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BATTING AVERAGE: A COMPOSITE MEASURE OF RISK FOR ASSESSING PRODUCT DIFFERENTIATION IN A SIMULATION MODEL

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ABSTRACT

The paper simulates how market power affects electricity retailing to households. A pseudo-random number seeding algorithm creates representative product differentiation in repeated drawings, for an incumbent and seven challengers. A ninth *player* competitor decides how to distinguish her product. The simulation creates an *efficient* starting market, adjusted for competitor dominance; and, over a 12-month horizon, uses topology to *develop* unexploited profit opportunities for all competitors. A *best* solution criterion punishes nonconformists. Results of repeated drawings *varying* opposition to the player's *constant* product differentiation feed a batting average risk assessment. Decision rules reward hits based on profit and year's end market share. The *market* simulation tool supports conjectural assessment of social policy – household direct access to wholesale power, incentive for product differentiation versus that for mergers and acquisitions, and allocation of deregulation benefits to shareholders versus ratepayers.

1 INTRODUCTION

Our paper explores the household retail residential electricity deregulation problem through a simulation methodology and exercise. Several issues are addressed:

1. What is an appropriate metric for survival risk in this market?
2. How does market power affect retailer customer retention ploys, and how do you simulate it?
3. How can you adapt market research results describing inducement to switch *from* a single incumbent to a market in which switching is *to* several retailers?
4. How do you account for the net present value of profit contribution against fixed cost, for continuous service providers with complex rate structures including base and peak load components?
5. What is the appropriate solver principle and method for assessing retailer benefit from participation in this market?
6. How do customer retention ploys contrast with (anticipated) mergers or acquisitions in providing retailer benefits, net of that provided from *the usual suspect* – workforce consolidation?
7. How do you validate input and results from a 12-month simulation capable of limitless repetition facing different circumstances and survival odds?
8. How do you assess the (player) survival risk of a particular product differentiation scheme against diverse schemes offered by a single retailer?

Section 2 describes our technical approach to dealing with these simulation, economic, and practical use issues. Section 3 explains simulation results of our validation exercise. Section 4 displays survival risk, market concentration, and other results of simulations in three states of nature – when *price wars* are certain, when *price peace* is certain, and when either war or peace is a foreseeable outcome. Section 5 concludes with what our simulations suggest about household electricity deregulation.

2 TECHNICAL APPROACH

Our approach is module-oriented, not object-oriented. If proven, it can be used for applications tailored to particular spatial markets and deregulated or privatized household electricity service, to particular spatial markets and small-to-medium business and institutional deregulated electricity service, to other continuously provided services' markets, and to other industries with differentiated products or services and excess capacity.

2.1 Survival Risk

We use a rule-based metric for survival risk – batting average. In each game of a *series*, our simulator computes or updates batting averages for the player and lowest-cost-of-supply (LCOS) challenger. A competitor gets a hit (from 2 *at bats*) if end-of-year market share equals or exceeds 1/9th, or share of positive annual market profit equals or exceeds 1/9th while end-of-year market share equals or exceeds 1/18th. Two hits reward market share and positive profit that each equals or exceeds 1/9th. Joint actions (e.g., mergers) require performance multiples.

Hence, our rules reward performance that equals or exceeds winning by lottery, except that survival is more important than making money. Figure 1 shows this.

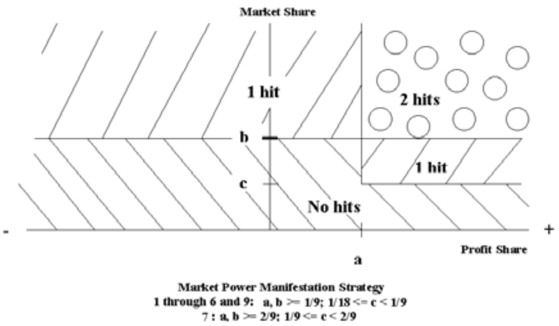


Figure 1: Batting Average Graph Shows Importance of Being Around at Year's End

Inequalities are 1/9th, multiples, or fractions of 1/9th because there are 9 competitors in our simulated market. Market power manifestation strategies are described next.

2.2 Market Power

Continuously provided services' markets tend to be *Bertrand* because it is difficult, although not impossible, to ration quantity produced as a means to optimize profitability. Because price is the adjustment mechanism, *game* competitors lower price to capture customers and price war ensues. (Dutta 1999 explains this in Chapter 5 of his text.) Long-distance telephone providers thwarted this tendency of continuously provided services' markets for a time, with a seemingly infinite variety of fixed-rate schemes. (MacAvoy 1996 describes how these schemes look different while providing equivalent profitability benefit across providers.) We offer fixed-rate product portfolios to test our simulator's ability to portray the *Cournot* behaviors they impose on this market. A Cournot behavior holds the price constant and seeks the most profitable level of output or number of customers at that price. This may appeal to Energy Services Providers (ESPs) vying against entrenched incumbents, because of the trade-off prudently designed flat rates can offer, favoring customer loyalty over current return.

