The Short-Run Effects of Time-Varying Prices in Competitive Electricity Markets

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We analyze the efficiency, distributional, and environmental effects of real-time pricing (RTP) adoption in the short run. Consistent with theory, our simulations of the PJM electricity market show that RTP adoption improves efficiency and compresses the distributions of loads and prices. Adoption increases average load but decreases operating profits with the largest decrease for oil-fired generation (59% when all customers adopt). Consumer surplus and welfare gains are modest (2.5% and 0.24% of the energy bill), and emissions of SO_2 and NO_x increase but CO_2 emissions decrease. Approximately 30% of these efficiency gains could be captured by varying flat rates monthly instead of annually. Monthly flat rate adjustment has many of the same effects as RTP adoption, captures more of the deadweight loss than time of use (TOU) rates, and requires no new metering technology.

1. INTRODUCTION

As electricity markets were restructured in the last decade, sophisticated auction mechanisms were developed to trade wholesale electricity and reveal wholesale prices. However, much less attention was paid to retail pricing of electricity,[1] and the opening of retail markets to competition has lagged.[2] Economic

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1. Exceptions include Borenstein and Holland (2005), Joskow (2000), and Joskow and Tirole (2004).
2. Some form of retail competition is established in Texas and Great Britain. Most other proposals for retail competition in the various states have been tabled.

theory describing efficient retail pricing of electricity is based on the well-known theory of peak-load pricing—known as real-time pricing (RTP) in current electricity policy debates.[3] Despite clear efficiency gains in theory, real-time pricing has encountered resistance from many quarters. To help understand this resistance, we analyze the short-run effects of time varying prices in the Mid-Atlantic electricity market known as PJM by constructing a simulation model of competitive wholesale and retail markets.[4,5] Using the model, we analyze the changes in surplus to different customers and producers and the environmental effects of RTP adoption.

The basic economic intuition of RTP adoption is straightforward. For customers not on RTP, retail service providers (whether public service utilities or competitive retailers) must procure sufficient power to cover retail demand at the predetermined flat retail price. With predetermined retail prices, demand in the wholesale market is very inelastic if no customers are on RTP. For customers on RTP, retail service providers pass through the wholesale price. If the wholesale price is high in a given hour, the RTP customers will conserve electricity and reduce the amount of electricity that must be procured. Conversely, if the wholesale price is low in a given hour, the RTP customers will increase their electricity consumption. Thus, RTP adoption by more customers increases the elasticity of the wholesale demand by rotating the demand around the flat retail rate.

The long-run theoretical effects of the increased demand elasticity from RTP adoption are described by Borenstein and Holland (2005). They show that off-peak quantities demanded and prices increase while peak quantities and prices decrease. This implies that the long-run equilibrium flat rate falls with RTP adoption, but that the effects on average loads and capacity are ambiguous. Borenstein and Holland also calculate long-run efficiency gains of three percent to 11% of the energy bill with RTP adoption. We find much smaller efficiency gains in the short run, which may help to explain why these efficiency gains have not been realized.

While much of the discussion of time-varying prices has focused on real-time pricing, prices could vary in other ways as well. In particular, flat rates for all hours can vary more or less frequently, or rates could vary by time of use. We compare the benefits of monthly flat rate adjustment with traditional time-of-use (TOU) rates. Surprisingly, we find that the former is superior.

We also examine the environmental impacts of RTP adoption. More specifically, we model how emissions of sulfur dioxide, SO_2, nitrogen oxides, NO_x, and carbon dioxide, CO_2, change in the PJM market as more and more customers adopt RTP. This analysis is complementary to Holland and Mansur (2004), which econometrically estimates the environmental effects of RTP adoption. For each NERC region in the U.S., their paper estimates how a reduction in demand vari-

3. See Borenstein, Jaske, and Rosenfeld (2002) for a general discussion of RTP. Real-time pricing usually has prices that vary every hour or every half hour.

4. Here "short run" refers to a fixed capital stock of generation capacity whereas "long run" refers to a variable capital stock. We do not analyze demand-side installation of technology for responding to real-time prices, which would presumably make response more price sensitive.

5. Other possible sources of resistance to RTP could be institutional or political. We do not explicitly model these sources.

ance (a likely outcome of RTP adoption) will affect the emissions of SO_2, NO_x and CO_2. They find that the impact differs depending on the generation technology characteristics of the region.

Section 2 presents the theoretical model, which incorporates the effects of RTP adoption on the retail rates paid by customers not on RTP. Section 3 discusses the data, and describes the simulation model. Section 4 presents the simulation results. With RTP adoption, we find in the short run that: (*i*) the distributions of loads and prices are compressed, (*ii*) all rates decrease, (*iii*) average loads increase, (*iv*) profits decrease for all generating sectors, (*v*) consumers surplus increases for all consumers, (*vi*) efficiency gains are modest, and (*vii*) emissions of SO_2 and NO_x increase, but emissions of CO_2 decrease. The robustness of the results to assumptions about demand, imports, generator outages, elasticity of peak demand, and homogenous customers is addressed in the appendix. Section 5 analyzes flat rates that vary by month or by time of use and compares both policies to annually varying flat rates. Section 6 concludes.

2. MODEL

To estimate the short-run effects of RTP adoption, we first model pricing in competitive electricity markets where some proportion of customers are on real-time pricing. A similar model is analyzed carefully in Borenstein and Holland so the model is only outlined here.[6]

Since electricity cannot be stored economically, demand must equal supply at all times. We assume there are T hours with retail demand in hour t given by $D_t(p)$ where $D'_t<0$.[7] A fraction, α, of the customers pays real-time prices, i.e., retail prices that vary hour to hour.[8] The remaining fraction of customers, $1-\alpha$, pay a flat retail price, $\bar{p}_t$, that is the same for every hour in a given period, *i.e.*, $\bar{p}_t = \bar{p}_{t'}$ if t and t' are in the same period.[9] We assume that α is exogenous and that customers on real-time pricing do not differ systematically from those on flat-rate pricing.[10] Aggregate (wholesale) demand from all customers is

6. Borenstein and Holland show that in the long run RTP adoption decreases flat rates, increases surplus to flat-rate customers, increases surplus to switchers, decreases surplus to RTP customers, and has an indeterminate effect on capacity and welfare. Our short-run simulations agree with these results except that all customers are made better off.

7. The additive separability assumption implies that cross-price elasticities are zero. Taylor *et al.* (2005) use the generalized McFadden functional form to estimate cross price elasticities. They find both positive and negative cross-price elasticities that are generally an order of magnitude smaller than own-price effects. See Herriges *et al.* (1993), Caves *et al.* (1987), and Patrick and Wolak (2001) for further demand elasticity estimates.

8. Following standard assumptions, we assume consumers are rational, e.g., information costs are small and customers respond to price signals.

9. Here the periods are years. In later simulations, we allow the flat rates to vary by month or by time of use

10. See Barbose *et al.* (2004), Moezzi *et al.* (2004), Matsukawa (2004), and Jenkins (2005) for discussions of demand response to actual RTP programs. Clearly, the share of customers adopting RTP will depend on market conditions. We explore the incentive to adopt RTP below.

then $\tilde{D}_t(p_t, \bar{p}_t) = \alpha D_t(p_t) + (1-\alpha)D_t(\bar{p}_t)$ which implies that $\tilde{D}_t$ is decreasing in $\bar{p}_t$ and p_t. When $\alpha = 0$, wholesale demand is perfectly inelastic. The larger the share of customers on RTP, the more elastic is wholesale demand.[11] Note that wholesale demand rotates around the point $(D(\bar{p}_t), \bar{p}_t)$ with RTP adoption.

Each of N generating units supplies electricity to the wholesale market based on its installed technology. We assume that generator n can produce up to capacity q_n at constant marginal cost, c_{nt}. Since marginal costs depend on fuel and other input prices, we allow the marginal cost for each unit to vary over the course of the year. A competitive generator would produce at capacity if the wholesale price, w_t, were above its marginal cost and would produce nothing if the wholesale price were below its marginal cost. Therefore, the supply curve from each generating unit is inverse-L shaped. The industry supply curve, S_t, is found by aggregating the supply from each generating unit for hour t.

The retail sector purchases electricity from the wholesale sector and distributes it to the final customers.[12] We assume the identical, competing retailers have transmission and distribution costs of c^d per MWh. The profits of the retail sector are then

$$\pi^r = \sum_{t=1}^{T} (\bar{p}_t - w_t - c^d)\,(1-\alpha)\,D_t(\bar{p}_t) + (p_t - w_t - c^d)\,\alpha\,D_t(p_t) \qquad (1)$$

The first term is the retail profit from serving the flat-rate customers and the second term is the retail profit from serving the RTP customers.

If there are no costs of switching retailers, Bertrand competition in the retail sector implies zero retail profits in equilibrium, *i.e.*, $\pi^r = 0$. Competition over real-time prices implies that each real-time price equals the wholesale price plus distribution costs, *i.e.*, $p_t = w_t + c^d$, and competition over the flat rates implies that each annual flat rate is the distribution cost plus the weighted average of wholesale prices for that period where the weights are the quantities demanded by the flat-rate customers, *i.e.*:

$$\bar{p}_t = c^d + \frac{\sum_{\tau\in\Phi_t} w_\tau D_\tau(\bar{p}_\tau)}{\sum_{\tau\in\Phi_t} D_\tau(\bar{p}_\tau)} \qquad (2)$$

for each t where Φ_t is the set containing all hours in the same period as hour t.[13] Equating supply and demand in the wholesale market for each t, *i.e.*, $S_t(w_t) = \tilde{D}_t(p_t, \bar{p}_t)$, completes the characterization of the equilibrium.

