Information Feedback Effects on Retail Electricity Markets

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Abstract

Debate persists about the most effective method of introduction and implementation of demand-side management (DSM) programs designed to increase the efficiency of retail electricity markets and better manage cyclical demand. Consumers have also shown aversion to these new programs and a lack of understanding for possible efficiency gains. To further explore the most effective method of DSM implementation, we investigate how differences in information feedback affect consumer demand during a transition phase to a real-time pricing program. In a laboratory setting, we compare the effects of direct and indirect feedback on market efficiency. Using a computer program modeled after the cyclical demand structure found in retail electricity markets, subjects participate in programs reflecting flat rate and real-time pricing programs that offer real-time price feedback. Results indicate that direct feedback does increase market efficiency and lessen aversion to implementation of real-time pricing contracts. Subjects are averse to real-time pricing prior to participation, indicating a need for better communication in order to ease transition for consumers and minimize preemptive complaints.

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I. Introduction

Recent changes in electricity markets have created possibilities for varied retail rate options. The development and installation of smart meters has also allowed utilities and potentially customers to view feedback on electricity consumption possible. Although numerous field studies have proven that the introduction of smart meters and rate changes allow consumers and utilities to save, consumers have issued complaints upon actual implementation. In order to better identify the problems causing complaints and propose more successful methods, we designed a laboratory experiment in order to control for variables that cannot be controlled or observed in field experiments.

Our experiment involves three treatments that examine the impact of feedback issued before transition to new pricing programs. We begin with the traditional flat rate pricing, then offer two types of feedback during flat rate pricing before participants begin a real-time pricing program with direct feedback. We look at the effect of indirect and direct feedback during the transition phase. Indirect feedback describes information on real-time prices offered at the end of the month, and direct feedback describes information on real-time prices offered during the month and at the end of the month. We also administer two questionnaires during the experiment to measure participants' perceptions to the new pricing program before and after implementation.

We find that the new pricing contract, real-time pricing with direct feedback, generates the highest efficiencies. We also find that direct feedback lessens aversion to the new phase, although participants were always somewhat averse to the new contract before implementation. After participation in the new contract, participants preferred real-time pricing the most, showing that these programs may be better received with time. Direct feedback offered during the old pricing contract generated the highest efficiencies on average, suggesting that direct feedback does improve efficiency and that direct feedback should play an important role in these programs.

Our paper is organized as follows. In Section 2, we offer more in-depth analysis of electricity markets and examine other studies that look at the effect of price feedback on demand response. Section 3 presents the design of our experimental treatments and discusses our theoretical predictions. Section 4 offers results on efficiency and questionnaire data obtained from the experiment. Section 5 describes our findings and the results of our hypothesis testing. Section 6 concludes our paper and sums up our results.

II. Background

A. Electricity Markets

Both the deregulation of electricity markets and the updating of electricity grids have led to greater possibilities for electricity markets. With more rate options permitted by Public Utility Commissions and government authorities, utilities can now establish rates that encourage consumers to shift their demand to more effective patterns. Smart meters allow utilities and consumers to receive real-time price and consumption information so that consumers can better react to price changes. Through the relaxing of policy and introduction of new technology, higher market efficiencies can be achieved.

Greater efficiency possibilities have emerged with the updating of electricity grids to the more technologically advanced “smart grid.” Included in these “smart grids” are “smart meters,” or advanced metering infrastructure, that provide utilities with real-time feedback on electricity consumption. This information allows utilities to offer demand-side management (DSM) programs to consumers including retail rates that more accurately reflect wholesale prices. Fluctuating rate structures were not previously available with analog meters that only provided cumulative data collected once a month by meter-readers. By offering rate structures that more closely reflect wholesale prices, consumers are encouraged to reduce their demand during hours when electricity is in high demand. By reducing demand during these hours, efficiency can be increased, and blackouts can be prevented by shifting load that cannot be sustained by generators.

Although smart meters allow utilities to offer varying rate structures, these rate structures would not be viable without the deregulation of electricity markets. Previously, in electricity markets that have not been deregulated, generators and retailers of electricity acted as natural monopolies regulated by state Public Utility Commissions. In these markets, utilities were locked into long-term retail contracts that only allowed them to charge consumers a single, flat rate price for every kilowatt-hour consumed. Utilities also could not measure real-time electricity consumption of individual consumers with analog meters. With these limitations, consumers could not be aware of nor could they respond to changes in fluctuating wholesale costs that reflect the cyclical demand structure for electricity. Providers of electricity also could not compete and reach a competitive equilibrium price that would more accurately reflect the changes taking place in the market.