We simulate market power impacts through price movements and competitors' pursuit of common objectives. The player chooses and weights one or any number of ways market power or structure may appear in a series of game simulations, as Table 1 shows.

Our *free* market is not free of the assumption that competitors respond to signals from other competitors gov-erning their price setting behaviors. In doing so, they never "take" a market price. While 4 defines the classic Bertrand price war (which it wages every time the player lands on it), only 2, 3, and 9 exclude price wars every time or game simulation. Unless we tell it not to, our simulator makes a random choice between war and peace, when played under 1 and 5 through 8. Finally, 7 and 8 are intended to permit us to test product differentiation versus (anticipated) mer-ger for strategic benefit, as well as the comparative benefit of mergers with smart product designers versus retailers with access to low-cost wholesale power.

Table 1: Market Power Manifestations

1.	Free market
2.	All competitors assume competition will raise price
3.	All competitors assume that while raising price, competition will cluster around flat rates offered
4.	All competitors assume competition will lower price
5.	(Players) react to inside information about what the incumbent's price will be
6.	(Players) react to inside information about what another challenger's price will be
7.	(Players) anticipate merger with one other challenger
8.	(Players) anticipate merger with two other challengers
9.	All competitors form a cartel

2.3 Switching to Several Retailers

Our simulator portrays a market with nine competitors, using customer data that only distinguishes incumbency from its absence. By assigning product attribute portfolios to non-player competitors at random, as well as assigning vectors of wholesale power costs to all challengers at random, and then competing every competitor against every other competitor (just two at a time), we can fabricate a household amenities or production possibilities frontier using an algorithm that recursively allocates market *potential* to energy services providers. (Roberts and Greene 1983 developed this technique for looking at market potentials for innovative automobile engine designs; Hamblin et al. 1990 extended it to electric and gas commercial cooling markets with complex energy and peak rate structures.) Our simulator fabricates frontiers portraying switching from the incumbent, retention by challengers, and new customer choice. In doing so, it supplies inputs to two solution modules that implement a system of equations and identities jointly determining net present value of profit contribution against fixed cost and market share (or equivalently, number of customers) for each service provider for all months of the year.

2.4 ESP Accounting

This system of 18 equations and identities was developed by Rust, Zahorik, and Keiningham 1995 to describe financial services' providers. Ratchford adapted their system to our problem by developing a demand component incorporating electric utility complex, base and peak load, rate structures. (Hamblin and Ratchford 1998 applied it first to an incumbent, single new entrant example, in a project for EPRI.) Ratchford also developed demand specifications for utility services' bundles.

2.5 Solver Principle and Method

Good customer retention stratagems must beat the odds. Proving success requires a sound competitive testing ground depicting opponent stratagems, a starting values simulator that dooms no opponent from the outset, and a solver that satisfies two criteria:

1. All competitors must win, and by the same rule. The economist's rule for winning market solutions is Pareto Efficiency. In our simulator, Pareto Efficiency bears its traditional meaning that no competitor be made worse off. Relative to "starting" profits from our starting values module, solver profits reveal, as yet unexploited, money making opportunities.
2. The best solution the solver can give should punish outliers who would break from the pack. In oligo-polistic markets, conformity is virtuous.

2.5.1 Competitive Testing Ground

Our approach selects from 15 ways ESPs might differentiate their product, and assigns these distinguishing attributes to eight arrays non-player competitors draw randomly from. Each array contains five attributes. A competitive game assignment is a random drawing of up to five attributes for the non-player competitors coupled with a random assignment of wholesale power costs to all challengers. The "birth date seeding algorithm" described in Section 2.7 insures statistical representation of all possible game assignments, as the number of series games played increases. Figure 2 shows the product differentiation part of the game assignment. In any particular game, a non-player competitor is assigned product attributes from only one of the eight arrays. For example, the incumbent might advertise with brand name TV spots, offer a reduced outage program, and the small utilities bundle from array 2. No other competitor would draw from that array.

The player selects any number up to 5 of the fifteen attributes that could be offered to a single household. That is, a single household can only receive one of the utility bundles and one of the flat-rate schemes offered. The player's chosen product portfolio remains the same for every series game, played against an opposing line-up that changes in every series game.

