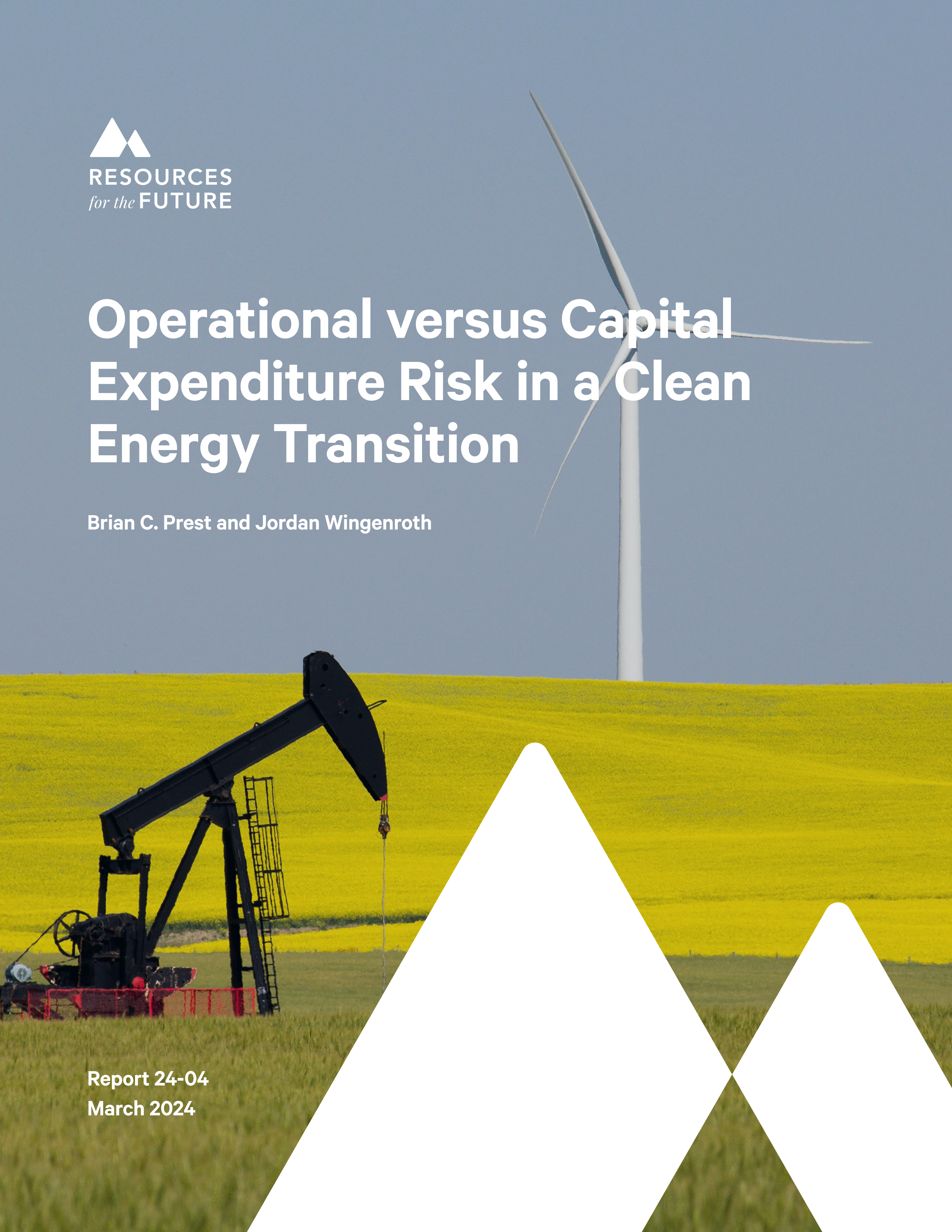

RESOURCES *for the* FUTURE

Operational versus Capital Expenditure Risk in a Clean Energy Transition

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About the Authors

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Abstract

This report analyzes the differences between risk profiles posed by fossil assets, such as natural gas power generation and gas-powered vehicles, and those of “green” alternatives, such as wind power and electric vehicles. Fossil assets tend to be exposed primarily to uncertainty in operational expenditures (OPEX) such as fuel prices, whereas green assets tend to be exposed primarily to uncertainty in capital expenditures (CAPEX). This report builds a quantitative dynamic economic model of investment under uncertainty that accounts for these different kinds of risk. The results show the relative value of such CAPEX-exposed green assets over OPEX-exposed fossil assets for reducing exposure to future cost uncertainty. The model’s key conclusions are that (1) correlated OPEX risk across assets implies that an all-green portfolio has lower uncertainty than an all-fossil one even when the assets themselves have similar total cost uncertainty, (2) adding a green asset option to an otherwise all-fossil investment strategy typically reduces cost uncertainty by more than adding a fossil option to an all-green strategy does, and (3) *actually owning* such a green asset almost uniformly reduces cost uncertainty by shielding society (investors and consumers) from OPEX risk. The primary mechanisms driving these results are threefold: first, an investment in CAPEX-exposed assets immediately resolves substantial cost uncertainty, second, spikes in fuel prices increase OPEX for all existing fossil assets whereas spikes in green CAPEX costs only affect new investments, and third, the availability of multiple options for future asset replacement decisions avoids locking in exposure to CAPEX risk.

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1. Introduction

Recent spikes in the price of crude oil have highlighted the risks to which individuals and the economy are exposed when reliant on vehicles that run on petroleum. In the electricity sector, fossil fuel–based power plants are similarly exposed to price volatility, as demonstrated by the spikes in recent years in natural gas and coal prices. The growing connection of US natural gas prices to increasingly volatile global markets may also serve to magnify the risk exposure of natural gas power generation. Many see clean energy investments, including zero-carbon electricity, battery storage, and electric vehicles (EVs), as ways to reduce such exposure to unpredictable commodity prices. On the other hand, a counterargument is that those clean energy assets are made using minerals that can also exhibit volatile prices. This raises the question, Will a clean energy transition simply substitute one kind of commodity price risk for another? We assess this question using a stochastic dynamic economic model drawing from the economic literature on investment under uncertainty (Dixit and Pindyck 1994), concluding that the answer is no because clean-energy technologies are exposed to qualitatively different kinds of risks.

While this concern about clean energy risk exposure has some surface-level plausibility, it neglects to recognize a key difference between the two kinds of price uncertainty. In particular, fossil fuel purchases such as natural gas for electricity generation or gasoline for internal combustion engines (ICEs) represent *operational expenses* (OPEX). Once one has invested in such a long-lived asset, one is typically exposed to OPEX risk for the entirety of the asset's useful life. By contrast, low-carbon "green" assets like renewable and nuclear power or EVs typically feature high capital expenditures (CAPEX) but minimal OPEX, resulting in little to no exposure to variable fuel costs over time.[1] While there remains uncertainty in the future CAPEX replacement cost of such a green asset at the end of its useful life, once the CAPEX is sunk to construct the project, it remains insulated from variable OPEX. Moreover, the option to switch to alternative technologies at the end of an asset's useful life further shields investors and consumers from future uncertainty in CAPEX.

In this report, we demonstrate this point quantitatively by developing a stochastic dynamic programming model that reveals differences in the nature of risk exposure associated with these two types of costs. For example, when gasoline prices spike, the owner of an ICE vehicle (ICEV) will immediately see a largely unavoidable surge in operating costs. Naturally, EV owners are insulated from this gasoline price risk, but they are also mostly insulated from potential increases in critical minerals. The most obvious reason for this is that the cost of those minerals was locked in when the vehicle was acquired. The model developed in this report is general enough to

[1] While operating expenditures entail more than just fuel costs, other operating and maintenance costs tend to be smaller and less uncertain than capital and fuel costs. See, for example, EIA (2022). For this reason, we consider OPEX uncertainty as effectively representing fuel price uncertainty.

represent choices between assets with OPEX-centric and those with CAPEX-centric risk profiles, but we also apply it to two specific examples of investment choices, considering first the choice between gasoline and electric vehicles, and second the choice between natural gas–fired and wind electricity.

Throughout this report, the key metric of interest representing exposure to cost uncertainty is the standard deviation of the present value (PV) of long-run discounted expenditures to build and operate the portfolio of assets. We focus on how three factors affect this standard deviation.

First, we consider the overall cost uncertainty across a portfolio of all-fossil or all-green assets, where each individual fossil or green asset nonetheless has similar total cost uncertainty. We find that an all-fossil portfolio creates positively correlated OPEX risks across the portfolio because spikes in fuel prices increase OPEX for all existing fossil assets whereas spikes in green CAPEX costs only affect new investments.

Second, we consider both the effect of adding the green investment option to an otherwise all-fossil investment strategy and the effect of adding the fossil investment option to an otherwise all-green investment strategy. By introducing the option to switch to a lower-cost investment when its price is lower, adding an investment option (whether fossil or green) is typically expected to reduce cost uncertainty, but the size of this effect can vary between the green and fossil assets.

Third, we consider the additional effect of actually having an all-green portfolio at a given point in time, rather than an all-fossil one, conditional on having both assets as options. Adding either asset as an option, whether fossil or green, generally reduces uncertainty in expenditures for both asset types (since the option need not be exercised), but actually having the green asset in hand further reduces uncertainty because it purely reduces exposure to OPEX risk, whereas future CAPEX risk is managed by investors' future optimizing behavior. For the same reason, switching from a green-dominated portfolio to a fossil-dominated one has the reverse effect and generally increases uncertainty because it purely increases exposure to OPEX risk, with little implication for future CAPEX risk.

