Variable Pricing and the Cost of Renewable Energy*

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Abstract

On a levelized-cost basis, solar and wind power generation are now cheaper than fossil fuels, but are intermittent. As a result, the benefits of using variable, marginal-cost retail pricing will grow. We evaluate the potential gains from dynamic pricing using a novel model of power supply and demand in Hawaii. The model breaks new ground by simultaneously optimizing generation and storage capacity with chronological operation of the system, including reserves, and a demand system with different interhour elasticities for different end uses. We find that in fossil systems, dynamic pricing improves welfare by just 2.6 to 4.6 percent of baseline expenditure, but rises to 8.5 to 23.4 percent in a 100 percent renewable system with otherwise similar assumptions. With more elastic demand, variable pricing can improve welfare by as much as 47 percent. Excluding pollution externalities, welfare-maximizing systems are projected to reach 75-90 percent renewable by 2045.

Keywords: Renewable energy, variable pricing, storage, demand response, optimization.
JEL codes: Q41, Q42, Q53

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1 Introduction

How much will it cost to eliminate use of fossil fuels? There is reason for optimism. Technological progress has lowered the cost of wind and solar power to make them increasingly competitive with coal and natural gas on a levelized basis. Battery storage costs are also falling, which should grow electric vehicle use and could help electric grids absorb intermittent renewable energy when it happens to be plentiful. Increasing integration of markets across regions and countries could further facilitate adoption of wind and solar, as they allow more flexible trading of power from times and locations with relatively high supply to those with relatively little. Nevertheless, recent research indicates that intermittency combined with the high cost of storage greatly increases the cost of renewable energy from a system perspective (Gowrisankaran, Reynolds and Samano 2016).

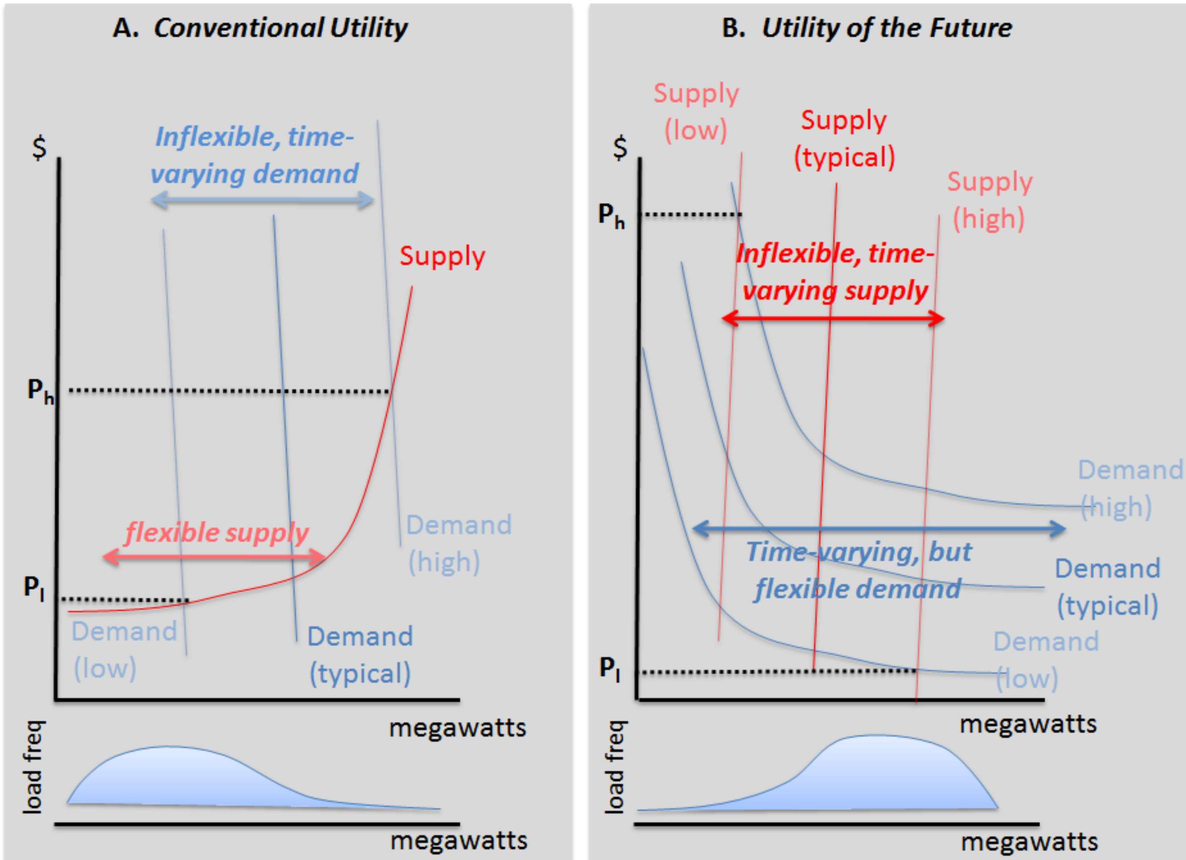
One reason earlier scholars find high costs from intermittency stems from the fact that capacity expansion models, used to optimize investments in new generation and storage, rarely consider chronological operation of the system. In high-renewable systems, or systems with storage, these decisions cannot be optimized independently (Fripp 2012). We are first to develop a model that simultaneously optimizes investments in generation capacity and storage together with how these resources will be chronologically employed, as well as chronological demand by customers. Such a model is necessary to determine the full range of potential benefits from efficient retail pricing in high-renewable systems.

A key challenge for intermittent renewables is that modern infrastructure has been built around electricity systems with centralized and easily controllable generation. Electric grids operate through balancing authorities that adjust electricity generation on timescales ranging from seconds to years, to perfectly balance presumably inelastic, time-varying demand (Figure 1, panel A). Although marginal generation costs vary over time in a conventional system, regulated retail prices tend to be flat, giving rise to well-known inefficiencies. But since incremental costs only spike during rare peak loads, the inefficiencies from flat rates are thought to be small, with most concern centered on market power as demand approaches capacity constraints (Borenstein and Holland 2005, Borenstein 2005, Blonz 2016). Utilities and generating companies have little incentive to change the current system, possibly because too few are aware of the possibilities associated with variable prices, or because it may not benefit them under cost-of-service regulatory structures that currently predominate at the distribution level. Customers have also been unenthusiastic about dynamic marginal-cost pricing, possibly because they lack confidence that they would individually benefit from it. The smoothing of costs when setting retail rates makes demand highly inflexible (inelastic) with respect to generation cost on a day-to-day, hour-to-hour basis, and current system planning and operation reflect this inflexibility.

Balancing almost entirely on the supply side and foregoing potential demand response creates some deadweight loss in existing power systems, but the loss will be much greater in power systems with a large share of intermittent renewables. Solar and wind power are the most cost-effective renewables, but the supply varies with sunlight and windspeed. When intermittent renewables make up a small to moderate share of total generation, the existing infrastructure can accommodate their variability in much the same way it has always managed variable demand. Variations in renewable energy are counterbalanced with directed variation in generation from fossil fuel plants. But as larger shares of renewable energy are accommodated using this conventional model, system-level costs may rise significantly above the levelized costs from any particular source. Controllable generation must be built or retained to compensate for periods of low renewable power production, and these plants may burn either polluting fossil fuels or high-cost biofuels. Providing spinning reserves from thermal power plants — ramping them up and down to compensate for short-term variations in demand or renewable production — requires running these plants at inefficient fractional load levels. Moreover, as more intermittent renewable power is added to the grid, eventually supply begins to exceed demand and storage capacity at certain times, and renewable energy must be curtailed (i.e., discarded). This creates diminishing returns for renewable power and raises average costs. In Hawai'i, Texas, Ireland and perhaps other places, a considerable amount of electricity is already curtailed, even while utility customers may simultaneously pay 30 cents per kWh or more for electricity. With retail prices far above the incremental cost of generation (zero or negative during curtailment), there appears to be inefficiency in the current system, even with renewable energy penetration far below the eventual goals in state renewable portfolio standards. Resolving this inefficiency would help to slow climate change.

To economists, the obvious solution to intermittency is real-time retail pricing that reflects the incremental cost and marginal willingness to pay for electricity. If electricity were priced at its incremental value and cost there would be new, powerful incentives to efficiently store energy on a distributed basis or otherwise shift consumption from times and places of relatively scarce renewable supply to times and places of plenty. Chemical storage of electricity in batteries or hydrogen remains expensive. However, critically, and potentially transformationally, electricity consumers already have access to many low-cost systems that store energy in different forms. By carefully timing water heating, electric vehicle charging and water pumping, using ice storage for cooling systems, making micro-adjustments for some kinds of refrigeration, or perhaps other means, electricity use can be shifted from seconds to many hours at low cost. Such mechanisms would need to be automated by smart devices acting on customers' behalf. These existing technologies can make electricity demand highly substitutable over time, at least over horizons up to a day or so. In addition to shifting the timing of electricity consumption within the day, customers facing dynamic prices can also adjust the total amount of power they consume each day, reducing total consumption during extended periods when power is scarce, or increasing it when power is abundant. We conceptualize this substitutability and overall elasticity with a more elastic demand in panel B of figure 1. While demand-side flexibilities would make intermittent renewable energy more cost effective from a system perspective, they will only be brought to market and adopted if pricing mechanisms incentivize them.

Figure 1: Conventional Utility and Utility of the Future



Notes: Intermittent renewables change the nature of the utility. The horizontal axis is power generated or consumed at a point in time, and the vertical axis is incremental willingness to pay (Demand) or incremental cost of generation (Supply). A stylized frequency distribution of load is shown at the bottom. Panel A shows a conventional utility with flexible supply that can ramp generation up and down with varying demand without greatly changing the incremental cost of power, except for rare peaking loads, so prices are typically low (P_l). Welfare gains have been gleaned from curbing peak loads with critical-peak pricing and demand charges for commercial users, which tie each firm's incremental price to its historical peak. Panel B shows a hypothetical utility of the future, with generation coming mainly from inflexible, time-varying intermittent renewables and real-time pricing. With highly volatile time-varying prices, storage and shiftable loads cause demand to become more flexible, especially in the lower price range, but prices can spike very high during unusual periods when supply is low and demand high.

In this paper we develop a novel model of power supply and demand to examine the extent to which variable pricing could plausibly increase the social benefits of renewable energy. The model is novel in the way it integrates investment in generation and storage capacity with real-time operation of the system, including an account of reserves, a demand system with different interhour elasticities for different end uses, as well as substitution between electric power and other goods and services. Both supply and demand sides of the model can also provide reserves. The model, an extension of Switch (Fripp 2012, Johnston, Maluenda, Henríquez and Fripp 2017), is open source and adaptable to other settings. Earlier versions of the model (lacking reserves and demand-side integration) have been implemented for California, the Western United States, and other areas (Fripp 2012, Nelson, Johnston, Mileva, Fripp, Hoffman, Petros-Good, Blanco and Kammen 2012, Mileva, Nelson, Johnston and Kammen 2013, Wei, Nelson, Greenblatt, Mileva, Johnston, Ting, Yang, Jones, McMahon and Kammen 2013, Ponce de Leon Barido, Johnston, Moncada, Callaway and Kammen 2015, Sanchez, Nelson, Johnston, Mileva and Kammen 2015, He, Avrin, Nelson, Johnston, Mileva, Tian and Kammen 2016).

Our study considers the island of Oahu, the most populous island (about 1 million) and county of Hawai'i, which comprises roughly two thirds of the state's population and consumes over three quarters of the state's power. The island supports a large urban city (Honolulu), plus a substantial tourist industry and several large military bases. Hawai'i is a particularly interesting focus for several reasons. First, its scale is large enough to be emblematic of larger, more complex systems, but small enough to be holistically modeled. Second, given Oahu's isolation and lack of connectivity to other Hawaiian islands, intermittency is an especially acute problem, since connectivity and trade with other regions is not economically feasible. Third, Hawai'i has the nation's, and perhaps the world's, most ambitious renewable portfolio standard – 100 percent renewable by 2045 – which makes our analysis especially relevant to actual policy implementation. Fourth, Hawai'i depends on oil for its power production, making wind and solar power cheaper than fossil fuels today, so it is first to face an economic crossover that other regions will face in the future, as wind and solar move toward undercutting natural gas and coal.

We use the model to: (1) estimate the cost, benefits and optimal generation mix of a 100 percent renewable energy system that accords with Hawai'i's renewable portfolio standard (RPS) as compared to a conventional fossil-fuel power system (Fossil) and a least-cost system with no constraints on the generation mix (Unconstrained); (2) evaluate the welfare improvement of having dynamic marginal-cost pricing as compared to flat price for each kind of system (RPS, Fossil, and Unconstrained); (3) evaluate how much those with high interhour substitutability of demand gain from dynamic pricing as compared to those with very little interhour substitutability.

Cost assumptions for a wide range of power generation and storage alternatives, from which an optimal portfolio is selected by the model, are based on those in the most recent (December, 2016) Power Supply Improvement Plan (PSIP) of the local utility, Hawaiian Electric Company (HECO).[1] We consider scenarios for which costs equal current-day assumptions, as well as scenarios that use the lower costs projected for renewable and battery technologies in 2045 in the PSIP. The analysis we perform here is a single-stage analysis in the sense that each scenario assumes the optimized system is built at one point in time, although pre-existing assets can be retained. We do this to make clear comparisons of highly-renewable and fossil systems in flat and dynamic pricing contexts, and to show how much renewable power would be selected in optimized systems with fixed versus dynamic marginal-cost pricing. In practice, an optimal plan would make investments gradually over time; Switch does have the capacity to formulate such a plan, even though we do not consider it in this paper. Such a model would

[1]See `https://www.hawaiianelectric.com/about-us/our-vision.`

be considerably slower to solve.

Consistent with earlier studies, we find that dynamic pricing of power provides little social benefit in fossil-fuel systems, only 2.6 to 4.6 % of baseline annual expenditure depending on cost and interhour substitutability. But dynamic pricing leads to a much greater social benefit of 8.5 to 23.4% in a 100% renewable system with otherwise similar assumptions. The other key finding is that high penetration renewable systems, including 100% renewable, are remarkably affordable. Indeed, the welfare maximizing (unconstrained) generation portfolio under the utility's projected 2045 costs and pessimistic interhour demand flexibility uses 79% renewable energy and improves welfare by 34.6% of baseline expenditure. With dynamic pricing, even a 100% renewable system is welfare improving over a fossil system, excluding gains from reduced pollution externalities. These results all derive from an assumed outer demand elasticity of just 0.1, and cost assumptions for renewable energy and batteries that some may regard as pessimistic. In other scenarios the benefits of real time pricing paired with renewable energy can be far greater.

The rest of the paper is organized as follows: Section 2 characterizes the demand system and how we calibrate it; Section 3 reviews the Switch model that optimizes investment and operations, as well as a Dantzig-Wolf algorithm used to equilibrate supply and demand and thereby optimize the joint system; Section 4 summarizes capital and input cost assumptions and the wide range of scenarios we consider; Section 5 summarizes the results; and Section 6 concludes.

2 Demand

The main novelty of this paper is the integration of a fully-specified interhour demand system with Switch, a state-of-the-art planning model that jointly optimizes investment and chronological, hourly operation of a power system. We therefore begin by describing the structure of the demand system and how we calibrate it.

2.1 A Nested-CES Demand System

The demand system is comprised as the sum of three nested, constant elasticity of substitution (CES) utility functions that represent different types of demand. The outer layer of each utility function assumes just two goods, electricity and all other goods, with a constant elasticity of substitution θ, which represents a demand elasticity. The nested layer considers electricity demand in each hour within each 24-hour day, with an interhourly elasticity of substitution σ. Aggregate demand in any given day is comprised as the weighted sum of three representative pseudo-customers with different σ values. Each pseudo-customer is assumed to maximize utility $U(x_1, x_2, \ldots, x_h, \ldots, x_{24}, Y|\sigma, \theta, \alpha, \beta_1, \beta_2, \ldots, x_h, \ldots, \beta_{24})$ subject to their budget constraint, $\sum_{h=1}^{24} p_h x_h + Y = M$, where x_h is electricity consumed in hour h, Y represents expenditure on all other goods with a constant price equal to 1 (i.e., money), α and β_h are share parameters that weight all other goods relative to electricity, and electricity in each hour relative to other other hours, and M is total income. M is calibrated by dividing total baseline electricity expenditure of a particular pseudo-customer in a day by the share of aggregate income spent on electricity. The α and β_h parameters are calibrated from the statewide share of income spent on electricity expenditure, and by baseline load shares allocated to each pseudo-customer.