	PRICE/PRODUCT DESIGN ATTRIBUTE CHOICES AVAILABLE TO NON-PLAYER COMPETITORS	1	2	3	4	5	6	7	8
1	Advertising with brand name TV spots	X	X	X	X	X	X	X	X
2	Renewables in supply mix	X	-	X	-	-	-	X	-
3	Conservation assistance	X	-	X	X	-	-	-	X
4	Reduced outages	X	X	-	-	-	X	-	-
5	Improved customer service	X	-	X	-	-	-	-	X
6	Performance-based fixed rate	-	X	-	-	-	X	-	-
7	Whole house surge protection	-	X	-	-	-	-	-	X
8	Landscape lighting	-	-	-	-	X	-	-	-
9	Home security system	-	-	-	-	X	-	-	X
10	2-way customer/utility datacom for appliance management	-	-	X	-	-	-	X	-
11	Bundled electricity, water, natural gas	-	X	-	X	-	-	-	-
12	Bundled electricity, water, natural gas, phone, intra/internet	-	-	-	-	X	-	X	-
13	Cash incentive to switch	-	-	-	X	-	X	-	-
14	Bonus points catalog to stay (Sprint offering)	-	-	-	X	-	X	-	-
15	2-year service contracts with penalty for breaking	-	-	-	-	X	-	X	-

Figure 2: Non-Player Attribute Selection Matrix

2.5.2 Starting Values Simulator

The Starting Values simulator equalizes return on base and peak power purchases as a way to drive a "Golden Step" convergence algorithm (described by Brent 1973) that would make competitors equally attractive to customers – if none were dominant. It does so by compensating households through price reductions for services not offered.

Dominant providers get larger price reductions indicating leverage they have tucked away in services they could have provided but chose not to provide. Note that our simulator portrays dominance unrelated to malicious intents by the incumbent or challengers.

Starting value base and peak load prices, for competitors not offering flat rates, are "solved" for January and October. October prices reflect imposition of a price cap on average price, of \$0.14/kWh – to mimic impacts of price caps proposed and implemented in states which have deregulated residential retail competition.

The flat-rate providers' average price depends on services offered. This, however, does not preclude them from treatment by the Starting Values module. It seeks peak and base load starting prices, for every month of the year, that satisfies the equal return decision rule; and subsequently, our simulator optimizes profit for these providers through number of customers served and TV spot advertising, not through price adjustments.

If a player selects fewer than five service enhancements, a random selection of attributes for price compensation is made. This selection excludes service attributes that could not be offered to a single household, and is repeated for every game in a series.

Starting values module price compensation conforms to Friedrich Hayek's description (1945) of how markets achieve efficiency without perfect information. Moreover, these prices are purged of the influence of energy factor prices; they depend on customer preference alone.

2.5.3 The Solver

The solver kicks off a Monte Carlo game that uses mathematical topology to find solutions. Topology maps and segments an all-competitor price/advertising solution space that governs drawings of *real* base and peak load price candidates for every competitor for the first and tenth months simulated, and *integer* number of TV advertising spots quarterly. The mathematical topology directs drawings through 51 strata of five segments of the solution space. The *real/integer*, multi-dimensional topology map portrays competitors who advertise as having more market power than those who don't and incumbents as having more market flexibility than new entrant challengers from outside the region or service area. Where an incumbent's flexibility is constrained by regulation (or re-regulation) our solver restricts the topology's solution space, for example, not to allow the incumbent to price below cost.

The solver reshapes and repositions the five solution-space segments ten times per game, yielding 50 distinctive topology maps or topolog*ies*. It searches repeatedly through the 51 strata of each topology for "solutions." A solution is a set of base- and peak- load prices, and advertising spots (zero for challengers not advertising) for all competitors (i.e., p^b_{i1}, p^b_{i10}, p^p_{i1}, p^p_{i10}, A_{i1}, A_{i4}, A_{i7}, A_{i10}; $i = 1,\ldots,9$) that satisfies the economic criterion of Pareto Efficiency: no competitor's profit contribution against fixed cost falls below its starting value or previous solution value *within this topology*. The Pareto efficient solution criterion changes in two circumstances:

1. Anticipated merger, acquisition, cartel – Then, Pareto Efficiency applies to the joint profit contribution of implicated competitors and the individual profit contributions of other competitors (if any are left).
2. Price war – Starting values are determined in the usual way, then shifted to a negative profitability segment of the solution space, with competitor-by-competitor relative profit contributions kept the same.

In a particular series, each of the 50 topologies may yield no solutions, one, or more than one solution. If a topology gives more than one solution, the last is always best because every competitor's profit contribution is equal to, or greater than, any previous solution's profit contribution for that competitor. This means that, across topologies, the solver selects a *best of the best* solutions from no more than 50 candidates.