11. This holds because $\tilde{D}(p_t, \bar{p}_t)$ is decreasing in α for $p_t > \bar{p}_t$, and $\tilde{D}(p_t, \bar{p}_t)$ is increasing in α for $p_t < \bar{p}_t$.

12. Under uncertainty, the announcement by the retailer of prices *ex ante* or *ex post* has important implications for risk sharing between the retailers and consumers.

13. These equilibrium conditions imply that our results are applicable to a regulated retail sector as long as the regulation ensures no (economic) profit for the regulated retailers and no cross-subsidization between RTP and flat-rate customers.

3. DATA AND SIMULATION MODEL

The study period covers two years from April to March beginning in April of 1998 and ending in March of 2000. We apply the model to the PJM electricity market, which covered parts of Pennsylvania, New Jersey, Maryland, and Delaware at that time.[14] Unless otherwise noted, all data are from various government and industry sources as detailed in Mansur (forthcoming). The 392 modeled fossil generating units, which range in capacity from 0.6 MW to 850 MW, account for approximately 60% of the electricity generated in PJM with the remainder being supplied primarily by nuclear power.[15] The largest fossil units are powered by coal (46% of fossil capacity) with the remainder powered by oil and natural gas (19% and 35% of fossil capacity).

Since the efficiency of each unit (measured by the heat rate in BTU per kWh) is publicly available, we can estimate the daily marginal cost of each unit from the costs of fuel and other inputs. Key input prices used in calculating the daily supply curves include prices of natural gas, heating oil, SO_2 permits, and NO_x permits.[16] Coal prices are assumed constant throughout the study period.

Demand is based on the electricity load reported by PJM. The load averaged 29,400 MWh across the study period with a minimum load of 17,461 MWh and a maximum load of 51,714 MWh. Wholesale electricity prices ranged from slightly negative to the price cap of $999 with an average wholesale price of $25.80 per MWh.

The simulation model uses the data from PJM to estimate the effect of more customers adopting RTP in competitive markets. In the simulation, we make a further assumption of identical, constant demand elasticities, but allow demand for each hour to have a different scale parameter.[17] The scale parameters are calculated from the observed hourly loads and rates in PJM.

The supply side of the model includes generation from fossil, nuclear, and hydropower.[18] We assume the fossil supply curve for each coal-, oil-, and gas-fired generation unit is inverse-L shaped where the marginal cost is calculated from the unit's heat rate and daily fuel prices. The capacity of each unit is derated by its expected outage factor.[19] Supply from nuclear and hydropower is assumed to be perfectly inelastic at its observed hourly levels throughout the simulations.

14. PJM had a negligible proportion of demand-responsive load during this period.

15. Hydroelectricity accounts for less than 2% of load, and imports/exports are less than 0.1% of load on average.

16. If firms have fixed contracts for fuel, we assume that they recognize that market prices reflect true opportunity costs.

17. Since demand is assumed to be of the form $D_t(p) = A_t p^{\epsilon}$, the scale parameter is A_t.

18. We also reduce the available supply by the amount of electricity required to regulate the stability of the electrical grid. The baseline simulation ignores imports, but we report the sensitivity of the results to an elastic import supply.

19. Generating units may be unavailable in certain hours for a variety of reasons. If a 100 MW generator, for example, is expected to be unavailable 6% of the time it is called, we treat the effective capacity of the generator as only 94 MW.

Nuclear power stations have very low marginal costs and, thus, run whenever possible. Hydropower in PJM is mostly from run-of-river dams which do not vary their output based on market conditions. The supply curve is found by aggregating the supply from each source. Figure 1a illustrates the supply curve for a given day. Of the fossil units, the coal-fired units have the lowest marginal costs, the gas-fired units are the mid-merit technology, and oil-fired units have the highest marginal costs.

Figure 1a. Supply Curve for all PJM Firms, April 1, 1999

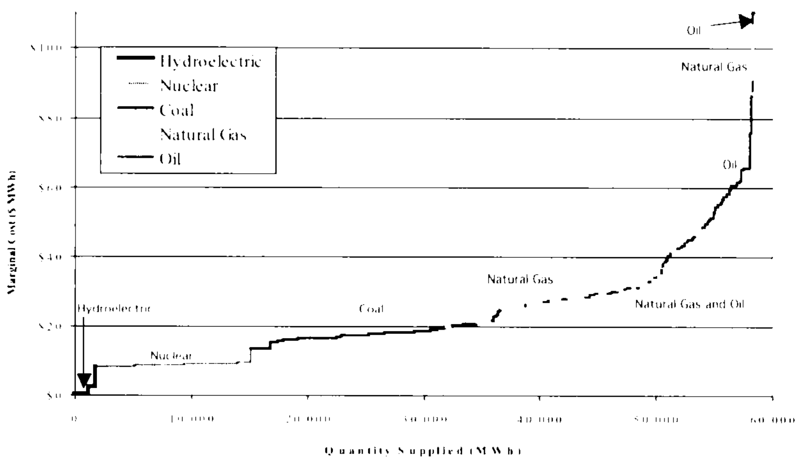
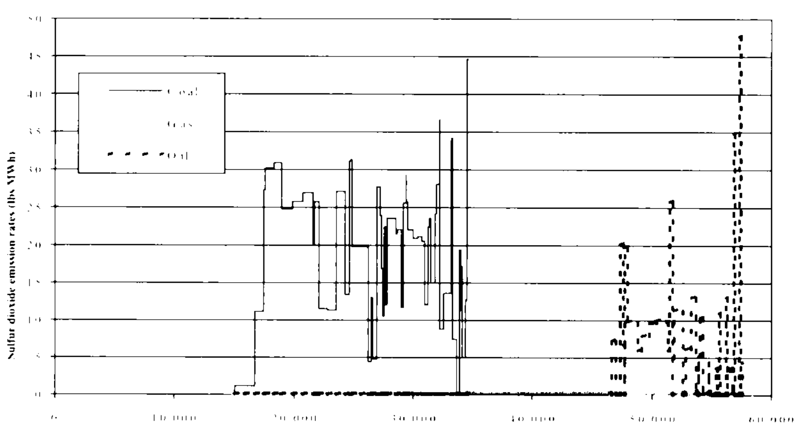


Figure 1b. Example of Sulfur Dioxide Emission Rates Varying Along a Supply Curve



Source: EPA's CEMS.

For a given flat retail price, the wholesale demand curve in any hour is completely determined, and a candidate wholesale market equilibrium can be calculated from the intersection of the wholesale supply and demand for each hour. These wholesale prices can be used to calculate profits to the retail sector for each year. If the retail profit for a year is positive (negative), the equilibrium flat rate for that year must be lower (higher) than the assumed flat rate. The flat rate for that year is then adjusted, and a new candidate wholesale market equilibrium and new retail profit are calculated. Iteration approaches the equilibrium flat rate and yields the equilibrium in the retail and wholesale markets.

The simulation model starts from observed loads and retail prices and estimates the competitive equilibrium in the wholesale and retail markets. Note however, that the resulting equilibrium prices may not be directly comparable to the observed market prices due to market imperfections, for example, regulation, market power, and intertemporal constraints. See Mansur (forthcoming).

4. RESULTS

The results of the baseline simulation are presented in Tables 1-4. The baseline simulation assumes a demand elasticity of 0.1 and an initial retail energy price of \$30 per MWh plus \$9 for stranded cost recovery with an additional charge of \$40 for T&D.[20] The baseline also assumes zero import supply elasticity and derated capacity. The sensitivity analysis in the appendix addresses each of these assumptions. We analyze here the effects of RTP adoption on loads, prices, profits, surplus and emissions.

4.1 Effects on Loads and Prices

Table 1 shows the changes in equilibrium loads, prices, and flat rates when the proportion of customers on RTP increases incrementally.[21] As expected, the load distribution is compressed when more customers adopt RTP. This is shown in Panel A where the maximum hourly load decreases (four percent when all customers adopt); the minimum hourly load increases (1.5% when all customers adopt); and the standard deviation decreases.[22] Figures 2a & 2b illustrate how the distribution of load is compressed as more customers adopt real-time pricing.

Panels B & C of Table 1 show how annual flat rates and hourly real-time prices change with RTP adoption. Annual flat rates decrease with RTP adoption,

20. A demand elasticity of 0.1 is consistent with Borenstein (2005a) and is within the range estimated by Taylor *et al.* (2005). The \$9 stranded cost is only used for demand calibration.

21. The actual increments are 0.1%, 33.3%, 66.6%, and 99.9%. The 0.1% of customers on RTP ensures the uniqueness of the equilibrium. The 0.1% of customers on flat rates, allows us to calculate an equilibrium flat rate.