Following Rutherford (2008), suppose there exists a unit expenditure function or an ideal price index (the minimum expenditure required to achieve baseline utility) in the "calibrated share form," a measure relative to baseline values. The expenditure function is:

$$e(p_h, p_{(-h)}, \bar{p_h}, \bar{p_{(-h)}}, \bar{U}) = \bar{U}\left(\alpha\left(\frac{p_Y}{\bar{p_Y}}\right)^{1-\theta} + (1-\alpha)\left(\sum_{h=1}^{n}\beta_h\left(\frac{p_h}{\bar{p_h}}\right)^{1-\sigma}\right)^{\frac{1-\theta}{1-\sigma}}\right)^{\frac{1}{1-\theta}} \tag{1}$$

where $\bar{U}$, $\bar{p_Y}$, $\bar{p_h}$ indicate baseline values for respective parameters, α is the calibrated share given the baseline value of $\bar{Y} = M - \sum_h \bar{x_h}\bar{p_h}$, $\alpha = \bar{Y}/M$, and β_h are calibrated shares of each day's electricity consumed by the pseudo-customer in each hour at the associated baseline prices $\bar{p}_h$.

Consumer welfare is measured by the indirect money metric utility function. That is, we can write indirect utility in terms of the income required at baseline prices to achieve the utility level achievable at prices p and income M, as:

$$V(p_h, \bar{p}_{-h}, M) = \frac{M}{e(p_h, p_{(-h)}, \bar{p_h}, \bar{p}_{-h}, \bar{U})} \tag{2}$$

From Roy's Identity, Marshallian demand is given by:

$$x_h(e(p_h, p_{-h}, \bar{p_h}, \bar{p}_{-h}), M) \quad = \quad -\frac{\partial V/\partial p_h}{\partial V/\partial M} = \frac{M}{e}\frac{\partial e}{\partial p_h}$$

The closed form solution of demand functions then can be written as a function of calibrated share parameters derived from a baseline load profile and the share of income spent on electricity at baseline prices.

$$\frac{x_h(p|\bar{p}, \sigma, \beta, M)}{\bar{p}} =$$

$$M\left(\alpha + (1-\alpha)\left(\sum_{j=1}^{24}\beta_j\left(\frac{p_j}{\bar{p_j}}\right)^{1-\sigma}\right)^{\frac{1-\theta}{1-\sigma}}\right)^{-1} \times (1-\alpha)\left(\sum_{j=1}^{24}\beta_j\left(\frac{p_j}{\bar{p_j}}\right)^{1-\sigma}\right)^{\frac{\sigma-\theta}{1-\sigma}} \times \beta_h\left(\frac{\bar{p_h}}{p_h}\right)^{\sigma} \tag{3}$$

In the computational model, we partition a baseline load profile, drawn from actual historical hourly demand, into three pseudo-customers, each with a different interhour substitutability parameter, $\sigma \in \{\sigma_l = 0.1, \sigma_m = 1, \sigma_f = 10\}$ and a different baseline demand profile, derived from historic loads. Pseudo customers thus differ with regard to their budget and with regard to their calibrated share parameters (β_h), because their load profiles differ. The calibrated share parameters also differ by day and season, to account for weather.

To formalize this demand system, denote the calibrated load shares on day d and pseudo-customer i by β^{id} and income by $M^{id} = \frac{E^{id}}{s}$, where E^{id} is the baseline expenditure of pseudo-customer i on day d, and s is the share of baseline state income spent on electricity. Thus, define the demand for a pseudo-customer i on day d in hour h as $x_h(p|\bar{p}, \sigma_i, \beta^{id}, M^{id})$, using the definition in equation 3. Aggregate demand on day d and hour h is given by the sum of the demands from the three pseudo-customers:

$$x_h^d(p|\bar{p}) = x_h(p|\bar{p}, \sigma_l, \beta^{ld}, M^{ld}) + x_h(p|\bar{p}, \sigma_m, \beta^{md}, M^{md}) + x_h(p|\bar{p}, \sigma_f, \beta^{fd}, M^{fd}) \tag{4}$$

This demand system provides an intuitive and relatively simple way to embody a range of heterogenous demand responses and inter-temporal substitutability of loads that vary over seasons and weather-related circumstances. The degree of interhour substitutability may under- or over-estimate actual technical possibilities. For example, it assumes the same degree of substitutability between any two hours within the same day. At least for some kinds of demand, substitutability may be greater for hours nearer in time. At the same time, the demand system assumes zero substitutability between days, when in reality substitution between late in one day and early in the next may be fairly elastic. While this later assumption may underestimate the overall degree of flexibility, the structure makes it easy to scale up a sample of representative days throughout the year to parsimoniously represent a portfolio of days with weather and demand that are chronologically matched with supply.

2.2 Shares of Flexible Demand

This section describes how we estimate baseline loads for each kind of pseudo-customer. We used hourly aggregate demand data for Oahu from the Federal Energy Regulatory Commission to calibrate hourly load shares that are coincident with solar and wind data used in modeling the supply side. This allows the model to account for the covariances between renewable supply and demand. However, because some kinds of demand are likely to be more time shiftable than others, we develop alternative interhour flexibility scenarios based on estimated load shares that are known to be shiftable using current technologies: air conditioning, water pumping and water heating.

Air conditioning demand is shiftable using ice storage, wherein ice is generated when electricity prices are low, and used for cooling instead of running the compressor when electricity prices are high. These systems can be retrofitted onto existing air-conditioning systems. A number of companies already market this technology to reduce *demand charges*[2], to respond

[2]Demand charges, which are common for commercial electricity customers, link monthly bills to the highest kW draw, typically averaged over a 15-minute period, from each commercial customer during the month or year. However, because peak demand by an individual customer is unlikely to coincide with the system

to real-time variation in prices, or provide contingency or regulating reserves to the balancing authority.[3] Such systems may only require different, smarter controllers and network connectivity. A considerable amount of flexible power is also used to pump water from aquifers to storage reservoirs and tanks on hillsides; water is then gravity fed to homes and businesses. Currently, most water pumping is done at night, because the water municipality receives a slight discount under current time-of-use pricing. There should be a considerable amount of flexibility in when pumping could occur, a flexibility that is mainly constrained by the capacity of water storage. A number of companies have also developed smart water heaters, which can heat proactively in relation to power availability (or prices) and typical use patterns instead of reactively to hot water use. All of these systems embody an implicit form of storage that may be much less expensive than batteries, compressed air, pumped-water hydroelectricity or other means. These systems can also provide a source of reserves to help maintain system stability in the face of unexpected load fluctuations.

By considering loads from only these three principle sources, we believe our estimates of demand-response potential should be conservative, because other kinds of electricity demand for which we could not obtain estimates, or for which current technologies do not exist, may nevertheless prove shiftable if appropriate incentives and technologies were to be made available. For example, refrigerator/freezers and swimming pool pumps likely have large, time-shiftable loads, but we do not explicitly consider them in this study because we were unable to obtain data on their real-time use.

Another consideration is that over 70 percent of total demand on Oahu derives from commercial customers, many of whom have electricity metered at 15 minute intervals or less to accommodate demand charges specified in commercial tariffs. The state is also developing plans to install smart meters for other customers. Even without smart meters, we expect that integrators could implement a wide range of demand-response services, including reserve provision, by using other forms of network connectivity to control power consumption of certain designated devices. Alternatively, devices could be programmed to forecast and respond to price signals automatically.

Estimates of shiftable load in each hour of each month are drawn from Navigant Consulting (2015), a private consulting report commissioned by Hawaiian Electric, a copy of which was submitted to the Public Utility Commission. Although much of the report is redacted, obscuring the methods used to estimate load shares from alternative uses, it is the only available load share data, specific to Oahu, that we have been able to obtain. The starting point for our estimates is a graph in the report depicting September 2025 projected end-use loads by

peak, demand charges may do little to improve efficiency relative to real-time pricing (Borenstein, Jaske and Rosenfeld 2002).

[3] *Regulating reserves* balance the electricity system in real time as demand fluctuates from moment to moment while *contingency reserves* keep the system stable in response to larger disruptions, such as a power plant unexpectedly falling off line.

hour of the day. We measured the bars in the graphs by hand to estimate load shares in each hour for this month, and summed those for air conditioning, water heating and water pumping to obtain an estimate for the mid-September share of potentially shiftable load. Because loads vary over time, and tend to be higher when it is warmer, presumably due to greater use of air conditioning, we adjusted load shares for other months to account for this seasonality. We made this adjustment using hourly load estimates provided in the Navigant report for February, May, August and November of 2014, but were not partitioned by end use. These hourly loads were regressed against a polynomial of hour-of-day and average temperature in each month.

$$\text{Load} = \beta_0 + \beta_1 h + \beta_2 h^2 + \beta_3 h^3 + \beta_4 PV + \beta_5 \mathrm{T}.$$

where h is hour per day, PV is distributed generation from photovoltaic solar (which may be associated with temperature), and T is temperature. We attribute temperature-sensitive load to air conditioning, and then using load shares given for September 2025 as a baseline, we infer the air conditioning share for the other months, linearly interpolating between February, May, August and Noveember. Load shares attributable to water pumping and water heating is assumed to be same across all months of the year.

We consider three different scenarios (optimistic, moderate, pessimistic), each of which assigns different shares of the potentially-flexible and other load to pseudo-customers with different interhour substitutability. The assumptions for each scenario are reported in table 1. In figures 2 and 3 we plot the implied shares of highly flexible, moderately flexible, and inflexible demand in total and by hour and month for each of the three scenarios.

In the end, we cannot know in advance how much demand is truly flexible or the appropriate elasticities to use, nor anticipate how much potentially flexible customers will choose to engage with a well-designed variable-pricing program. We anticipate that commercial customers would comprise the bulk of participating flexible demand. Because commercial customers comprise over 70% of Oahu's load and commercial loads have a large share of potentially-shiftable load, the optimistic scenarios assume that a large majority, but not all, of commercial customers with shiftable load would actively participate in a demand response program. That optimistic scenario might be justified by the historically high participation of commercial customers in real-time marginal-cost pricing programs like the one in Georgia. We anticipate that participation could be even greater in future Hawai'i, since price variation will presumably be far greater and advanced computing technologies could make participation convenient and relatively low cost.

2.3 Demand-Side Reserves

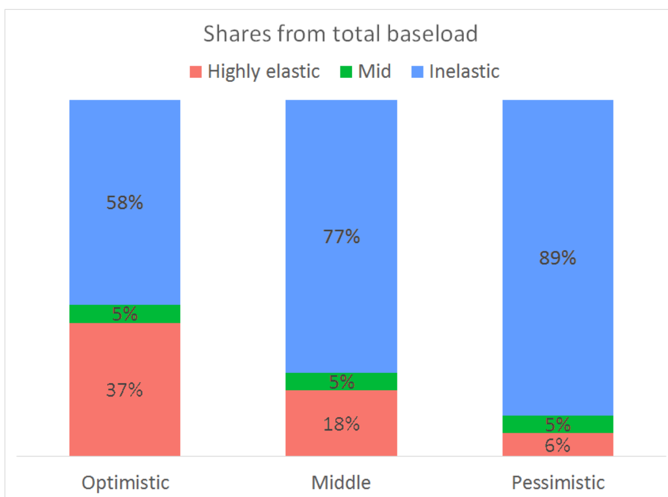
Up reserves normally refer to residual capacity by dispatchable generators that can ramp up in the event that a power plant drops offline, wind or solar energy generation unexpectedly falls, or demand suddenly spikes. Reserves can also be provided by the demand side, and this

Table 1: Share of shiftable load

	σ	Optimistic	Moderate	Pessimistic
Share of potentially flexible load (water pumping, water heading and air conditioning)				
Highly Flexible	10	67%	33%	15%
Somewhat Flexible	1	5%	5%	5%
Highly Inflexible	0.1	28%	62%	80%
Other load				
Highly Flexible	10	15%	8%	0%
Somewhat Flexible	1	5%	5%	5%
Highly Inflexible	0.1	80%	88%	95%

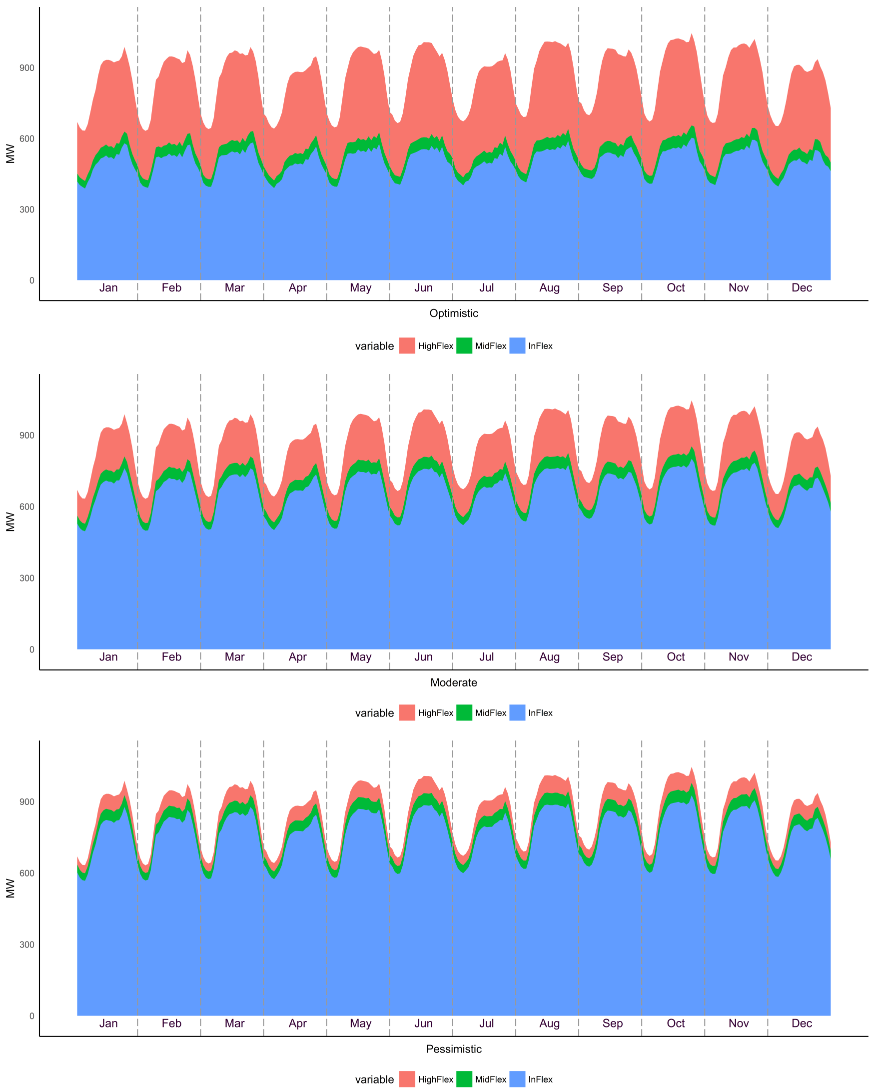
Notes: Shares of flexible and inflexible shares in each scenario.

Figure 2: Demand flexibility scenarios



is typically what power engineers call *demand response*, while economists normally connect the term to the more general idea of price-sensitive demand. Historically, demand-side up reserves have involved contracts between the balancing authority (e.g., utility or ISO) and large-scale users of electricity that give the balancing authority the ability and right, in exchange for a rate reduction, to remotely reduce or terminate power supply to participating customers during certain critical events (note that “up” reserves are specified from a generation perspective, so they correspond to *reducing* load). In Hawai'i, residential customers have also participated in a program that gives residential customers a $3 monthly discount in exchange for allowing the utility to suspend power supply to water heaters during critical events. Similarly, *down reserves* correspond to the option of quickly ramping down a power plant or increasing energy

Figure 3: Demand flexibility scenarios by hour and month



The graphs show three scenarios for interhour demand flexibility, optimistic, moderate, pessimistic, respectively. Note that all demand types are assumed to have the same overall demand elasticity for electricity (0.1 in the the baseline case). Flexible, midflex and inflexible loads are assumed to have within-day interhour elasticities of substitution equal to 10, 1 and 0.1 respectively.

use in the event of a net supply surge, which might result from a sudden falloff of demand or supply surge from intermittent renewables.

The model presented here includes demand-side participation in reserve markets for both up and down reserves, with only highly-flexible demand types assumed to participate. Reserves can also be supplied by the supply side, either from batteries or dispatchable generators. On the demand side, we incorporate reserve provision into flexible-type demand by applying a net cost that includes sale of up and down reserves and purchase of energy, all at real-time prices. We define these as follows:

$$x_h^u = x_h^* \tag{5}$$
$$x_h^d = \max(x_h) - x_h^* \tag{6}$$

where x_h^* is energy use in hour h, x_h^u is demand-side up-reserves provision (option to decrease demand) in hour h, x_h^d is demand-side down-reserves provision (option to increase demand) in hour h, $\max(x_h)$ is the maximum electricity demand when price equals an imposed minimum ($1 per MWh). The minimum price limits demand that could otherwise rise to infinite levels given the constant-elasticity structure of the demand system. The flexible pseudo-customer chooses x_h^* (and implicitly x_h^u and x_h^d), resulting in a net cost given as follows:

$$\begin{aligned} \text{Net Cost} &= p_h^* x_h^* + p_h^u x_h^u + p_h^d x_h^d && (7)\\ &= p_h^* x_h^* + p_h^u x_h^* + p_h^d \cdot (\max(x_h) - x_h^*) && (8)\\ &= x_h^* \cdot (p_h^* + p_h^u - p_h^d) + p_h^d \max(x_h), && (9)\end{aligned}$$

i.e., the incremental cost per unit of consumption is $p_h^* + p_h^u - p_h^d$.

