levelized cost for large and small hydro is assumed. In California, only small hydro less than 30MW is eligible for the RPS.

[17] The draft policy setting out California’s proposed cap-and-trade system can be found at: http://www.climatechnage.ca.gov/events/2007-06-12_mac_meeting/2007-06-01_MAC_DRAFT_REPORT.PDF.

[18] Synapse Energy Economics, Inc, "Climate Change and Power: Carbon Dioxide Emissions Costs and Electricity Resource Planning," prepared by Lucy Johnston, Ezra Hausman, Anna Sommer, Bruce Biewald, Tim Woolf, David Schlissel, Amy Rocshelle, and David White, June 8, 2006. Available at: http://www.synapse-energy.com/Downloads/SynapsePaper.2006-06.0.Climate-Change-and-Power.A0009.pdf.

[19] The IAP developed a component of the costs that can be attributed to wind by netting out imbalance costs, specifically those costs for regulation and load following. In the IAP study, based on an extreme penetration scenario aimed at 33%, these costs were estimated at \$0.21/MWh for regulation and \$0.07/MWh to \$0.48/MWh for load following resulting in a \$0.69/MWh cost for integrating the wind resource. This is consistent with a previous study called the Cost of Integrating Renewables (available at: http://www.abcsolar.com/pdf/500-04-054.pdf), which clearly defines the total costs and the costs associated with "integrating" a generator per market participation rules.

[20] The analysis also excludes the impacts of local interconnection costs and resource saturation. Specifically, only so much wind resource capacity can be interconnected to the transmission system grid at the local level. This issue can be addressed by creating multiple wind resources, each reflecting a specific local area, and performing the portfolio analysis with additional constraints.

[21] Awerbuch, S, J. Jansen, L. Buerskens, and T. Drennen, "The Cost of Geothermal Energy in the Western US Region: A Portfolio-Based Approach," Sandia National Laboratories, March 2005.

[22] HPR is defined as: HPR = $(P_2 – P_1) / P_1$ where P_t is the price/cost at time *t*. All SD and correlation estimates refer to the HPRs, not the actual price/cost levels themselves.

[23] In principle, the O&M cost category should include outlays for property taxes, insurance, and other non-maintenance categories. These would most likely exhibit lower risk and potentially dampen the results of Table 1.

[24] Note that for a fixed-cost technology $\sigma_j = 0$ or nearly so. This reduces σ_p, since two of the three terms in Equation 2 are reduced to zero. It is also easy to see that σ_p declines as $\rho_{i,j}$ falls below 1.0.

[25] Green, R. (2006). "Carbon tax or carbon permits: the impact on generators' risks," Institute for Energy Research and Policy, University of Birmingham, September. Available at: http://ideas.repec.org/p/bir/birmec/07-02.html

[26] EU-ETS is the Carbon Trading Scheme within the European Union. The first compliance phase is from 2005 to 2007, while the second compliance phase continues from 2008 to 2012.

[27] Awerbuch, S., and M. Berger, "Energy Security and Diversity in the EU: A Mean-Variance Portfolio Approach," IEA Report Number EET/2003/03, Paris: February. Available at: http://library.iea.org/dbtw-wpd/textbase/papers/2003/port.pdf; Roques, F., W. Nuttall, D. Newberry, R. de Neuville, and S. Connors, "Nuclear Power: A Hedge against Uncertain Gas and Carbon Prices?" *The Energy Journal* 27 (4), pp. 1-24.

[28] Current California policy, as described in the 2005 IEPR, has prohibited development of new nuclear facilities since 1976 because of a continuing lack of a permanent waste-storage facility. See 2005 IEPR, p. 84.

[29] This study uses the 2006 CA electricity generation shares that were published in the California Energy Commission's 2006 Net System Power Report, CEC-300-1007-007, April 2007. Available at: http://www.energy.ca.gov/2007publications/CEC-300-2007-007/CEC-300-2007-007.PDF. These values were then used as the basis to develop the projected 2020 business as usual (BAU) electricity generation shares. Specifically, the generation growth was held constant for Coal, Nuclear, Hydro (Large and Small), and Solar PV technologies, and the CA-BAU assumes that renewable energy account for 20 percent of the total generation in 2020.

[30] These expository bounds will be refined in the final report.

[31] For nuclear, the 2005 IEPR reaffirmed California's policy that suspended construction of new nuclear power plants beginning in 1976. No growth in new coal technology due to Senate Bill 1368 which limits GHG emissions to below CCGT emissions and also because we assume that carbon sequestration will not be sufficiently mature to play a part in California generation mix through 2020. No growth in new large hydro is assumed although small increases in small hydro or increased efficiency in large hydro are possible. We leave the variability of hydro output for future consideration in the final report.

[32] This estimate is based on an annual electric consumption in 2020 of 310.2 TWh ($\$0.022/\text{kWh} \times 310.2 \times 10^9 \text{kWh} = \$6.8$ billion).

[33] This is true only to the extent that the underlying generating costs shown in the Figure reflect all economic cost. However, since the costs shown in the Figure do not fully incorporate some economic costs such as investment grants that benefited some of these technologies (e.g., wind and nuclear), the resulting climate change mitigation may cost more than what in the Figure suggests.

[34] Renewables share does not include solar PV.

[35] CORWM, Committee On Radioactive Waste Management. (2006). "Managing our Radioactive Waste Safely." Available at: http://www.corwm.org.uk/pdf/Chapter09.pdf.