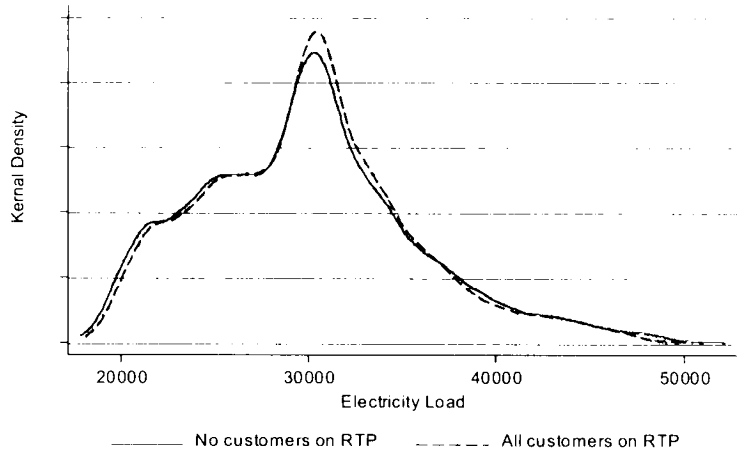
22. This standard deviation shows that the variance falls over the entire sample. One might expect that the within-day variance would also fall with RTP adoption. In fact, the average within-day coefficient of variation falls from 13.6% to 13.0% if all customers adopt RTP.

Table 1. Changes in Equilibrium Load, Flat Rates and Realtime Prices from RTP Adoption

Panel A: Hourly load in MW				
Percent of customers on Hourly Rates (α)	Mean	std. dev.	min	max
0%	29,901	5,923	17,820	52,183
33%	29,930	5,822	17,944	51,459
67%	29,943	5,723	18,014	50,749
100%	29,954	5,629	18,083	50,143
Panel B: Annual flat rates				
α	Mean	std. dev.	min	max
0%	$66.77		$62.58	$70.94
33%	$66.32		$62.54	$70.10
67%	$66.24	—	$62.51	$69.95
100%	$66.14	—	$62.48	$69.80
Panel C: Hourly real-time prices				
α	Mean	std. dev.	min	max
0%	$65.20	$17.89	$54.91	$1,039.00
33%	$64.95	$9.84	$54.92	$164.01
67%	$64.90	$9.49	$55.24	$154.37
100%	$64.84	$9.11	$55.27	$151.39

Notes: Elasticity is 0.1, initial flat retail price $30 with $40 for T&D and $9 for stranded cost recovery. Reported prices include T&D.

Figure 2. Kernel Density Estimates of Electricity Load Distribution (in MWh)



Note: The kernel density was estimated using the Epanechnikov kernel-weight function in Stata with 300 points used in the estimation.

which benefits the flat-rate customers.[23] The average real-time price is lower than the average flat rate, because in each month the load-weighted average, which is the flat rate, puts higher weight on high-priced peak periods. Like the flat rate, the average and maximum real-time prices fall as more customers adopt RTP. The effect on the maximum real-time price, which occurs at five PM on July 23, 1999 in each simulation, is particularly dramatic. With no customers on RTP, the maximum real-time price would be at the price cap.[24] Indeed the price cap is binding in four hours when no customers are on RTP.[25] However, if even a third of customers are on RTP, the wholesale price cap no longer is binding in any hour and the maximum price drops to $164. The minimum price increases slightly as more customers adopt RTP since demand increases in low price periods. Note also that the variance of the real-time prices falls since off-peak prices increase but peak prices decrease. Thus the distribution of hourly real-time prices, like the distribution of load, is compressed with RTP adoption.

4.2 Distributional Effects and Efficiency of RTP Adoption

To analyze the benefits of RTP adoption, we estimate the changes in wholesale profits, consumer surplus, and deadweight loss.[26] Table 2 shows the effects on wholesale supply and profits to various sectors from RTP adoption. The first panel of Table 2 decomposes the load increase shown above into supply changes from coal-, oil-, and gas-fired fossil generation. This decomposition shows that RTP adoption, which increases total load, increases the supply from coal-fired generation, but decreases the supply from oil- and gas-fired generation.[27]

To understand these changes in supply, we analyze the changes in supply for peak and non-peak hours in panels B and C of Table 2. We define *peak hours* as those hours in which wholesale energy prices are above $30 (approximately 1800 hours per year) and *non-peak hours* as those hours in which wholesale energy prices are below $30 (approximately 7000 hours per year)[28]. As more customers adopt RTP, the relative changes in peak and non-peak supply help explain the effects in Panel A. For load, the peak decrease of 1.3% is slightly larger than the off-peak increase of 0.8%. However, since there are almost four times as many off-peak hours, the latter effect dominates, and consequently total load increases. For coal-fired generation, the off-peak increase in generation of 1.3% swamps the

23. Borenstein and Holland prove that the long-run flat rate declines as customers adopt RTP, but do not derive an equivalent short-run result.

24. The wholesale price cap was $999. The $40 adder for transmission and distribution yields a retail real-time price of $1,039.

25. The price cap was actually binding for seven hours in PJM during this time period.

26. Competition in the retail sector ensures that retailers earn no economic profits and thus are unaffected by RTP adoption.

27. Supplies of nuclear and hydroelectric power are perfectly inelastic by assumption, so they are not affected by RTP.

28. The $30 cut-off is arbitrary and does not lead to an entirely consistent labeling of hours. However, the cutoff illustrates the relevant points.

Table 2. Effects on Wholesale Supply and Profits of RTP Adoption

Panel A: Average hourly supply (in MW)				
Percent of customers on Hourly Rates (α)	Load	Coal	Oil	Gas
0%	29,901	15,926	345	1,873
33%	0.10%	0.4%	-3.0%	-0.9%
67%	0.14%	0.7%	-6.2%	-2.2%
100%	0.18%	0.9%	-9.2%	-3.4%
Panel B: Average hourly supply (price > \$30)				
α	Load	Coal	Oil	Gas
0%	37,068	18,248	1,170	5,651
100%	-1.3%	-0.1%	-12.4%	-6.0%
Panel C: Average hourly supply (price < \$30)				
α	Load	Coal	Oil	Gas
0%	28,002	15,310	127	871
100%	0.8%	1.3%	0.5%	2.5%
Panel D: Average hourly operating profit				
α	Load	Coal	Oil	Gas
0%	\$164,967	\$147,225	\$4,055	\$13,688
33%	-6%	-3%	-47%	-26%
67%	-7%	-4%	-53%	-30%
100%	-9%	-5%	-59%	-34%

Table 3. Welfare and Consumer Surplus of RTP Adoption

Percent of customers on Hourly Rates (α)	DWL per hour	DWL as a percent of the energy bill	Hourly average change from α=0: ΔCS RTP All	ΔCS RTP Per "cust"	ΔCS Flat All	ΔCS Flat Per "cust"	ΔCS as percent of the energy bill
0%	\$1,936	0.24%	\$4	\$0.09	\$0	\$0.00	0.00%
33%	\$1,232	0.16%	\$5,083	\$0.31	\$8,850	\$0.27	1.74%
67%	\$592	0.08%	\$11,863	\$0.36	\$5,330	\$0.32	2.15%
100%	\$0	0.00%	\$20,436	\$0.41	\$19	\$0.38	2.55%

Note: When α is 0% in the table, 0.1% of customers are on RTP. Similarly, when α is 100% in the table, 99.9% of customers are on RTP.

modest decrease in peak-hour generation leading to an increase overall. For oil- and gas-fired generation, a much larger proportion of the generation occurs during peak hours. The substantial reductions in peak-hour generation (six percent to 12%) thus offset the more modest increases in off-peak generation, despite the fact that these increases occur for more hours.

Panel D of Table 2 shows that generator operating profits decrease with RTP adoption. The increase in coal-fired supply might suggest that coal-fired generation would benefit from RTP adoption since they would increase their market share. In addition, off-peak prices would increase, so margins off peak might increase. However, Table 1 showed that the average real-time price decreases, and this effect dominates. For coal-fired generation, operating profit declines by three percent when a third of the customers adopt RTP and would decline by five percent if all customers adopted RTP.

For oil- and gas-fired generation, the decrease in supply, coupled with the decrease in peak and average prices, implies that losses are quite dramatic. Note that adoption of RTP by only a third of customers would decrease profits of oil-fired generators by 47%. Gas-fired generator profits also decrease quite dramatically, dropping by 26% if only a third of the customers adopted RTP. Since coal is the dominant fuel source in PJM, the losses to all fossil-fired generation are less dramatic, (nine percent if all customers adopt RTP and six percent if only a third of customers adopt) but still substantial.

Since supply from nuclear and hydropower is perfectly inelastic and marginal operating costs are small, we approximate the change in profit by changes in revenue. Reflecting the fall in the average wholesale price, revenues for nuclear and hydropower only decrease slightly (1.5%) when all customers adopt RTP.