2.4 Calibration of Hourly Demand Shares

We calibrate demand scenarios by estimating the share of aggregate load in each hour and each month used for three potentially shiftable loads: water heating, water pumping and air conditioning. Typically these uses of power can be shifted many hours at relatively low cost using existing technologies. We then suppose optimistic (67%), midline (33%) and pessimistic (15%) scenarios, each of which assumes a different share of these potentially-shiftable loads will actually have high interhour substitutability within a day (elasticity = 10). Across all scenarios we assume just 5% of baseline demand has moderate substitutability between hours (elasticity = 1). We assume that 80-95% of remaining load (not for water heating, water pumping or air conditioning) is highly inelastic between hours (elasticity = 0.1). The optimistic scenario could be achieved with widespread adoption of real-time pricing and automated demand-response systems by commercial users alone.

We use a baseline model that assumes an overall demand for energy (capturing substitution between electricity and all other goods) that is highly inelastic (elasticity = 0.1), which is consistent with a recent estimate with a strong study design and relatively similar climate and marginal price profile (Ito 2014). While some studies find larger demand elasticities, they tend to be based on poorer study designs and we believe it is important to have a baseline model that is reasonably conservative. Within our model, this outer elasticity captures demand response over longer time horizons, which helps with seasonal imbalance and episodic weather, and adjusts overall scale modestly depending on average prices. However, because it seems possible that new technologies and energy demands might arise in a world with highly variable (and often free or nearly free) electricity, we also consider scenarios with larger demand overall elasticities (0.5, 0.9 and 2.0).

2.5 Electric Vehicles

An important consideration for modeling future power systems with high-penetration renewables is the potential growth of electric vehicles. Electric vehicles represent a new source of power demand and, given their large and growing battery sizes, a new source of power storage or interhour flexibility that might also provide reserves. Like demand-side flexibility, it is highly uncertain how quickly electric vehicles may grow as a share of the vehicle fleet. Given the unique nature of power demand from electric vehicles, plus the fact that they comprise a small share of historical loads used to calibrate the demand functions described above, we treat them separately. We also consider scenarios with a wide range of electric vehicle adoption, 0.5% (the current share), 50% and 100%. In variable pricing environments we assume that vehicle charging is optimally scheduled to least-cost times in each day, and thus makes high-penetration renewable systems easier to achieve, but do not allow for any interday substitution of charging (which will likely be feasible). In fixed-price environments we assume vehicle charging occurs as soon as vehicles arrive at home or work, based on trip inventories from the National Household Travel Survey (Fripp 2017, Das 2015, FHA 2009). This shifts up the evening peak more than other times, and makes high-penetration renewable systems more costly.

3 Switch 2.0

Switch[4] (Fripp 2012, Johnston et al. 2017) is open-source power planning software that uses mixed-integer linear programming to minimize the net present value of the cost of electricity production subject to operation and policy constraints. The main decision variables are generation capacities at each candidate project site and the amount of power to produce or store at each project site during each hour of the planning period. Constraints require adequate power to satisfy demand plus reserves during all hours, and satisfaction of any exogenous policy constraints, such as a renewable portfolio standard (RPS).

[4] `http://www.switch-model.org`

Switch combines an operational model, similar in detail to production cost models such as GE MAPS or Plexos, and a long-term capacity expansion model, similar to Ventyx Strategist or PowerSimm Planner. Commercial capacity planning models typically consider the distribution of loads exogenously imposed on a system, neglecting price response by customers. Moreover, conventional planning or expansion models generally use unordered sets of time steps, and thus do no have enough temporal detail to model the operation of power systems with a large share of time-varying renewables. Such power sources may need to be curtailed or be balanced by interhour load shifting or energy storage, which can only be modeled accurately with chronological time steps. In contrast to conventional capacity planning models, conventional production cost models can optimize chronological management, but assume fixed generation portfolios that must be selected by other means. Efficient integration of renewables can be greatly enhanced by simultaneously considering both capacity and chronological operation decisions, as does Switch (Fripp 2012, Johnston et al. 2017, Nweke, Leanez, Drayton and Kolhe 2012, Sullivan, Eurek and Margolis 2014).

3.1 Mathematical Formulation of Switch

Here we provide a brief overview of the core equations used by Switch. A more complete documentation of the software can be found in Johnston et al. (2017).

Switch 2.0 has a modular architecture that reflects the modularity of actual power systems. Most power system operators follow rules that maintain an adequate supply of power, and most individual devices are not concerned with the operation of other devices. Similarly, core modules in Switch define spatially and temporally resolved balancing constraints for energy and reserves, and an overall social cost. Separate modules represent components such as generators, batteries or transmission links. These modules interact with the overall optimization model by adding terms to the shared energy and reserve balances and the overall cost expression. They can also define decision variables and constraints to govern operation of each technology. This approach makes it possible for users to add, remove or alter modules, representing different system components and formulations without unexpected interactions with other parts of the model. Consequently, Switch 2.0 can be readily customized to address the needs of a given study or region.

In the treatment below, we have omitted elements that define regional load zones and power transfers between these zones, since our model of Oahu has only a single zone. However, transmission constraints would be of critical importance for applications to larger geographical areas that are connected, such as the continental United States. We have similarly omitted definitions for multiple investment periods, since we use a single stage for this study.

3.1.1 Objective Function

The objective function minimizes the net present value of all investment and operation costs:

$$\min \sum_{c^{\mathrm{f}} \in \mathcal{C}^{\mathrm{fixed}}} c^{\mathrm{f}} + \sum_{t \in \mathcal{T}} w_t^{\mathrm{year}} \sum_{c^{\mathrm{v}} \in \mathcal{C}^{\mathrm{var}}} c_t^{\mathrm{v}} \tag{10}$$

Function (10) sums over sets of fixed costs $\mathcal{C}^{\mathrm{fixed}}$ and variable costs $\mathcal{C}^{\mathrm{var}}$. Each fixed cost component $c^{\mathrm{f}} \in \mathcal{C}^{\mathrm{fixed}}$ is a model object, specified in units of dollars per year. This object may be a variable, parameter or expression (calculation based on other components). Variable cost components c^{v} are indexed by timepoint (t) among all study timepoints ($\mathcal{T}$) and specified in units of dollars per hour. The term c_t^{v} is the element with index t from component c^{v}, i.e., a variable cost that occurs during timepoint t. The weight factor w_t^{year} scales costs from a sampled timepoint to an annualized value. For this study, we select one 24 hour day from each month of the year, so that the time points t specify actual hours. The weights multiply the individual days by about 30 such that the accounting reflects costs over an entire year.

Plug-in modules add components to the fixed and variable cost sets to represent each cost that they introduce. For example, the generator-building module adds the total annual fixed cost for all generators and batteries (capital repayment and fixed operation and maintenance) to the $\mathcal{C}^{\mathrm{fixed}}$ set, and the generator-dispatch module adds variable costs (fuel and variable O&M) for these facilities to $\mathcal{C}^{\mathrm{var}}$. The specification is generic so that models of different granularity may be considered depending on the needs of a particular problem and computational expense.

3.1.2 Operational Constraints

Power Balance: Specifies that power injections and withdrawals must balance during each time point. Injections are mainly output from power plants and battery storage, and withdrawals are mainly customer loads and battery charging. As with the objective function, plug-in modules add model objects to $\mathcal{P}^{\mathrm{inject}}$ and $\mathcal{P}^{\mathrm{withdraw}}$ to show the amount of power injected or withdrawn by each system component during each timepoint. For this study, production components were defined by the standard generation modules, and withdrawal components were defined by the standard electric vehicle model and a purpose-built responsive demand module.

$$\sum_{p^{\mathrm{i}} \in \mathcal{P}^{\mathrm{inject}}} p_t^{\mathrm{i}} = \sum_{p^{\mathrm{w}} \in \mathcal{P}^{\mathrm{withdraw}}} p_t^{\mathrm{w}}, \qquad \forall t \in \mathcal{T} \tag{11}$$

Dispatch: Power generation from a source (e.g., a power plant) must fall below its committed (turned on) capacity $W_{g,t}$ during time point t multiplied by a capacity factor $\eta_{g,t}$, that may vary with exogenous factors like solar radiation or wind speed.

$$P_{g,t} \le \eta_{g,t} W_g, \qquad \forall g \in \mathcal{G}, \forall t \in \mathcal{T} \tag{12}$$

Additional constraints further limit operation:

$$W_{g,t} \leq K_g, \qquad \forall g \in \mathcal{G}, \forall t \in \mathcal{T} \tag{13}$$

$$d_g^{\min} W_{g,t} \leq P_{g,t}, \qquad \forall g \in \mathcal{G}, \forall t \in \mathcal{T} \tag{14}$$

Equation 13 constrains the commitment choice to fall below the installed capacity K_g (possibly multiple identical units); equation 14 limits dispatch by a minimum-load constraint that applies to many power plants.

Minimum up and down times: The amount of capacity started up ($U_{p,t}$) or shut down ($V_{p,t}$) during each hour in each generation project is calculated via

$$W_{g,t} - W_{g,t-1} = U_{g,t} - V_{g,t}, \qquad \forall g \in \mathcal{G}, \forall t \in \mathcal{T} \tag{15}$$

Additional constraints require that all capacity that was started up during an uptime look back window ($\hat{\tau}_g^{\mathrm{u}}$, defined for each project technology) is still online, and that all capacity that was shutdown during the downtime look back window ($\hat{\tau}_g^{\mathrm{d}}$) remains uncommitted.

$$W_{g,t} \geq \sum_{t'=t-\hat{\tau}_g^{\mathrm{u}}}^{t} U_{g,t'}, \qquad \forall g \in \mathcal{G}, \forall t \in \mathcal{T} \tag{16}$$

$$W_{g,t} \leq K_g^{\mathrm{G}} - \sum_{t'=t-\hat{\tau}_g^{\mathrm{d}}}^{t} V_{g,t'}, \qquad \forall g \in \mathcal{G}, \forall t \in \mathcal{T} \tag{17}$$

The variable $U_{g,t}$ is also used to determine startup costs for each plant (not shown).

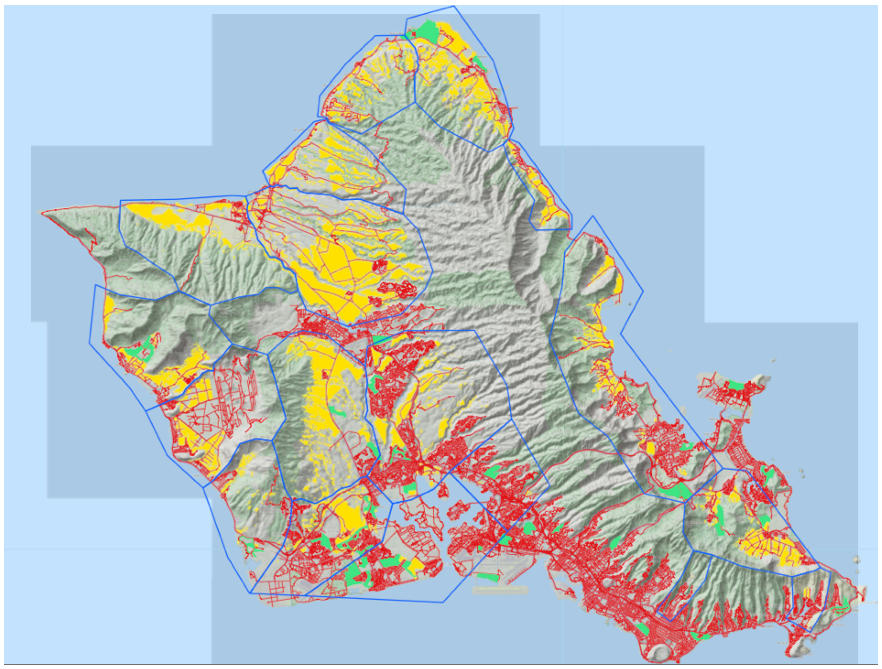
3.2 Oahu Configuration of Switch

Switch is configured based on Hawai'i's 2007 power system data, together with finely gridded, coincident, chronological wind and solar radiation data. Capital cost and fuel cost assumptions are based on Hawaiian Electric Company's recent Power Supply and Improvement Plan (`https://www.hawaiianelectric.com/about-us/our-vision`). Renewable resource potential is derived from screening available land resources as described below.

3.2.1 Utility-Scale Solar

Land available for utility-scale solar was restricted to parcels zoned for agricultural or country use, excluding Class A agricultural land per Hawai'i statute. This is conservative because it excludes a significant amount military land, and the military plans to install a considerable amount of solar. We also excluded land with a slope greater than 10%, land within 50 meters of street centerlines, and parcels with any directional dimension less than 60 meters. We assume fixed-panel photovoltaic installations use six acres per MW (AC) of capacity and that tracking photovoltaic installations use 7.5 acres per MW (AC) of capacity. These are roughly in the lower quartile of the national statistics indicated by the National Renewable Energy Laboratory (NREL)[5]. Fixed photovoltaic has a ground cover ratio of 0.68 and tracking systems have a cover ratio of 0.45. These assumptions affect the capacity factor when the sun is low. We then use NREL's PV Watts tool to calculate hourly output for each 4 km cell using irradiance data from the National Solar Radiation Database (NSRDB). The map of lands considered are shown in figure 4.

Figure 4: Land Available for Utility-Scale Solar



The map shows land that is assumed to be available for utility scale solar installations on Oahu given zoning and other technical and legal constraints (shown in yellow). Each area circled in blue is entered as a separate generation project in Switch, with different projects having different capacity limits and hourly production profiles. Red lines indicate roads.

3.3 Rooftop Solar

Rooftop solar potential was estimated from roof area from Google Map images. Visual review of many roofs indicates accurate identification. We assume 40 percent coverage of roofs, which is equivalent to 15 percent of roofs being flat with 70 percent coverage and 85 percent are sloped with 35 percent coverage. We estimate total capacity assuming 12 percent efficiency with 1000 W/m^2 irradiance (capacity = 120 W/m^2). Hourly output was estimated using PV Watts and the NSRD. figure 5 shows an image of rooftops on Oahu, including a closeup of the UH Mānoa campus.

[5]See `http://www.nrel.gov/docs/fy13osti/56290.pdf`.

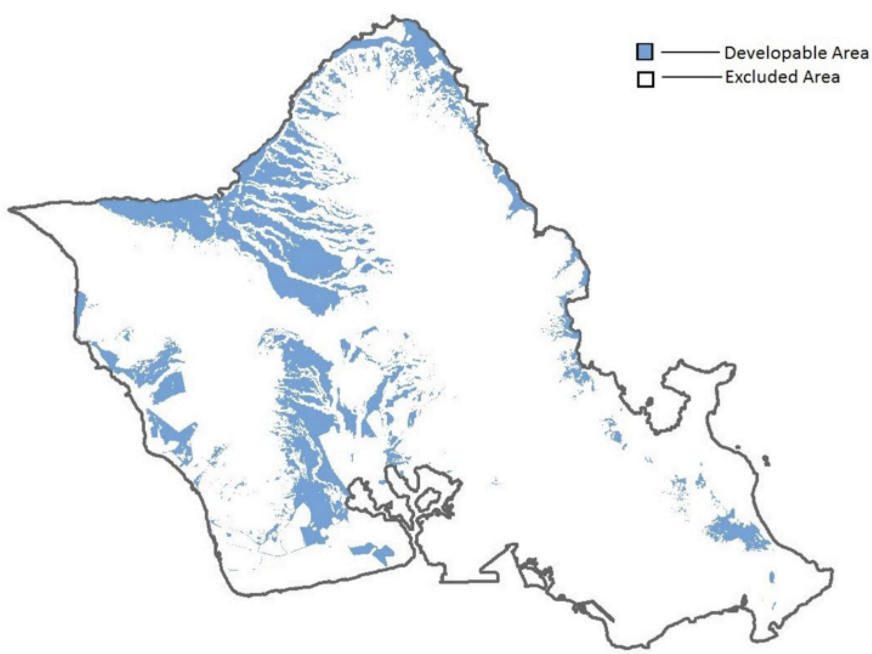
Figure 5: Estimating Potential Rooftop Solar

The bottom image shows rooftop space islandwide (in lighted in yellow). The image on top shows a closeup of part of the Mānoa campus to demonstrate accuracy of rooftop identification.

3.4 Wind Potential

On shore wind potential was estimated using a screening of available land similar to solar. Only land zoned for agriculture or country and not within 300 meters of other zones was considered. Slopes were restricted to 20 percent grade or less, and not within 30 meters of steep slopes, to eliminate narrow ridge tops and valleys. A map of areas potentially developable for wind is show in figure 6. We considered wind turbine density of 8.8 megawatts (MW) per square kilometer (km^2), which is conservatively less dense than the current Kahuku wind farm already installed on the island (12.9 MW/km^2), but on the high end of 5-8 MW/km^2 that is estimated by Denholm, Hand, Jackson and Ong (2009). Potential turbines were clustered by region into separate scalable projects. Hourly behavior of each potential project—its coincident potential capacity—is calculated based on historical meteorological modeling conducted for the Oahu Wind Integration and Transmission Study (Corbus, Schuerger, Roose, Strickler, Surles, Manz, Burlingame and Woodford 2010). For all practical purposes, there is an unlimited supply of off-shore wind potential with a high capacity factor of an estimated 43 percent, which enters the model as a single scalable resource.