To do this, it applies an egalitarian, volumetric criterion that, for example, says two competitors making \$50 each is 25 times better than if one competitor made \$100 and the second \$1. The egalitarian criterion simulates a salient characteristic of market power – punishment of competitors who undercut the pack. By it, conforming, collusive solutions beat cut-throat solutions that often produce greater total profitability – summed across competitors for the market. The egalitarian solution criterion likewise punishes the most innovative, customer-benefit-laden product differentiation schemes.

2.6 Customer Retention Versus Merger

Because the player is a "conscious actor" who identifies anticipated merger partners among the new entrant challengers, her performance can bias the contribution to batting average of market power manifestations 7 and 8. Our approach minimizes bias by holding her to a decision rule that she always anticipate merger with the lowest-wholesale-power-cost ESP who advertises. We then decompose batting average attained to show the relative contribution of *non-merger* and *merger* market power manifestations, at different levels of product differentiation.

2.7 Validation of Input and Results

Analyzing survival risk through repeated simulations of the first year in a deregulated market conforms to a non-terminating simulation, for which no natural event tells us we are done. Additionally, while there is no start-up time, as we might encounter in a blast furnace simulation for example, there is reason to believe that survival risk for the player relative to the LCOS changes with the number of repeated simulations. These are serious considerations (discussed in Chapter 9 of Law and Kelton 1991), because game simulations are time consuming – at least 3 minutes per single simulation on a 1.5 Ghz Pentium 4 – and even a modest simulation design requires comparison of different states of nature (e.g., price wars all the time) *and* market states (e.g., incumbent differentiates by more than its Standard Offer).

2.7.1 Validation of Input

Our input validation looks at the random number seeds produced to give statistically representative game assignments. We inspect statistical representation and how well we satisfy *good* pseudo random number properties at 30, 60, and 90 games – for two series representing many and few game assignments in the reported results.

2.7.1.1 The Seed Problem

Our seeding method receives an initial seed from the computer clock and uses it in steps to draw birth date components: AD or BC, month, day, year less than one million; that is, the birth date range is from –1,231,999,999 to +1,231,999,999. An algorithm transforms the limits so that the higher and lower bounds, if drawn, yield integers within 5% of +/- 2^{31}- 2. (Integer bounds for seeding Delphi

Pascal's random number generator are +/- 2^{31}- 1.) These transformed integers are used, in turn, to draw seeds:

$$SEED = Random\ (transformed\ integer). \quad (1)$$

We would like for our transformation to produce seeds uniformly scattered over 95% of the seeding range in 30 game simulations. This has two distinct advantages:

1. From our constant subpopulation of approximately 730,000,000, we can draw samples representing 95% of the entire population of game assignments. Metaphorically, our seeding transformation floats the sub-population across the surface of the total game assignment population, which varies with player settings governing non-player product differentiation options.
2. Because the birth date appears on every report, we can reproduce any one game of a series. This is useful for explaining suspect simulation results to clients.

The remaining 5% of the seeding range is used by our solver. That is, 100% of the seeding range is available for price peace, or else price war topology subspaces. A successful simulation finds solutions in 40,800 180-tuple Monte Carlo drawings, each unique. An unsuccessful simulation reseeds and tries again up to three times – for a maximum of 163,200 180-tuple drawings, each unique.

While *our* seeding transformation doesn't use the linear congruential method (which has undesirable properties according to Judd 1998), the drawings from Delphi's generator could well be from an LCM random number generator (e.g., a Pascal variant of the Marse and Roberts FORTRAN generator described in Appendix 7A of Law and Kelton 1991).

2.7.2 Validation of Results

Validation of batting averages for the player and LCOS at 30, 60, and 90 games requires appeal to portfolio theory, in the context of the game assignment problem. As simulator architects, we might "happen to know" the best overall product design for a particular state of nature (for example, price wars never occur). In this instance, we might expect to dominate the LCOS at all 30-game benchmarks by selecting a highly differentiated flat rate, 2-year service contract, trading off profitability for the reduced survival risk our batting average metric favors. The LCOS, stuck with random portfolio assignments, only a few of which entail the flat rate, 2-year service contract, is unlikely to beat us at the plate because our flat rate lock-in and the market power *game* isolate customers from the lowest energy factor cost obtainable from the LCOS.