[36] See 2005 IEPR, p 84.

[37] Other techniques have also been applied. For instance, Stirling (1996, 1994) develops maximum-diversity portfolios based on a considerably broader uncertainty spectrum. Though radically different in its approach, his diversity model yields qualitatively similar results. See, Stirling, A. 1994 "Diversity and ignorance in electricity supply – Addressing the solution rather than the problem". *Energy Policy* (22:3), pp. 195-216; Stirling, A. 1996 *On the Economics and Analysis of Diversity,* Paper No. 28 Science Policy Research Unit (SPRU) University of Sussex, Available at: http://www.sussex.ac.uk/spru.

[38] Sieminski, A., "Varying Views on the Future of the Natural Gas Market Secrets of Energy Price Forecasting, 2007 EIA Energy Outlook, Modeling, and Data Conference Washington DC, March 28, 2007. Available at: http://www.eia.doe.gov/oiaf/aeo/conf/sieminski/sieminski.ppt.

APPENDIX: ESTIMATING EXPECTED CO_2 EMISSIONS RISK

Our aim is to estimate the risk or standard deviation (SD) of annual CO_2 prices and their correlation with fossil fuel prices. These estimates represent required inputs to our CA generating portfolio optimization model. In a portfolio context, the relevant risk measure is the SD of the *holding-period-return*s (HPRs) of annual prices. HPR is defined as:

$$HPR = (P_2 - P_1) / P_1$$

where, P_t is the price of CO_2 (or fossil fuel) at time *t.* All our SD and correlation estimates refer to the HPRs, not the actual price levels themselves.

CO_2 Prices/Returns

Because CO_2 is not traded in CA we must use EU prices. However, EU data is limited because CO2 has only been trading for about 18 months. Given this short history, we lack essential information on the behaviour of *annual* CO_2 HPRs from which we might estimate the CO_2 price (HPR) SD and its correlation with (the HPR of) fuels prices. Although we have 18 months of *daily* CO_2 HPRs, the daily frequency is not comparable to our other portfolio risk estimates, which are annual. This analysis therefore represents a first attempt to infer the behaviour of *annual* CO_2 HPRs from the limited historical data. While in a sense, we have built a significant analytic superstructure on top of a fairly limited foundation of historic data, others may find our procedures useful and applicable as the body of historic data expands and the derived estimates thereby become more reliable.

We infer the annual statistics we need using two principal methodologies (1) an analytical approach and (2) a Monte Carlo simulation. The reasonableness and robustness of the results are determined using various sensitivity analyses. Table A-1 summarizes the final set of CO_2 SD and correlation estimates we used in portfolio optimization. The remainder of this annex describes the procedures we used to obtain these results.

Table A-1. Summary of CO_2 SD and correlation estimates

CO_2 SD	CO_2-Gas ρ	CO_2-Coal ρ
0.26	0.68	-0.49

1.1 Method I: Analytical Approach

Green (2006) develops a relationship for the price CO_2 expressed as a function of the price of gas and coal:

$CO_2 = 3.\ 15 \times G - 4.77 \times C$,

where CO_2, *G* and *C* represent the price of CO_2, gas and coal, respectively.

One potentially feasible approach to estimate annual CO_2 HPR SD from the historical CO_2 and fuel price data can be written as follows:

CO_2 HPR = $(X_2 - X_1) / X_1$, where X = G – C.

Applying this approach yields a CO_2 HPR SD in excess of 0.7, a value that seems unacceptably high because it far exceeds the annual HPR SD of fossil fuels.[i] Thus, direct application of Green's (2006) formula to the historical data, which relies on the price level relationship between CO_2, gas and coal, does not seem to provide realistic estimates of annual CO_2 SD.

As opposed to relying on the price *level* relationship, however, it seems conceptually equally appropriate to extend Green's (2006) approach and begin directly with an expression for the CO_2 HPR level relationship. Specifically, as a starting point, we assume a linear and unitary relationship (i.e. all coefficients = 1.0) for the annual HPR level relationship as follows:

[CO_2 price HPR] = [gas price HPR] – [coal price HPR] (Eq. 1)

Equation 1 extends Green's (2006) CO_2 price-level formula to an annual HPR level relationship. To test the robustness of the unitary aspects of this HPR level relationship (and the resulting CO_2 SD and correlation estimates), we perform sensitivity analyses by introducing additive and multiplicative perturbative random variables to this HPR level relationship above utilizing Monte Carlo simulation technique (See, e.g. Part II, Scenario I). The simulation results show that the resulting CO_2 SD and correlation estimates are quite robust to the unitarity assumptions.

Equation 1 assumes the equilibrium behaviour of rational economic agents. Specifically, the higher the natural gas price is, the greater the number of economic agents who will switch from gas to coal, which emits more CO_2. (i.e. the substitutability effect). This produces an outward shift of the demand curve in the CO_2 market, which raises CO_2 price, other things being equal. In the same manner, the faster the *increase* in natural gas price is (i.e. higher gas HPR), the faster the switch from gas to coal will be, and, hence, the faster the increase in CO_2 price will be (higher CO_2 HPR). We would, therefore, expect CO_2 HPRs to be positively correlated with gas HPRs.