In principle, these effects depend on the current uncertain CAPEX and OPEX costs and the probability distributions of their future trajectories. For example, if the fossil asset's OPEX costs are currently high and are expected to remain high into the future, having the green asset (either simply as an option or actually held in one's portfolio) will substantially reduce uncertainty, as it offers a way to reduce exposure to persistently high fuel costs. By contrast, if OPEX costs are low and expected to remain low, then the green asset's added value is smaller.

To demonstrate the qualitative difference between these two kinds of assets, we start by showing cost uncertainty at CAPEX and OPEX values that harmonize the means and standard deviations of the fossil and green assets' costs, while nonetheless letting those values vary over time. This isolates the conceptually distinct effects of CAPEX versus OPEX uncertainty. The results demonstrate that adding the green investment option to an otherwise all-fossil investment strategy reduces the uncertainty in the present value of expenditures, and on average, it causes a greater reduction than does adding a fossil option to an all-green strategy. The results also demonstrate that the value of *owning* the green asset, rather than simply having the option to do so, nearly uniformly reduces cost uncertainty by shielding investors and consumers from OPEX risk without necessarily locking them into future CAPEX risk.

We then use CAPEX and OPEX calibrations based on more realistic data about uncertain future prices for fossil fuels (gasoline and natural gas) and green technologies (EVs and onshore wind). The projections we use feature a modest upward drift in fossil fuel prices over time with a relatively high degree of volatility, whereas wind power and EV prices are projected to gradually decline and exhibit more stability (Larsen et al. 2023). These differences magnify the conceptual advantage found for green technologies in the stylized model where the central cost values are assumed to be harmonized. Deploying the model with recent historical data on fossil versus green energy costs demonstrates the current risk-reducing advantages of green assets.

These conclusions come with a number of caveats, however. While the dynamic programming model allows for a nuanced treatment of decision-making under uncertainty, it nonetheless requires simplifying assumptions that do not fully reflect all the complexities of the real world. For example, we model only two types of technologies, fossil and green, when the real set of assets is much richer and more nuanced than that. In Section 4, we note other factors omitted from the model for simplicity, such as national security and political risks and the role of hedging.

2. Methods

2.1. Model Formulation

To develop a simple model that captures the CAPEX/OPEX dynamics described in Section 1, we consider an investor maintaining a mixed portfolio with some combination of fossil and green assets, where each asset can be thought of as a power plant or a vehicle. The investor manages this portfolio with the goal of minimizing the expected present value of operating costs. The investor can be thought of either as a company or as a social planner minimizing the total social costs of maintaining a portfolio of assets needed to meet energy service demands. Thus the model and its lessons are applicable not only to investors but also to consumers and society writ large.

Each asset has a useful life of L years, where we focus on the case of $L = 10$ years. These assets are characterized by upfront CAPEX costs denoted k_f and $k_{g,t}$ and annual OPEX costs $c_{f,t}$ and c_g. As indicated by the subscript t representing time, the only distinction between these two assets is that for the fossil asset, OPEX $c_{f,t}$ is uncertain and varies over time (owing to uncertainty in oil or natural gas prices), whereas for the green asset, CAPEX $k_{g,t}$ is the uncertain variable. Each cost parameter is assumed to follow geometric Brownian motion with drift, meaning year-on-year changes are normally distributed with known percentage drift parameters μ_g and μ_f and percentage volatility parameters σ_g and σ_f.

The investor maintains and operates a portfolio of L assets and thus replaces one retiring asset each year.[2] The portfolio of $L-1$ legacy assets that are not retiring is denoted by the vector $A_t = \{a_{1,t}, \ldots, a_{L-1,t}\}$ with $a_{i,t} \in \{g, f\}$. The first subscript on each $a_{i,t}$ reflects each asset's remaining useful life, meaning $a_{i,t}$ will retire in period $t+i$.

The state space is thus defined by the green asset's capital cost $k_{g,t}$ and the fossil asset's operating cost $c_{f,t}$, as well as the portfolio of legacy assets represented by A_t. The timeline for the investor's decision and the resolution of uncertainty is as follows: in period t, the investor observes the current known values of CAPEX costs $k_{g,t}$, OPEX costs $c_{f,t}$, and the existing portfolio of legacy assets A_t, collectively referred to as the "state." Based on this state and the known probability distributions, the investor makes a decision to build either the fossil asset or the green one to replace the retiring asset. Once the investment decision is made, the investor immediately pays the capital cost k_f or $k_{g,t}$ for the chosen asset. For simplicity, the new asset begins operating immediately at annual costs of $c_{f,t}$ and c_g for the fossil and green assets, respectively. We then move to period $t+1$, where the legacy asset portfolio A_{t+1} is updated based on the newly chosen asset and the retiring one,[3] and new values of $k_{g,t+1}$ and $c_{f,t+1}$ are realized. In period $t+1$, the investor faces an analogous investment based on the new state. The investor is assumed to use a discount rate of $r = 10\%$ per year (Dixit and Pindyck 1994).

We can write this investment problem in terms of the recursive Bellman equation, denoted $V(k_{g,t}, c_{f,t}, A_t)$, which represents the cost-minimizing present value of the flow of current and future expenditures:

$$V(k_{g,t}, c_{f,t}, A_t) = N_{f,t} c_{f,t} + N_{g,t} c_g$$

$$+ \min \begin{Bmatrix} k_f + c_{f,t} + \dfrac{1}{1+r} E\left[V(k_{g,t+1}, c_{f,t+1}, A_{t+1}) \middle| fossil\right], \\ k_{g,t} + c_g + \dfrac{1}{1+r} E\left[V(k_{g,t+1}, c_{f,t+1}, A_{t+1}) \middle| green\right] \end{Bmatrix}$$

[2] For simplicity, we set the life of the asset in years equal to the portfolio size, which itself is staggered in increments of one year. This implies that the investor is making a single discrete decision each year: whether to invest in a fossil or green asset to replace the retiring asset that is at the end of its useful life.

[3] That is, the values of $a_{i,t}$ each shift left by one, representing one year of aging, $a_{i,t+1} = a_{i+1,t}$ for $i \in \{1, \ldots, L-2\}$, and the last element of A_t, $a_{L-1,t}$, is replaced by $\{f\}$ if a fossil asset is chosen in period t and by $\{g\}$ otherwise.

where $N_{f,t}$ is the number of legacy fossil assets in the portfolio ($N_{f,t} = \sum_i 1\left[a_{i,t} = \{f\}\right]$), and $N_{g,t}$ is the number of legacy green assets ($N_{f,t} + N_{g,t} = L - 1$). In this recursive form, $V\left(k_{g,t}, c_{f,t}, A_t\right)$ represents the cost-minimizing present value of the infinite flow of capital and operating expenditures. The first row of the Bellman equation represents the cost of operating the legacy fossil and green assets at today's fuel costs; this is dictated by past choices and is unaffected by today's investment decision. The two rows inside the minimization operator represent the costs of choosing the fossil and green assets, respectively. The first two terms of each row inside the minimization operator correspond to the immediate CAPEX and OPEX expenditures, whereas the final term represents the consequences of this investment choice for discounted expected future expenditures. This final term reflects how uncertainty in future OPEX drives immediate decisions. For example, even if current fossil fuel prices are low and hence annual OPEX $c_{f,t}$ is low, uncertainty in their future values over the L-year life of the asset will affect today's investment decision through this final term.

We use a technique called "value function iteration" (Dixit and Pindyck 1994) to solve this model for the optimal choice of whether to replace the retiring asset in each period with a new fossil or green one, a choice that depends on the current state: current CAPEX and OPEX values, their future probability distributions, and the current portfolio of legacy assets. Finally, we use Monte Carlo simulation to calculate the degree of uncertainty in future costs, as measured by the standard deviation of PV total expenditures. We solve the model and compute this uncertainty metric under three alternative investment approaches: the optimal strategy, an all-fossil strategy, and an all-green strategy. The second and third strategies represent scenarios where only one option is assumed to be available; these serve as benchmarks against which we compare the cost-minimizing strategy.

2.2. Parameterizing the Model

Because the present value of expenditures depends on both current CAPEX and OPEX cost values, we begin by focusing on their values when the two assets are defined in a stylized but symmetric fashion to feature the same central CAPEX and OPEX parameters: that is, $k_{t,g} = k_f$ and $c_g = c_{f,t}$ at initial time t. Their probability distributions are calibrated such that the present values of costs over a single cycle of $L = 10$ years have the same expectations and standard deviations.[4] This harmonizes the overall average and variance in costs across the assets (Table 1), meaning the only

[4] Specifically, we first set $\mu_f = \mu_g = 0$, meaning no drift. Because $k_{g,t} = k_f$ and $c_g = c_{f,t}$ in the initial period, this zero-drift assumption aligns expected costs. We then choose $\sigma_g = 5\%$ and numerically solve for the value of σ_f such that it equalizes the variances in the present value of total expenditures of a single asset purchased L years into the future. We compute the present value of the costs of a *future* asset purchase to induce uncertainty in $k_{g,t+L}$. Note that because the fossil OPEX volatility parameter applies only to OPEX, which is a smaller portion of total costs than CAPEX in this example, σ_f must be larger than σ_g to equalize the variance in total expenditures.

difference between the two assets is what *kind* of cost uncertainty they are exposed to—CAPEX or OPEX. This therefore isolates the distinct effects of each kind of risk exposure.