Figure 6: Potential wind farm locations



The map shows land that is assumed to be available for on-shore wind development.

3.5 Time points and build scenarios

The model solves for a 30-year planning horizon and 12 representative days in each investment period, each representing a typical day from each month (the 15th), while constraining the model to achieve the state's 100 percent renewable energy goal by 2045 in the 100% scenarios. We also solve models that constrain generation to be purely traditional fossil fuels, plus a model that is unconstrained, and simply maximizes welfare (and minimizes costs) ignoring pollution externalities. The analysis we perform here is a single stage analysis in the sense that each scenario assumes all new assets are built at one point in time (i.e., 2045). Switch is designed to consider a series of investment windows so as to optimize a long-run plan or transition. However, because our focus in this paper is on the value of variable pricing, we chose to simplify this part of the problem so as to provide more clarity about the long-run tradeoffs of this critical policy choice. It is also possible to add more sample days to gain a fuller representation of the joint distributions of time, weather, supply and demand; this does not appear to change our results in a substantial way, but may be useful for fine-tuning an actual resource plan.

3.6 Equilibrium: Merging Switch with Demand

Iterations between Switch and the demand system were completed as follows. First, we solve Switch for a baseline load profile, which is connected to either actual 2007 loads or projected loads for 2045 (differences are discussed below). Tentative prices are derived as marginal costs (shadow values of the constraints specified in equation 11), and these are offered to the demand system. The demand system returns optimal quantities given these prices, and also reports Marshallian consumer surplus minus a fixed offset – i.e., the line integral of demand taken from baseline prices to offered prices. [6] Switch then minimizes the cost of serving the new quantities, sending new prices based on marginal costs. During successive iterations, Switch constructs a linearized demand system from the convex hull of the demand and total willingness to pay (consumer surplus plus total expenditure). In other words, it approximates total willingness to pay as a convex combination of willingness to pay from prior iterations (i.e., any linear combination of prior bids with total weight of 100%). During each iteration, Switch chooses a new system design to maximize welfare (willingness to pay minus cost) and offers new prices. This cycle repeats until there is no further improvement in total surplus from having new prices offered and receiving new bids.

This method is a Dantzig-Wolfe decomposition of the joint supply-demand problem (Dantzig and Wolfe 1960). With this method, solutions from the supply problem, in which consumers are given quantities based on the linearized demand function, represent a lower bound on surplus; solutions from the demand problem, in which consumers can choose any amount they want without changing prices, provide an upper bound on surplus. We stop iterating when the difference between these two measures is less than 0.1 percent of baseline electricity expenditure.

[6] To find the correct competitive equilibrium in this iterative manner requires that we use Marshallian surplus rather than compensating or equivalent variation. Because nested-CES utility is well behaved and homothetic, this integral is not path dependent (Takayama 1982). And because income effects are small, owing to the fact that electricity expenditure is a small share of income, this measure of surplus is also very similar to compensating and equivalent variation or money-metric utility. For this reason, we only report Marshallian consumer surplus.

4 Cost assumptions and scenarios

4.1 Cost Assumptions

The inputs for the Switch model are based on Hawaiian Electric Company's Power Supply Improvement Plan (PSIP) and are summarized in table 2. The report lays out projected costs each year from 2016 through 2045, and we consider models with costs at each endpoint to show sensitivity of results to cost assumptions.

Table 2: Summary of Cost Assumptions

		Capital cost ($/MW)		Unit cost ($/MMBtu)		Op. & Maint.
Category	Description	2016	2045	2016	2045	($/MW/Yr.)
New power generators						
	Combined Cycle Gas/Oil	1,653,242	1,415,952			17,452
	Central Tracking PV	2,856,257	1,680,388			22,970
	Distributed PV	3,650,295	1,511,097			-
	Diesel Barge	1,323,183	1,323,328			34,214
	Diesel MCBH	3,162,083	2,855,884			33,844
	Diesel Schofield	2,481,336	2,241,312			33,844
	Offshore Wind	6,205,598	3,882,934			96,710
	Onshore Wind	2,459,329	1,986,498			27,400
	Pumped Hydro	3,033,333	3,033,333			
Storage						
	Battery	484,283 ($/MWh)	146,639 ($/MWh)			
	Hydrogren Electrolyzer	1,596,797	697,014			
	Hydrogen Fuel Cell	990,562	528,787			
	Hydrogen Liquifier	42,997	42,997			
Inputs for fossil power plants						
	Biodiesel			30.37	48.68	
	Coal			2.74	3.60	
	Diesel			10.48	32.50	
	LNG bulk			6.26	22.01	
	LNG container			10.52	14.38	
	LSFO			7.95	29.56	
	Pellet Biomass			14.00	14.00	

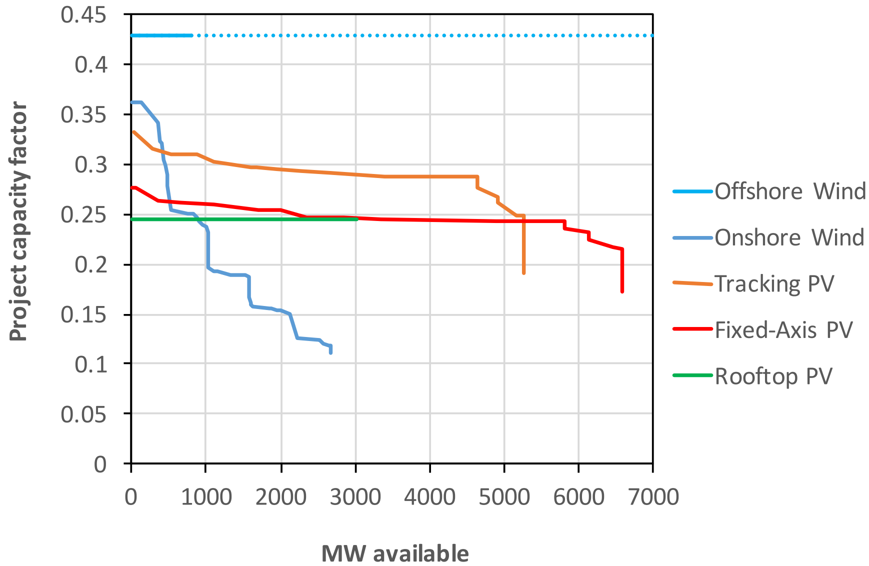
Note: Cost assumptions are derived from Hawaiian Electric Company's Power Supply Improvement Plan from December 2016. See `https://www.hawaiianelectric.com/about-us/our-vision`.

We summarize average capacity factors (normalized production potential) for the renewable sources in figure 7. In the optimization model, capacity factors for each project vary by hour. While projects with higher average capacity factors are more likely to be selected from the optimization routine, the timing of output also matters.

4.2 Scenarios

We solve the full model under a large number of scenarios to explore sensitivity of results to different assumptions. Specifically, the scenarios span all combinations of the following sets of assumptions. Solving many scenarios also allows us to check internal consistency of results, which is useful for developing some confidence that the models converged correctly.

Figure 7: Average output and potential capacity of renewable energy sources on Oahu



The graph shows the resource capacity of different potential sources of renewable energy, each ordered from highest average output (capacity factor) to lowest. For perspective, peak demand on Oahu is about 1000 MW. A project with a 0.25 capacity factor would produce an average of 25% of its nameplate capacity throughout the year.

Interhour demand flexibility	(3) **Pessimistic, Middling, Optimistic**.[7]
Cost assumptions	(2) HECO PSIP for 2016, **2045**.
Overall electricity demand	(4) **0.1**, 0.5, 0.9, 2.0.
Electric vehicle share	(3) 0.5%, **50%**, 100%.
Policy Objective	(3) **Fossil, 100% Renewable, Unconstrained.**
Baseline load profile	(2) **Projected 2045**, Actual 2007.
Pricing scenario	(2) **Flat**, Variable marginal-cost prices.

Most of the different sets of assumptions have been detailed above. We described the different interhour demand flexibilities in sections 2.2 and 2.4. Cost assumptions for 2016 and 2045 are summarized in table 2. Overall demand is likely inelastic, so we focus mainly on results with an overall demand elasticity for electricity of 0.1 (the elasticity of substitution between electricity and all other goods). However, we do consider models with larger elasticities because some scholars may find these more plausible, and because new uses for electricity may arise that can make use of inexpensive electricity that would likely arise for significant stretches under high-renewable scenarios. New intermittent demands may be more elastic.

The two load profiles, actual 2007 and projected 2045, differ mainly in their degree of variability, including seasonality. Current demand tends to be considerably higher during

[7]Baseline scenario in boldface.

Summer and early Fall, while loads that the Hawaiian Electric Company projects for 2045 are considerably flatter. Because seasonal variability may be more costly to manage than intraday variability, comparison of these scenarios provides some sense of this cost of seasonality. We do not have a strong sense of why Hawaiian Electric Company believes the load profile will become flatter in the future, but we have augmented historical loads to match their projections for peak and average load in 2045. Because HECO reports a projected peak load of 1065 MW and average of 861.4, but the historical peak and average were 1249 and 955 (in 2007), the profile is flatter for 2045 than it is for 2007.[8]

Much of our discussion focuses on welfare differences between flat and variable, marginal-cost pricing, and those scenarios are crossed with all other sets of assumptions. Considering all combinations of the above scenarios yields $3 \times 2 \times 4 \times 3 \times 3 \times 2 \times 2 = 864$ scenarios. Computing time required to solve a single scenario can range from less than an hour for flat-price scenarios, to nearly two days for some of the dynamic scenarios where many different resources are on the margin. We used the University of Hawai'i's high performance computing facility with hundreds of state-of-the-art cores to solve many models simultaneously. Although space constrains us from reporting all individual scenarios, we have characterized many of them here, and have developed a website with drop down menus that will allow readers to explore details of any particular scenario (`http://www2.hawaii.edu/~mjrobert/power_production/`).

In addition to the above scenarios, we also solved models along a path wherein we constrain the percent renewable to a range of values between the least cost (unconstrained) portfolio and 100% renewable, holding all else the same. This allows us to trace out the social cost (loss in producer plus consumer surplus) of additional renewable energy under each set of assumptions. Note that we *do not* consider the external cost of pollution emissions. The idea is that whatever benefits society may glean from renewable energy above the minimum cost, such as reduced pollution externalities, ought to be weighed against these cost curves.

Welfare calculations consider changes in Marshallian consumer surplus (CS), producer surplus (PS), and charging costs for electrical vehicles (EV), which are treated separately but included in total CS. We also calculated CS for each type of pseudo-customer, each having different interhour flexibility and base load profiles. CS changes are similar to compensating or equivalent variation, given the relatively small share of expenditure, so we do not report CV or EV. Producer surplus is the change in revenue minus total cost. Note that these calculations do not include fixed customer charges or rebates, which could be used to change the overall balance of welfare between customers and producers. For this reason, it may be more meaningful to focus on changes in total surplus and differences across pseudo-customers. Also note that we do not explicitly account for fuel savings that may derive from greater EV use. Comparison of low versus high EV scenarios are meant to show how EVs could change the

[8]We derived projected future baseline demand by multiplying the historical loads by 0.693 and adding 200 MW.

value of variable versus fixed pricing, since EVs embody a potentially large block of flexible demand.

5 Results

To ease comparison of scenarios, results are reported as the difference between a particular scenario and a baseline scenario. In most cases, the baseline scenario, indicated by the bold-faced sets of assumptions in the list above, assumes fossil-based generation, future 2045 costs and projected load profile, flat pricing and an overall demand elasticity for electricity of 0.1 (the elasticity of substitution between electricity and all other goods). Note that under flat pricing scenarios, interhour demand flexibility has no bearing on the outcome. We choose this scenario as the baseline because we presume that it is the future that utilities envision in the absence of renewable energy. To make welfare calculations easy to interpret, we report these as percent differences from the baseline level of total expenditure on electricity.

5.1 Main Results

Table 3 reports the main results for scenarios with projected 2045 loads and costs. Comparing different rows from this table, one can infer the value of variable pricing under both fossil and high-penetration renewable systems. One can also infer the value of having more or less optimism about the degree of interhour flexibility of demand. Finally, we can see how much the projected cost trends favor renewables, by comparing current (2016) costs and projected costs in 2045.

We present a larger set of results graphically in figures 17 and 10. The first figure shows the value of real time marginal cost pricing in comparison to flat pricing, all else the same. The second figure shows the social cost of a 100 percent renewable system (negative change in producer plus consumer surplus) against fossil and unconstrained baseline scenarios, all else the same.

To illustrate what a few scenarios look like in real time, figure 8 shows both consumption and production mixes by hour and season for middling demand flexibility, the scenarios that sit between the paired optimistic and pessimistic demand flexibility in table 3. For higher resolution depictions of all 864 scenarios, see the interactive website at: `http://www2.hawaii.edu/~mjrobert/power_production/`, which allows users to select desired scenarios from a series of drop down menus.

Finally, in figure 11 we show how the social cost of renewable energy rises as the share of renewable energy is gradually increased from the optimal portfolio (greatest social welfare, excluding pollution externalities) to 100 percent renewable. The graphs summarize a large number of scenarios and generally illustrate the value of variable versus flat pricing, the role of electric vehicles, interhour demand flexibility and overall demand elasticity, and current versus future technology assumptions.

The main observations that we can take from these results are:

- A small amount of demand-side flexibility is valuable. We can see this by observing that the pessimistic scenarios, with less than one sixth the amount of flexible demand as the optimistic cases, still benefit at least half as much from variable marginal-cost pricing as the optimistic scenarios.
- Under current costs, the unconstrained system is mostly fossil fuels (4 - 5.6 percent renewable), however under future projected costs, the unconstrained system is mostly renewable (73 - 80 percent). Increasing renewable energy shares 5-15 percentage points above these baselines tends to be inexpensive.
- Dynamic pricing in the unconstrained scenarios lowers costs while increasing the share of renewables. This value increases over time as the cost of renewables relative to fossil fuels declines, and renewable energy makes up a larger share of electricity in unconstrained scenarios.
- A 100 percent renewable system is projected to be less costly than a fossil system by 2045, but only under dynamic pricing.
- The value of dynamic pricing accrues mostly to consumers and may actually reduce producer surplus, while total surplus always increases with dynamic pricing. Adjustments in fixed charges could change this imbalance.
- Dynamic marginal cost pricing is considerably more valuable the greater the penetration of renewable energy, rising from about 2.6% under the baseline scenario with pessimistic demand flexibility, to 23.4 percent in a 100 percent renewable system with optimistic demand flexibility. Note that if the overall demand elasticity were larger, the value of dynamic pricing would also be greater, as high as 47 percent when $\theta = 2$ and the portfolio is constrained to be 100 percent renewable (results reported in the appendix).
- The production and consumption profiles indicate that in high-renewable scenarios, the value of the variable pricing mainly derives from considerably less use of batteries. In scenarios with more elastic overall demand, much greater value is realized by growing demand during low cost times when renewable energy is abundant.
- While variable pricing benefits more flexible demand types more than inflexible demand types, even inflexible demand types tend to benefit from variable pricing, and in some cases, nearly as much as flexible demand types.[9]
- Optimal dynamic prices vary a lot between days as well as within days, with many days having zero or near-zero prices nearly all day, and other days having very high prices all day, even midday during peak sun. Put another way, storage and interhour substitution

[9]This analysis accounts for the estimated baseline load profiles of more-flexible and less-flexible demand, but it *does not* account for individual heterogeneity of load profiles across customers. Residential customers, for example, may have little midday demand and high morning and evening demand, which would be more costly to serve.