In addition, a similar argument suggests that CO_2 prices (HPR) should be *negatively* correlated with coal prices (HPR). The linear functional form and the unitary coefficients that we have adopted here in Equation 1 are purely for analytical tractability. To check for the robustness of this assumption, we conduct Monte Carlo simulations, as described in more detail below. (See, e.g. Part II, Scenario I).

Equation 2 summarizes the covariance structure between CO_2 and fossil fuels.

$$\begin{aligned} &Var(CO_2) = Var(gas) + Var(coal) - 2Cov(gas, coal) \qquad \text{(Eq. 2)} \\ &Cov(CO_2, gas) = Var(gas) - Cov(gas, coal) \\ &Cov(CO_2, coal) = Cov(gas, coal) - Var(coal) \end{aligned}$$

We used annual historical gas and coal prices to compute the annual HPRs and the corresponding fuel covariance matrix. These values are used to calculate the annual CO_2 SDs and CO_2 correlations with the fossil fuel prices. Table A-2 summarizes the resulting CO_2 SD and correlation estimates applying Equation 2 to the historical time-series data.

Table A-2. Summary of CO_2 SD and correlation estimates using analytical approach

CO_2 SD	CO_2 -Gas ρ	CO_2 -Coal ρ
0.18	0.69	-0.31

The resulting annual CO_2 SD of 0.18 (Table A-2) is larger than the *daily* CO_2 SD of 0.05, or the monthly CO_2 SD of 0.15. These two estimates are obtained directly from historical CO_2 price data. This is consistent with the intuition that the *long-term* or annual standard deviation of CO_2 prices (HPRs) should be larger than the *short-term*—i.e. monthly and daily HPR SDs.

Table A-3. Estimated CO_2 HPR Standard Deviations

Daily HPRs	Monthly HPRs	Annual HPRs
0.05	0.15	0.18
Historic data	Historic Data	Eq. (2)

The only other reported CO_2 correlation estimates of which we are aware are reported by Roques, (2006), although these are based on price *levels*, not HPR values. Table A-4 below compares the two sets of estimates. Despite significant differences in estimation approach and methodology, two results are in reasonable agreement with each other.

Table A-4. Comparison of Estimated CO_2 Correlations

	CO_2 -Coal	CO_2 -Gas
A-Y (Analytical Method)	-0.31	0.69
Roques (2006)	-0.46	0.45

Source: Awerbuch-Yang and Roques (2006)

1.2 Method II: Monte Carlo Approach

This section describes a series of Monte Carlo simulations from which we estimate annual SD values for CO_2, along with correlations against annual fuel price HPRs. In Part I, we describe the methodology to estimate the HPR level SD of the simulated CO_2 prices. In Part II, we describe the methodology to estimate the HPR level correlations of annual CO_2 and fossil fuel prices. Finally, in Part III, we describe the methodology to estimate CO_2 price distribution in year 2020 (in addition to the usual CO_2 HPR level SD and correlations with fossil fuels) using Green's (2006) formula. In each case, our estimates of the annual HPR CO_2 SD and correlation values are based on 2,000 Monte Carlo experiments.

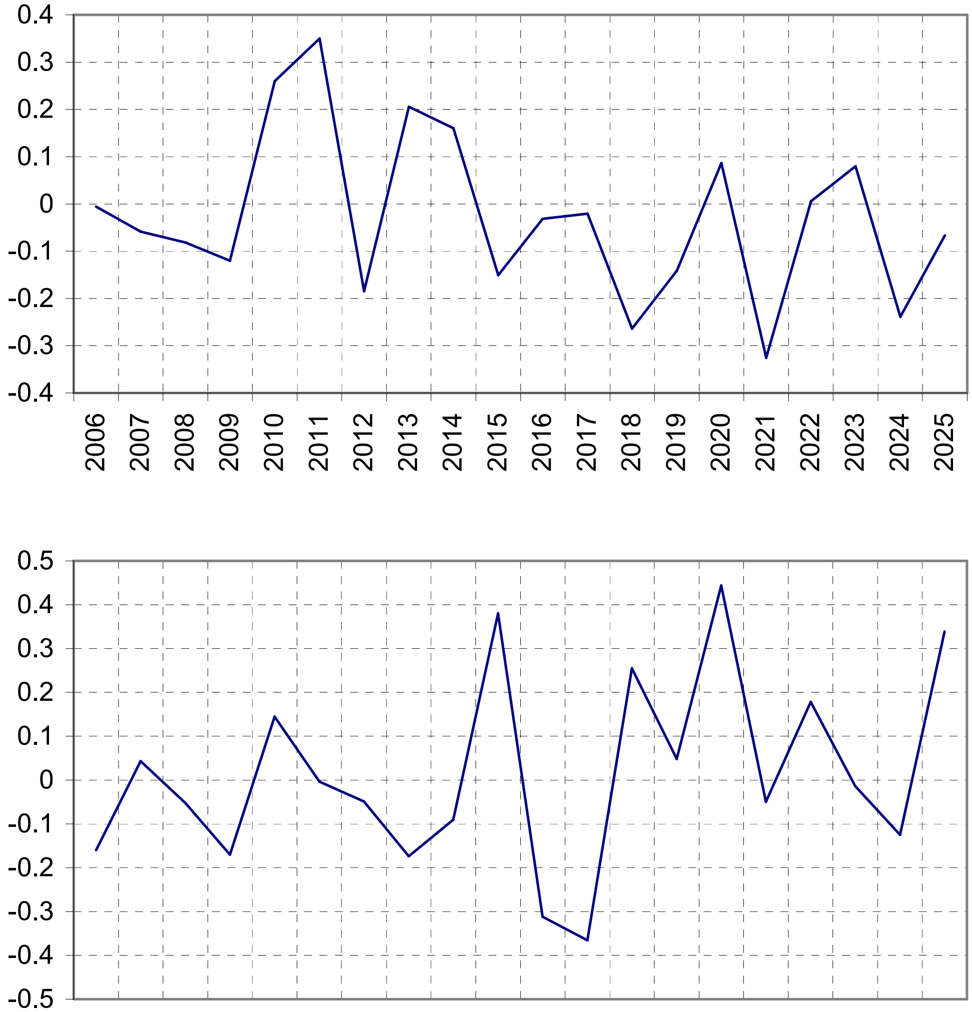
Part I: Standard Deviations of annual CO2 price HPRs