Table 1. Parameter Calibrations

	Cost-harmonized		Vehicle choice example		Power plant choice example	
Variable	Fossil	Green	Fossil	Green	Fossil	Green
CAPEX value (\$, k_f, $k_{g,t}$)	\$450M	\$450M	\$31.23k	\$39.09k	\$297.6M	\$464.6M
OPEX value (\$/year, $c_{f,t}$, c_g)	\$25M	\$25M	\$1,141	\$746	\$21.21M	\$0
Drift (%, OPEX for fossil, CAPEX for green, μ_f, μ_g)	0%	0%	0.67%	–1.16%	3.66%	–1.76%
Volatility (%, OPEX for fossil, CAPEX for green, σ_f, σ_g)	12.23%	5%	13.85%	4.80%	14.49%	5.80%

Note: In all cases, the values reported for uncertain variables (e.g., green CAPEX) correspond to the central initial value. The fossil OPEX volatility in the "cost-harmonized" columns was computed numerically to align the mean and variance of total expenditures.

We also consider two examples based on historical data of competing clean and fossil-fuel investments. The first example models a choice between EVs and ICEVs. The second is a power generation example where the fossil asset is represented by a natural gas power plant and the green asset by onshore wind (Table 1). In both cases, we calibrated the model using data from the "Rhodium Climate Outlook" (Larsen et al. 2023), which presents estimates of future fossil fuel prices, EV battery costs, and renewable energy capital costs. These estimates are probabilistic, a key feature that allows us to estimate volatility parameters for our model. Scaling from the variables included in the report to realistic OPEX and CAPEX representations also required the use of other domain-specific resources.

For the example of choosing between two vehicles, we estimate the parameters of the $k_{g,t}$ and $c_{f,t}$ distributions using projected EV battery costs in 2050 (in \$/kWh) and Brent crude oil prices in 2030 (in \$/barrel), as well as standard deviations thereof and corresponding contemporaneous values, all taken from the "Rhodium Climate Outlook" (Larsen et al. 2023; see Appendix A for details of this calculation).[5] We also estimate corresponding (constant) k_f and c_g values. ICEV prices (k_f) and the

[5] The "Rhodium Climate Outlook" projects costs for renewable energy sources in 2050 and costs for fossil-fuel energy sources in 2030.

relationship between battery prices and EV CAPEX ($k_{g,t}$) are based on a white paper by the International Council on Clean Transportation (Slowik et al. 2022), from which we chose the "crossover" type of vehicle with a battery range of 250 miles. For $c_{f,t}$, we converted Brent crude oil price and price uncertainty projected for 2030 to gasoline prices based on a simple least-squares regression using historical data from the Federal Reserve Economic Data (FRED) database (R^2 = 0.94) for the "US Regular All Formulations Gas Price" variable (EIA, n.d.d). Because the starting value in the "Rhodium Climate Outlook" data was for 2022, a year with a spike in oil prices that has since reversed, we calibrated the model beginning in 2023 using the Brent crude oil data in FRED (IMF, n.d.). We then converted gasoline prices to operating expenses by unit conversion based on estimates of miles per gallon for a crossover ICEV (Slowik et al. 2022) and average annual mileage per driver (FHWA, n.d.). We estimated c_g using the same annual mileage estimate, an estimate of power efficiency for a crossover EV (Slowik et al. 2022), and average US residential electricity costs in $/kWh (EIA, n.d.a).[6] Once the model was calibrated, we deployed it using historical EV battery (BloombergNEF 2023) and gasoline (EIA, n.d.d) prices to demonstrate its behavior in the context of actual observed price trends and fluctuations.

For the power generation example, we use an analogous method with simpler conversions (see Appendix B for details of this calculation). We base $k_{g,t}$ on projections for onshore wind overnight capital cost in 2050 ($/kW) and $c_{f,t}$ on Henry Hub natural gas price in 2030 ($/MMBtu), calibrating the model for a start year of 2023 using Henry Hub data from FRED (EIA, n.d.c) because of the 2022 price spike. We source k_f estimates from the National Renewable Energy Laboratory's "Annual Technology Baseline" (NREL 2023), specifically using the average 2023 value for combined cycle plants. The $k_{g,t}$ and k_f parameters are calculated to scale the size of the systems to generate the same amount of electricity given their differing capacity factors (Prest et al. 2021) and to capitalize fixed operations and maintenance costs (NREL 2023) of wind and natural gas plants using the same 10-year lifespan and 10 percent discount rate. We convert $c_{f,t}$ values from Henry Hub data to $/MWh using heat rate data for natural gas combined cycle plants (EIA, n.d.b), plus estimated variable operations and maintenance costs (NREL 2023). Since fixed operating and maintenance costs were capitalized into the CAPEX parameters and thus captured in $k_{g,t}$, we assume no operating expenditures for the wind asset, yielding $c_g = 0$. We use

[6] The assumption of a deterministic OPEX for EVs is weaker than in the wind case. In reality, EVs face OPEX risk from electricity prices, which do fluctuate over time, although much less than oil or gas prices do. Accounting for electricity price uncertainty is beyond the scope of our model, which assigns all green cost risk to CAPEX uncertainty. Future work could extend this model to allow for both assets to face both kinds of uncertainty, but that would introduce considerably more conceptual and computational complexity.

historical data for installed wind power project costs (Wiser et al. 2023) and Henry Hub natural gas prices (EIA, n.d.c) to examine the model in a real-world context, as with the vehicle choice example.

3. Results

We present the results for our three scenarios in turn. For the stylized cost-harmonized scenario, to build intuition, we present detailed model results on cost exposure under alternative strategies and scenarios and at a variety of starting CAPEX/OPEX cost values. We focus on three key metrics: (1) how cost uncertainty compares under an all-fossil strategy versus under an all-green one, (2) how much adding the green (or fossil) option to the choice set reduces cost uncertainty, and (3) how much the acquisition of an all-green portfolio reduces cost uncertainty. We then move on from the stylized, cost-harmonized scenarios to more realistic, empirically calibrated ones representing power generation and vehicle choice. We deploy these models on the realized historical movements of fossil fuel prices (driven by Henry Hub natural gas prices for the power generation example and gasoline prices for the vehicle example) and green CAPEX values (driven by onshore wind capital costs for the power generation example and electric vehicle battery costs for the vehicle example).

3.1. Cost-Harmonized Scenario

Figure 1 shows the uncertainty in PV costs, as measured by the standard deviations of long-run (100-year) discounted expenditures, under three strategies: fossil-only, green-only, and the optimal strategy with both options. All values in Figure 1 are based on the harmonized cost parameterizations shown in Table 1; that is, the results shown there correspond to a deterministic green OPEX cost that is equal to the current value of the uncertain fossil OPEX (both $25 million/year) and a deterministic fossil CAPEX that is equal to the current uncertain green CAPEX value (both $450 million). The key distinction is whether cost uncertainty owes to CAPEX or OPEX uncertainty.

Figure 1 demonstrates that realized uncertainty is highest under the fossil-only strategy, lower under the green-only strategy, and lower still under the optimal strategy that permits the investor to choose the cheaper option in response to relative prices that change over time. The portfolio's overall cost uncertainty is lower under the green-only strategy (second column) than under the fossil-only strategy (first column) even though we calibrated the parameters such that individual green and fossil assets have the same mean and variance of total expenditures. The fact that the fossil-only portfolio's uncertainty is larger owes to the correlated risks created by fuel lock-in. If fuel prices spike, it increases OPEX expenditures for all fossil assets in one's portfolio, thereby creating positively correlated risks across fossil assets. By contrast, if green CAPEX costs spike, it only affects the capital costs of new investments.

The uncertainty reductions from the two columns on the left side to those on the right represent how optionality reduces uncertainty by allowing investors to respond to evolving price fluctuations. Adding the green asset to a fossil-only strategy (going from the first column to the third or fourth) reduces uncertainty more than adding the fossil asset to a green-only strategy (second column to third or fourth).

In addition, we can observe the uncertainty reduction not merely from having the *option* to choose the green asset but in fact from *having* an all-green portfolio, which can be seen by comparing the two columns on the right-hand side. The final column shows the uncertainty in costs when both options are available and the investor currently owns an all-green portfolio. Uncertainty is lowest in this case because (1) the all-green portfolio shields the investor from OPEX (fuel price) uncertainty in the short run (that is, at least until the asset portfolio turns over L years in the future), and (2) having both options in the investor's choice set allows them to adjust to any potential spikes in green CAPEX prices.

The bar charts in Figure 1 show the relative uncertainties at the starting values of CAPEX and OPEX costs that harmonize their cost parameters, as shown in Table 1. These results depend, of course, on the current CAPEX and OPEX values. For example, if fossil fuel prices are currently low, the uncertainty in fossil OPEX might naturally be smaller, and vice versa, which would affect the interpretation of Figure 1. Thus, Figure 2 shows the analogous bar charts at low and high values of fossil OPEX and green CAPEX. The benefits of optionality (i.e., the reduction in the standard deviation going from a fossil-only or green-only strategy to the optimized one) are largest when there are larger differences in current costs of the two asset types—for example, when fossil fuel prices are high but the costs of green assets are low (bottom right panel of Figure 2), since the option of gaining access to the lower-cost asset is appealing and helps hedge against risk. By contrast, when both assets are cheap or both are expensive (bottom left or top right panel), the benefit of optionality is smaller.

Figure 3 further generalizes the results in Figure 2 by showing the standard deviation in PV costs for all values of current fossil OPEX prices (bottom left axis) and green CAPEX prices (bottom right axis). Panels a and b show these under the fossil-only and green-only strategies. Naturally, these results depend only on their own respective price values, with uncertainty increasing with current cost levels.