By contrast, we chose to validate player versus LCOS performance in the less predictable state of nature where price wars may or may not occur. In this situation, the player is *stuck with* the unchanging aspect of her best overall product design, while the LCOS randomly shuffles through product diversity, some of which better suits the war or peace of the game at hand, in the context of what all competitors are offering customers. Unless she draws an unusual preponderance of *high* energy factor cost assignments, the player portfolio dominates a first while because overall, our simulator architects' status ensures that it is an envelope or frontier service technology, and the LCOS hasn't drawn enough game assignments to reap the benefits of portfolio diversity. But as game assignments increase, the LCOS may be expected to achieve portfolio diversity that rewards it with a batting average exceeding that for the player. However, after a number of series games that depends on the total number of game assignments available to draw from, the LCOS uses up the frontier power of diversity and falls from grace relative to the player as it accumulates a disproportionate number of off-frontier or below-frontier game assignments. Summing up, portfolio theory following the arguments of Sir John Hicks (1967) leads us to expect the relative survival risk of player and LCOS, when price wars may or may not occur, to first favor the player (unless her energy factor price draws are particularly adverse), then switch to the LCOS as diversity's payoff kicks in, but eventually fall off, relative to the player, as the diversity in game assignments exhausts itself. (We speed up exhaustion of frontier portfolio opportunities for the LCOS by our random seed's attempt to maximize the probability of drawing game assignments *without replacement*.) The same reasoning leads us to further expect diversity's survival benefit to the LCOS to endure longer when there are more product portfolio game assignments to draw diversity from, unless the larger number of game assignments is counterbalanced by more favorable energy factor costs for the player than when the market setting dictated fewer game assignments.

2.8 Diverse Differentiation from Competitors

Imagine the worst case – when the maximum benefit from product diversity rewards the LCOS. To concord with portfolio theory and the luck of player-to-challenger-slot draws, we would like to compare survival risk from different product differentiation schemes at the different game points in the series where benefit from LCOS diversity has peaked. However, we don't want to select a peak after so few games that our sample is not representative, nor do we want to ignore the diminishing incremental impact of hits on batting average as *at bats* increase. We also contribute to LCOS diversity through *periodic* mergers, in all series but two reported in Section 4, by stepping through market power manifestations. If game assignments are random and uniform, statistically representative performance should repeat itself incrementally as a series lengthens. Because game solution time is a scarce resource, and because we don't know how many game repetitions best depict strategic learning in this market, our appeal to portfolio theory provides a conservative basis for deciding where to make batting average risk assessment comparisons across different series. These considerations informed our selection procedure of plotting batting average for every series game and selecting the LCOS peak ending its longest number of consecutive increases – with a minimum series length in the neighborhood of 30.

3 MODEL VALIDATION SIMULATION RESULTS

We validated our methodology at the game assignment limits for which contention regarding this market suggested results would be of general interest, with simulation weights establishing 2 to 1 odds that price wars would ensue. The larger number of game assignments describes a market in which the incumbent differentiates at much as it can (a municipal utility, for example), at least four non-player challengers must advertise their brand names, and any non-player competitor offering renewables in supply, a performance-based flat rate, or a cash incentive to switch providers must also advertise its brand name. Otherwise, non-player competitors can do anything from the array assigned to them, including neither advertising nor offering any service enhancements. Game assignments approximate 24 trillion, in the most likely case. The smaller number of game assignments describes a market in which the incumbent provides Standard Offer Service and no-frills direct access to wholesale power (recommended by Joskow 2001 as "the benchmark against which the social benefits and costs of retail competition and the best mechanisms to realize these benefits should be judged"), and non-player challengers always advertise and offer at least two additional service enhancements. Game assignments approximate 1.3 billion, in the most likely case.

3.1 Birth Date Seeds' Input

For the two validations, Table 2 looks for evidence of non-uniformity at 30, 60, and 90 games.

We constructed the test by dividing each 30-game increment into 8 segments of approximately 510 million, assigning 3¾ draws to each segment. We cannot reject the null hypothesis that the random seeds are uniform.

Table 2: Test Results For Rejecting Null Hypothesis that Series is Uniform (if $X^2_{0.5} > 14.067$)

Game Numbers/Assignments		$X^2_{0.5}$
1-30	Large	10.533
	Small	2.533
31-60	Large	5.733
	Small	4.133
61-90	Large	3.600
	Small	4.133

Over 90 games, we conducted tests identified by Judd (1998) as defining good pseudo-random numbers.

1. Zero serial correlation at all lags – SAS Proc ARIMA found no autoregressive or moving average components. SAS Time Series Forecasting System found no evidence of time series. The tests confirmed that both series were white noise.
2. A few long runs, where each draw is greater than (less than) its predecessor. The first series contains seven runs of 3 and two runs of 4; the second, two runs of 3 and one of 4.

3.2 Batting Average Results

Table 3 shows the energy-factor-price-player assignments to challenger slots conditioning our expectations that batting average performance conform to portfolio theory. It recommends two caveats:

1. In the first (*large* number of game assignments) validation, the player is more likely never to dominate the LCOS in the first 30 games, because of its 2 to 1 ratio of *high* to *low* factor price drawings.
2. The second (*small* number of game assignments) validation relative to the *large*, may exhibit slower player batting average recovery as LCOS diversity peters out, because of the 39 to 29 ratio of *high* to *high* factor price drawings over games 31 to 90.