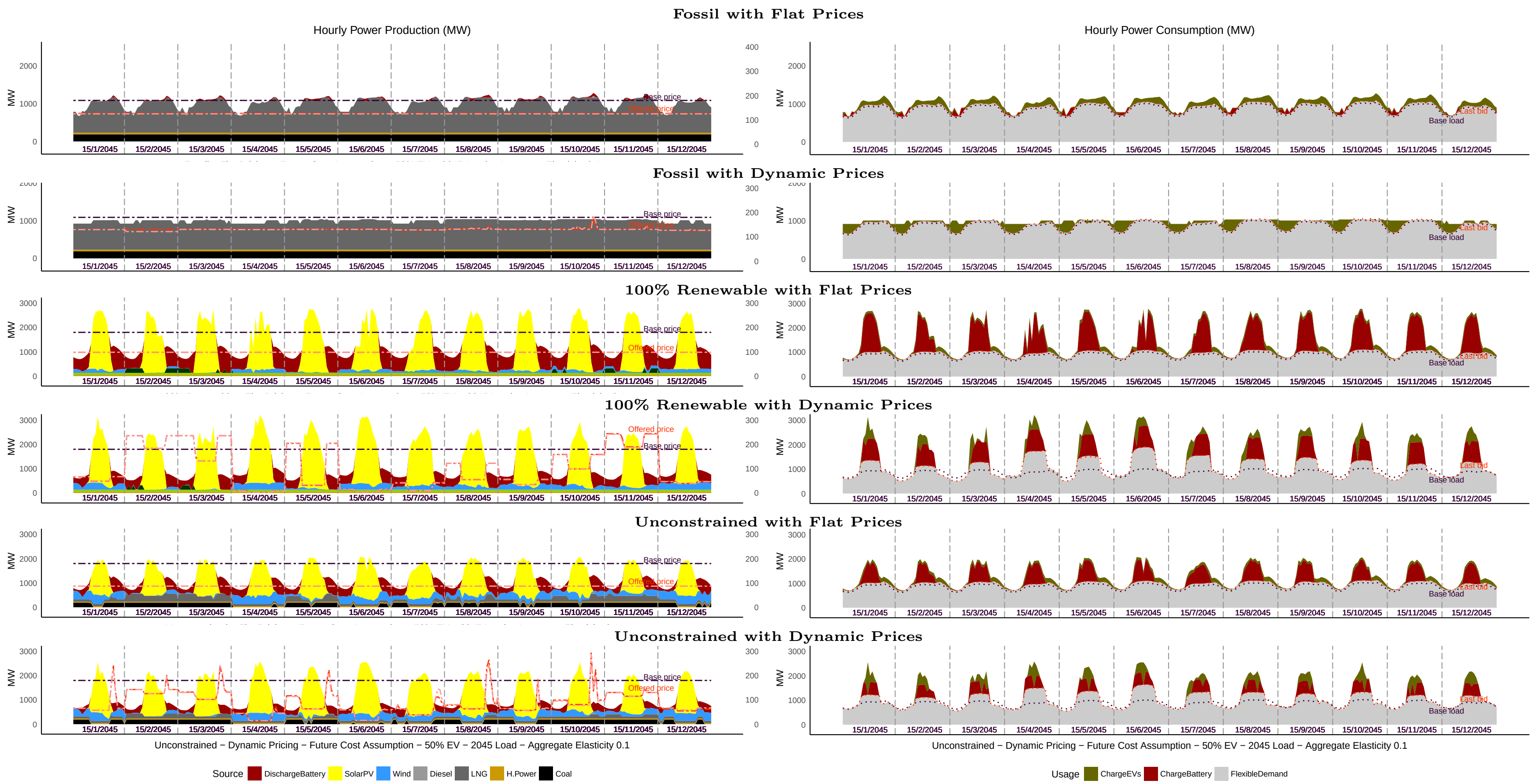
can arbitrage away much of the price differences between hours, but low-sun/low-wind days may have high prices all day.

Table 3: Main Results: Change in surpluses relative to baseline future fossil system with flat prices as a percent of baseline expenditure.

(1) Policy Objective	(2) Cost	(3) Demand Flexibility	(4) Pricing	(5) % Renewable	(6) Price ($/MWh)	(7) Mean Q (MWh/hr.)	(8) SD of Price ($/MWh)	(9) Δ CS (%.)	(10) Δ EV Cost (%)	(11) Δ PS (%)	(12) Δ TS (%)	(13) Δ CS Highflex (%)	(14) Δ CS Midflex (%)	(15) Δ CS Inflex (%)	(16) Δ TS Dyn (%)
Fossil	Current	Optimistic	Flat	4.12	87	944	0	33.6	-41.8	8.1	41.7	30.9	30.9	30.9	4.6
			Dynamic	3.99	62	980	2	58.9	-58.2	-12.6	46.3	51.8	51.8	51.8	
		Pessimistic	Flat	4.12	87	945	0	36.1	-37.2	5.1	41.2	31.5	31.5	31.5	4.1
			Dynamic	4.01	61	972	0	54.1	-57.4	-8.8	45.3	53.1	48.2	47.8	
	Future	Optimistic	Flat	4.27	124	906	0	Baseline							3.4
			Dynamic	4.31	131	900	3	-4.9	-2.7	8.4	3.4	-5.8	-5.8	-5.8	
		Pessimistic	Flat	4.28	126	904	0	Baseline							2.6
			Dynamic	4.25	107	912	0	8	-20.8	-5.5	2.6	14.8	6.3	5.4	
100% Renewable	Current	Optimistic	Flat	100	173	871	0	-38.9	36	-1.6	-40.5	-38.3	-38.3	-38.3	23.4
			Dynamic	100	128	959	86	-12.6	-15.5	-4.5	-17.1	3.1	-15.9	-25.7	
		Pessimistic	Flat	100	171	871	0	-37.1	33.8	-2.9	-40	-35	-35	-35	13.9
			Dynamic	100	137	931	96	-24.8	-14.9	-1.3	-26.1	6.4	-17.8	-28.9	
	Future	Optimistic	Flat	100	98	931	0	25	-30	-28.6	-3.6	21.2	21.2	21.2	13.7
			Dynamic	100	84	1047	75	39.3	-52.9	-29.2	10.1	43.4	30.9	26.2	
		Pessimistic	Flat	100	98	931	0	25.3	-29.1	-28.9	-3.6	22.4	22.4	22.4	8.5
			Dynamic	100	92	1016	80	33.9	-51.5	-29	4.9	45.2	31.7	27	
Unconstrained	Current	Optimistic	Flat	5.39	88	943	0	34.8	-23.7	6.9	41.7	29.7	29.7	29.7	4.6
			Dynamic	3.99	62	980	2	58.9	-58.2	-12.6	46.3	51.8	51.8	51.8	
		Pessimistic	Flat	5.63	82	949	0	38.3	-37.7	2.9	41.2	35.9	35.9	35.9	4.1
			Dynamic	4.02	61	972	0	53.4	-57.4	-8	45.3	53.1	47.8	47.3	
	Future	Optimistic	Flat	73	87	944	0	35.4	-35.7	-6	29.4	30.6	30.6	30.6	9.3
			Dynamic	80	71	994	32	45.5	-55.3	-6.7	38.7	45.7	37.5	34.4	
		Pessimistic	Flat	73	87	944	0	35.4	-34.7	-6.3	29.1	31.6	31.6	31.6	5.5
			Dynamic	79	79	976	39	39.3	-54.4	-4.8	34.6	47.1	36.3	32.4	

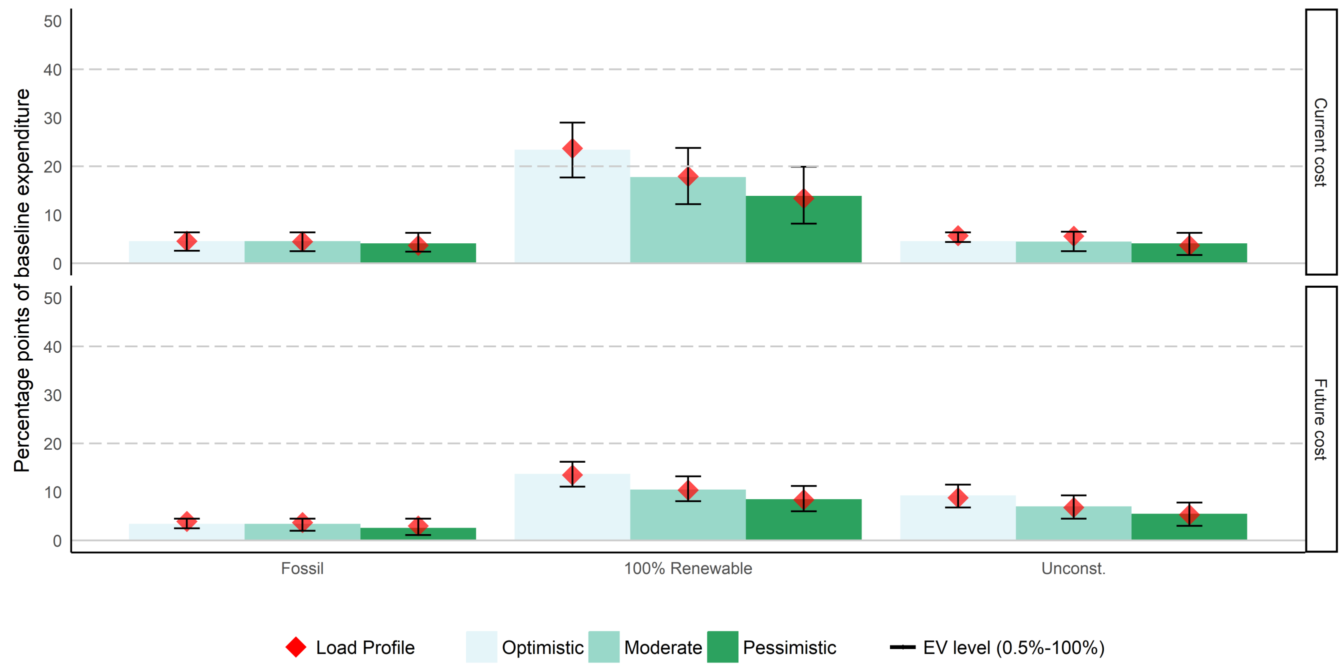
Notes: In all of the scenarios presented in this table, the overall demand elasticity for electricity (θ) equals 0.1, the baseline load profile is that projected for 2045, and electric vehicles are assumed to comprise 50% of the fleet. Each scenario (row in the table) is defined by assumptions delineated in the first four columns. The first column (Policy Objective) indicates exogenous constraints determined by policy: The Fossil scenario restricts any new installation of renewable energy, but is otherwise least cost; the 100% Renewable scenario reflects the intended outcome of the State's Renewable Portfolio Standard, and the Unconstrained scenario maximizes welfare without any constraints on the mix of power plants. The second column indicates whether current costs (2016) or the present value of future costs projected for 2045 from HECO's Power Supply and Improvement Plan are assumed. The third column indicates the degree of demand flexibility, as detailed in table 1. The fourth column indicates whether retail prices are flat or dynamic (time-varying and equal to marginal cost). The remaining columns summarize the outcomes of the conditionally optimized system: average price, average quantity, standard deviation of price, and changes in surpluses from the baseline case (fossil system, future costs, and flat pricing). All changes welfare are reported as the percent difference relative to the baseline level of expenditure on electricity. %ΔEV is simply the percent change in charging costs for electric vehicles from the base case. Note that ΔCS includes EV changes. We also examine changes in welfare for different demand flexibilities, which only matters for dynamic pricing scenarios. The last column reports the social value of dynamic pricing holding all else the same.

Figure 8: Hourly production and consumption profiles for several scenarios with middling interhour demand flexiblity.



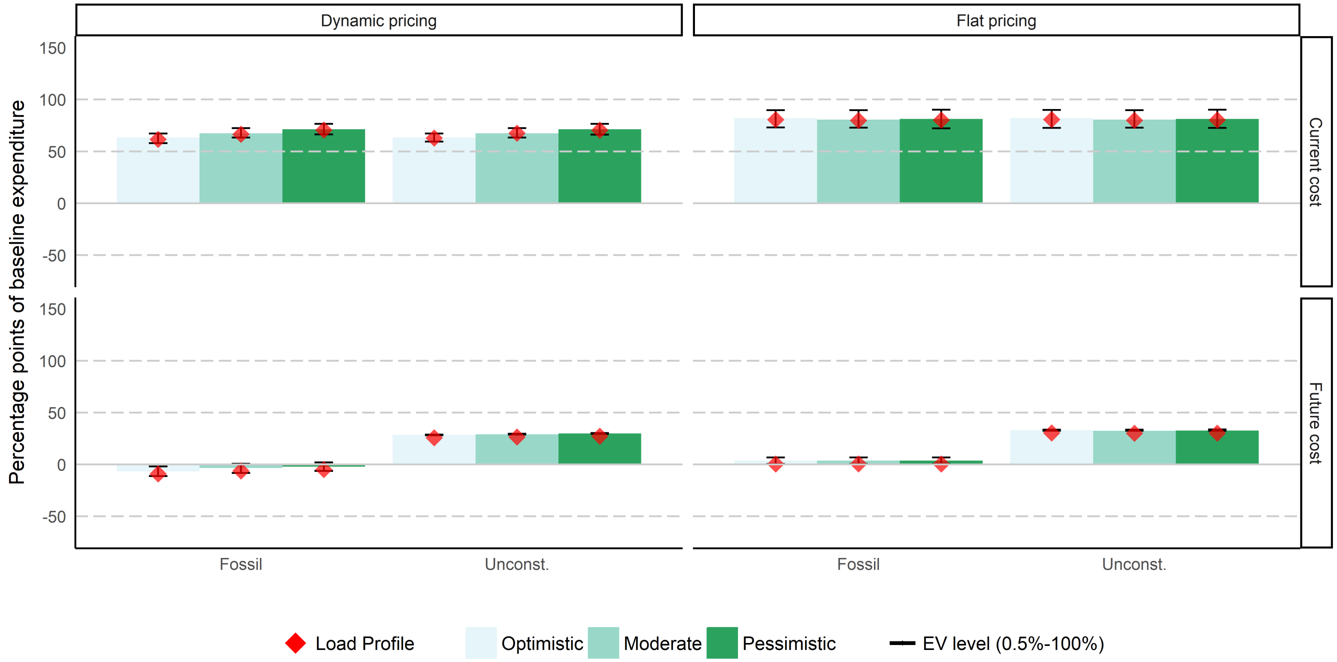
The scenarios presented above assume the middling scenario for interhour substitutability of demand, an inelastic overall demand elasticity for electricity equal to 0.1, a baseline demand profile projected for 2045, a vehicle fleet with 50% electric vehicles, and costs of production as projected for 2045 in HECO's Power Supply and Improvement Plan. The first two rows show fossil-fuel systems with flat and dynamic, real-time pricing; the next two rows show 100% renewable systems with flat and dynamic pricing; and the last two rows show the welfare-maximizing systems (resource unconstrained) with flat and dynamic pricing. Higher resolution graphs for all scenarios can be viewed at the website: `www2.hawaii.edu/~mjrobert/power_production/`.

Figure 9: Surplus gain from dynamic pricing under different policy, cost and demand flexibility scenarios.



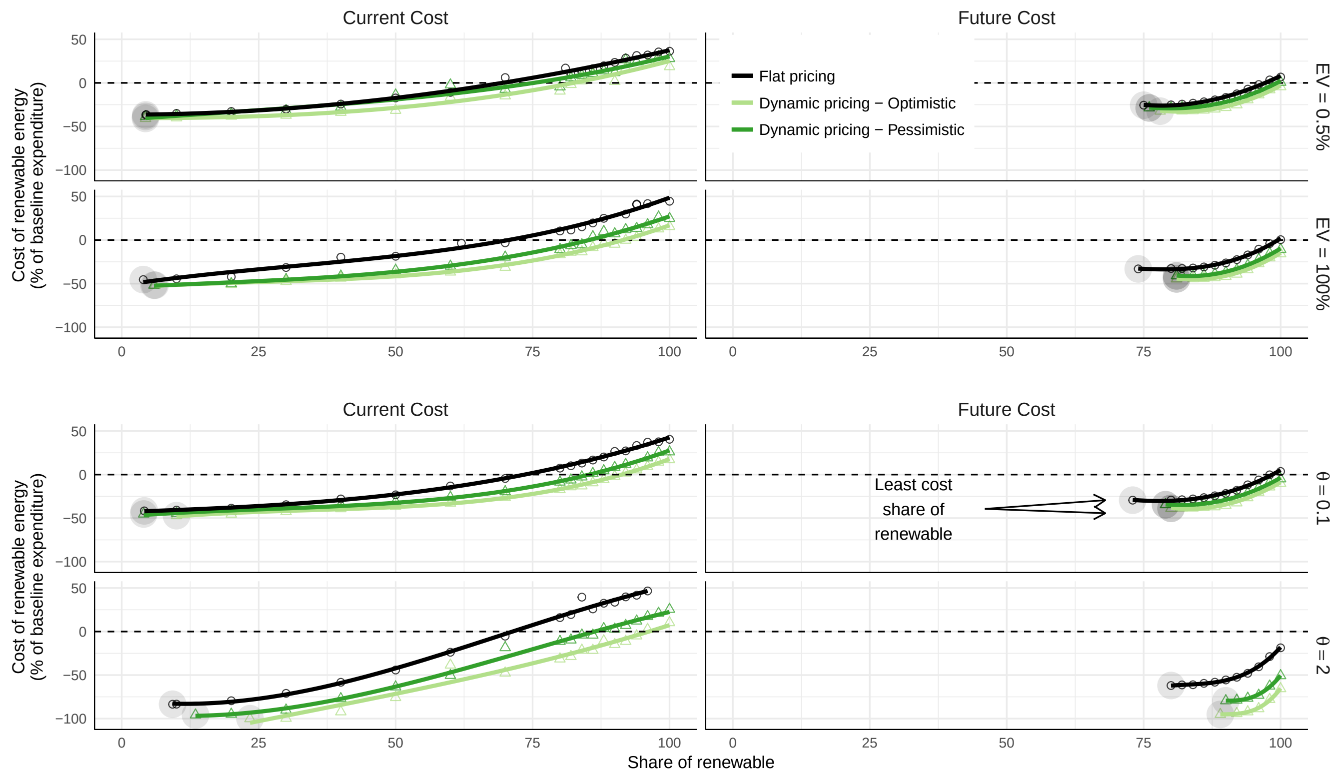
The graph shows the difference in total economic surplus with real-time marginal-cost pricing and total surplus when prices are flat, holding all else the same. Total surplus change is reported as a percentage of baseline (flat price) expenditure on electricity. The graph depicts all scenarios with an overall demand elasticity of 0.1; results for larger overall elasticities are shown in the appendix. The top row shows the value of variable pricing under current costs; the bottom row shows the value of variable pricing under projected future costs (2045). The horizontal axis shows the policy scenario: fossil, 100% renewable or unconstrained (maximum surplus, regardless of source). The bars show the baseline case with 50 percent electric vehicle fleet and 2045 load profile, the diamonds show the 2007 load profile, and the error bars show how results differ with 0.5 percent and 100 percent electric vehicles–more electric vehicles always increase the value of variable pricing.