Panels c and d of Figure 3 show uncertainty under the optimized strategy across both options, where the investor is starting from a state with either an all-fossil portfolio (panel c) or an all-green portfolio (panel d). These surfaces somewhat resemble the lower envelope of panels a and b, reflecting the investor optimizing between the two options, but with several nuanced results worth highlighting. First, cost uncertainty is smaller under the all-green portfolio (panel d relative to panel c) because it insulates the investor from OPEX risk. Second, cost uncertainty in the all-green portfolio depends substantially less on fossil OPEX prices, as illustrated by the slope along the OPEX axis being smaller in panel d than in panel c. For example, in the region where green CAPEX is at its lowest (bottom left of the surface in each panel), cost uncertainty increases with OPEX prices (i.e., along the bottom left axis) in the all-fossil portfolio (panel c) but not in the all-green portfolio (panel d).

Panels e and f demonstrate the reductions in uncertainty from adding the green and fossil options to an otherwise all-fossil or all-green strategy, respectively. Naturally, the green option reduces uncertainty more when it is cheaper than the fossil asset (i.e., when fossil OPEX is high and green CAPEX is low), and vice versa for the fossil option. Consistent with the results in Figure 1, the green option reduces uncertainty more on average across the range of OPEX and CAPEX values shown in Figure 3, a range that is symmetric about the cost-harmonized case in Figure 1.

Finally, panel g shows the uncertainty reduction within the optimized strategy case from owning an all-green portfolio relative to an all-fossil one—that is, uncertainty reduction from panel d versus c. This is nearly always negative (99 percent of the time) across the range of current OPEX/CAPEX prices, indicating that owning the green asset yields broad uncertainty reductions regardless of the current state of OPEX/CAPEX prices.

These results illustrate the way in which assets with low OPEX risk can reduce exposure to volatility in fuel prices. They nonetheless reflect an abstract model with harmonized parameters. Thus in Sections 3.2 and 3.3, we deploy the model reflecting more realistic parameters representing power generation and vehicle investments. In each section, we solve the model again using the updated parameterizations and run it based on historical realizations of fossil fuel price (OPEX) and green capital costs (CAPEX) over the past decade.

Figure 1. Uncertainty in Net Present Value of Costs, Cost-Harmonized Scenario, at Starting OPEX and CAPEX Values

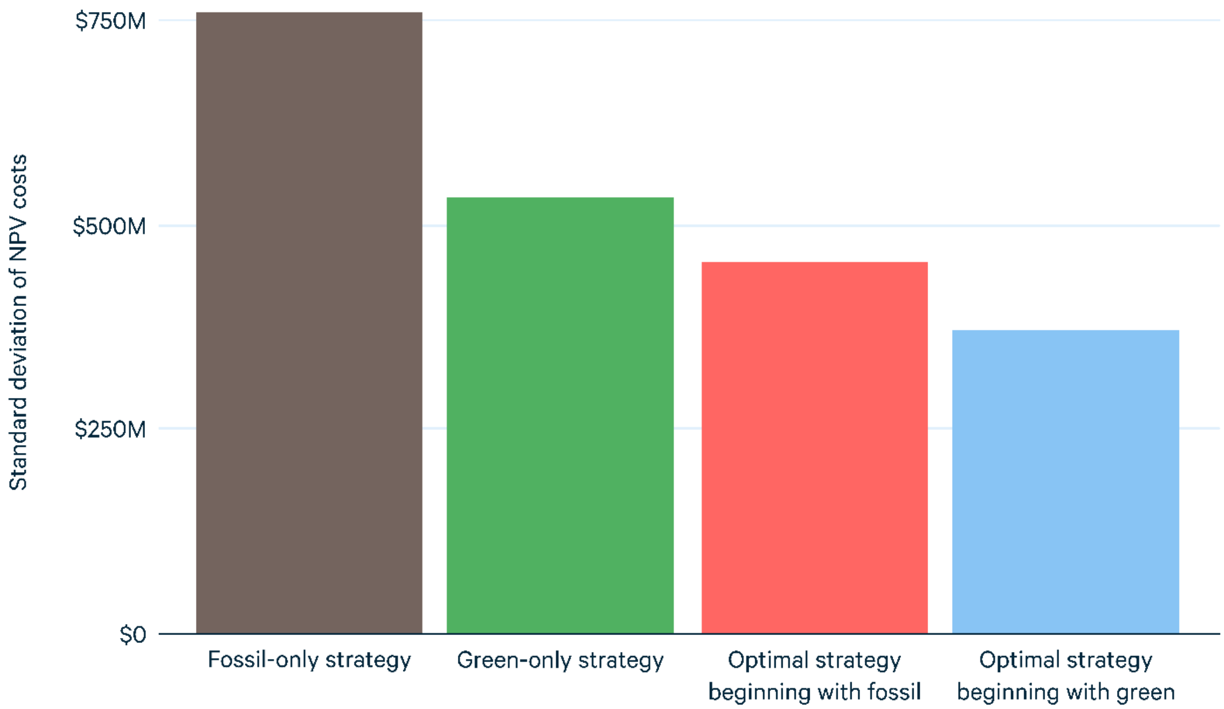


Figure 2. Uncertainty in Net Present Value of Costs, Cost-Harmonized Scenario, at Low and High OPEX and CAPEX Values

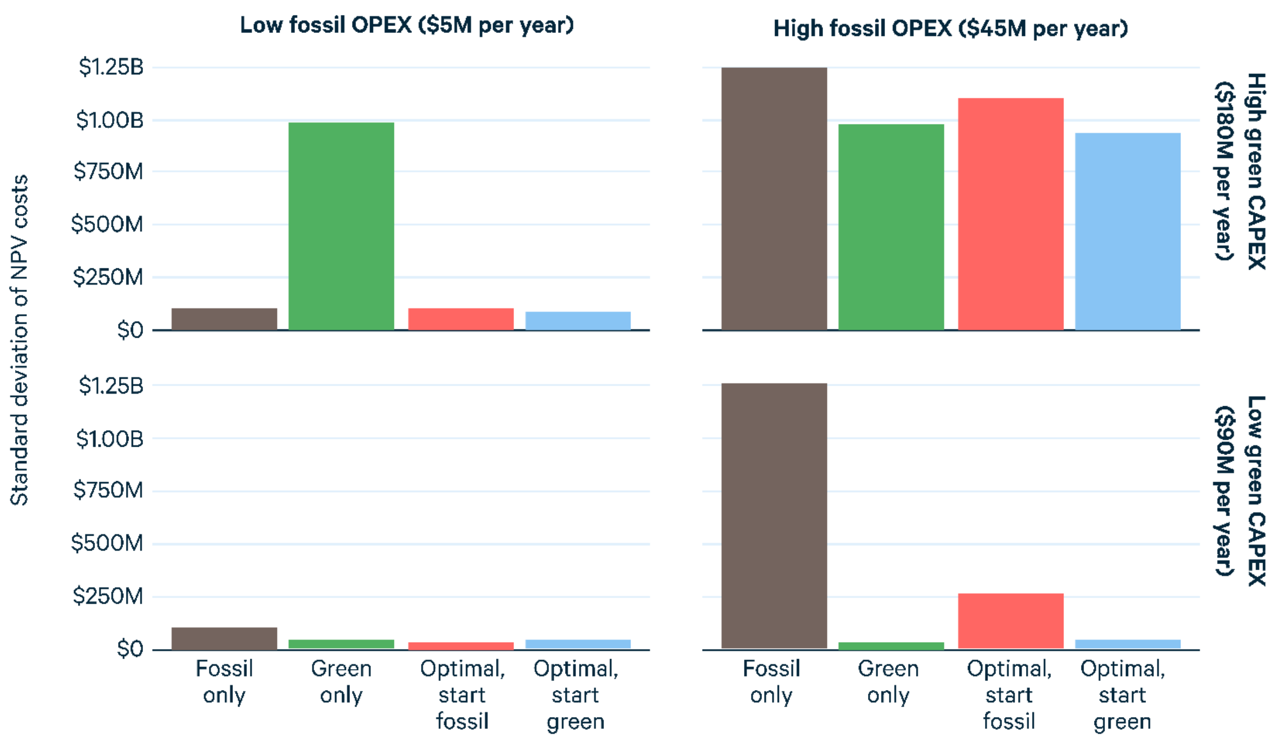
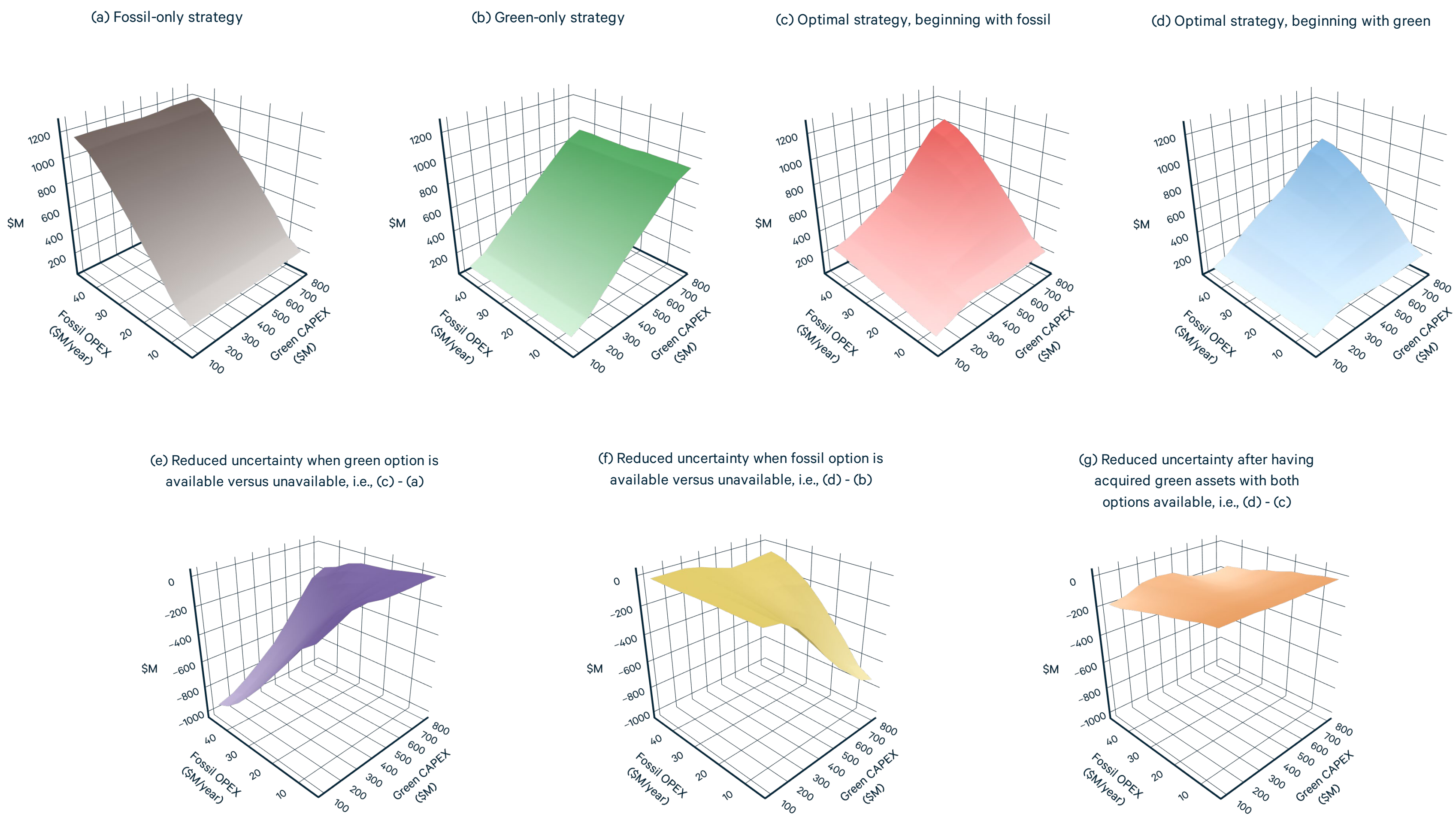