Due to the cyclical nature of demand for electricity, different generators are needed to supply consumers depending on the time of day. During peak demand hours without demand-side management, utilities may be forced to operate more expensive generators to accommodate higher levels of demand. For a marginal increase in demand, the cost can increase significantly, limiting generators' abilities to recompense losses. These higher costs then must be reflected in retail rates as utilities must pay a higher price to obtain the electricity during peak hours. These cyclical fluctuations can lead to high market inefficiencies as neither consumer nor producer surpluses are maximized—producers experience high costs and consumers experience high prices.

However, more electricity markets are now being deregulated with the technological advancements of the grid. In a deregulated electricity market, the generation, transmission, and distribution sectors of electricity do not operate as natural monopolies and can experience competition. Retail prices can be determined by uniform clearing price auctions, otherwise known as day-ahead or day-of spot markets. With the addition of smart meters that provide real-time information, utilities can offer consumers dynamic prices for electricity that vary depending on the level of demand, better reflecting prices determined by the spot market. Utilities may offer a more expensive rate for periods of peak demand and a reduced rate during non-peak hours in order to reduce the demand and the need to operate the most expensive generators. If the utilities are able to shift demand, then they will have to pay less to obtain electricity from the generators while the consumers can cut expenses by shifting their consumption to non-peak hours. Both consumers and utilities benefit and efficiency is increased.

Despite the efficiency gains projected, in the recent introduction of new programs and technology to deregulated electricity markets, some consumers have questioned whether their electricity bills have increased as a result of these changes (Structure Consulting Group, LLC 2010). If retail prices are determined by spot markets instead of a flat rate structure bound by long-term contracts, then the retail prices will fluctuate more in line with the wholesale market. If consumers participate in a dynamic pricing program and do not shift their demand, then they have to pay the significantly higher price charged during peak hours, thus decreasing their consumer surplus. In some cases, the higher prices paid during peak hours may decrease their surplus more than if they had continued with the flat rate pricing program.

Even if they do not switch to a demand-side management dynamic pricing program, the move from long-term contracts to spot markets means greater market volatility. In theory, these spot markets should increase competitiveness between utilities and lower the price of electricity. However, DSM programs offer more volatile price structures which may alarm consumers. Even if consumers adhere to a flat rate pricing program and do not significantly increase their consumption to account for the change in temperature, they may still see a noticeable increase in price per kwh on their electricity bill. With flat rate pricing, consumers were not able to observe the market volatility or understand that demand for electricity is cyclical. With that knowledge, they may be more alarmed by prices that suddenly spike for periods of high temperature than they would have been by a flat rate price increase. Upon recent implementation of DSM programs, consumers have not been able to easily view their consumption patterns or the prices as they fluctuate based on time of day and consumption. With no additional information feedback accompanying these new fluctuating prices, consumers have in some cases been unaware of the new price structure and cannot react or change consumption accordingly.

Also, the Public Utility Commissions in these deregulated markets have raised the electricity rates to offset the initial costs of implementing the advanced metering infrastructure. Taking into account all of the other factors that also have an effect on the price of electricity such as weather and high levels of consumption, it is possible that electricity rates have, in fact, risen. However, increased competition between retailers and new dynamic rate structures should have resulted in consumer savings. Despite this effort, the complaints by consumers in some areas have been widespread enough to warrant investigations.

Within the CAISO region, the California Public Utilities Commission recently investigated whether PG&E, a California utility, was measuring and billing electric usage accurately. Their report was spurred by multiple complaints and lawsuits against PG&E for skyrocketing electricity bills that began after the implementation of advanced metering infrastructure (Fehrenbacker 2009). Their report revealed that PG&E did not suitably assist consumers in their understanding of hourly usage patterns, and that they did not effectively communicate information about smart meters and the accompanying rate changes. They identified gaps in customer services and processes related to high bill complaints, and determined certain PG&E practices to be partially non-compliant relative to industry best practices (Structure Consulting Group, LLC 2010).

These complaints and the lack of comprehension of electricity demand structures raised the question as to whether the implementation of demand-side management programs does lead to increased consumer surpluses and increased market efficiency. Although demand-side management has proven effective in increasing market efficiency and consumer and producer surpluses in a number of field studies (Hammerstrom 2007, Navalón 2010, Ehrhardt-Martinez 2010), the comprehension problem rivaled whether the information consumers were receiving about these changes was satisfactory in easing the transition and increasing overall efficiency.

In an attempt to create a method of realizing higher efficiencies predicted by field experiments, we take a closer look at the problem of comprehension and implementation. We question whether a transition period easing consumers into these new programs may be beneficial to their understanding and inclination toward demand-side management programs. We postulate that if consumers have a better understanding of the DSM programs before beginning a new contract, then they will contribute to greater market efficiencies and will be less averse to these changes. We examine two types of feedback, direct and indirect, offered to consumers prior to implementation of a specific DSM program, real-time pricing. Direct feedback offers information on prices that would be achieved under a real-time pricing contract both during consumption and at the end of each month, even if the consumer is still participating in a traditional flat rate pricing contract. Indirect feedback offers the same information, but only at the end of the month.