Subject to these caveats, batting average performance conformed closely to our portfolio-theory expectations. In the first validation, the LCOS peaks at game 55; the player achieves dominance at game 69. In the second, the player dominates prior to game 34, the LCOS peaks at game 70, and the player and LCOS are approaching each other at game 90. With 2 to 1 odds favoring price wars, the player may never achieve dominance a second time.

Table 3: Four Lowest and Highest Energy Factor Price Draws by Player

Game Numbers/ Assignments		Lowest	Highest
1-30	Large	10	20
	Small	12	18
31-60	Large	17	13
	Small	12	18
61-90	Large	14	16
	Small	9	21

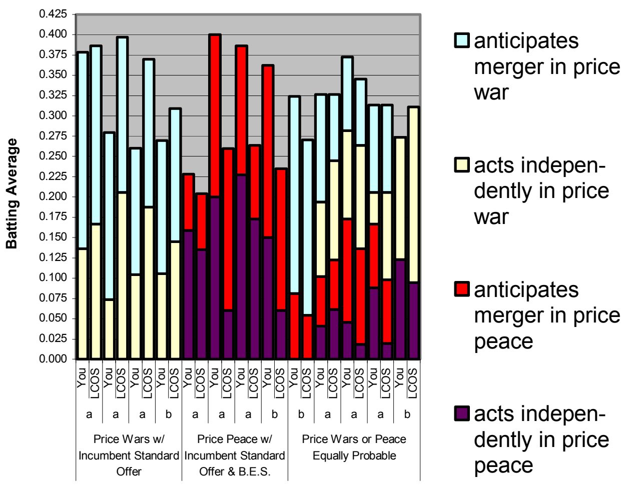
4 SURVIVAL RISK SIMULATION RESULTS

Figure 3 displays survival risk simulation results. We discuss our results by state of nature – price wars or else price peace versus price wars or peace – with four scenarios each for wars only and peace only, and five for wars *or* peace. We also distinguish by the incumbent's product differentiation. With the exception of Scenario 9 (for wars or peace), market power weights governing independent action and anticipated mergers each total 0.5 for all cases presented with anticipated mergers possible.

4.1 One Thing, or Else the Other

Figure 3 shows that, in price wars, anticipated mergers unambiguously benefit *you*, the player, by more than product differentiation by itself. In fact, *your* anticipated mergers also benefit the LCOS by as much or more than its product diversity alone in two of the four price war scenarios presented (the first and fourth, from left to right, described in detail in Table 4 below). Figure 3 shows additionally that lowest risk (highest batting average) for the player, in price wars, accompanies least product differentiation – depicted in the 2 left bars.

For the player's survival risk in price peace, Figure 3 shows that *your* anticipated mergers contribute to lowering player *and* LCOS risk by as much or more than acting independently does – in two of four cases. It shows additionally that more product differentiation tends to be better than less; however, the least risk (highest batting average) attended 4 product differentiating options – depicted in the 2 left-of-center bars (11 and 12), rather than the maximum of 5 possible.



a. challengers always advertise with options 2, 6, or 13 (Fig. 2)
b. all non-player challengers advertise and do at least two other things.

Figure 3: Survival Risk Simulation Results

Basic Electricity Service (B.E.S) conforms to the no-frills direct access to wholesale power recommended by Joskow (2001). Our simulator allocates a challenger slot to B.E.S. and prices it at its monthly base and peak wholesale power costs plus a nominal charge for distribution and embedded cost recovery. Because the challenger slot changes from game to game, B.E.S. approximates the cost and benefit of providing customer direct access to a spot market – but as if the wholesale power were bilaterally contracted for a year. By design, all challenger slot wholesale prices are below the incumbent's. Our definition of B.E.S., *from the incumbent*, follows Joskow's recommendation *for new entrant ESP's* who buy wholesale electricity at prices lower than those prevailing in the "organized" wholesale market by striking bilateral forward contracts with generators – supporting price hedges that generators can use to secure lower cost financing. Our B.E.S. has a built-in insurance hedge against market price volatility and against weather more extreme than the average or typical, seasonal degree-day fluctuations embedded in our simulator's wholesale price series for peak load. In just 12 games of 160 price peace simulations did B.E.S. get more than 5% of end-of-year market share (EOYMS). See Table 4. B.E.S. does less well as player and other challengers' product differentiation increases.