Figure 3. Uncertainty in Net Present Value of Costs, Cost-Harmonized Scenario, by Current OPEX/CAPEX Cost Values



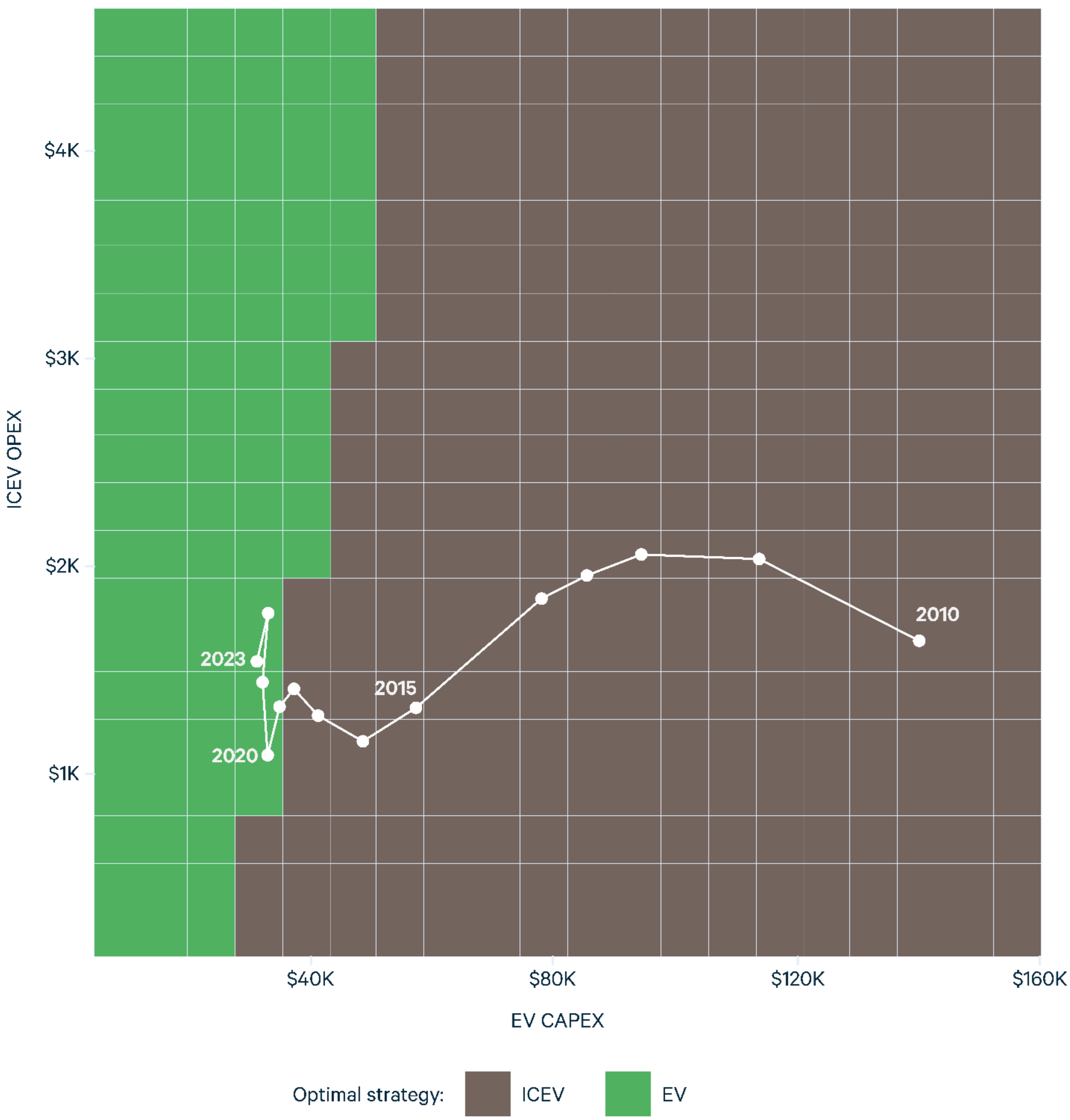
3.2. Vehicle Choice Example: ICEV versus EV

Figure 4 shows the model deployed historically for the vehicle choice scenario, where each vehicle lasts $L = 10$ years and the investor manages a fleet of 10 vehicles, replacing one each year. Each panel has colored lines that correspond with the analogues to the strategies previously discussed: ICEV only (brown), EV only (green), optimized starting with an ICEV fleet (red), and optimized starting with an EV fleet (blue). The blue and green lines, reflecting relatively green portfolios, show less exposure to variable fuel prices, as exhibited by the lower volatility in OPEX costs (panel a). Further, the option to diversify one's portfolio over time reduces the overall level and volatility of OPEX costs, as shown by similarities in both OPEX and CAPEX costs toward the end of the time period. Because the price of EVs was much higher in the early to mid-2010s, an all-EV strategy pursued then would have been quite expensive (panel b); therefore, the optimized model avoids EVs until 2019, at which point it begins purchasing EVs exclusively, regardless of the composition of the original portfolio (panel c). This results in a diversified portfolio of an approximately even number of ICEVs and EVs in the fleet by 2021–23. This significantly reduces the exposure to the spike in OPEX during these years amid the post-pandemic rise in oil prices. While an all-EV strategy beginning in 2014 would have completely eliminated the exposure to the price of gasoline, it would not have been optimal in our model because it would have required investing in early-stage EVs before they came close to reaching cost parity.

Figure 5 shows the movement of historical fossil OPEX values (on the *y*-axis, driven by variation in oil prices) and EV CAPEX values (on the *x*-axis, driven by variation in battery prices) during the historical window. This demonstrates the rapid decline in EV prices over the past decade, which brought EVs to cost parity in expected-value terms over the past several years. The brown region in this figure reflects price points where it is optimal for the investor to buy an ICEV, and the green region is where an EV is optimal. Note that the notion of optimality in this model accounts for the expected drift and volatility of future OPEX and CAPEX prices. In some sense, it is fortuitous in this modeling exercise that EVs become optimal in 2019, leading to diversification of the modeled fleet just before oil prices spiked. If EV prices had been somewhat higher or expectations about future oil prices had been lower, the model may not have diversified in time, and the exposure to the 2021–23 oil price spike would have been more severe.