In estimating the CO_2 HPR SD using Monte Carlo technique, we assume the following:

1. The *mean level* of annual CO_2 HPR exhibits no trend and does not change significantly over the next 20 years. This assumption is consistent with actual observations from other financial markets.

2. The *volatility* of annual CO_2 HPR exhibits an upward trend. This assumption captures our 'ignorance' about future policy changes, technological innovations, market environment changes, etc. Figure A-1 shows illustrative samples of simulated annual CO_2 HPR over the next 20 years.

Figure A-1. Illustrative samples of simulated CO_2 HPR over the next 20 years



In estimating the reasonable CO_2 HPR SD using the Monte Carlo approach, we developed three scenarios:

1. <u>Scenario I:</u> Annual CO_2 HPR is drawn from i.i.d. (independently and identically distributed) normal distribution with linearly interpolated mean and standard deviation. When random variables $X_1, \ldots, X_n$ are drawn from the same distribution and are independently distributed, they are said to be i.i.d. In addition, normality is easily justifiable by a simple application of Central Limit Theorem (CLT) because we focus on annual frequency. This is also consistent with modelling on most financial markets.

2. Scenario II: Annual CO_2 HPR follows an AR(1) process with i.i.d. normal random shocks we assumed in Scenario I. AR(1) represents the first order autoregressive model. The population AR(1) model for the time series Y(t) can be written as: $Y(t) = \beta_0 + \beta_1 * Y(t-1) + u(t)$, where the errors u(t) are serially uncorrelated. The AR(1) model is widely used as a basis in many time series, regression, and forecasting methodologies such as a certain forecast of inflation. The AR(1) coefficient is estimated from historical HPR data. It is important to note that the AR(1) model is also consistent with the efficient market hypothesis. An efficient market implies zero serial correlation (random walk) at higher frequency, but does not preclude the possibility of serial correlation at lower frequency, as is the case here with annual HPR.

3. Scenario III: Major shocks in CO_2 markets (in contrast to the i.i.d. normal random shocks modelled in Scenarios I and II) are introduced in Scenario III. Specifically, these major shocks, once having occurred (*ex post*), can significantly affect the volatility of CO_2 markets. At the same time, the occurrence of such events is random and has uncertain magnitude (*ex ante*). To capture these features, we introduce an additional random component whose probability and magnitude simulates the impact of such major events in the future CO_2 market on the resulting CO_2 SD estimates.

Among three scenarios listed above, Scenario III best represents the reality of the CO_2 market. Table A-5 summarizes the results for our first two scenarios (i.e. normal i.i.d. and AR(1) process, respectively). The simulated CO_2 SD value is approximately 0.25, and the corresponding 95% bound ranges between 0.17 and 0.32.

Table A-5. Summary of Scenario I and Scenario II Results—Monte Carlo Results: CO_2 HPR Standard Deviations

	mean	median	95% bounds
Scenario I: i.i.d. normal	0.25	0.25	[0.18, 0.32]
Scenario II: AR(1)	0.24	0.24	[0.17, 0.32]

Table A-6 summarizes results for Scenario III (i.e. AR(1) process with major shocks in the CO_2 market) with various combinations of key parameters (i.e. probability ('prb') and magnitude ('mag') of unknown major shocks or surprises in the CO_2 market). These shocks may be conceptually similar to the concepts of 'surprise' and 'ignorance' (e.g. Stirling, 1994, Shackle 1972).[ii] The simulated CO_2 price standard deviations range between 0.24 and 0.35 depending on the expected magnitude and probability for the occurrence of major shocks over the next 20 years. The corresponding 95% bound ranges between 0.18 and 0.53. As shown in Table A-6, the resulting CO_2 SD estimates are quite stable over the wide range of assumptions regarding the probability and magnitude of major shocks on the CO_2 market over the next 20 years. For example, the resulting CO_2

SD estimates range between 0.24 and 0.28, when the probability of major shocks varies from 0.05 (i.e. major shocks occur once in entire simulation time period) to 0.4 (i.e. major shocks occur eight times), and the corresponding magnitude of major shocks varies from 2 (i.e. the magnitude of the shock is two standard deviations from the mean) to 5 (i.e. five SD from the mean). The CA portfolio optimization, therefore uses the CO_2 HPR SD value of 0.26, which corresponds to the reasonable assumption that the probability and magnitude of major shocks over the next 20 years is approximately 0.2 and 5, respectively (See Table A-6).