The effects of RTP adoption on consumer surplus and welfare are presented in Table 3. Since we have assumed a constant demand elasticity of 0.1, consumer surplus would be unbounded. First, to simplify calculations when the price cap is binding and to bound consumer surplus, we assume that consumers get no surplus when the price cap is binding. Next, we normalize consumer surplus to zero when no customers are on RTP and analyze the changes in consumer surplus.[29] The consumer surplus measure is then the change in surplus from the surplus if all customers were on flat rates. The First Welfare Theorem implies that the efficient allocation of electricity is attained by a competitive equilibrium when all customers are on RTP. Deadweight loss (DWL) is then calculated as the difference in welfare from that attained when all customers are on RTP.[30]

Table 3 shows that welfare increases by $700 per hour if a third of the customers adopt RTP and by $1,936 per hour (or $17.0 million per year) if all customers adopt. To put these numbers in perspective, the entire wholesale energy market would be worth $7 billion per year. Thus, the welfare increase (avoided deadweight loss) is only 0.24% of the wholesale energy bill as all customers adopt RTP. These short-run welfare benefits are modest.

To analyze changes in consumer surplus, we separately analyze changes to customers on flat rates and on RTP. Since the numbers of customers on RTP and flat rates are changing as more customers adopt RTP, the consumer surplus

29. Since the flat rate is approximately $67 when no customers are on RTP, our measures of consumer surplus are the change in surplus from a price of $67.

30. Although Borenstein and Holland show that welfare does not necessarily increase monotonically as more customers adopt RTP, they argue that the conditions under which welfare could actually decrease are fairly unusual. We find here that welfare does indeed increase monotonically as more customers adopt RTP, even with finer increments to α than reported here.

measures in Table 3 show both the consumer surplus of all customers on RTP (or on flat rates) as well as the consumer surplus per "customer" on RTP (or on flat rates). The per-customer measures assume a hypothetical customer with 0.002% of the total load. This hypothetical customer would be very large with approximately 500 kW of peak demand.

Comparing the per-customer results shows that customers obtain higher surplus on RTP than on flat rates. This difference in surplus (less any switching or additional metering costs) is the surplus gain of the marginal RTP adopter. Since the difference is declining slightly (from \$0.09 per hour to \$0.03) as more customers adopt RTP, the incentive to adopt RTP, which is relatively small, is decreasing in α.

Adopting RTP may be costly for some customers. As a sensitivity analysis, we assume that RTP adoption will cost between one and ten cents per hour.[31] In contrast, the potential benefits of adopting RTP are between nine and 41 cents per hour for our customer (see Table 3). However, the *incremental* benefits of adopting, as opposed to staying on a flat rate, are between three and nine cents. Therefore, a simple benefit-cost analysis argues that customers in our simulation are likely to adopt, but only if costs are less than three cents per hour.

Table 3 also shows a free-rider effect of RTP adoption. If a customer adopts RTP along with all other customers, he would gain \$0.41 per hour. However, if all other customers (except himself) adopt RTP, he would capture 93% of the benefits (\$0.38) without incurring any additional costs. This free-rider effect, together with the modest benefits and weak incentive to adopt, may help explain the ambivalence of many customers toward RTP.

As more customers adopt RTP, the surplus per RTP customer is increasing (from \$0.09 per hour to \$0.41). This implies that an existing RTP customer is made better off by more customers adopting RTP. Thus, RTP adoption has a positive effect on existing RTP customers. Similarly, since surplus per flat-rate customer is increasing in α, RTP adoption has a positive impact on existing flat-rate customers. However, generator profits are decreasing as more customers adopt RTP, so adoption has a negative effect on generators. On net, our simulations find that RTP adoption has a negative impact on other customers and firms.[32]

4.3 Environmental Effects of RTP Adoption

Since RTP would alter the electricity consumption patterns and electricity generation technologies used, RTP would also change the emissions of a variety of pollutants. This change in emissions will depend on the relative emissions

31. We thank an anonymous referee for suggesting this range of costs.

32. Borenstein and Holland show that in the long run RTP adoption has a negative pecuniary externality on existing RTP customers, but a positive externality on existing flat-rate customers. Since producer surplus is unchanged in the long run, the externality can be either positive or negative.

Table 4. Environmental Effects of RTP Adoption

Panel A: All fossil hourly emissions

Percent of customers on Hourly Rates (α)	Fossil supply	SO_2	NO_x	CO_2
0%	18,144	294,109	174,512	74,995
33%	0.00%	0.00%	0.00%	0.00%
67%	0.07%	0.39%	0.14%	-0.08%
100%	0.13%	0.75%	0.26%	-0.16%

Panel B: Coal-fired hourly emissions

α	Supply	SO_2	NO_x	CO_2
0%	15,926	293,256	162,915	64,670
100%	0.93%	1.28%	1.33%	1.29%

Panel C: Oil-fired hourly emissions

α	Supply	SO_2	NO_x	CO_2
0%	345	768	4,857	2,971
100%	-9.19%	-13.08%	-17.89%	-17.94%

Panel D: Gas-fired hourly emissions

α	Supply	SO_2	NO_x	CO_2
0%	1,873	84	6,739	7,354
100%	-3.40%	-5.34%	-6.87%	-5.58%

Note: Emissions of SO_2 and NO_x are in pounds. Emissions of CO_2 are in thousand pounds.

of the different generation technologies used in baseload and peak generation.[33] Figure 1b shows the marginal emissions rates for SO_2 as generation increases to 60,000 MW along the supply curve. The emissions rates have high variance both within and across fuel types and are not highly correlated with marginal cost. Thus, we cannot simply predict the effect of RTP adoption on emissions from the marginal emissions rates. Instead, we use the model to simulate changes in emissions of three pollutants: SO_2, NO_x and CO_2.[34, 35]

Since RTP adoption leads to an increase in average hourly load, emissions would increase if emissions were constant per MWh. However, Table 4 shows that only SO_2 and NO_x emissions increase as more customers adopt RTP, while CO_2 emissions actually decrease.[36] SO_2 emissions increase by 0.75% if all

33. Some customers may respond to real-time prices by utilizing installed backup generation, which may have different emissions rates. We do not model backup generation.

34. RTP adoption would also likely affect, for example: emissions of other pollutants, timing of emissions, use of rivers and dams, generation of nuclear waste, and siting of new capacity. These additional environmental effects are potential issues to be addressed in future work.

35. Some pollutants may be subject to cap-and-trade regulation, which we do not model. Under CAT regulation, predicted increases in emissions would actually be increases in demand for permits. Furthermore, there may be regional environmental effects.

36. Holland and Mansur (2004) estimate the environmental effects of RTP from a reduction in demand variance. Their econometric estimates show for PJM that emissions of NO_x and CO_2 decrease but the change in SO_2 emissions is not significant. The results here differ since average load (and therefore emissions) increases.

customers adopted RTP even though fossil supply would increase by only 0.13%. This occurs because SO_2 emissions *rates* are increasing (from an average of 16.21 to 16.36 lbs per MW of supply) as more customers adopt RTP. Similarly, NO_x emissions rates increase with RTP adoption, and CO_2 emissions rates decrease.

To understand the differential effects on SO_2, NO_x, and CO_2 emissions, we separately analyze the emissions from coal-, oil-, and gas-fired generation in Panels B, C, & D of Table 4. The coal-fired units are primarily for baseload generation, and hence their emissions of all three pollutants increase with RTP adoption. That the percentage increase in emissions for each pollutant is greater than the percentage increase in supply indicates that RTP adoption leads to a shift in coal-fired generation toward relatively dirtier plants.

Although the supply of oil- and gas-fired generation decreased by nine and three percent, respectively, if all customers were to adopt RTP, the corresponding decreases in emissions are even larger: 13%-18% for oil-fired emissions and five to seven percent for gas-fired emissions. The greater percentage decreases in emissions than in supply indicates that RTP adoption shifts generation away from the dirtier oil- and gas-fired units.

Since emissions of all three pollutants are increasing from coal-fired units but decreasing from oil- and gas-fired units, the net effect for each pollutant depends on the relative emissions from the different types of units. Although coal accounts for 88% of fossil supply, it accounts for over 99% of SO_2 emissions and 93% of NO_x emissions. It is not surprising that for these pollutants the increase in emissions from coal-fired generation is larger than the decrease in emissions from other sources. On the other hand, coal-fired generation accounts for a smaller proportion of CO_2 emissions (86%) and the emissions reductions from oil- and gas-fired generation leads to a reduction in total emissions of CO_2.[37]

4.4 Discussion

To test the sensitivity of our results to the various parameter assumptions, we analyze alternative, reasonable parameter assumptions in the appendix. First, the model depends on the distribution of demands. We test the sensitivity of our model to the assumptions about demand shifters and then to the assumptions about demand elasticities. Next we allow for elastic import supply and simulate random outages at generators instead of simply derating capacity by the expected outage factor. Finally, demand elasticities are allowed to vary by time of use, and heterogeneous customers are modeled with different load profiles.

The results are robust to varying these assumptions. In particular, load and price distributions are compressed, average load increases, average price decreases, profits decrease, welfare increases, SO_2 and NO_x emissions increase and

37. To understand this result, note that coal units are on average more efficient (have lower heat rates) than the other fossil units. The upper tail of coal units also has lower CO_2 emissions per MWh than the upper tail of oil units.