Figure 4. Historical Simulations, Vehicle Choice Example

Figure 5. Optimal Strategy Matrix with Historical OPEX/CAPEX Values, Vehicle Choice Example



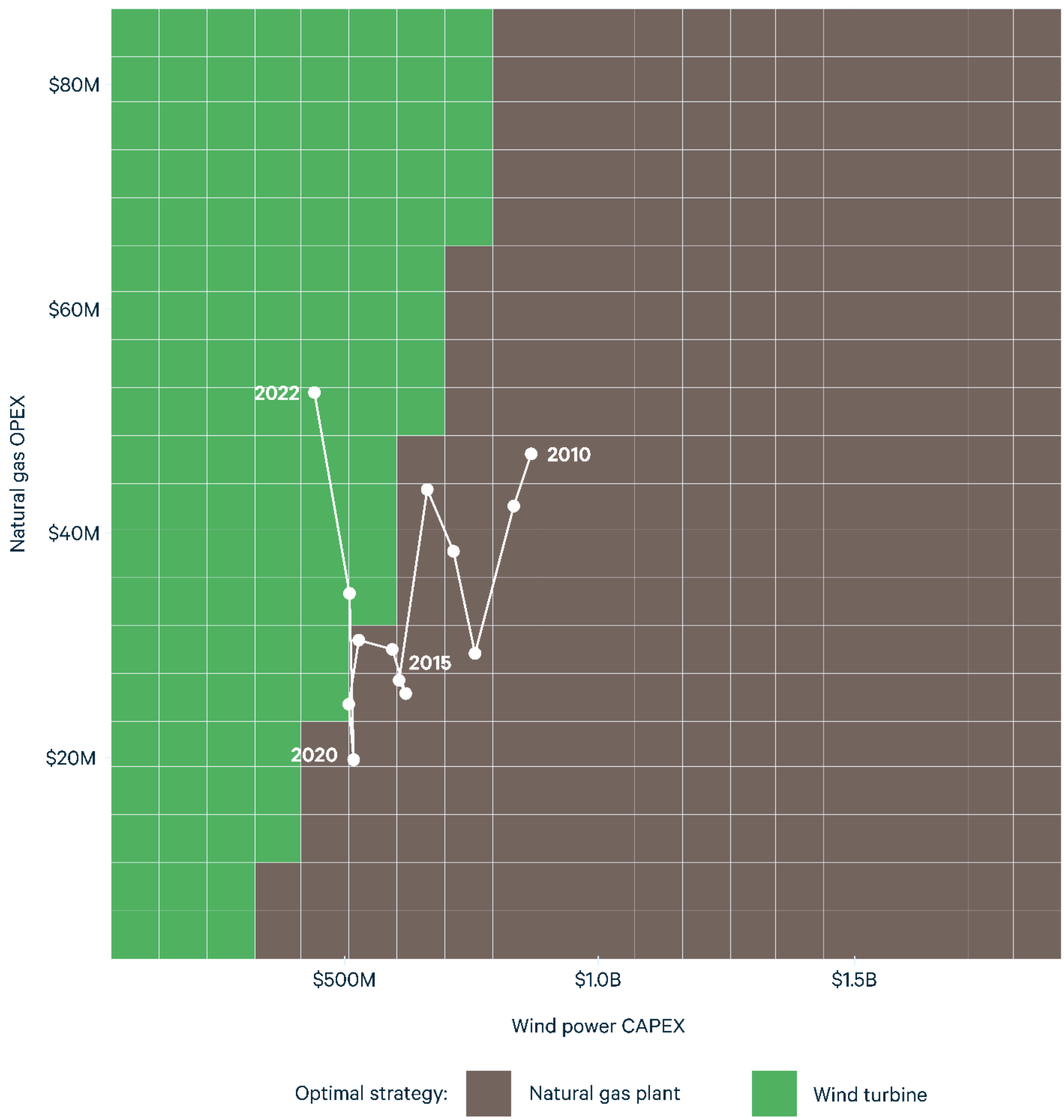
3.3. Power Plant Choice Example: Natural Gas versus Wind

Figure 6 shows the historical simulation for the power plant scenario. Once again, the all-fossil strategy features large exposure to natural gas prices, as illustrated by the volatility in OPEX in the brown line in panel a. While the all-wind strategy (green line) would eliminate that OPEX exposure, high wind CAPEX costs in the early years imply that wind investments do not reach (unsubsidized) cost parity until 2019. As a result, in the optimal strategy scenarios (red and blue lines), high wind prices in the first half of the decade coupled with falling natural gas prices result in a gas-heavy portfolio by 2020. Only in 2019, 2021, and 2022 does the model start investing in wind, somewhat conveniently ahead of the large spikes in natural gas prices that occurred in 2021–22. While this investment in wind is somewhat last-minute, it serves to mitigate exposure to natural gas prices relative to the all-gas strategy (compare the red and blue lines with the brown one in panel a).

The greater variation in fossil OPEX in Figure 7 than in Figure 5 highlights the fact that natural gas prices have historically been more volatile than gasoline prices, which could lead to more instances of the optimal investment choice changing from year to year, as it does in the model between years 2018 (gas), 2019 (wind), and 2020 (gas). An important caveat to this example is that our model's optimization procedure does not reflect the many complexities in the electricity grid, such as wind's intermittency, the value of dispatchable capacity, and other fuels, all of which would affect the optimal resource mix in practice. In that sense, this application remains highly stylized, but it nonetheless illustrates the value of low-OPEX assets in hedging against fuel price risk.

Figure 6. Historical Simulations, Power Plant Choice Example

Figure 7. Optimal Strategy Matrix with Historical OPEX/CAPEX Values, Power Plant Choice Example



4. Discussion

Our results demonstrate that green assets—which tend to have higher capital costs but low or no operating costs—can help insulate households and the economy from uncertain future fuel prices. In addition to the differences we have already discussed, other nuanced factors implicit in our model are also worth drawing out. The first relates to the time value of money. For example, while the cost of replacing an electric vehicle at the end of its useful life remains, and spikes in the prices of critical minerals can affect those long-run expenditures, those risks occur in the future, whereas operational costs occur repeatedly throughout the life of the investment. The time value of money means this future risk is less important than equivalent near-term risks. This factor is captured implicitly in Figures 1–3, which show the uncertainty in *discounted* costs.

Second, a key insight from economics is that the ability to optimize over multiple options allows consumers to reduce both costs and risk. In particular, consumers can further insulate themselves from exposure to future critical mineral costs by optimizing over what kinds of minerals are used to replace an asset at the end of its useful life. For example, if the price of cobalt rises in the future, nothing is forcing consumers to buy cobalt-based batteries if other options exist or are developed in the future, such as iron phosphate–based alternatives (for example, as Ford began to implement in some of its 2023 vehicles; see Miller 2023) or—setting aside climate concerns—returning to a conventional ICEV if no other cost-effective alternatives emerge in the coming decades. As our model features only one type of green asset, this is an additional benefit of CAPEX-centric investments not captured in our results. Future work could demonstrate this value by adding other types of green assets representing alternative types of low-carbon power generation or EV battery chemistries.

The model and its results nonetheless come with caveats. First, we focus on how cost uncertainty varies across assets with a specific kind of risk profile: OPEX risk versus CAPEX risk. In practice, there may be other relevant aspects of risk exposure. For example, the geographic distribution of risks, such as the concentration of certain resources in individual countries with particular political or economic situations, may inject national security or political economy dynamics that do not lend themselves to incorporation into a quantitative economic model. However, to the extent that those risks simply make a particular resource's price more volatile, this factor could be represented in our model by a larger volatility parameter.

We also abstract away from the role of hedging contracts. We deem this an acceptable simplification for several reasons. First, hedging contracts are often short-duration products and generally are relatively thinly traded beyond a few years.[7] Second, while

[7] For example, see the analysis in Davis (2024) demonstrating essentially no trading in 2024 of Henry Hub natural gas futures delivering beyond 2026.

investors can individually use hedges to mitigate exposure to cost shocks, society as a whole cannot rely on financial engineering to eliminate real resource risks. Hedge contracts simply change who bears the cost of a resource shock. If the cost of producing a resource spikes, society pays this cost one way or another. For the same reason, we abstract away from pass-through of natural gas prices into wholesale electricity prices.

Finally, for computational reasons, our model assumes a 10-year useful life of each asset.[8] This may be a reasonable assumption in the context of vehicles, but it certainly understates the typical useful life of a power plant. Thus in the power generation example, this 10-year life assumption understates the true risk exposure of the fossil asset because the true cumulative OPEX costs and duration of fuel "lock-in" are both larger than we assume. We reserve an extension of the model to represent longer useful lifetimes for future work.

5. Conclusions

We began this paper with a question: Will a clean energy transition simply substitute one kind of commodity price risk for another? Since this question is fundamentally a dynamic one about unknown future pathways of alternative prices, we have addressed it by building a stochastic dynamic programming model that accounts for uncertainty in both fossil fuel prices and future capital costs of low-carbon assets. The results suggest that the answer to the question is no: investments in green assets today reduce exposure to volatile fuel prices without necessarily locking us into any particular future CAPEX risks. These conclusions flow from three key factors: first, the decision to invest in an asset tied to a particular fuel to operate (e.g., natural gas power plants or gasoline-powered vehicles) locks one into exposure to volatile fuel prices for the life of the asset, and therefore spikes in fuel prices increase OPEX for all existing fossil assets, whereas spikes in green CAPEX costs only affect new investments. Second, and by contrast, in the context of an asset with primarily CAPEX rather than OPEX exposure, the investment decision resolves cost uncertainty immediately. Third, while uncertainty remains about the *future* replacement cost at the end of the asset's useful life, an optimizing investor is not bound to choose the same asset type in a future investment decision. Should CAPEX costs rise in the future, an optimizing investor will consider other options to minimize costs.

The model developed herein demonstrates these insights quantitatively using a dynamic model of optimal investment under uncertainty given two stylized asset choices: fossil (OPEX-exposed) and green (CAPEX-exposed). Our cost-harmonized

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[8] The state space of the legacy asset portfolio, denoted $A_t = \{a_{1,t}, \dots, a_{L-1,t}\}$, has a dimension size of 2^{L-1} because each of the $L-1$ legacy assets could take on one of two values (green or fossil). For $L = 10$ years, this dimension is a moderately manageable 512 potential portfolio permutations. For $L = 25$ years, this becomes an unmanageable 16.8 million different portfolio permutations over which to solve the model.

results demonstrate that otherwise equivalent CAPEX-exposed assets reduce exposure more than OPEX-exposed ones do. Moreover, by deploying the model using the past decade of realized volatility in fossil fuel prices and green capital costs, we show how the green investments served to mute exposure to the rise in oil and gas prices in recent years. Finally, these conclusions would be amplified by a factor that remains uncaptured by our model: technological innovation. Whereas our model features only one stylized fossil and one green asset, the set of low-carbon technologies is likely to expand over time. This diversity further reduces risk exposure by providing more options that investors can leverage to minimize cost and risk. So, does an energy transition simply swap one risk for another? The qualitatively different types of risk posed by green versus fossil investments mean that the answer is a clear no.