Several states – Massachusetts, California, Texas, and New Jersey most notably – offer some form of B.E.S., *De-fault*, or *Direct Access* service. Rose (2001) reports that 1.8% of California residential service was Direct Access on June 15, 2000; the number had shrunk to 0.86% by May 15, 2001. Massachusetts Electric (2002) reports that 24% of its customer base in all service classes now receive Default Service. There, all customers who either opened an account after March 1, 1998 and are not now being served by a Competitive Power Supplier, or were served by a CPS in the past and have switched, receive Default Service. Residential Default rates under the variable rate pricing option from November 2001 through April 2002, were above B.E.S. from the LCOS every month, and above B.E.S. from our three next-lowest cost providers about 55% of the time.

Because our simulator's B.E.S. is a customer choice option, not assigned, it serves the "benchmark" purpose Joskow (2001) envisioned for it. Its poor performance validates the attractiveness of Figure 2's product attributes.

For each state of nature, Table 4 shows 3 levels of player product differentiation; notes *a* and *b* below Fig. 3 show minimum levels of non-player product differentiation. In price wars, we included a performance-based flat rate (option 6) in scenarios 2 and 4. We did so to test the ability of a market, in which 4 non-player challengers might draw flat rates as well, to raise the floor of the price war, while yielding a respectable batting average/survival risk. We were modestly successful in terms of survival risk; however, we cannot be sure that an alternative choice not including a flat rate would show improved survival risk with increasing product differentiation. However, we switched to a flat rate offer after observing the poor perfor-mance of scenario 3, which included options 3, 4, and 5 – reported by Cai, Deilami, and

Table 4: Summary of Price War, or else Price Peace, Results (Scenarios 1 – 8)

Price War Scenarios (1 to 4 left to right, Fig. 3)				
Options Selected (Fig. 2)	1,4	1,4,6,11	1,3,4,5,10	1,4,6,11
Market Power Weights (Table 1)	1 - 0.25, 4 - 0.25, 7 - 0.375, 8 - 0.125			
LCOS Peak Game #	33	34	60	38
Market Concentration (through peak game)	89.10%	89.16%	89.81%	84.76%
Ave. NPV profit per customer month				
Incumbent	$8.37	$7.33	$7.86	$7.71
Player	-$0.74	$10.27	-$1.34	$9.54
LCOS	$0.49	-$1.58	-$0.57	$0.38
Ave. % customers per customer month				
Incumbent	90.26%	90.78%	90.68%	90.59%
Player	2.40%	2.03%	1.88%	1.76%
LCOS	4.87%	4.15%	4.93%	3.45%
Price Peace Scenarios (5 to 8 left to right, Fig. 3)				
Options Selected (Fig. 2)	1,4	1,4,11,15	1,4,9,11,15	1,4,11,15
Market Power Weights (Table 1)	1 - 0.3, 2 - 0.1, 3 - 0.1, 7 - 0.375, 8 - 0.125			
LCOS Peak Game #	37	29	33	30
Market Concentration (through peak game)	83.71%	82.05%	75.62%	83.45%
Ave. NPV profit per customer month				
Incumbent	$16.13	$16.28	$15.27	$16.98
Player	$21.55	$8.31	$16.57	$8.81
LCOS	$23.57	$20.41	$19.33	$20.57
Ave. % customers per customer month				
Incumbent	91.55%	90.78%	90.12%	90.08%
Player	1.73%	3.65%	3.42%	2.93%
LCOS	1.73%	1.55%	1.95%	3.22%
Results over 40 game series				
# of B.E.S. games with EOYMS above 5%	4	4	3	1
Maximum B.E.S. EOYMS	31.88%	26.78%	18.60%	5.02%

Train (1998) to be highly valued by Sacramento Municipal Utility District customers. Scenario 3 also included utility-customer data communication, which we simulated as switching about 10% of the customer bill from a peak to a base load charge.

All Table 4 results other than batting average are unweighted averages. Market concentration, measured as the end-of-year market share of the top two finishers conforms to our expectation that it be higher in war, where the incumbent and LCOS benefit from low search and low wholesale power costs, respectively. That it is lower in war when all non-player challengers must advertise and do 2 or more other things implies product differentiation enhances competitiveness in price wars. The per-customer-month results are presented to remind us that our rules for batting average emphasize starting strong in year 2, at the expense of overall first-year performance. In terms of profitability and customers, they also show little motivation for the incumbent to abandon its Standard Offer service. Player profitability per customer month benefits from a flat rate in price wars, and suffers from it in price peace. The 2-year service contract (flat rates) offered in price peace represent an ESP emphasis on customer lifetime value.

4.2 One Thing or the Other

With two scenario exceptions, Figure 3 shows the contribution to batting average of anticipated mergers versus independent action in war and peace. Overall, anticipated mergers always benefit the player more than product differentiation alone – confirming the impact we expect from restricting competition while increasing product diversity.