CO_2 emissions decrease.[38] Shifting demand to the right increases average load and prices and increases the benefit of RTP adoption but the percentage changes are not dramatically different. Increasing the demand elasticity causes RTP adoption to have stronger effects. In particular, the efficiency benefit as a percentage of the energy bill doubles when the demand elasticity doubles. Increasing the import elasticity is similar to increasing the demand elasticity. Explicitly modeling random outages in a Monte Carlo simulation (instead of simply derating capacity) has little effect on the results. Allowing different peak and off-peak elasticities has little effect on the results except as noted in footnote 38. Finally, modeling heterogeneous customers shows slightly larger effects when the load of customers who adopt RTP covaries more strongly with system load. However, these customers most likely would not be the first to adopt RTP since they benefit from a cross subsidy under flat rates.

The model described above cannot capture all the intricacies of the actual PJM electricity market. In particular, market power and metering costs are important features of the market which likely would be affected by RTP adoption.[39] Market power has been shown to be a substantial concern in restructured electricity markets including PJM.[40] This problem is exacerbated by the inelasticity of wholesale demand.[41] Incorporating market power in this analysis would likely strengthen our results. First, the efficiency gains from RTP adoption would likely be greater since the gains from eliminating market power would be in addition to the gains from improved retail pricing. This additional effect might make RTP adoption more attractive to customers than is estimated by our model. Second, the losses to generators exercising market power would be even greater than the losses estimated here since generators would also lose some rents from market power.

Metering costs would affect the proportion of customers adopting RTP. If metering and switching costs are insignificant, all competitive customers would adopt RTP. Conversely, if metering costs are excessive no competitive customers would adopt RTP. Borenstein, Jaske, and Rosenfeld (2002) argue that real-time metering costs are not excessive, especially for large industrial customers. While real-time metering costs may be large for residential customers, economies of scale from automated meter reading may lead to modest real-time metering costs even for residential customers. Switching costs, however, could be substantial, see Price (2004).

38. The only exception is that in one simulation with elastic peak demand and inelastic off-peak demand average load decreased and NO_x emissions decreased.

39. The assumptions of zero cross-price elasticities and of homogeneous customers, common in electricity policy analysis, are unlikely to affect the analysis substantially. See Borenstein and Holland. In addition, we do not explicitly model the political economy, behavioral aspects and dynamics of RTP adoption.

40. See, for example, Borenstein, Bushnell and Wolak (2002), Joskow and Kahn (2002) and Mansur (forthcoming).

41. Borenstein *et al.* (2002) argue that RTP adoption would lessen the inefficiencies of market power. This has been supported by simulations, Bushnell (2005), and experiments, Rassenti *et al.* (2003).

5. VARYING FLAT RATES BY MONTH AND BY TIME OF USE

The baseline simulation presented above assumes that retail electricity rates are set once a year and then remain fixed for the entire year. In regulated markets, retail rates are generally fixed for substantial periods of time and are only adjusted following rate cases or special requests to the regulators. During the transition period in California and in other restructuring markets, retail electricity rates have been capped for extended periods of time.[42] Even in competitive retail markets such as the UK, there are sometimes limits on how frequently the retail rates can change (Price 2004). Despite the fact that retail rates often do not vary monthly, there is no technological reason that rates cannot vary as often as meters are read. In fact, flat rates have varied more frequently in San Diego, New York, New England, and Ontario, for example.[43]

Another dimension along which electricity rates have sometimes varied is by time of use (TOU). Typically, three to four different rates might apply throughout the year depending on season and time of use. For example, a current program by one utility in PJM (PPL Electric Utilities) has three rates: a winter rate from October to May, a summer peak rate on weekdays from noon to seven PM, and a summer off-peak rate. In this section, we estimate the gains from allowing the flat retail rates to vary by month or by time of use for the above TOU program.

Allowing flat rates to vary by month or by time of use will have benefits if load and/or wholesale prices are correlated with months or time of use. Monthly correlation could be due to seasonal effects or to changes in input costs. TOU correlation could additionally capture changes in demand throughout the day. In fact, only a small share of the variations in load and price can be explained by either monthly or TOU variation.[44] This weak correlation suggests that varying flat rates by month or by time of use would not yield large benefits.

The simulation results with flat rate variation by month and by time of use are presented in Table 5. The table presents the annual fixed rate baseline with no customers on RTP and compares that with annual fixed TOU rates for all customers from the PPL program, monthly fixed rates, and 100% RTP adoption (*i.e.*, the efficient allocation).

Table 5 shows that flat rate variation by month or TOU has effects similar to RTP adoption even if no customers are on real-time prices. In particular, the distributions of load and prices are compressed, and the price cap is not binding in any hour when flat rates vary by month or TOU. As with RTP adoption, profits for all fossil generators decrease with flat rate variation by month or TOU.

42. In California, capped retail rates were not indexed to input costs and were to remain in effect until stranded costs were recovered.

43. Reiss and White (2003) and Bushnell and Mansur (2005) find significant customer response to the price variation in San Diego. After a period of varying rates, the rates in San Diego were set again at the frozen retail rate.

44. Regressing load on 24 month dummies has an R^2 of 0.25. This means that only 25% of the variation in load can be explained by differences across months. Similarly months only explain 7% of the price variation. Regressing load (price) on six TOU dummies has an R^2 of 0.24 (0.11).

Table 5. Effects of TOU and Monthly Flat Rate Variation

Panel A: Hourly load in MW				
Fixed rates	Mean	std. dev.	min	max
Annual	29,901	5,923	17,820	52,183
TOU	29,921	5,850	17,893	51,572
Monthly	29,927	5,836	17,874	51,743
100% RTP	29,954	5,629	18,083	50,143
Panel B: Hourly real-time prices				
Fixed rates	Mean	std. dev.	min	max
Annual	\$65.20	\$17.89	\$54.91	\$1,039.00
TOU	\$65.01	\$10.15	\$54.91	\$175.80
Monthly	\$64.99	\$9.92	\$54.92	\$169.56
100% RTP	\$64.84	\$9.11	\$55.27	\$151.39
Panel C: Average hourly operating profit				
Fixed rates	Fossil	Coal	Oil	Gas
Annual	\$164,967	\$147,225	\$4,055	\$13,688
TOU	\$156,187	\$143,664	\$2,296	\$10,227
Monthly	\$155,558	\$143,145	\$2,198	\$10,214
100% RTP	\$150,840	\$140,173	\$1,658	\$9,008
Panel D: Welfare				
Fixed rates	DWL	DWL as pct of energy bill	Lost CS	Lost CS as pct of energy bill
Annual	\$1,936	0.24%	\$20,451	2.55%
TOU	\$1,644	0.21%	\$9,154	1.17%
Monthly	\$1,329	0.17%	\$7,822	1.00%
100% RTP	\$0	0.00%	\$0	0.00%

Flat rate variation by month or TOU does capture a significant proportion of the efficiency gains of time-varying prices. Panel D of Table 5 shows that approximately 15% of the deadweight loss is eliminated by putting all customers on TOU rates (from \$1,936 per hour DWL to \$1,644). More surprising though, fully 30% of the deadweight loss is eliminated by allowing flat rates to vary monthly. This is equivalent to putting a third of customers on RTP when the remaining customers are on an annual flat rate. Similarly, a large proportion of the lost consumer surplus is attained simply by allowing flat retail rates to vary monthly. Thus, despite the low explanatory power of months or time of use, allowing flat rates to vary by TOU captures a reasonable proportion of the efficiency gains. Allowing flat rates to vary monthly captures a larger proportion of the efficiency gains than TOU and could be implemented with traditional meters.

6. CONCLUSION

Despite well-understood theoretical efficiency gains, real-time pricing has been plagued by a lack of enthusiasm on the part of many policy makers.

This work analyzes the effects of time-varying prices on market participants, efficiency, and the environment.

We apply a model of RTP adoption in competitive markets to the PJM electricity market. Consistent with theory, RTP adoption compresses the distributions of load and wholesale prices, *i.e.*, maximums decrease, minimums increase and variances decrease. Moreover, average loads increase and all rates decrease on average. The decrease in maximum prices is noteworthy since much concern has been expressed about exposing unsuspecting customers to extreme price variation. We find that with only a third of customers on RTP, the maximum price drops from the price cap to only $164 per MWh. Thus having a few customers on RTP insulates the market from extreme price swings.

The change in the distribution of load from RTP adoption is reflected in the shifts in supply: coal-fired, baseload generation increases while oil- and gas-fired, peak-load generation decreases. The changes in the price and load distributions also affect operating profits. Despite the fact that generation from coal-fired units is increasing, the effect of the falling average price is stronger, and coal-fired operating profits drop by five percent in our baseline. Operating profits decline more sharply for the other fossil generators—up to 60% for oil-fired generators and 35% for gas-fired generators—since generation as well as prices decrease with RTP adoption. These decreases in short-run operating profits may explain some of the resistance to RTP adoption.

The welfare increase is only 0.24% of the wholesale energy bill if all customers adopt RTP. This short-run welfare benefit is modest. For the same demand elasticity, Borenstein and Holland find long-run welfare benefits of RTP adoption that range from three percent to 11% of the total energy bill. This suggests that a large proportion of the benefits of RTP adoption occur from avoiding unnecessary construction of additional generating units.[45]

All consumers, *i.e.*, those already on RTP, those on flat rates and those who switch, benefit from RTP adoption. The gains in consumer surplus are large enough to offset the lost generator profits so efficiency increases with RTP adoption. However, the consumer surplus gains are relatively small, approximately 2.5% of the energy bill in our baseline. The estimated incentive to adopt RTP is also not large. The consumer surplus gains of switching to RTP are declining as more customers adopt. For our hypothetical (very) large customer, the maximum surplus gain is $0.09 per hour or about $800 per year. In addition, by free riding on the RTP adoption of other customers, a customer can attain up to 90% of the benefit of RTP adoption without incurring any additional metering costs. The modest short-run gains, their dispersion across many customers, and free riding may explain the ambivalence of many customers toward RTP adoption.