Table A-6. Monte Carlo results for Scenario III as a function of the assumed probability and magnitude of uncertain shocks on the CO_2 market over the next 20 years—Estimated CO_2 HPR SD (Scenario III) and 95% bounds

mag\ prb	0.05	0.1	0.15	0.2	0.25	0.3	0.35	0.4
2	0.24	0.24	0.25	0.25	0.25	0.25	0.25	0.25
	0.18 0.32	0.18 0.32	0.17 0.32	0.18 0.32	0.18 0.32	0.18 0.33	0.18 0.33	0.18 0.33
3	0.24	0.25	0.25	0.25	0.25	0.25	0.26	0.26
	0.18 0.32	0.17 0.33	0.18 0.33	0.18 0.33	0.18 0.33	0.18 0.34	0.18 0.34	0.18 0.34
4	0.24	0.25	0.25	0.25	0.26	0.26	0.26	0.26
	0.18 0.32	0.18 0.33	0.18 0.33	0.18 0.34	0.18 0.35	0.19 0.34	0.19 0.35	0.19 0.36
5	0.25	0.25	0.26	**0.26**	0.26	0.27	0.27	0.28
	0.17 0.33	0.18 0.34	0.18 0.34	0.18 0.35	0.19 0.35	0.19 0.36	0.19 0.37	0.20 0.38
6	0.25	0.26	0.26	0.27	0.27	0.28	0.28	0.29
	0.18 0.33	0.18 0.34	0.18 0.35	0.19 0.35	0.19 0.37	0.19 0.38	0.19 0.39	0.20 0.41
7	0.25	0.26	0.26	0.27	0.28	0.29	0.29	0.30
	0.18 0.33	0.18 0.35	0.18 0.36	0.19 0.38	0.19 0.39	0.20 0.41	0.20 0.42	0.20 0.43
8	0.25	0.26	0.27	0.28	0.29	0.30	0.31	0.31
	0.18 0.34	0.18 0.35	0.19 0.38	0.19 0.40	0.19 0.42	0.20 0.42	0.21 0.45	0.21 0.45
9	0.25	0.27	0.28	0.29	0.30	0.31	0.32	0.33
	0.18 0.34	0.18 0.38	0.19 0.40	0.19 0.43	0.20 0.44	0.20 0.45	0.21 0.48	0.21 0.51
10	0.26	0.27	0.29	0.30	0.31	0.32	0.34	0.35
	0.18 0.35	0.18 0.39	0.19 0.43	0.19 0.44	0.20 0.47	0.21 0.50	0.21 0.51	0.22 0.53

Part II: Correlation of annual CO_2 and fossil fuel HPRs

Estimating correlations of annual CO_2 HPR and fossil fuel HPRs is important in portfolio optimization because the magnitude and the sign of the correlations directly impacts the resulting optimized fossil fuel generation share in the presence of CO_2 constrained market. Our Monte Carlo estimates of the correlations of annual CO_2 and fossil fuel HPRs are based on the following two assumptions:

1. CO_2 price HPR = gas price HPR – coal price HPR. This is the same assumption we used in the analytical approach described in Method I section (see Eq. 1).

2. The covariance structure of coal and gas HPRs are stable over time.

To test the sensitivity of these two assumptions, we introduce random perturbations to the HPR level relationships over the entire simulated time period, as described more fully below.

Similar to the methodology described in Part I, our Monte Carlo estimates of reasonable CO_2 HPR correlations are based on the simulation of the following two scenarios:

1. Scenario I (Simulations with normal i.i.d.): We simulate gas and coal HPRs simultaneously, maintaining their covariance structure estimated from our sample. Then, we calculate the estimated CO_2 HPR. Two random perturbations are introduced to test the sensitivity of our assumed covariance structure on our estimated CO_2 HPR:

    a. Additive perturbation: CO_2 Price HPR = gas price HPR – coal price HPR + ε_a

    b. Multiplicative perturbation: CO_2 price HPR = gas price HPR – ε_m * coal price HPR

In both cases, ε_a and ε_m are random variables. The random perturbations test the robustness of the unitary HPR relationship.

2. Scenario II (Simulations with AR(1) process): Same as Scenario I, except that we use an AR(1) process to simulate the underlying trivariate time series. Scenario II better represents the reality of the CO_2 and fossil fuel time series, because AR(1) process assumption is more realistic than i.i.d. process assumption in simulating the underlying CO_2 and fossil fuel data.

Table A-7 summarizes the Scenario I results. As shown in Table A-7, our simulated correlation values are quite robust over the wide ranges of additive (‘add’) and multiplicative (‘coef’) perturbation assumptions. For example, the mean value of CO_2 and Gas HPR correlation estimates ranges between 0.63 and 0.73 when the additive perturbation assumptions are varying between 0.05 and 0.15, and the multiplicative perturbation assumptions are varying between 0.05 and 0.3. The similar observations can be made in CO_2 and Coal HPR correlation estimates.