References

BloombergNEF. 2023. "Lithium-Ion Battery Pack Prices Hit Record Low of $139/kwh." **https://about.bnef.com/blog/lithium-ion-battery-pack-prices-hit-record-low-of-139-kwh/**.

Davis, L. 2024. "What Can Futures Markets Tell Us about Biden's LNG Pause?" Energy Institute Blog. Energy Institute at Haas. **https://energyathaas.wordpress.com/2024/02/12/what-can-futures-markets-tell-us-about-bidens-lng-pause/**.

Dixit, A. K., and R.S. Pindyck. 1994. *Investment under Uncertainty*. Princeton, NJ: Princeton University Press.

EIA (US Energy Information Administration). 2022. Levelized Costs of New Generation Resources in the *Annual Energy Lookout 2022*. March. **https://www.eia.gov/outlooks/aeo/pdf/electricity_generation.pdf.**

———. n.d.a. "Electric Power Monthly." Accessed January 12, 2024. **https://www.eia.gov/electricity/monthly/epm_table_grapher.php?t=epmt_5_6_a**.

———. n.d.b. "Form EIA-860: Annual Electric Generator Report," Table 2. Accessed January 12, 2024. **https://www.eia.gov/electricity/annual/html/epa_08_02.html**.

———. n.d.c. "Henry Hub Natural Gas Spot Price (MHHNGSP)." FRED, Federal Reserve Bank of St. Louis. Accessed January 12, 2024. **https://fred.stlouisfed.org/series/MHHNGSP.**

———. n.d.d. "US Regular All Formulations Gas Price (GASREGW)," FRED, Federal Reserve Bank of St. Louis. Accessed January 12, 2024. **https://fred.stlouisfed.org/series/GASREGW**.

FHWA (US Federal Highway Administration). n.d. "Average Annual Miles per Driver by Age Group." Accessed January 12, 2024. **https://www.fhwa.dot.gov/ohim/onh00/bar8.htm**.

IMF (International Monetary Fund). n.d. "Global Price of Brent Crude (POILBREUSDM)." FRED, Federal Reserve Bank of St. Louis. Accessed January 12, 2024. **https://fred.stlouisfed.org/series/POILBREUSDM**.

Larsen, K., H. Pitt, M. Mobir, S. Movalia, A. Rivera, E. Rutkowski, M. Tamba, K. McCusker, and T. Houser. 2023. "Rhodium Climate Outlook: Probabilistic Projections of Energy, Emissions and Global Temperature Rise." Rhodium Group. **https://rhg.com/research/rhodium-climate-outlook-2023/**.

Miller, C. 2023. "2023 Ford Mustang Mach-E Now Costs Less and Ekes Out More Range." *Car and Driver*, May 2, 2023. **https://www.caranddriver.com/news/a43771885/2023-ford-mustang-mach-e-costs-less-more-range/**.

NREL (National Renewable Energy Laboratory). 2023. "2023 Annual Technology Baseline." Golden, CO: National Renewable Energy Laboratory. **https://atb.nrel.gov/**.

Prest, B., D. Burtraw, and K. Palmer. 2021. *Waiting for Clarity: How a Price on Carbon Can Inspire Investment*. Washington, DC: Resources for the Future. **https://media.rff.org/documents/Rpt_21-08_final.pdf**.

Slowik, P., A. Isenstadt, L. Pierce, and S. Searle. 2022. *Assessment of Light-Duty Electric Vehicle Costs and Consumer Benefits in the United States in the 2022–2035 Time Frame*. International Council on Clean Transportation. **https://theicct.org/publication/ev-cost-benefits-2035-oct22/**.

Wiser, R., M. Bolinger, B. Hoen, D. Millstein, J. Rand, G. Barbose, N. Darghouth, W. Gorman, S. Jeong, E. O'Shaughnessy, and B. Paulos. 2023. *Land-Based Wind Market Report: 2023 Edition*. Berkeley, CA: Lawrence Berkeley National Laboratory (LBNL). **https://emp.lbl.gov/wind-technologies-market-report**.

Appendix A. EV and ICEV Model Parameters

Expanding on the explanation in Section 2, this appendix delineates the entire process by which we calculated all model parameters presented in Table 1 for the example of choosing between EVs and ICEVs (μ_f, μ_g, σ_f, σ_g, k_f, the initial value of $k_{g,t}$, the initial value of $c_{f,t}$, and c_g). To do so, we used data from a number of sources: the "Rhodium Climate Outlook" (Larsen et al. 2023); a white paper published by the International Council on Clean Transportation (Slowik et al. 2022); the "US Regular All Formulations Gas Price" (EIA, n.d.d) and "Global Price of Brent Crude" (IMF, n.d.) time series from the FRED database; average US residential electricity prices from the "Electric Power Monthly" dataset (EIA, n.d.a); and average annual miles per driver (FHWA, n.d.).

A.1. Drift and Volatility Parameters

The role of the drift (μ) and volatility (σ) parameters in the geometric Brownian motion of $k_{g,t}$ and $c_{f,t}$ can be formalized as follows:

$$\mathrm{E}\left[k_{g,t+h} \middle| k_{g,t}\right] = k_{g,t} e^{\mu_g h},$$

$$\mathrm{Var}\left[k_{g,t+h} \middle| k_{g,t}\right] = k_{g,t}^2 e^{2\mu_g h}\left(e^{\sigma_g^2 h} - 1\right),$$

$$\mathrm{E}\left[c_{f,t+h} \middle| c_{f,t}\right] = c_{f,t} e^{\mu_f h},$$

$$\mathrm{Var}\left[c_{f,t+h} \middle| c_{f,t}\right] = c_{f,t}^2 e^{2\mu_f h}\left(e^{\sigma_f^2 h} - 1\right),$$

where $\mathrm{E}[x_{t+h}|x_t]$ is the expected value—and $\mathrm{Var}[x_{t+h}|x_t]$ is the variance—of variable x at time $t + h$, contingent on the value of x at time t. Solving for μ yields:

$$\mu_g = \ln\left(\mathrm{E}\left[k_{g,t+h} \middle| k_{g,t}\right] / k_{g,t}\right) / h,$$

$$\mu_f = \ln\left(\mathrm{E}\left[c_{f,t+h} \middle| c_{f,t}\right] / c_{f,t}\right) / h.$$

Solving for σ yields:

$$\sigma_g = \sqrt{\ln\left(\mathrm{Var}\left[k_{g,t+h} \middle| k_{g,t}\right] / \mathrm{E}\left[k_{g,t+h} \middle| k_{g,t}\right]^2 + 1\right) / h},$$

$$\sigma_f = \sqrt{\ln\left(\mathrm{Var}\left[c_{f,t+h} \middle| c_{f,t}\right] / \mathrm{E}\left[c_{f,t+h} \middle| c_{f,t}\right]^2 + 1\right) / h},$$

In the context of our model, t is a time near the present day, and $k_{g,t+h}$ and $c_{f,t+h}$ are projected values h years in the future relative to t. We use future projections sourced from the "Rhodium Climate Outlook" (Table A.1), but several steps are required to convert these values into OPEX and CAPEX units before μ and σ parameters can be calculated.

Table A.1. Projected EV Battery Costs and Oil Prices

Variable	Year	Future expected value	Standard deviation	2022 value	Unit of measurement
EV batteries	2050	\$112.00	\$86.88	\$240.83	\$/kWh
Brent crude oil price	2030	\$88.08	\$43.46	\$100.90	\$/barrel

Source: Larsen et al. (2023).

To calculate drift and volatility parameters for $k_{g,t}$, we converted EV battery price expressed in \$/kWh to the total price of an EV using values from the International Council on Clean Transportation white paper (Slowik et al. 2022), arbitrarily choosing a "crossover" body type and a range of 250 miles. We assumed that the only projected change in vehicle price was attributable to change in battery price, so we used a baseline vehicle cost corresponding to the estimated 2022 cost of an EV with our chosen specifications (\$39,543) and a conversion factor based on a power efficiency of 0.34 kWh/mile. Using this conversion and the formulas for μ_g and σ_g, we find

$$\mu_g = \frac{\ln\left(\frac{39{,}543 + 250 \times 0.34 \times (112 - 240.83)}{39{,}543}\right)}{2050 - 2022} = -1.16\%,$$

$$\sigma_g = \sqrt{\frac{\ln\left(\frac{(250 \times 0.34 \times 86.88)^2}{\left(39{,}543 + 250 \times 0.34 \times (112 - 240.83)\right)^2} + 1\right)}{2050 - 2022}} = 4.80\%,$$

noting that variance depends only on the source of uncertainty—the EV battery price—and applicable conversion factors. All vehicle prices from Slowik et al. (2022) were estimated from their Figure 4 using appropriate graphics software. Lastly, while the values shown in Appendixes A and B are rounded, precise values were used to calculate model parameters.