The environmental effects of RTP adoption studied here depend on the relative emissions of the available generation technologies. In aggregate, we find that SO_2 and NO_x emissions increase with RTP adoption, but that CO_2 emissions

45. Additional benefits of RTP may come from avoiding unnecessary construction of transmission, although we know of no studies quantifying these benefits.

decrease. Comparing changes in emissions with changes in generation shows that RTP shifts generation toward dirtier coal-fired generators but away from dirtier oil- and gas-fired generators. Since coal-fired generation increases with RTP adoption, emissions of all pollutants also increase from coal-fired generation. However, RTP adoption reduces emissions from high-cost oil- and gas-fired generators. Since coal-fired generation accounts for a very large proportion of SO_2 and NO_x emissions, the emissions increases from coal-fired generators offset the reductions from other generators, and net emissions increase. With CO_2, coal-fired generators account for a smaller proportion of total emissions, and thus the decreased emissions from oil- and gas-fired generators offset the increased emissions from coal-fired generators for a net reduction.

Although the simulations do show an efficiency increase from RTP adoption, this must be compared against any additional costs of installing metering equipment. On the other hand, flat retail rates could be adjusted monthly without requiring any additional technology. Our simulations show that varying flat rates monthly has similar effects on load, prices, surplus, profits, efficiency, and emissions as real-time pricing. In fact, we find that approximately a third of the efficiency gains from real-time pricing can be captured by simply varying flat retail rates monthly. This benefit is larger than the gains from putting all customers on TOU rates and is approximately the same as putting a third of customers on RTP while the other customers are on annual flat rates but does not require additional metering technology.

Capturing some of the benefits of RTP adoption through monthly variation in flat rates maintains the insurance features of flat rates. Flat rates protect customers against "accidental" consumption during extremely high-priced periods. Monthly variation in flat rates would maintain some of this insurance but at a lower efficiency cost.

The benefits of monthly variation in flat rates depend on customers being able to observe, and respond to, changing rates (though to a lesser degree than with RTP). Bushnell and Mansur (2005) find evidence that customers facing this type of billing in San Diego responded more to the previous month's bill than to current price information. However, customer response is likely to improve over time as customers adapt to new billing structures.

Although our simulation model only analyzes the PJM electricity market, the results would be similar for other regions with similar generation portfolios. From theory, RTP adoption will improve welfare and will compress the distributions of loads and prices. It is also likely that RTP adoption will decrease average prices, although whether average load would increase or decrease in a given region is unclear. Generator profits will likely decrease in other regions, however, the precise decomposition of the lost profits is uncertain. Furthermore, consumer surplus gains in other regions will probably be a small proportion of the energy bill for most customers at least in the short run. However, the environmental effects, which depend on the emissions rates of the generation technologies, most likely will vary across different regions.

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APPENDIX

A.1. Demand Shift Calibration

The baseline simulation calibrates the demand shift factor for each hour based on the observed hourly load and the average retail price of $79. We test the model by assuming the average retail price is $5 lower and $5 higher. Assuming a lower initial energy price of $25, instead of $30, would be the same as decreasing the demand shift factor for each period since the observed load is assumed to result from a lower price. Conversely, assuming a $35 initial energy price calibrates the hourly demand shift factors at higher levels. Intuitively, increases in demand will increase prices and loads and also increase the benefits from RTP adoption because more hours intersect the supply curve on its inelastic portion.

Table A.1. presents simulation results from calibrating the demand shifters from initial energy prices of $25 (Shift 25) and $35 (Shift 35) and compares them to the baseline discussed above. The table shows the results from the simulations when no customers are on RTP, and the percentage change column indicates the change when all customers adopt RTP. Panel A of Table A.1. shows the effects on load of RTP adoption. The distribution of demand is compressed in all three simulations, *i.e.*, the maximum decreases, the minimum increases and the standard deviation decreases. Note that the mean, minimum and maximum loads are all higher for the higher demand shifter. However, the percentage changes in these parameters from 100% RTP adoption are quite similar across the three simulations.

Panel B of Table A.1. shows that the distribution of prices is also compressed with RTP adoption for each of the simulations. For the higher demand simulation, the prices are higher and the reduction in average price is greater with RTP adoption (0.61% versus 0.28%) since more hours occur on the inelastic portion of the supply curve. The reduction in the variance of prices from RTP adoption is larger in the two higher demand simulations since the price cap is binding for some periods but is never binding for the low demand simulation.

Panel C of Table A.1. shows the effects on profits of RTP adoption. For each of the demand shift assumptions, profits decrease for each type of fossil-fired generation. Profits decrease quite precipitously for oil- and gas-fired generation (up to 60%) but this reflects the fact that these profits were inflated by the hours in which the price cap was binding.

Thus far, the major differences between the simulations with different demand shifters have hinged on whether or not the price cap was binding. Since clearing the market by a non-market mechanism (the price cap) represents a shift in surplus from consumers to producers, we would not expect efficiency differences if the price cap is or is not binding. Panel D of Table A.1. shows that the avoided deadweight loss is quite robust to the demand shift assumption, with approximate efficiency gains of 0.25% of the energy bill for each simulation.

Panel E of Table A.1. shows that the changes in emissions are quite robust to the demand shift assumptions. Namely, SO_2 and NO_x emissions increase with RTP adoption, but CO_2 emissions decrease.

Table A.1. Effects of Changing Demand Shift Calibration

Panel A: Hourly load in MW

	Mean	% change	std. dev.	% change	min	% change	Max	% change
Shift 25	29,733	0.13%	5,890	-4.95%	17,730	1.33%	52,004	-4.10%
Baseline	29,901	0.18%	5,923	-4.96%	17,820	1.48%	52,183	-3.91%
Shift 35	30,071	0.19%	5,956	-5.00%	17,917	1.54%	52,184	-3.50%

Panel B: Hourly real-time prices

	Mean	% change	std. dev.	% change	min	% change	Max	% change
Shift 25	$64.77	-0.28%	$10.09	-11.60%	$55	0.69%	$170	-11.14%
Baseline	$65.20	-0.55%	$17.89	-49.08%	$55	0.66%	$1,039	-85.43%
Shift 35	$65.48	-0.61%	$19.41	-52.24%	$55	0.66%	$1,039	-85.43%

Panel C: Average hourly operating profit

	Fossil	% change	Coal	% change	Oil	% change	Gas	% change
Shift 25	$151,900	-4.12%	$139,390	-2.63%	$2,308	-34.79%	$10,202	-17.51%
Baseline	$164,967	-8.56%	$147,225	-4.79%	$4,055	-59.10%	$13,688	-34.19%
Shift 35	$171,900	-9.38%	$152,207	-5.14%	$4,621	-60.96%	$15,072	-36.42%

Panel D: Surplus

	DWL	DWL as pct of energy bill	ACS	ACS as pct of energy bill
Shift 25	$1,856	0.24%	$10,362	1.33%
Baseline	$1,936	0.24%	$20,451	2.55%
Shift 35	$2,004	0.25%	$23,004	2.82%

Panel E: Emissions

	SO_2	% change	NO_x	% change	CO_2	% change
Shift 25	291,491	1.14%	172,386	0.39%	73,950	-0.24%
Baseline	294,109	1.24%	174,512	0.48%	74,995	-0.15%
Shift 35	296,695	1.28%	176,643	0.50%	76,061	-0.16%

Note: "Shift 25" refers to an initial energy price of $25, and "Shift 35" refers to an initial energy price of $35. The baseline uses an initial energy price of $30.

Note: The values in the "levels" columns, e.g., "Mean", are from the simulation with no customers on RTP. The values in the "% change" columns show how the preceding statistic changes when all customers adopt RTP.