Table A-7. Scenario I Results (IID approximation)

Gas HPR and CO_2 HPR

add\coef	0.05	0.1	0.15	0.2	0.25	0.3
0.05	0.73	0.73	0.72	0.73	0.73	0.73
	0.53 0.87	0.52 0.88	0.49 0.89	0.48 0.89	0.47 0.90	0.45 0.92
0.1	0.69	0.69	0.69	0.69	0.69	0.68
	0.49 0.85	0.46 0.85	0.46 0.86	0.46 0.86	0.43 0.87	0.39 0.87
0.15	0.64	0.63	0.64	0.64	0.63	0.63
	0.41 0.82	0.39 0.81	0.39 0.82	0.36 0.82	0.36 0.83	0.36 0.83
0.2	0.58	0.58	0.58	0.58	0.58	0.58
	0.31 0.78	0.31 0.78	0.32 0.78	0.31 0.78	0.30 0.78	0.30 0.80
0.25	0.53	0.52	0.52	0.52	0.53	0.52
	0.25 0.75	0.25 0.75	0.24 0.75	0.24 0.76	0.23 0.76	0.23 0.77
0.3	0.48	0.47	0.47	0.46	0.48	0.47
	0.16 0.72	0.17 0.72	0.16 0.72	0.15 0.71	0.18 0.73	0.16 0.73

Coal HPR and CO_2 HPR

add\coef	0.05	0.1	0.15	0.2	0.25	0.3
0.05	-0.50	-0.50	-0.48	-0.49	-0.48	-0.48
	-0.75 -0.18	-0.75 -0.18	-0.75 -0.13	-0.76 -0.13	-0.78 -0.07	-0.78 -0.03
0.1	-0.47	-0.47	-0.47	-0.47	-0.46	-0.46
	-0.73 -0.16	-0.73 -0.15	-0.74 -0.12	-0.74 -0.12	-0.76 -0.09	-0.77 -0.05
0.15	-0.43	-0.44	-0.43	-0.42	-0.42	-0.42
	-0.69 -0.10	-0.70 -0.11	-0.71 -0.08	-0.73 -0.05	-0.72 -0.05	-0.74 0.00
0.2	-0.40	-0.40	-0.39	-0.40	-0.38	-0.38
	-0.67 -0.08	-0.69 -0.05	-0.69 -0.04	-0.69 -0.03	-0.71 0.00	-0.72 0.03
0.25	-0.36	-0.37	-0.36	-0.36	-0.36	-0.35
	-0.65 -0.03	-0.66 -0.02	-0.66 0.00	-0.67 0.02	-0.68 0.03	-0.68 0.08
0.3	-0.32	-0.32	-0.32	-0.32	-0.31	-0.31
	-0.63 0.03	-0.63 0.04	-0.62 0.04	-0.65 0.07	-0.63 0.09	-0.65 0.10

In addition, it is important to note that the results summarized in Table A-7 above are also consistent with our analytical approach described in detail *supra*. Specifically, our analytical results on CO_2 correlations, as shown in Table A-8, fall within the 95% bound of the results summarized in Table A-7.

Table A-8. Summary of the analytical approach results

Correlation	Gas-CO_2	Coal-CO_2
Analytical Method	0.68	-0.31

Table A-9 summarizes the Scenario II results. Similar to the Scenario I results, our simulated correlation values are quite robust over the wide ranges of additive (‘add’) and multiplicative (‘coef’) perturbation assumptions. For example, the mean value of CO_2 and Gas HPR correlation estimates ranges between 0.62 and 0.72 when the additive perturbation assumptions are varying between 0.05 and 0.15, and the multiplicative perturbation assumptions are varying between 0.05 and 0.3. The similar observations can be made in CO_2 and Coal HPR correlation estimates as well. Therefore, in our CA generating portfolio optimization analysis, we use the CO_2 and fossil fuel correlation values that correspond to the additive and multiplicative perturbation assumptions of 0.1 (See Table A-9). This choice is reasonable because the resulting correlation estimates do not vary materially over the wide range of key parameter assumptions.

Table A-9. Scenario II Results (AR(1) approximation)

Gas HPR and CO_2 HPR

add\coef	0.05	0.1	0.15	0.2	0.25	0.3
0.05	0.72	0.72	0.72	0.72	0.72	0.71
	0.51 0.87	0.51 0.87	0.48 0.88	0.48 0.89	0.46 0.90	0.42 0.91
0.1	0.68	**0.68**	0.68	0.68	0.68	0.68
	0.46 0.84	0.44 0.84	0.43 0.85	0.43 0.86	0.41 0.86	0.42 0.88
0.15	0.63	0.62	0.63	0.62	0.63	0.62
	0.39 0.81	0.38 0.81	0.37 0.82	0.37 0.82	0.37 0.83	0.35 0.83
0.2	0.57	0.57	0.57	0.57	0.56	0.57
	0.30 0.78	0.31 0.78	0.31 0.77	0.29 0.78	0.27 0.77	0.29 0.79
0.25	0.51	0.51	0.51	0.51	0.51	0.51
	0.24 0.74	0.22 0.75	0.22 0.74	0.20 0.75	0.20 0.75	0.21 0.75
0.3	0.46	0.46	0.47	0.46	0.47	0.46
	0.18 0.71	0.15 0.72	0.16 0.71	0.16 0.72	0.15 0.72	0.14 0.71