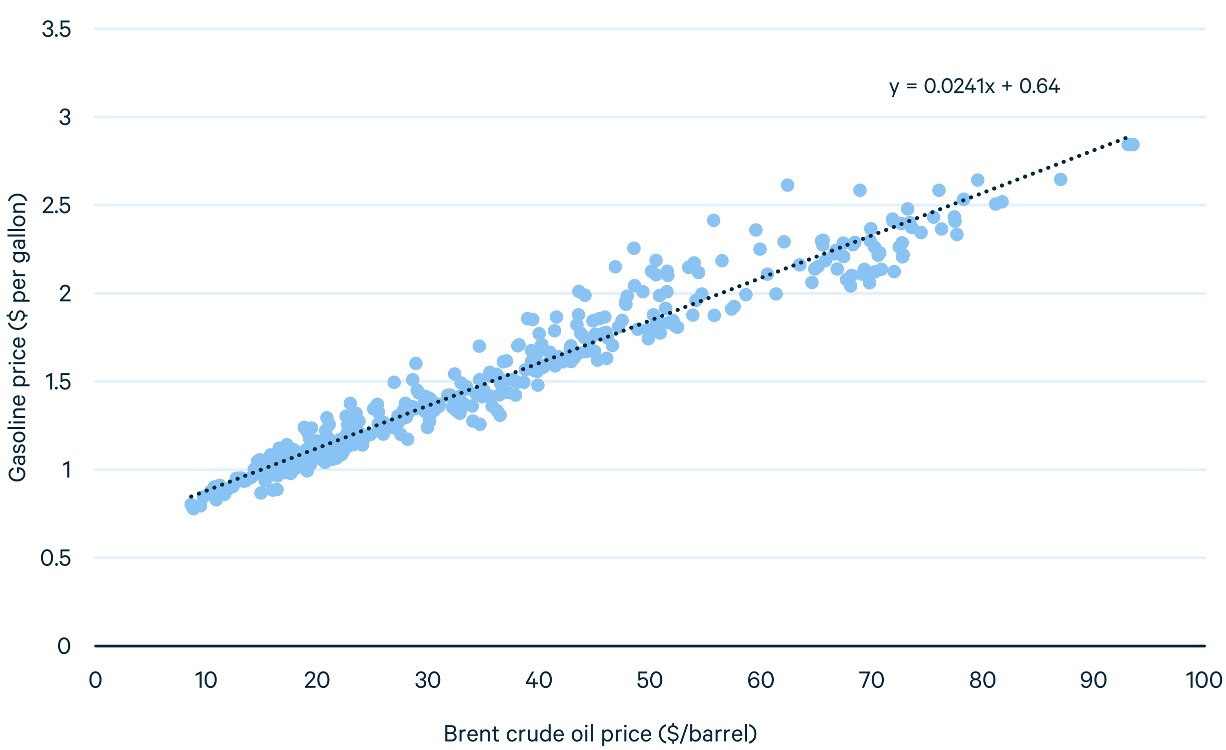
As a first step toward calculating drift and volatility parameters for $c_{f,t}$, we used the mean (\$82.81) of the January–October 2023 values (\$84.08, \$83.63, \$79.26, \$83.54, \$75.75, \$74.98, \$80.11, \$85.17, \$92.67, \$88.95) of the global price of Brent crude from FRED (IMF, n.d.) in place of a 2022 starting value to avoid having our results biased by the 2022 price spike, which has since reversed. The November and December values were not available at the time of our analysis, but we still used $t = 2023$. Brent crude prices and gasoline prices are highly correlated, with the latter being the relevant variable for our example of ICEVs. Using historical monthly data from FRED for both variables (IMF, n.d.; EIA, n.d.d), spanning from September 1990 to October 2023, we conducted ordinary least squares regression, arriving at slope and intercept coefficients of 0.0241 and 0.64 for converting from crude oil prices to gasoline prices, with an R^2 value of 0.94 (Figure A.1). Using this conversion and the formulas for μ_f and σ_f, we found

$$\mu_f = \frac{\ln\left(\frac{0.0241 \times 88.08 + 0.64}{0.0241 \times 82.81 + 0.64}\right)}{2030 - 2023} = 0.67\%,$$

$$\sigma_f = \sqrt{\frac{\ln\left(\frac{(0.0241 \times 43.46)^2}{(0.0241 \times 88.08 + 0.64)^2} + 1\right)}{2030 - 2023}} = 13.85\%,$$

noting that variance depends only on the source of uncertainty—crude oil price—and the slope coefficient. No intercept is used when estimating variance, and the subsequent conversions used to arrive at annual OPEX are not important for estimating ratios.

Figure A1. Linear Regression to Convert between Crude Oil and Gasoline



A.2. OPEX and CAPEX Values

Estimating initial values for $k_{g,t}$ and $c_{f,t}$ and constant values for k_f and c_g is straightforward. For $k_{g,t}$, we used the 2022 EV price from Slowik et al. (2022) along with our μ_g estimate to find a value for our start year of 2023:

$$k_{g,t} = e^{\ln(39{,}543) - 0.01158} = \$39{,}088.$$

For k_f, we used the estimate of the 2023 price for a crossover ICEV from Slowik et al. (2022): $31,229. For $c_{f,t}$, we used the 2023 gasoline price that we estimated using the regression methods described in Appendix A.1, transforming to annual OPEX with conversion factors for miles per gallon (mpg) and average annual miles per driver. Slowik et al. (2022) give values for 2020 (28.0 mpg) and 2022 (30.1 mpg), so we estimated the 2023 value using simple extrapolation, producing a value of 31.15 mpg. Using this and the estimate of 13,476 annual miles per driver (FHWA, n.d.), we arrived at an annual OPEX estimate of

$$c_{f,t} = (0.0241 \times 82.81 + 0.64) \div 31.15 \times 13{,}476 = \$1{,}141.$$

We estimated c_g using the same annual mileage estimate, the estimate of power efficiency used to estimate μ_g and σ_g, and average US residential electricity costs in $/kWh, estimated at $0.1629 (EIA, n.d.a): $c_g = 13{,}476 \times 0.34 \times 0.1629 = \$746$.

Appendix B. Natural Gas and Wind Model Parameters

Determining model parameters for the onshore wind versus natural gas example was simpler than for the EV versus ICEV example because fewer conversions were required. Data sources used include the "Rhodium Climate Outlook" (Larsen et al. 2023); "2023 Annual Technology Baseline" (NREL 2023); *Waiting for Clarity* (Prest et al. 2021); the "Henry Hub Natural Gas Spot Price" time series from FRED (EIA, n.d.c); and heat rate estimates from the "Annual Electric Generator Report" (EIA. n.d.b).

B.1. Drift and Volatility Parameters

As with the vehicle choice example, future projections were taken from the "Rhodium Climate Outlook" (see Table B.1). No conversions were required to calculate μ_g and σ_g; we did so using only the values from this one source:

$$\mu_g = \frac{\ln(928/1519.08)}{2050 - 2022} = -1.76\%,$$

$$\sigma_g = \sqrt{\frac{\ln(291.76^2/928^2 + 1)}{2050 - 2022}} = 5.80\%.$$

Similarly to crude oil, natural gas experienced a price spike in 2022 that later reversed, so we used 2023 values to calculate $c_{f,t}$ as we did for the vehicle choice example. Data were available from the “Henry Hub Natural Gas Spot Price” time series on FRED (EIA, n.d.c) for January–November 2023 ($3.27, $2.38, $2.31, $2.16, $2.15, $2.18, $2.55, $2.58, $2.64, $2.98, $2.71), producing a mean value of $2.54. Using this in place of the 2022 value from Table B.1, we calculated μ_f and σ_f:

$$\mu_f = \frac{\ln(3.28/2.54)}{2030 - 2023} = 3.66\%,$$

$$\sigma_f = \sqrt{\frac{\ln(1.30^2/3.28^2 + 1)}{2030 - 2023}} = 14.49\%.$$

See Appendix A for derivation of the formulas used here.

Table B1. Projected Natural Gas and Onshore Wind Prices

Variable	Year	Future expected value	Standard deviation	2022 value	Unit of measurement
Wind land overnight capital cost	2050	$928.00	$291.76	$1,519.08	$/kW
Henry Hub natural gas price	2030	$3.28	$1.30	$6.45	$/MMBtu

Source: Larsen et al. (2023).

B.2. OPEX and CAPEX Values

We sought to estimate costs for onshore wind and natural gas plants with equal power generation, choosing a scale of 1 million MWh per year for convenience. To convert from prices expressed in \$/kW to $k_{g,t}$ and k_f values representing total CAPEX for such a plant, we used estimates from the literature of fixed annual operations and maintenance costs (NREL 2023) and capacity factors (Prest et al. 2021), as well as the same 10-year lifespan and 10 percent discount rate as was used throughout the model. Similarly to the vehicle choice example, we also used μ_g to estimate 2023 prices from the 2022 value for the onshore wind variable in Table B.1. Using these data along with a conversion factor between \$/kW and \$/million MWh per year ($1{,}000{,}000{,}000/8{,}760 = 114{,}155$) yielded the following estimates:

$$k_{g,t} = \left[e^{\ln(1519.08) - 0.0176} + \sum_{i=1}^{10} 29.35(0.9^i) \right] \div 0.409 \times 114{,}155$$
$$= \$464.6 \text{ million},$$

$$k_f = \left[1254.4 + \sum_{i=1}^{10} 30.65(0.9^i) \right] \div 0.550 \times 114{,}155 = \$297.6 \text{ million}.$$

For $c_{f,t}$, we estimated the sum of fuel costs and variable operations and maintenance costs. We converted fuel costs from \$/MMBtu to \$/MWh using the estimated average combined cycle heat rate for 2022 from the "Annual Electric Generator Report" (EIA, n.d.b), subsequently adding our estimate of variable operations and maintenance costs based on values from the "2023 Annual Technology Baseline" (NREL 2023), also in \$/MWh. Lastly, we multiplied by 1 million to reach 1 million MWh per year of generation:

$$c_{f,t} = (2.54 \times 7.596 + 1.94) \times 1{,}000{,}000 = \$21.21 \text{ million}.$$

Having capitalized fixed operating and maintenance costs within $k_{g,t}$, we assumed zero variable operating and maintenance costs (and zero fuel costs) for onshore wind, yielding $c_g = 0$.