Table A.2. Effects of Changing Demand Elasticity

Panel A: Hourly load in MW

	Mean	% change	std. dev.	% change	min	% change	max	% change
Elast .05	29,663	0.06%	5,881	-2.59%	17,670	0.56%	52,027	-2.31%
Baseline	29,901	0.18%	5,923	-4.96%	17,820	1.48%	52,183	-3.91%
Elast .2	30,351	0.42%	6,005	-9.39%	17,977	3.94%	52,184	-5.88%

Panel B: Hourly real-time prices

	Mean	% change	std. dev.	% change	min	% change	max	% change
Elast .05	$64.72	-0.15%	$10.13	-6.12%	$55	0.07%	$170	-9.23%
Baseline	$65.20	-0.55%	$17.89	-49.08%	$55	0.66%	$1,039	-85.43%
Elast .2	$65.80	-0.74%	$19.47	-56.24%	$55	0.73%	$1,039	-87.14%

Panel C: Average hourly operating profit

	Fossil	% change	Coal	% change	Oil	% change	Gas	% change
Elast .05	$150,866	-2.30%	$138,477	-1.42%	$2,290	-20.00%	$10,099	-10.24%
Baseline	$164,967	-8.56%	$147,225	-4.79%	$4,055	-59.10%	$13,688	-34.19%
Elast .2	$178,867	-11.26%	$157,976	-6.22%	$4,873	-70.46%	$16,018	-43.02%

Panel D: Surplus

	DWL	DWL as pct of energy bill	ACS	ACS as pct of energy bill
Elast .05	$983	0.13%	$5,664	0.73%
Baseline	$1,936	0.24%	$20,451	2.55%
Elast .2	$3,714	0.45%	$29,896	3.59%

Panel E: Emissions

	SO_2	% change	NO_X	% change	CO_2	% change
Elast .05	290,458	0.57%	171,563	0.18%	73,558	-0.16%
Baseline	294,109	1.24%	174,512	0.48%	74,995	-0.15%
Elast .2	300,769	2.46%	180,134	1.04%	77,798	-0.12%

Note: "Elast .05" refers to an assumed demand elasticity of 0.05, and "Elast .2" refers to an assumed demand elasticity of 0.2. The baseline has an assumed demand elasticity of 0.1.

Note: The values in the "levels" columns, e.g., "Mean", are from the simulation with no customers on RTP. The values in the "% change" columns show how the preceding statistic changes when all customers adopt RTP.

A.2. Demand Elasticities

Table A.2. presents the analysis of three different demand elasticity assumptions: elasticities of 0.05, 0.1 (the baseline scenario), and 0.2.[46] As above, the table shows the results from the simulations when no customers are on RTP and the percentage change that results when all customers adopt RTP. A higher elasticity assumption has two effects. First, since equilibrium prices are on average lower, more elastic demand generally increases demand. Second, more elastic demand has

46. Estimates of demand elasticities vary greatly. This range is generally viewed as plausible. For example, Borenstein and Holland use long-run elasticities of 0.1, 0.3, and 0.5.

greater price response and, hence, greater potential benefits from RTP adoption.

Panels A & B of Table A.2. show that the distributions of load and price are compressed by RTP adoption in all the simulations. The decreases in the standard deviation show that the distributions are compressed more with RTP adoption for higher demand elasticities. The average price and load are higher for more elastic demand, which reflects the increased demand which results from the higher demand elasticity.

Panels C & D of Table A.2. show the effects on surplus. Profits decrease with RTP adoption for all types of fossil generation for each elasticity assumption. Declines are larger for more elastic demand and, as above, are largest for oil-fired generation. With more elastic demand, the efficiency gains are larger (here up to 0.45% of the energy bill) and consumer surplus gains are also larger.

Panel E of Table A.2. shows that the changes in emissions are robust to the demand elasticity assumption: namely, emissions of SO_2 and NO_x increase but CO_2 emissions decrease with RTP adoption with larger changes for more elastic demand.

A.3. Elastic Import Supply

On average imports/exports are negligible, accounting for less than 0.1% of the average load of approximately 30,000 MW. However, during the sample period imports ranged from imports of over 18,000 MW to exports of almost 6,000 MW. In this section, we compare the baseline, which has perfectly inelastic import supply, with two different assumptions about the import supply elasticity.

We define an import supply curve based on the historical prices and an assumed slope. We assume that imports are positive above the historical price and negative below it, *i.e.*, exports are positive below the historical price. The import supply elasticity for each hour is either 856/ or 428/. The coefficient of 856 is used in Mansur (forthcoming), but represents a high value, so we compare the results with half this value, *i.e.*, a slope of 428. The assumed functional form allows for a very elastic import supply at small quantities, but very inelastic supply at large quantities. The import surplus is then found by integrating under the import supply curve.[47]

Table A.3. presents the simulation results from increasing the import supply elasticity. Panels A & B show that RTP adoption compresses the load and price distributions with greater decreases in price variance for more elastic import supply. Panel C shows that operating profit for all types of fossil-fired generation decreases with RTP adoption with the greatest decreases for oil-fired generation. Efficiency gains from RTP adoption are slightly smaller for more elastic import supply assumptions. This obtains because more imports mean that the equilibrium is on the steep portion of the fossil supply curve in fewer hours. Panel E shows

47. Alternatively, we could have used the historical imports and historical price together with an elasticity to define the import supply curve. Under this assumption, several hours would have implied non-PJM autarky prices greater than $999, which would require several additional assumptions.

Table A.3. Effects of Changing Import Elasticity

Panel A: Hourly load in MW

	Mean	% change	std. dev.	% change	min	% change	max	% change
Baseline	29,901	0.18%	5,923	-4.96%	17,820	1.48%	52,183	-3.91%
Imp 428	29,897	0.20%	5,921	-4.99%	17,815	1.56%	51,362	-2.90%
Imp 856	29,883	0.26%	5,916	-4.97%	17,799	1.74%	51,225	-3.06%

Panel B: Hourly real-time prices

	Mean	% change	std. dev.	% change	min	% change	max	% change
Baseline	$65.20	-0.55%	$17.89	-49.08%	$55	0.66%	$1,039	-85.43%
Imp 428	$65.21	-0.71%	$20.67	-56.27%	$54	0.84%	$1,039	-85.54%
Imp 856	$65.35	-1.04%	$26.34	-65.79%	$48	0.00%	$1,039	-85.82%

Panel C: Average hourly operating profit

	Fossil	% change	Coal	% change	Oil	% change	Gas	% change
Baseline	$164,967	-8.56%	$147,225	-4.79%	$4,055	-59.10%	$13,688	-34.19%
Imp 428	$168,033	-10.97%	$147,654	-6.06%	$4,945	-65.80%	$15,434	-40.38%
Imp 856	$176,868	-15.92%	$150,723	-8.76%	$6,949	-74.81%	$19,196	-50.83%

Panel D: Surplus

	DWL	DWL as pct of energy bill	ΔCS	ΔCS as pct of energy bill
Baseline	$1,936	0.24%	$20,451	2.55%
Imp 428	$1,776	0.22%	$25,684	3.20%
Imp 856	$1,367	0.17%	$37,462	4.61%

Panel E: Emissions

	SO_2	% change	NO_X	% change	CO_2	% change
Baseline	294,109	1.24%	174,512	0.48%	74,995	-0.15%
Imp 428	292,223	1.26%	173,584	0.49%	74,624	-0.15%
Imp 856	290,407	1.31%	172,677	0.55%	74,261	-0.06%

Note: The baseline has perfectly inelastic import supply. "Imp 428" refers to an assumed import supply elasticity of 428/Q, and "Imp 856" refers to an import supply elasticity of 856/Q.

Note: The values in the "levels" columns, e.g., "Mean", are from the simulation with no customers on RTP. The values in the "% change" columns show how the preceding statistic changes when all customers adopt RTP.

that the changes in emissions are robust to various assumptions about import supply elasticity.

A.4. Random Outages

Generators are subject to random outages due to a variety of technical failures. When such outages occur, electricity generation from the unit typically ceases until the malfunction can be corrected and the generator returned to synchronization with the grid. To account for random outages, the baseline simulation derates each unit's capacity by its expected outage factor. If the relationship between generation and welfare is sufficiently concave (convex), then Jensen's Inequality says that the welfare at the average generation level is greater (less) than the average welfare. To test whether this relationship is sufficiently concave or convex, we simulate random outages.

A Monte Carlo simulation focuses on July 1998, one of the months with the highest prices. Each unit either generates or not based on a three hundred random draws. We then use the resulting supply curve to calculate an equilibrium in the 300 wholesale markets. The equilibrium flat rate, which yields zero profits across the 300 markets, can be interpreted as the flat rate with zero expected profits.

Table A.4. presents the random-outage simulation results and compares them with the July 1998 results from the baseline. The results are remarkably similar. The main differences stem from the fact that the price cap is binding in

Table A.4. Random Outage Simulation for July 1998

Panel A: Hourly load in MW

	Mean	% change	std. dev.	% change	min	% change	max	% change
Baseline	33,365	0.08%	7,026	-4.52%	19,630	1.99%	49,208	-2.37%
Random Outages	33,358	0.10%	7,020	-4.50%	19,626	1.74%	49,198	-1.80%

Panel B: Hourly real-time prices

	Mean	% change	std. dev.	% change	min	% change	max	% change
Baseline	\$66.41	-0.11%	\$7.29	-6.31%	\$56	0.02%	\$89	-3.43%
Random Outages	\$66.47	-0.17%	\$9.63	-28.35%	\$56	0.14%	\$1,039	-90.64%

Panel C: Average hourly operating profit

	Fossil	% change	Coal	% change	Oil	% change	Gas	% change
Baseline	\$210,790	-2.15%	\$186,603	-0.92%	\$3,892	-17.84%	\$20,295	-10.39%
Random Outages	\$212,397	-2.78%	\$186,965	-1.18%	\$4,309	-23.56%	\$21,123	-12.72%

Panel D: Surplus

	DWL	DWL as pct of energy bill	ΔCS	ΔCS as pct of energy bill
Baseline	\$1,230	0.13%	\$6,670	0.72%
Random Outages	\$1,263	0.14%	\$10,530	1.13%

Panel E: Emissions

	SO_2	% change	NO_X	% change	CO_2	% change
Baseline	335,903	0.91%	216,673	-0.11%	97,482	-0.84%
Random Outages	335,507	0.90%	216,802	-0.19%	97,624	-0.90%

Note: "Baseline" here refers to the equilibrium for just July 1998. "Random Outages" refers to the Monte Carlo simulation.