Coal HPR and CO_2 HPR

add\coef	0.05	0.1	0.15	0.2	0.25	0.3
0.05	-0.51	-0.51	-0.51	-0.50	-0.49	-0.49
	-0.75 -0.19	-0.77 -0.19	-0.76 -0.16	-0.77 -0.14	-0.78 -0.10	-0.79 -0.06
0.1	-0.49	**-0.49**	-0.47	-0.47	-0.47	-0.46
	-0.74 -0.18	-0.74 -0.17	-0.75 -0.13	-0.75 -0.11	-0.76 -0.10	-0.77 -0.04
0.15	-0.45	-0.45	-0.44	-0.44	-0.43	-0.43
	-0.71 -0.11	-0.72 -0.11	-0.73 -0.08	-0.73 -0.07	-0.74 -0.04	-0.74 -0.01
0.2	-0.40	-0.40	-0.40	-0.40	-0.40	-0.39
	-0.68 -0.06	-0.69 -0.05	-0.68 -0.04	-0.69 -0.02	-0.71 -0.02	-0.72 0.03
0.25	-0.37	-0.36	-0.37	-0.36	-0.36	-0.36
	-0.65 -0.05	-0.65 -0.02	-0.67 -0.03	-0.67 0.01	-0.69 0.04	-0.69 0.05
0.3	-0.33	-0.33	-0.33	-0.33	-0.32	-0.33
	-0.63 0.01	-0.63 0.03	-0.64 0.03	-0.64 0.04	-0.65 0.06	-0.66 0.08

Part III. Monte Carlo Simulations based on Green's Price Level Formula

We also performed Monte Carlo simulations based on Green's (2006) equilibrium condition relating price *levels* of gas, coal, and CO_2. Specifically, we estimated the three important parameters used in CA portfolio optimization: CO_2 price distribution in year 2020, CO_2 HPR SD, and correlations between CO_2 HPR and fossil fuels. In CA portfolio optimization, we varied the CO_2 price based on the estimated range of CO_2 price distribution in year 2020 and analyzed the impact of CO_2 price on optimal CA mix. Our Monte Carlo estimates of the CO_2 price distribution and corresponding CO_2 HPR SD and correlation values are based on the following three assumptions:

1. We follow Green's (2006) approach by assuming the following equilibrium condition in terms of price levels of CO_2, gas, and coal: i.e. $P_{co2} = 3.15 P_{gas} - 4.77 P_{coal}$.

2. The average price levels of gas and coal are increasing. Table A-10 summarizes our fuel price assumptions. These values were obtained from IEA historical import prices and EIB 2020 forecasts.

3. As usual, we use AR (1) process for gas and coal price levels.

Table A-10. Summary of fossil fuel price assumptions ($/MWh)

	2003	2020
Gas	20.35	28.2
Coal	8.23	13.7

In developing the scenario, we again introduce random perturbations into the equilibrium condition. In this case, the equilibrium condition is Green's (2006) price level formula rather than the HPR level relationship we used in Equation 1. We also consider both additive shocks of the form,

$$P_{co2} = 3.15 P_{gas} - 4.77 P_{coal} + \varepsilon \,;$$

and multiplicative shocks of the form,

$$P_{co2} = (3.15 + \varepsilon_1) P_{gas} - (4.77 + \varepsilon_2) P_{coal} \,.$$

The HPRs of CO_2, gas and coal are computed from the corresponding simulated price level values.

Table A-11 summarizes the estimated AR coefficients used in our Monte Carlo simulations. The AR coefficients were estimated from the IEA fuel prices data.

Table A-11. Summary of the AR coefficients

	Coal	Gas
AR coefficient	0.9379	0.7152

The Monte Carlo CO_2 price-level results for 2020 along with corresponding SD estimates are summarized in Table A-12. Specifically, 95% bound of projected

CO_2 price level in year 2020 ranges between 5 and 57 dollars per tonne of CO_2, and the expected average values are approximately $30 per tonne. Our Monte Carlo estimated mean CO_2 price in 2020 is below the corresponding EIB projected estimate of $47 per tonne, although the EIB estimate lies within our 95% bound estimate. In order to better understand the effects of varying CO_2 prices and to ensure that we cover the range of our 95% bound estimates, the CA portfolio optimizations were run for CO_2 prices ranging from $10 to $30 per tonne.

Table A-12. Simulated results for CO_2

Projected CO_2 Price level in 2020

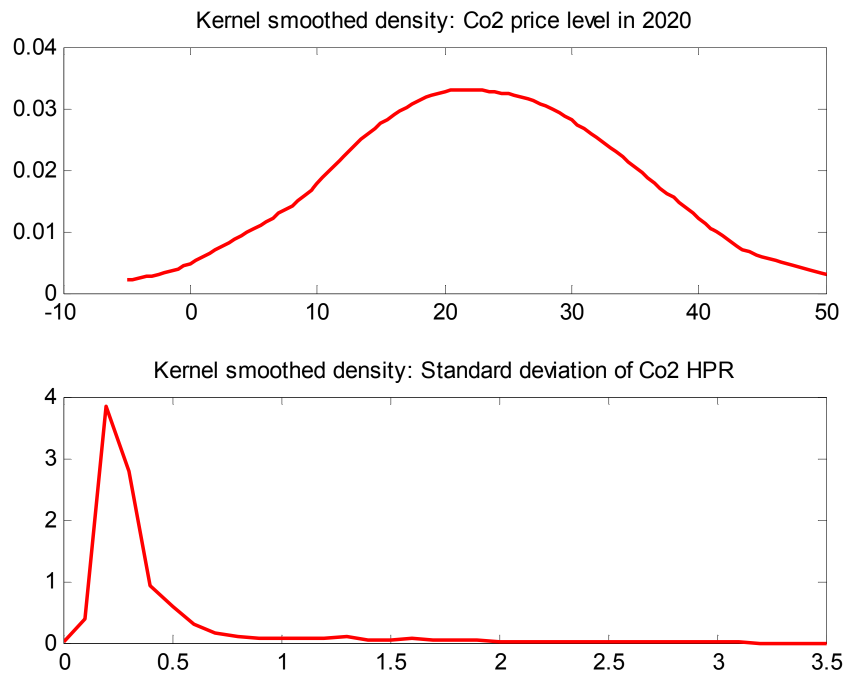
mean	Median	95% bound
$31.28	$31.18	[$5.44, $57.28]