Table 5 compares price war batting averages with those attained in price peace. These are equivalent to a baseball switch hitter averages *by hand*. When the incumbent provides its Standard Offer and B.E.S., the player bats higher war-handed than peace-handed. In the second 2 sce-narios (10 and 11, Fig. 3), player options include the per-formance-based flat rate (option 6). Price-war performance is better when the flat rate is lower; hence, her scenario 10 war-handed batting average, with less product different-tiation in the rate, is higher than her scenario 11's. Figure 3 confirms that her scenario 11 average is higher, overall.

Table 5: Summary of Results when Price War and Peace are Equally Probable (Scenarios 9 – 13)

Price Peace or War Equally Probable (9 to 13 left to right, Fig. 3)					
Incumbent Options (Fig. 2)	1,3,B.E.S.	1,3,B.E.S.	1,3,B.E.S.	5 from any array	3 or more from any array
Player Options (Fig. 2)	1	1,4,6	1,4,6,11	1,4,6,11	1,4,10,11
Market Power Weights (Table 1)	7 - 1.0	1 - 0.1, 2 - 0.1, 3 - 0.1, 4 - 0.2, 7 - 0.4, 8 - 0.1			1 - 0.2, 2 - 0.4, 4 - 0.4
LCOS Peak Game #	37	29	34	31	32
Player Price Peace Ave.	0.200	0.217	0.352	0.370	0.224
Player Price War Ave.	0.409	0.423	0.393	0.268	0.333
LCOS Price Peace Ave.	0.133	0.261	0.278	0.217	0.172
LCOS Price War Ave.	0.364	0.385	0.411	0.393	0.479
Market Concentration (through peak game)	88.83%	81.23%	81.18%	90.81%	88.51%
Ave. NPV profit per customer month					
Incumbent	$12.62	$11.28	$9.17	$7.56	$6.57
Player	$12.73	$9.00	$8.18	$10.52	$10.55
LCOS	$4.38	$2.14	$7.47	$2.86	$3.28
Ave. % customers per customer month					
Incumbent	90.71%	90.67%	90.86%	92.42%	91.55%
Player	0.15%	2.05%	2.39%	2.88%	2.48%
LCOS	4.08%	3.29%	2.04%	2.69%	2.84%
Results over 42 game series					
# of B.E.S. games with EOYMS above 5%	2	2	2	Not Applicable	
Maximum B.E.S. EOYMS	14.12%	7.76%	16.24%		

The player loses her war-handed advantage in Scenario 12, when her flat rate bumps up against 5-option pro-duct differentiation from the incumbent – including equally probable competing flat-rate offers and opportunities to lower its option-loaded price to gain market share. Higher market concentration and incumbent % customers per month reflect its success at retaining more customers with more product differentiation. In Scenario 13, both the incumbent and non-player challengers differentiate *aggressively*, selecting 3 or more options from the Figure 2 array randomly assigned to them. The player regains her war-handed advantage by not offering a flat rate, allowing her to price lower relative to flat rates that are more likely for all her (*aggressive*) competitors. Figure 3 confirms that the player's Scenario 13 batting average suffers overall, without merger opportunities. By contrast, the player does better against aggressive challengers in Scenario 9, where she only advertises and merges with the lowest-cost challenger who advertises. Her Fig. 3 batting average and Table 5 profit per customer month are higher; her % customers is lower because customers most often prefer the aggressive product differentiation from the merger partner.

5 CONCLUSIONS

Our validation and survival risk simulation results conform to expectations we set for them as economists and marketing science professionals. This gives confidence to implications the results suggest regarding household electricity deregulation:

1. In an uncertain market, merger fosters survival by more than product differentiation alone.
2. No-frills wholesale service competes poorly with product differentiation including service attributes offered by municipals and cooperatives such as SMUD and Glasgow Electric Plant Board.
3. Product differentiation receives survival risk benefit from fixed or flat rates common in other continuously provided service industries, but also the prevalent mode chosen by Massachusetts households *assigned* Default Service.
4. Profitability and % customers per customer month are resilient for the Incumbent's Standard Offer. Customers increase with differentiation exceeding the Standard Offer; however, profitability suffers from the incidence of flat rates.
5. IOUs may prefer the Standard Offer to product differentiation because flat rates needed to protect it defer compensation and shareholder rewards. With deregu-lation, they may rather *assign* Default Service to qual-ifying customers and invest in unregulated ventures.
6. Deregulation's likely benefit to households from IOU's will come through Default Service, not service enhancements. Absent some form of direct access, deregulation favors the shareholder (and/or benefits IOU compensation).

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