Note: The values in the "levels" columns, e.g., "Mean", are from the simulation with no customers on RTP. The values in the "% change" columns show how the preceding statistic changes when all customers adopt RTP.

several of the draws of the random outage simulation whereas it never binds in this month for the baseline simulation. The binding price cap leads the prices to have a larger standard deviation and maximum and larger declines in both with RTP adoption. It also implies that consumer surplus gains are larger. Despite this difference, the simulation is remarkably robust to modeling random outages. In particular, the efficiency gains of RTP adoption (0.13% and 0.14% of the energy bill) are virtually identical.

A.5. Different Peak and Off-peak Elasticities

Taylor *et al.* (2005) estimate that demand elasticities are larger in peak periods than in off-peak periods. The baseline simulation assumes that elasticities are identical in all hours. To model differing elasticities, we allow the elasticity to vary across peak and non-peak hours where the peak period is defined according to the PPL Electric Utilities program described in Section 5.

Table A.5. presents the results from varying the demand elasticity. The first row, "0.15 & 0.1," has more elastic peak demand than the baseline and shows more compression of the load distribution on the upper tail. The third row, "0.1 & 0.05," has less elastic non-peak demand than the baseline and thus show less compression of load and prices on the lower tails. Changes in profit are unaffected by changing the elasticities. Like changing demand elasticity overall, surplus increases are greater when demand is more elastic.

The fourth row, "0.15 & 0.05," uses elasticities that approximate the estimates of Taylor *et al.* for industrial customers. These results are similar to the baseline except that average load and NO_x emissions decrease with RTP adoption.

A.6. Heterogeneous Customers

The baseline simulation assumes that RTP adopters do not differ systematically from non-adopters. RTP adopters could differ from non-adopters in a number of dimensions, *e.g.*, scale and elasticity. If customers do not differ, then there is no cross-subsidization in a flat rate system. However, if a customer's load covaries less strongly with the system load (*i.e.*, if the customer has a flatter load profile), then the customer pays a subsidy through the flat rate system to customers with peakier load profiles. Therefore, customers with flatter load profiles would likely adopt RTP first to avoid subsidizing other customers.

To model customers with different load profiles, we define a customer's β, analogous to the financial β, implicitly by:

$$\frac{l_{it} - \bar{l}_i}{l_i} = \beta_i \frac{L_t - \bar{L}}{L} \tag{3}$$

where l_{it} is customer i's load in hour t, $\bar{l}_{it}$ is customer i's average load, is system load in hour t, and $\bar{L}$ is average system load. Note that if β_i, then customer i's load is a constant fraction of the system load, whereas if β_i is greater (less) than one, then customer i's load is peakier (flatter) than system load.

Table A.6. presents the results of simulations where 50% of customers adopt RTP. In the simulation "Beta 1.1," the adopters have a load that is ten percent more peaky than the system load, and in the "Beta 0.9" simulation, the adopters have a load that is ten percent flatter than the system load. The results show a larger

Table A.5. Effects of Changing Peak and Off-peak Elasticities

Panel A: Hourly load in MW

Peak and Off-Peak Elasticity	Mean	% change	std. dev.	% change	min	% change	max	% change
0.15 & 0.1	29,921	0.14%	5,965	-5.59%	17,815	1.51%	52,184	-5.10%
Baseline	29,901	0.18%	5,923	-4.96%	17,820	1.48%	52,183	-3.91%
0.1 & 0.05	29,681	0.02%	5,924	-3.27%	17,669	0.57%	52,183	-3.91%
0.15 & 0.05	29,704	-0.03%	5,969	-3.94%	17,668	0.57%	52,184	-4.63%

Panel B: Hourly real-time prices

	Mean	% change	std. dev.	% change	min	% change	max	% change
0.15 & 0.1	\$65.29	-0.69%	\$19.36	-53%	\$54.91	0.66%	\$1,039	-85.43%
Baseline	\$65.20	-0.55%	\$17.89	-49%	\$54.91	0.66%	\$1,039	-85.43%
0.1 & 0.05	\$64.95	-0.51%	\$17.84	-47%	\$54.87	0.07%	\$1,039	-85.14%
0.15 & 0.05	\$65.04	-0.65%	\$19.31	-51%	\$54.87	0.07%	\$1,039	-85.14%

Panel C: Average hourly operating profit

	Fossil	% change	Coal	% change	Oil	% change	Gas	% change
0.15 & 0.1	\$168,114	-10%	\$148,806	-6%	\$4,587	-64%	\$14,801	-39%
Baseline	\$164,967	-9%	\$147,225	-5%	\$4,055	-59%	\$13,688	-34%
0.1 & 0.05	\$159,977	-8%	\$142,756	-4%	\$3,985	-54%	\$13,316	-33%
0.15 & 0.05	\$163,268	-10%	\$144,442	-5%	\$4,488	-60%	\$14,418	-38%

Panel D: Surplus

	DWL	DWL as pct of energy bill	ACS	ACS as pct of energy bill
0.15 & 0.1	\$2,111	0.26%	\$24,790	3.08%
Baseline	\$1,936	0.24%	\$20,451	2.55%
0.1 & 0.05	\$1,167	0.15%	\$17,880	2.27%
0.15 & 0.05	\$1,342	0.17%	\$22,435	2.83%

Panel E: Emissions

	SO_2	% change	NO_X	% change	CO_2	% change
0.15 & 0.1	294,169	1.26%	174,859	0.31%	75,227	-0.44%
Baseline	294,109	1.24%	174,512	0.48%	74,995	-0.15%
0.1 & 0.05	290,485	0.59%	171,869	0.01%	73,768	-0.45%
0.15 & 0.05	290,593	0.59%	172,259	-0.19%	74,022	-0.77%

Note: "0.15 & 0.1" refers to a peak elasticity of 0.15 and an off-peak elasticity of 0.1. The baseline has elasticity 0.1 peak and off peak. Other rows defined similarly. The values in the "levels" columns, e.g., "Mean", are from the simulation with no customers on RTP. The values in the "% change" columns show how the preceding statistic changes when all customers adopt RTP.

Table A.6. Analysis of Heterogeneous Customers (With 50% Adoption)

Panel A: Hourly load in MW

	Mean	% change	std. dev.	% change	min	% change	max	% change
Beta 1.1	29,901	0.12%	5,923	-2.56%	17,820	0.87%	52,183	-2.16%
Baseline	29,901	0.12%	5,923	-2.55%	17,820	0.89%	52,183	-2.11%
Beta 0.9	29,901	0.12%	5,923	-2.55%	17,820	0.92%	52,183	-2.05%

Panel B: Hourly real-time prices

	Mean	% change	std. dev.	% change	min	% change	max	% change
Beta 1.1	\$65.20	-0.43%	\$17.89	-46.00%	\$55	0.02%	\$1,039	-85.05%
Baseline	\$65.20	-0.43%	\$17.89	-46.00%	\$55	0.02%	\$1,039	-84.91%
Beta 0.9	\$65.20	-0.43%	\$17.89	-45.95%	\$55	0.02%	\$1,039	-84.84%

Panel C: Average hourly operating profit

	Fossil	% change	Coal	% change	Oil	% change	Gas	% change
Beta 1.1	\$164,967	-6.84%	\$147,225	-3.64%	\$4,055	-50.30%	\$13,688	-28.41%
Baseline	\$164,967	-6.84%	\$147,225	-3.64%	\$4,055	-50.17%	\$13,688	-28.33%
Beta 0.9	\$164,967	-6.83%	\$147,225	-3.65%	\$4,055	-50.05%	\$13,688	-28.25%

Panel D: Surplus

	Efficiency gain	Efficiency gain as pct of energy bill	ACS	ACS as pct of energy bill
Beta 1.1	\$1,037	0.13%	\$15,674	1.96%
Baseline	\$1,031	0.13%	\$15,664	1.96%
Beta 0.9	\$1,024	0.13%	\$15,656	1.95%

Panel E: Emissions

	SO_2	% change	NO_X	% change	CO_2	% change
Beta 1.1	294,109	0.69%	174,512	0.29%	74,995	-0.05%
Baseline	294,109	0.69%	174,512	0.29%	74,995	-0.04%
Beta 0.9	294,109	0.69%	174,512	0.29%	74,995	-0.04%

Note: In the "Beta 1.1" simulation, the 50% of customers who adopt RTP have a load that covaries with the system load with $\beta=1.1$. In the baseline, all customers are homogeneous, i.e., $\beta=1$. In the "Beta 0.9" simulation, the 50% of customers who adopt have $\beta=0.9$.

Note: The values in the "levels" columns, e.g., "Mean", are from the simulation with no customers on RTP. The values in the "% change" columns show how the preceding statistic changes when 50% of customers adopt RTP.

effect of RTP adoption when the adopters' load covaries more strongly with system load. However, the customers with flatter load profiles would be the first adopters under customer choice due to the subsidies inherent in the flat rate system.