Figure 10: Cost of 100 percent renewable energy system under different policy, cost and demand flexibility scenarios.



The graph shows the difference in total economic surplus with a 100 percent renewable system versus the baseline scenario given on the horizontal axis, holding all else the same. Total surplus change is reported as a percentage of baseline expenditure on electricity. The graph depicts all scenarios with an overall demand elasticity of 0.1; results for larger overall elasticities are shown in the appendix. The top row shows the value of variable pricing under current costs; the bottom row shows the value of variable pricing under projected future costs (2045). The horizontal axis shows the policy scenario: fossil, 100% renewable or unconstrained (maximum surplus, regardless of source). The bars show the baseline case with 50 percent electric vehicle fleet and 2045 load profile, the diamonds show the 2007 load profile, and the error bars show how results differ with 0.5 percent and 100 percent electric vehicles–more electric vehicles always increase the value of variable pricing.

Figure 11: The social cost of renewable electricity relative to a fossil future with flat pricing.



Each line shows the social cost—the loss in total economic surplus (PS + CS)—as the share renewable electricity rises above the least-cost share, holding all else the same. Social cost is measured as percent of expenditure in the baseline scenario, which is a predominantly fossil system with flat pricing in the year 2045. Thus, values less than zero imply a welfare improvement compared to using a conventional fossil system in the future (excluding externalities). Graphs on the left assume current (2016) costs, while graphs on the right assume future (2045) costs. Comparison of the top two rows shows the influence of electric vehicles (EV), contrasting the current fleet share of 0.5 percent EV with 100 percent EV. In the top two rows the overall demand elasticity is fixed at the baseline of $\theta = 0.1$. Comparison of the bottom two rows shows the influence of a more elastic demand ($\theta = 2$ versus $\theta = 0.1$), while holding the EV share fixed at 50 percent. In all graphs, black lines show the social cost with flat prices; dark green line show the social cost with variable prices and pessimistic interhour substitutability; and the light green lines show social cost with variable prices and optimistic interhour substitutability.

5.2 Supplementary results

In the appendix we report results from scenarios that are exactly like those reported in table 3, except we change individual assumptions that were held constant across all scenarios in the main results. We also replicate figures 17 and 10 for different overall demand elasticities. These results mainly show that the value of dynamic pricing increases considerably, and the social cost of renewable energy falls, with a greater share of electric vehicle use and a higher overall demand elasticity.

6 Discussion

We developed the first integrated model of power supply, nonlinear demand, storage and reserves that simultaneously optimizes investment and chronological management of the system, with and without constraints on the share of renewable energy. The model is open source and generalizable to other settings with multiple nodes, transmission considerations, and multiple investment windows. We use this model to evaluate the benefits of variable pricing in comparison to flat pricing for fossil-based, unconstrained and high-renewable systems on Oahu, Hawai'i's most populous island. We find that variable pricing is considerably more valuable in high-renewable systems, that a large share of renewables will soon be optimal, even excluding externalities, and that the optimal renewable share is higher with variable pricing than it is with flat pricing.

Optimal power systems with a high share of renewables can use batteries and/or demand response to cost-effectively manage day-night and other short-term variations in supply. The larger challenge with intermittent renewables concerns seasonality and episodic or prolonged shortfalls in power generation. The optimized system manages these variations by striking a balance between overbuilding generation capacity for normal and resource rich times and, during resource poor times, using high-cost biofuels in traditional power plants and increasing prices to limit demand.[10] Unlike current fossil-based power systems wherein the main benefit of variable pricing comes from limiting peak demand, the benefits of variable pricing in high-renewable systems are multifaceted, lowering the cost of day-night balance, helping to limit generation capacity by staving off demand during resource lean times (not necessarily peak demand), and allowing greater social benefit from higher electricity use during resource rich times.

The last phenomenon—new uses of low-cost power—is a key source of value from variable pricing in high-renewable systems, especially when overall demand is more elastic. Although existing empirical studies suggest that demand is inelastic, we speculate that some of the inelas-

[10]Switch also includes a hydrogen storage option, wherein excess generation produced in resource rich times is used to make hydrogen from water, which is then stored for fuel cell generation in resource lean times. This technology is not economic in most of our scenarios, but does show up in limited capacity in a few of them. Similarly, a pumped-water hydropower option that would make use of an existing reservoir is not economic in any of our scenarios.

ticity stems from the fact that retail pricing tends to be flat. It is hard to know how demand could evolve in an environment with long spells of essentially free energy. Currently cost-prohibitive energy uses, like desalination, may be both flexible in their timing and economic in high-renewable systems with long stretches of cheap power. Alternatively, new long-term, low-cost storage options may arise if appropriately incentivized. While flexible uses of low-cost power are speculative, they do seem plausible, and are what we have in mind in scenarios with higher demand elasticities. The benefit of more elastic demand is two-fold: it includes the extra surplus from more electricity consumption while making it easier to curb demand during resource lean times.

Some have suggested that the viability of low-cost, high-penetration renewable energy reflects Hawai'i's unique characteristics: the state is rich in wind and solar resources, but must otherwise import fossil fuels a great distance, making fossil fuels expensive relative to renewable alternatives. The unconstrained options also rule out additional installations of new coal-fired power plants. Still, the cost assumptions used in this analysis are fairly conservative, especially in light of rapid technological advancement in the last few years. By some estimates, such as Bloomberg New Energy Finance and Lazard,[11] current renewable energy and battery technology costs already rival Hawaiian Electric Company's projections for 2045 (Lazard 2017).

At the same time, renewable energy in Hawai'i is in some ways more challenging than other locations, due to its extreme isolation. In continental regions, which have much more connectivity, transmission provides another, potentially lower-cost method of managing intermittency challenges, as well as transferring renewable power from areas rich in renewable resources to areas that are renewable energy poor. The modeling framework presented here can be used to assess the substitution possibilities between transmission and demand response, and generally optimizing high-dimensional chronological power systems in a realistic way. Solving such a model would be computationally expensive, perhaps two orders of magnitude more expensive that our model of the island of Oahu, but potentially feasible with solution algorithms that could subdivide the larger problem and thereby make use of modern parallel computing.

We believe these results provide credible evidence that high-penetration renewable energy is viable at reasonable economic cost in many places soon. The low cost of renewable energy greatly strengthens the case for real-time dynamic pricing options at the retail level.

[11] See `https://about.bnef.com/blog/` and `https://www.lazard.com/perspective/levelized-cost-of-energy-2017/`

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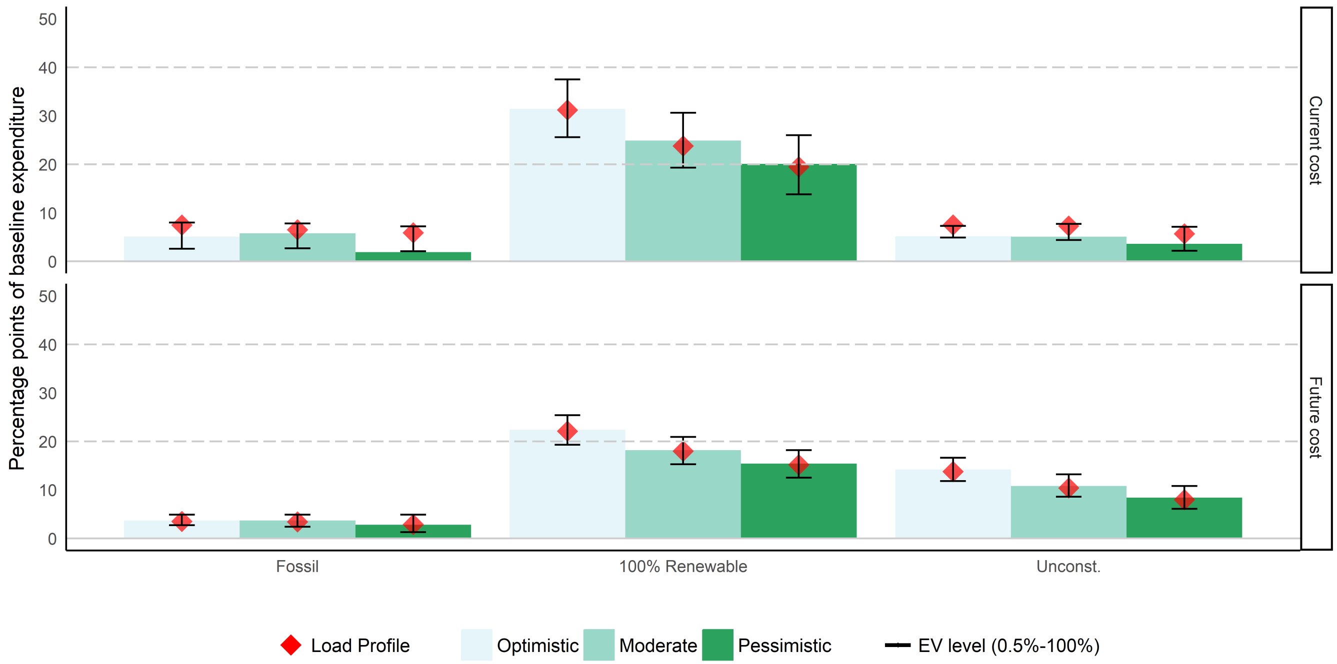
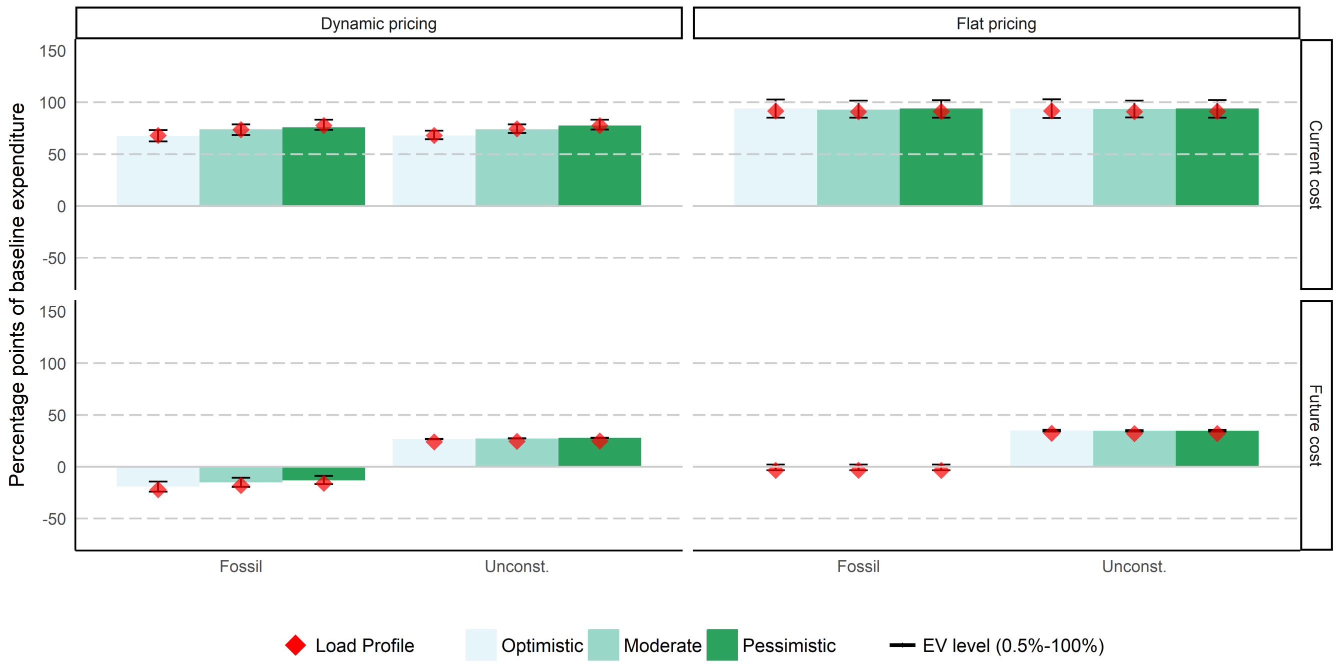
A Supplementary Results

Figure 12: Surplus gain from dynamic pricing under different policy, cost and demand flexibility scenarios when the overall demand elasticity equals 0.5.



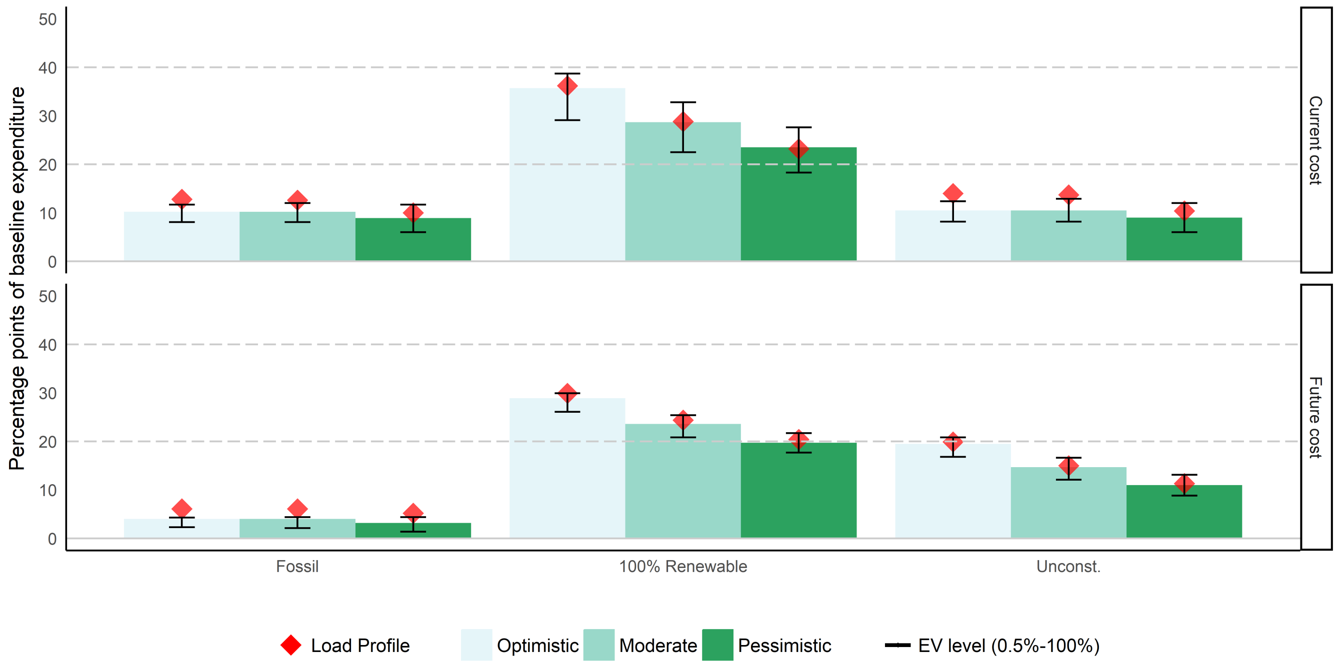
The graph shows the difference in total economic surplus with real-time marginal-cost pricing and total surplus when prices are flat, holding all else the same. Total surplus change is reported as a percentage of baseline (flat price) expenditure on electricity. The graph depicts all scenarios with an overall demand elasticity of 0.5 instead of 0.1 as reported in the main paper. The top row shows the value of variable pricing under current costs; the bottom row shows the value of variable pricing under projected future costs (2045). The horizontal axis shows the policy scenario: fossil, 100% renewable or unconstrained (maximum surplus, regardless of source). The bars show the baseline case with 50 percent electric vehicle fleet and 2045 load profile, the diamonds show the 2007 load profile, and the error bars show how results differ with 0.5 percent and 100 percent electric vehicles–more electric vehicles always increase the value of variable pricing.

Figure 13: Cost of 100 percent renewable energy system under different policy, cost and demand flexibility scenarios when the overall demand elasticity equals 0.5.