SD of CO_2 HPR

mean	median	95% bound
1.31	0.27	[0.15, 1.96]

Figure A-2 shows the CO_2 price and SD distribution. In contrast to the CO_2 price level distribution (top of Figure A-2), the distribution of the standard deviation of the simulated CO_2 HPR (bottom of Figure A-2) is highly skewed. Therefore, the median SD (i.e. 0.27) is a better measure of the CO_2 HPR risk. Note that the median SD estimate is consistent with our base case SD estimate of 0.26 used in our CA portfolio analysis.

Figure A-2. CO_2 Price and SD distribution



The Monte Carlo simulation results for the CO_2 HPR correlations are summarized in Table A-13. The mean values of correlations between CO_2 HPR and Gas and Coal HPRs are 0.73 and 0.12, respectively. These estimates are consistent with our base case estimates used in the CA portfolio optimization within 95% bound, except for CO_2-Coal HPR correlation estimates.

Table A-13. Simulated correlation

Correlation between CO_2 HPR and Gas HPR

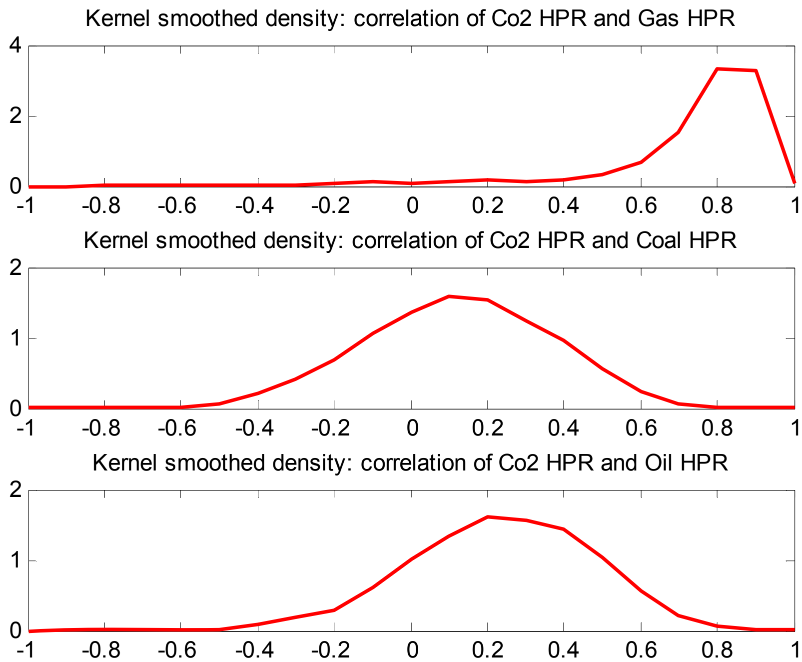
mean	median	95% bound
0.73	0.81	[0.17, 0.92]

Correlation between CO_2 HPR and Coal HPR

mean	median	95% bound
0.12	0.12	[-0.29 , 0.50]

Finally, Figure A-3 shows the distribution of simulated correlations between CO_2 and fossil fuels.

Figure A-3. Simulated correlation distribution of CO_2 and fossil fuels



1.3 Summary and Conclusion

This Appendix describes the procedures we used to produce estimates of the risk (HPR Standard Deviation) of annual CO_2 prices and their correlation with fossil fuel prices. It described two general methodologies, i.e. an analytical approach and a set of Monte Carlo simulation, that enable us to make numerical estimates of CO_2 SD and correlations. An analytical model based on HPR level equilibrium approach (as described in Equation 1) is used to determine the CO_2 SD and the correlation, and these values are compared to the ones obtained from Monte Carlo simulation. We also perform various sensitivity analyses to test the reasonableness and robustness of our obtained CO_2 SD and correlation values. In addition, Green's (2006) price level formula is used to estimate CO_2 price distribution in year 2020. The results of this study represent required inputs to our CA generating portfolio optimization model.

The following table summarizes the final set of CO_2 SD and correlation estimates we applied in CA portfolio optimization.

Table A-14. Final set of CO_2 SD and correlation estimates applied to CA portfolio optimization

CO_2 SD	CO_2-Gas ρ	CO_2-Coal ρ
0.26	0.68	-0.49

In addition, in order to better understand the effects of varying CO_2 prices, and to insure that we cover the range of our 95% bound estimates of our CO_2 price distribution in year 2020, we ran the portfolio optimizations for CO_2 prices ranging from $10 to $30.00 per tonne.

[i] An alternative approach to estimating annual CO2 risk uses estimated historic monthly CO_2 SD under an assumption of a random walk as follows: Annual CO_2 HPR SD = SQRT[12] × monthly CO_2 HPR SD; this also yields a high value in excess of 0.5.

[ii] A discussion of these concepts in the context of mean-variance portfolio theory and Stirling diversity analysis is given in Awerbuch, Stirling, et al. (2006).