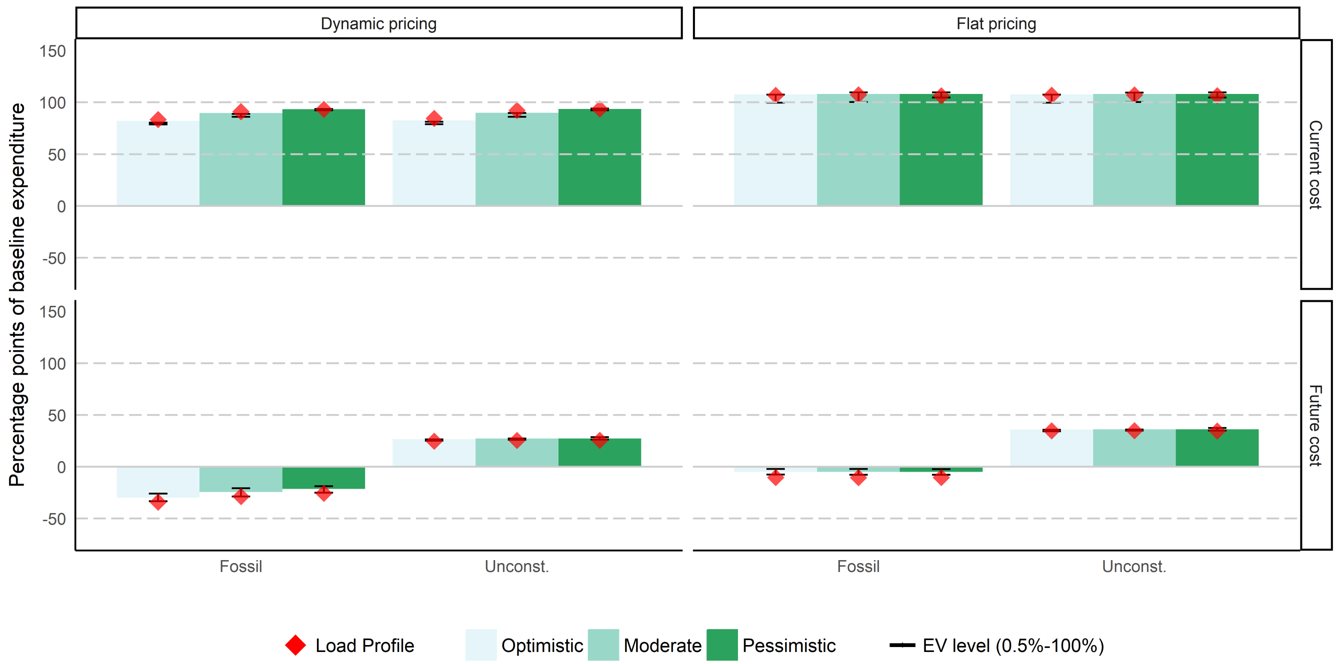
The graph shows the difference in total economic surplus with a 100 percent renewable system versus the baseline scenario given on the horizontal axis, holding all else the same. Total surplus change is reported as a percentage of baseline expenditure on electricity. The graph depicts all scenarios with an overall demand elasticity of 0.5 instead of 0.1 as reported in the main paper. The top row shows the value of variable pricing under current costs; the bottom row shows the value of variable pricing under projected future costs (2045). The horizontal axis shows the policy scenario: fossil, 100% renewable or unconstrained (maximum surplus, regardless of source). The bars show the baseline case with 50 percent electric vehicle fleet and 2045 load profile, the diamonds show the 2007 load profile, and the error bars show how results differ with 0.5 percent and 100 percent electric vehicles–more electric vehicles always increase the value of variable pricing.

Figure 14: Surplus gain from dynamic pricing under different policy, cost and demand flexibility scenarios when the overall demand elasticity equals 0.9.



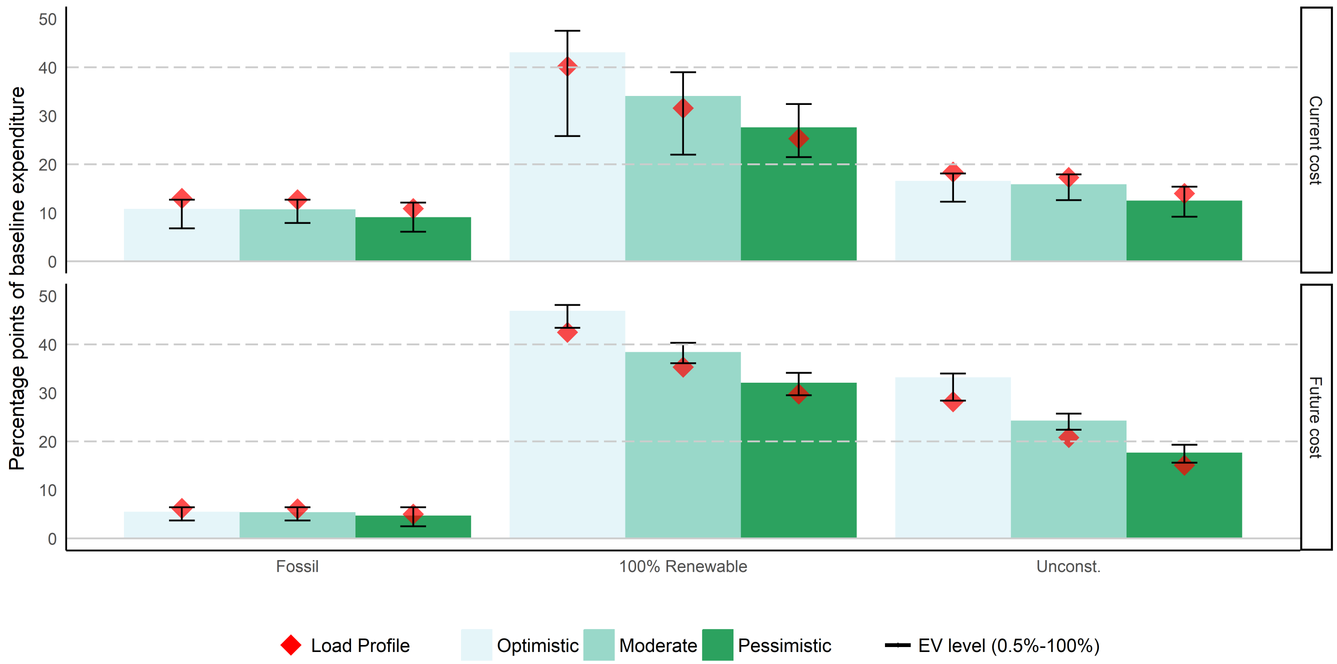
The graph shows the difference in total economic surplus with real-time marginal-cost pricing and total surplus when prices are flat, holding all else the same. Total surplus change is reported as a percentage of baseline (flat price) expenditure on electricity. The graph depicts all scenarios with an overall demand elasticity of 0.9 instead of 0.1 as reported in the main paper. The top row shows the value of variable pricing under current costs; the bottom row shows the value of variable pricing under projected future costs (2045). The horizontal axis shows the policy scenario: fossil, 100% renewable or unconstrained (maximum surplus, regardless of source). The bars show the baseline case with 50 percent electric vehicle fleet and 2045 load profile, the diamonds show the 2007 load profile, and the error bars show how results differ with 0.5 percent and 100 percent electric vehicles–more electric vehicles always increase the value of variable pricing.

Figure 15: Cost of 100 percent renewable energy system under different policy, cost and demand flexibility scenarios when the overall demand elasticity equals 0.9.



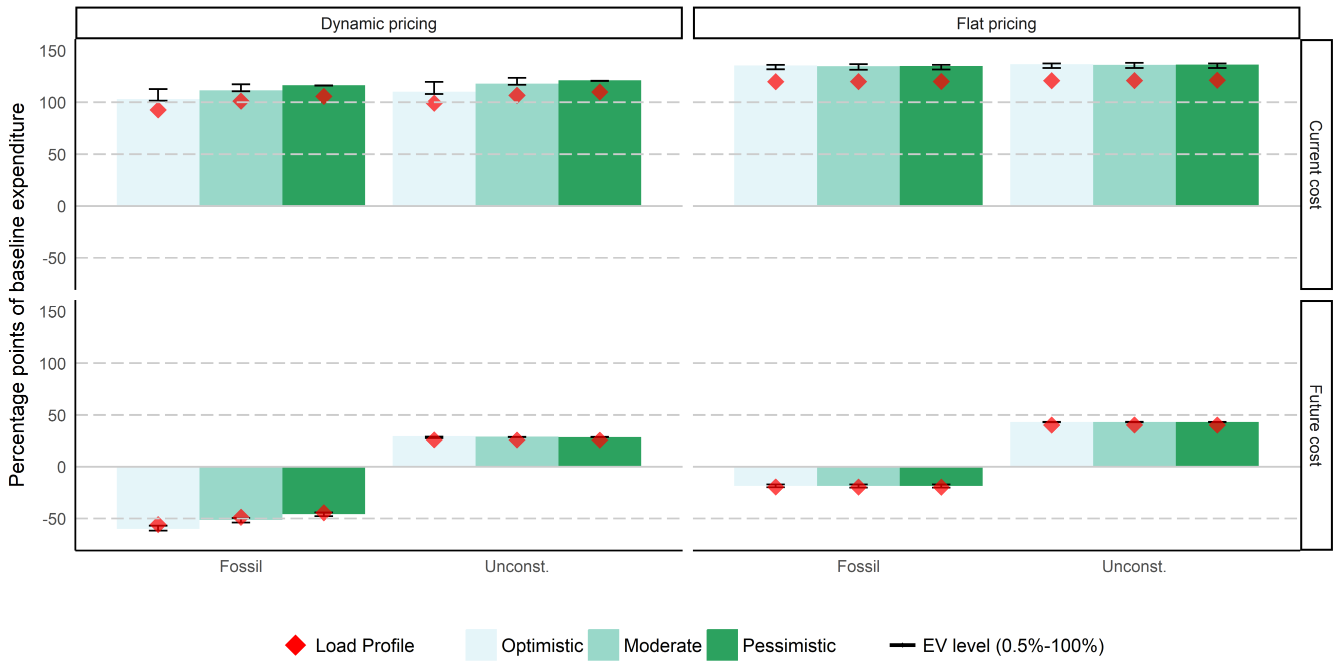
The graph shows the difference in total economic surplus with a 100 percent renewable system versus the baseline scenario given on the horizontal axis, holding all else the same. Total surplus change is reported as a percentage of baseline expenditure on electricity. The graph depicts all scenarios with an overall demand elasticity of 0.9 instead of 0.1 as reported in the main paper. The top row shows the value of variable pricing under current costs; the bottom row shows the value of variable pricing under projected future costs (2045). The horizontal axis shows the policy scenario: fossil, 100% renewable or unconstrained (maximum surplus, regardless of source). The bars show the baseline case with 50 percent electric vehicle fleet and 2045 load profile, the diamonds show the 2007 load profile, and the error bars show how results differ with 0.5 percent and 100 percent electric vehicles–more electric vehicles always increase the value of variable pricing.

Figure 16: Surplus gain from dynamic pricing under different policy, cost and demand flexibility scenarios when the overall demand elasticity equals 2.



The graph shows the difference in total economic surplus with real-time marginal-cost pricing and total surplus when prices are flat, holding all else the same. Total surplus change is reported as a percentage of baseline (flat price) expenditure on electricity. The graph depicts all scenarios with an overall demand elasticity of 2 instead of 0.1 as reported in the main paper. The top row shows the value of variable pricing under current costs; the bottom row shows the value of variable pricing under projected future costs (2045). The horizontal axis shows the policy scenario: fossil, 100% renewable or unconstrained (maximum surplus, regardless of source). The bars show the baseline case with 50 percent electric vehicle fleet and 2045 load profile, the diamonds show the 2007 load profile, and the error bars show how results differ with 0.5 percent and 100 percent electric vehicles–more electric vehicles always increase the value of variable pricing.

Figure 17: Cost of 100 percent renewable energy system under different policy, cost and demand flexibility scenarios when the overall demand elasticity equals 2.



The graph shows the difference in total economic surplus with a 100 percent renewable system versus the baseline scenario given on the horizontal axis, holding all else the same. Total surplus change is reported as a percentage of baseline expenditure on electricity. The graph depicts all scenarios with an overall demand elasticity of 2 instead of 0.1 as reported in the main paper. The top row shows the value of variable pricing under current costs; the bottom row shows the value of variable pricing under projected future costs (2045). The horizontal axis shows the policy scenario: fossil, 100% renewable or unconstrained (maximum surplus, regardless of source). The bars show the baseline case with 50 percent electric vehicle fleet and 2045 load profile, the diamonds show the 2007 load profile, and the error bars show how results differ with 0.5 percent and 100 percent electric vehicles–more electric vehicles always increase the value of variable pricing.

Table 4: Supplementary Results: Surplus changes relative to baseline if actual loads from 2007.

(1) Policy Objective	(2) Cost	(3) Demand Flexibility	(4) Pricing	(5) % Renewable	(6) Price ($/MWh)	(7) Mean Q (MWh/hr.)	(8) SD of Price ($/MWh)	(9) Δ CS (%.)	(10) Δ EV Cost (%)	(11) Δ PS (%)	(12) Δ TS (%)	(13) Δ CS Highflex (%)	(14) Δ CS Midflex (%)	(15) Δ CS Inflex (%)	(16) Δ TS Dyn (%)
Fossil	Current	Optimistic	Flat	3.78	91	1043	0	32.7	-28.6	8.2	40.9	27.8	27.8	27.8	4.6
			Dynamic	3.64	63	1085	4	57.7	-56.6	-12.2	45.5	50.9	50.9	50.9	
		Pessimistic	Flat	3.78	91	1043	0	32.6	-27.1	8	40.7	28.3	28.3	28.3	3.7
			Dynamic	3.65	61	1084	0	56.4	-56.1	-12	44.4	53	50.4	50.2	
	Future	Optimistic	Flat	3.90	125	1005	0	Baseline							3.9
			Dynamic	3.89	121	1007	11	4.4	-10.4	-0.6	3.9	2.3	2.3	2.3	
		Pessimistic	Flat	3.90	125	1004	0	Baseline							3
			Dynamic	3.91	116	1004	10	0.4	-13.2	2.6	3	7.6	-1.3	-2	
100% Renewable	Current	Optimistic	Flat	100	171	967	0	-41.1	40.7	1.3	-39.8	-36.4	-36.4	-36.4	23.7
			Dynamic	100	128	1063	87	-12.2	-14.4	-3.9	-16.1	3.1	-16.1	-26	
		Pessimistic	Flat	100	172	967	0	-39.1	39.6	-0.4	-39.5	-36.5	-36.5	-36.5	13.4
			Dynamic		133	1034	91	-22.2	-14.8	-3.9	-26.1	7.5	-16.1	-26.9	
	Future	Optimistic	Flat	100	98	1033	0	25.3	-29.5	-25.7	-0.4	21.4	21.4	21.4	13.5
			Dynamic	100	84	1159	75	39	-51.3	-25.9	13.1	43.1	30.8	26.4	
		Pessimistic	Flat	100	98	1033	0	25.3	-28.2	-25.7	-0.4	22	22	22	8.4
			Dynamic	100	92	1127	82	33.5	-49.9	-25.5	8	44.6	31	26.6	
Unconstrained	Current	Optimistic	Flat	3.68	72	1072	0	49.6	-44.9	-8.7	41	43.3	43.3	43.3	5.7
			Dynamic	6.24	74	1067	7	47.9	-48.8	-1.2	46.7	41.8	41.8	41.8	
		Pessimistic	Flat	3.68	70	1072	0	49.4	-43.4	-8.7	40.7	45.6	45.6	45.6	3.7
			Dynamic	3.65	61	1083	0	55.9	-56.1	-11.5	44.4	53	50	49.7	
	Future	Optimistic	Flat	74	88	1046	0	34.4	-34.7	-4.4	30	30	30	30	8.8
			Dynamic		72	1105	38	44.1	-53.7	-5.3	38.8	45.6	38.7	34.5	
		Pessimistic	Flat	74	88	1046	0	34.4	-33.3	-4.6	29.8	30.6	30.6	30.6	5.3
			Dynamic	81	80	1085	42	38.2	-52.2	-3.1	35.1	45.9	35.2	31.2	

Notes: Like table 3, except baseline demand is tied to actual 2007 loads, not projected loads for 2045.

Table 5: Supplementary Results: Surplus changes relative to baseline if fewer electric vehicles (0.5 percent).

(1) Policy Objective	(2) Cost	(3) Demand Flexibility	(4) Pricing	(5) % Renewable	(6) Price ($/MWh)	(7) Mean Q (MWh/hr.)	(8) SD of Price ($/MWh)	(9) Δ CS (%.)	(10) Δ EV Cost (%)	(11) Δ PS (%)	(12) Δ TS (%)	(13) Δ CS High-flex (%)	(14) Δ CS Midflex (%)	(15) Δ CS Inflex (%)	(16) Δ TS Dyn (%)
Fossil	Current	Optimistic	Flat	4.39	60	982	0	54	-54.2	-17.3	36.7	54.5	54.5	54.5	2.6
			Dynamic	4.30	50	1002	1	63.2	-61.8	-23.9	39.3	62.9	62.8	62.8	
		Pessimistic	Flat	4.51	77	955	0	38.8	-44.8	-2.8	36.1	39.8	39.8	39.8	2.4
			Dynamic	4.35	49	990	1	56.7	-63.7	-18.2	38.5	63.9	56.7	55.8	
	Future	Optimistic	Flat	4.76	126	904	0	Baseline							2.5
			Dynamic	4.70	120	911	12	7.1	-14.1	-4.7	2.5	5.2	4.7	4.7	
		Pessimistic	Flat	4.76	126	904	0	Baseline							1.1
			Dynamic	4.74	111	908	5	3.4	-18.4	-2.4	1.1	12	3.4	2.5	
100% Renewable	Current	Optimistic	Flat	100	164	876	0	-29.2	31.1	-7.1	-36.3	-29.6	-29.6	-29.6	17.7
			Dynamic	100	126	961	86	-12.5	-14.2	-6.1	-18.6	5.7	-13.6	-23	
		Pessimistic	Flat	100	161	877	0	-29.3	23.6	-6.8	-36.1	-27.3	-27.3	-27.3	8.2
			Dynamic	100	134	936	95	-23.2	-19.9	-4.7	-27.9	10	-15.3	-26.4	
	Future	Optimistic	Flat	100	98	931	0	22.9	-25.1	-29.6	-6.7	22.5	22.5	22.5	11.1
			Dynamic	100	84	1043	74	34.2	-48.1	-29.8	4.4	44.4	31.4	27.2	
		Pessimistic	Flat	100	98	931	0	22.9	-25.1	-29.6	-6.7	22.6	22.6	22.6	6
			Dynamic	100	91	1008	80	29.2	-49.7	-29.9	-0.7	46	31.7	27.5	
Unconstrained	Current	Optimistic	Flat	4.49	76	960	0	41.8	-29.5	-5.3	36.4	40.7	40.7	40.7	4.4
			Dynamic	4.34	57	987	5	56.7	-59.3	-15.9	40.8	57.6	57.1	57.1	
		Pessimistic	Flat	4.39	61	982	0	54.3	-54.4	-17.6	36.6	53.2	53.2	53.2	1.7
			Dynamic	4.34	49	993	1	57.8	-63.7	-19.5	38.3	63.9	58.1	57.4	
	Future	Optimistic	Flat	75	93	937	0	26.1	-27.7	-0.4	25.6	26.8	26.8	26.8	6.8
			Dynamic		71	995	32	40.2	-50.7	-7.8	32.4	46.8	38.6	35.6	
		Pessimistic	Flat	75	93	936	0	26.4	-27.8	-0.7	25.6	26.4	26.4	26.4	3
			Dynamic	76	79	973	38	33.9	-51.7	-5.2	28.6	47.5	36	32.3	

Notes: Like table 3, except the share of electric vehicles is 0.5% (the current share of the fleet) instead of 50%.

Table 6: Supplementary Results: Surplus changes relative to baseline if more electric vehicles (100 percent).

(1) Policy Objective	(2) Cost	(3) Demand Flexibility	(4) Pricing	(5) % Renewable	(6) Price ($/MWh)	(7) Mean Q (MWh/hr.)	(8) SD of Price ($/MWh)	(9) Δ CS (%.)	(10) Δ EV Cost (%)	(11) Δ PS (%)	(12) Δ TS (%)	(13) Δ CS High-flex (%)	(14) Δ CS Midflex (%)	(15) Δ CS Inflex (%)	(16) Δ TS Dyn (%)
Fossil	Current	Optimistic	Flat	3.77	91	941	0	34.9	-31.8	10.4	45.3	27.4	27.4	27.4	6.4
			Dynamic	3.71	77	958	5	48.3	-41.3	3.5	51.7	38.9	38.9	38.9	
		Pessimistic	Flat	3.77	91	941	0	32.4	-22	13	45.5	27.1	27.1	27.1	6.3
			Dynamic		75	956	0	47.6	-45.6	4.2	51.8	41.1	38.1	37.8	
	Future	Optimistic	Flat	3.88	125	905	0	Baseline							4.5
			Dynamic	3.88	121	907	10	3.1	-5.3	1.4	4.5	3.2	3.2	3.2	
		Pessimistic	Flat	3.88	124	905	0	Baseline							4.5
			Dynamic	3.87	121	910	11	5.8	-10.9	-1.3	4.5	2.6	2.4	2.4	
100% Renewable	Current	Optimistic	Flat	100	166	872	0	-42.2	33.8	-2.3	-44.5	-32.7	-32.7	-32.7	29
			Dynamic	100	128	957	88	-13	-9.7	-2.5	-15.5	3.4	-16.3	-25.5	
		Pessimistic	Flat	100	171	871	0	-41.9	29.6	-2.8	-44.7	-37	-37	-37	19.9
			Dynamic	100	137	930	96	-24.9	-13.4	0.1	-24.8	4.7	-19	-30.3	
	Future	Optimistic	Flat	100	98	931	0	26.4	-24.5	-26.7	-0.4	21.6	21.6	21.6	16.2
			Dynamic	100	85	1048	75	42.6	-46.7	-26.8	15.8	43	31.1	26.2	
		Pessimistic	Flat	100	98	931	0	27	-28	-27.4	-0.4	21.3	21.3	21.3	11.2
			Dynamic	100	93	1021	83	37.9	-50.3	-27.1	10.8	44.3	30.7	25.5	
Unconstrained	Current	Optimistic	Flat	3.93	75	960	0	49.5	-36	-4.1	45.4	41	41	41	6.4
			Dynamic	6.09	73	962	4	52.5	-44.6	-0.7	51.8	42.7	42.7	42.7	
		Pessimistic	Flat	4.67	89	941	0	33.4	-19.9	12.1	45.5	28.7	28.7	28.7	6.3
			Dynamic	5.88	72	961	4	49.8	-49.6	2	51.8	42.9	41.5	41.4	
	Future	Optimistic	Flat	74	89	942	0	35.9	-30.3	-2.8	33.1	29.7	29.7	29.7	11.5
			Dynamic	81	73	993	36	47.9	-48.4	-3.3	44.6	44.4	36.5	33.2	
		Pessimistic	Flat	75	88	942	0	36.6	-34.1	-3.3	33.3	29.7	29.7	29.7	7.8
			Dynamic	81	80	977	41	43.8	-53	-2.7	41.1	45.6	35.1	31	

Notes: Like table 3, except the share of electric vehicles is 100% instead of 50%.

Table 7: Supplementary Results: Surplus changes if overall demand elasticity = 0.5

(1) Policy Objective	(2) Cost	(3) Demand Flexibility	(4) Pricing	(5) % Renewable	(6) Price ($/MWh)	(7) Mean Q (MWh/hr.)	(8) SD of Price ($/MWh)	(9) Δ CS (%.)	(10) Δ EV Cost (%)	(11) Δ PS (%)	(12) Δ TS (%)	(13) Δ CS Highflex (%)	(14) Δ CS Midflex (%)	(15) Δ CS Inflex (%)	(16) Δ TS Dyn (%)
Fossil	Current	Optimistic	Flat	3.11	82	1283	0	48.4	-38.2	2.5	50.9	35.1	35.1	35.1	5.1
			Dynamic	2.68	61	1508	2	77.7	-59.7	-21.6	56	53.4	53.4	53.4	
		Pessimistic	Flat	3.11	84	1283	0	45.6	-36	5.3	50.9	33.5	33.5	33.5	1.9
			Dynamic	2.46	49	1648	0	90	-66.5	-37.2	52.8	63.5	61.9	61.7	
	Future	Optimistic	Flat	3.76	125	1043	0	Baseline							3.7
			Dynamic	3.80	127	1033	4	-0.4	-6.1	4.1	3.7	-2	-2	-2	
		Pessimistic	Flat	3.76	125	1043	0	Baseline							2.8
			Dynamic	3.64	107	1083	0	9.1	-20	-6.3	2.8	14.3	6.9	6.4	
100% Renewable	Current	Optimistic	Flat	100	171	888	0	-43.6	39.9	0.5	-43.1	-36.2	-36.2	-36.2	31.4
			Dynamic	100	128	1064	62	-11.5	-15.5	-0.1	-11.7	1.8	-19.5	-28.3	
		Pessimistic	Flat	100	173	886	0	-45.3	39.9	2.1	-43.1	-37.2	-37.2	-37.2	20.1
			Dynamic	100	138	989	80	-27.9	-13	4.9	-23	3.2	-21.4	-32.3	
	Future	Optimistic	Flat	100	102	1159	0	26.8	-27.9	-26.2	0.6	18.8	18.8	18.8	22.4
			Dynamic	100	82	1370	37	48.6	-53.2	-25.6	23	42.3	29.1	25.2	
		Pessimistic	Flat	100	102	1159	0	24.5	-26	-23.9	0.6	18.8	18.8	18.8	15.4
			Dynamic	100	91	1277	41	38.4	-50.8	-22.4	16	43	28.8	24.7	
Unconstrained	Current	Optimistic	Flat	3.23	83	1283	0	48.3	-37.7	2.7	50.9	34.1	34.1	34.1	5.2
			Dynamic	2.67	60	1509	2	78.5	-60	-22.5	56.1	53.6	53.6	53.6	
		Pessimistic	Flat	3.23	84	1283	0	45.4	-35.2	5.5	50.9	33.5	33.5	33.5	3.6
			Dynamic	2.56	50	1581	1	84	-66.4	-29.5	54.5	63.2	57.7	57.2	
	Future	Optimistic	Flat	76	94	1205	0	35.8	-33.7	-0.4	35.4	25	25	25	14.2
			Dynamic	84	76	1366	21	52.4	-53.4	-2.9	49.6	42.9	33.6	30.6	
		Pessimistic	Flat	77	95	1204	0	32.5	-31	3	35.4	24.8	24.8	24.8	8.4
			Dynamic	81	88	1272	33	40.1	-52.3	3.7	43.8	44.1	29.9	26.6	

Notes: Like table 3, except the the overall demand elasticity (θ) equals 0.5 instead of 0.1

Table 8: Supplementary Results: Surplus changes if overall demand elasticity = 0.9

(1) Policy Objective	(2) Cost	(3) Demand Flexibility	(4) Pricing	(5) % Renewable	(6) Price ($/MWh)	(7) Mean Q (MWh/hr.)	(8) SD of Price ($/MWh)	(9) Δ CS (%.)	(10) Δ EV Cost (%)	(11) Δ PS (%)	(12) Δ TS (%)	(13) Δ CS Highflex (%)	(14) Δ CS Midflex (%)	(15) Δ CS Inflex (%)	(16) Δ TS Dyn (%)
Fossil	Current	Optimistic	Flat	2.43	86	1673	0	50.9	-22.1	10.6	61.6	32.8	32.8	32.8	10.2
			Dynamic	2.22	78	1840	3	66.7	-46.6	5.1	71.8	39.6	39.5	39.5	
		Pessimistic	Flat	2.43	86	1673	0	51	-22.2	10.7	61.7	32.7	32.7	32.7	8.9
			Dynamic	2.28	66	1791	4	63.8	-56.2	6.8	70.6	49.9	37.8	36.1	
	Future	Optimistic	Flat	3.34	127	1187	0	Baseline							4
			Dynamic	3.37	128	1179	3	-0.4	-7	4.4	4	-0.7	-0.7	-0.7	
		Pessimistic	Flat	3.34	127	1188	0	Baseline							3.2
			Dynamic	3.24	112	1230	0	6.1	-18.8	-2.8	3.2	12.1	3.4	2.8	
100% Renewable	Current	Optimistic	Flat	100	170	903	0	-44.4	35.1	-1.7	-46.1	-33.2	-33.2	-33.2	35.7
			Dynamic	100	128	1155	45	-14.2	-16.2	3.7	-10.4	3.1	-18.3	-27	
		Pessimistic	Flat	100	169	923	0	-40.1	28.3	-6.1	-46.3	-32.6	-32.6	-32.6	23.5
			Dynamic	100	138	1032	65	-27.9	-15.9	5.1	-22.8	3.7	-19.8	-30.6	
	Future	Optimistic	Flat	100	102	1440	0	30.4	-28	-25.4	5	19.6	19.6	19.6	28.9
			Dynamic	100	82	1818	28	56.5	-52.7	-22.5	33.9	42.6	29.1	25.5	
		Pessimistic	Flat	100	102	1440	0	30.5	-28.2	-25.5	5	19.4	19.4	19.4	19.7
			Dynamic	100	91	1641	34	46.7	-52.5	-22	24.7	43.2	29	25.3	
Unconstrained	Current	Optimistic	Flat	2.44	87	1673	0	50.4	-22.6	11.2	61.6	32.4	32.4	32.4	10.5
			Dynamic	7.49	75	1912	3	72.5	-49	-0.4	72.1	42.3	42.3	42.3	
		Pessimistic	Flat	2.44	87	1673	0	50.4	-22.7	11.2	61.7	32.2	32.2	32.2	9
			Dynamic	3.22	64	1803	3	64.3	-57.5	6.4	70.7	51.9	38.1	36.2	
	Future	Optimistic	Flat	81	98	1493	0	35.4	-29.9	5.5	40.9	22.8	22.8	22.8	
			Dynamic	87	78	1834	20	59.5	-53.1	0.9	60.4	43.1	31.8	29	19.5
		Pessimistic	Flat	81	99	1491	0	36.3	-30.6	4.7	41	22.5	22.5	22.5	11
			Dynamic	85	90	1642	30	47.8	-53.5	4.2	52	43.9	29.4	26.3	

Notes: Like table 3, except the the overall demand elasticity (θ) equals 0.9 instead of 0.1

Table 9: Supplementary Results: Surplus changes if overall demand elasticity = 2

(1) Policy Objective	(2) Cost	(3) Demand Flexibility	(4) Pricing	(5) % Renewable	(6) Price ($/MWh)	(7) Mean Q (MWh/hr.)	(8) SD of Price ($/MWh)	(9) Δ CS (%.)	(10) Δ EV Cost (%)	(11) Δ PS (%)	(12) Δ TS (%)	(13) Δ CS Highflex (%)	(14) Δ CS Midflex (%)	(15) Δ CS Inflex (%)	(16) Δ TS Dyn (%)
Fossil	Current	Optimistic	Flat	1.78	110	2324	0	33.5	-2.4	48.6	82.2	14.9	14.9	14.9	10.8
			Dynamic	1.64	104	2522	4	45.6	-21	47.5	93	19.4	19.1	19.1	
		Pessimistic	Flat	1.78	110	2324	0	33.6	-10.2	48.4	82	15.1	15.1	15.1	9.1
			Dynamic	1.65	92	2512	7	47.1	-39.6	44	91.1	30	19.5	18.1	
	Future	Optimistic	Flat	2.42	128	1672	0	Baseline							5.5
			Dynamic	2.33	126	1742	4	4.1	-3.2	1.4	5.5	2	1.8	1.8	
		Pessimistic	Flat	2.42	129	1673	0	Baseline							4.7
			Dynamic	2.30	115	1772	5	6.5	-21.6	-1.8	4.7	11.5	2.9	2.1	
100% Renewable	Current	Optimistic	Flat	100	168	967	0	-50	38.3	-3.4	-53.3	-30.6	-30.6	-30.6	43.1
			Dynamic	100	126	1471	30	-17.4	-10.4	7.2	-10.2	4.5	-18.2	-26.6	
		Pessimistic	Flat	100	171	945	0	-53	36.7	-0.1	-53.1	-32.6	-32.6	-32.6	27.6
			Dynamic	100	138	1156	50	-34.5	-17.8	9	-25.5	5.5	-19.9	-29.1	
	Future	Optimistic	Flat	100	117	2043	0	20.8	-9.6	-2.1	18.7	9	9	9	46.9
			Dynamic	100	100	2659	25	45.3	-32	20.3	65.6	27.1	13.6	10.5	
		Pessimistic	Flat	100	117	2043	0	20.9	-17.4	-2.3	18.6	9.3	9.3	9.3	32.1
			Dynamic	100	104	2515	30	43.6	-43.5	7.1	50.7	33	18.7	15.6	
Unconstrained	Current	Optimistic	Flat	9.28	107	2382	0	37.7	-4.6	45.7	83.5	17.1	17.1	17.1	16.6
			Dynamic	23.42	105	2503	6	44.4	-18.9	55.8	100.1	18.5	18.3	18.3	
		Pessimistic	Flat	9.28	107	2382	0	37.9	-12.5	45.4	83.3	17.2	17.2	17.2	12.5
			Dynamic	13.47	88	2546	4	46.7	-40	49.1	95.8	32.5	19.8	17.8	
	Future	Optimistic	Flat	80	103	2563	0	47.4	-19.4	14.6	62	19.9	19.9	19.9	33.2
			Dynamic	89	97	2820	21	53	-34	42.2	95.2	29.4	16.9	14.1	
		Pessimistic	Flat	80	104	2563	0	47.9	-27.3	13.9	61.8	19.7	19.7	19.7	17.7
			Dynamic	90	101	2638	28	49.8	-46.1	29.7	79.5	35.3	20.8	17.9	

Notes: Like table 3, except the the overall demand elasticity (θ) equals 2 instead of 0.1