We hypothesize that market efficiency is increased when consumers receive real-time feedback in addition to information they receive on their monthly bill when enrolled in flat rate pricing programs. We also hypothesize that additional real-time price feedback during flat rate pricing programs can ease the transition to a real-time pricing program. Since the cyclical structure of demand for electricity is complex, consumers may not understand the rate changes and will not be able to use DSM to increase their surpluses. Based on the report sanctioned by the California Public Utilities Commission, we hypothesize that market efficiency and consumer surpluses can be increased when consumers receive additional real-time feedback either during consumption or at the end of the month ceteris paribus. Research suggests that additional feedback during consumption can lead to increased market efficiency (Ehrhardt-Martinez et al. 2010). Our research will expand upon this topic and examine how additional price feedback affects consumer decisions in a laboratory setting. The results of this study will allow utilities to inform consumers via communication or their billing in a manner that encourages consumers to manage their electricity demand more effectively. These changes will potentially lead to greater savings for utilities and consumers and greater market efficiency.

B. Literature

The relevance of using controlled laboratory experiments to study resource allocation mechanisms and auction techniques in electricity markets has been addressed for decades in experimental settings (Smith, 1980; Williams, 1980; Weiss, 1999; Nicolaisen, 2001; Rassenti et al. 2002). However, most of the emphasis of these studies has been on increasing efficiency through changes in the supply-side of wholesale electricity markets. Although Rassenti et al. (2002) reviewed the importance of supply-side bidding and altering current wholesale market structure mechanisms, they also point out the importance of using demand-side bidding as an instrument to discipline prices in the hourly spot market. Rassenti et al. (2002) suggest that the effects of demand-side bidding can be used to provide incentives for retail customers to reduce demand or switch their time-of-day consumption from higher to lower cost periods. They compare the previous structure to an airline that would charge all passengers an identical regulated monthly access fee and fixed price per mile travelled regardless of other factors such as destination, flight time, time of seek, season or holidays, and flier's willingness to pay. With this analogy, we might better understand the ineffectiveness of flat rate pricing. While this analogy and analysis is still focused on demand-side bidding in the wholesale market, we can use this theory to better grasp how changes in deregulation can impact possibilities for efficiency gains created by shifts in retail consumers' usage patterns.

Rassenti et al. (2000, 2002) cite how experimental market research has proved that utility demand-side bidding in auction experiments exploring wholesale markets has successfully controlled market power and price spikes. Players in these experiments have consisted of generators and retailers instead of retailers and end-users. Our experiment consists of retailers and end-users with robots acting as retailers and humans acting as end-users. Our laboratory experiment builds on the theory of Rassenti et al. (2000, 2002) by using a computerized retail market structure in which consumer demand is cyclical. Participants select the number of units they wish to purchase in two types of pricing contracts. We propose that when participants are able to receive more information about the structure of demand in the market, overall market efficiency will increase. This laboratory experiment is the first of its kind that examines the effect of feedback on retail electricity markets in transition to a real-time pricing contract.

Numerous field experiments also examine the effect of various demand-side management programs on increasing electricity savings and market efficiency. Many focus on the role of feedback and price information in these DSM programs (Winett et al. 1978, Battalio et al. 1979, Gaskell et al. 1982, Hutton et al. 1986, Wilhite and Ling 1995, Roberts et al. 2004, Allen and Janda 2006, Mountain 2008, Parker et al. 2008). As of 2010, a total of thirty-six studies had been implemented throughout various parts of the world between 1995 and 2010 (Ehrhardt-Martinez et al. 2010). The average household electricity savings ranged from 3.8 percent to 12 percent depending on the type of feedback received. "Direct" feedback, or real-time feedback, proved to be the most successful in increasing electricity savings with average savings between 9.2 percent and 12 percent. "Indirect" feedback, or feedback provided after consumption occurs, resulted in average savings between 3.8 percent and 8.4 percent. Ten studies focused on direct feedback while the remaining twenty-six studies focused on indirect feedback.

Although these studies did prove that increasing the amount of feedback offered to consumers can increase electricity savings and that direct feedback is more effective than indirect feedback, there are many factors that cannot be controlled and accounted for in a field study. Some studies also introduced other psychological factors such as competition between consumers that could have contributed to these savings. In order to narrow the focus on consumer response to direct and indirect feedback and control for factors such as weather, preference, and other individual consumer differences that could affect consumption, we have developed a laboratory experiment. Our experiment compares direct feedback and indirect feedback in flat rate pricing programs prior to transitioning to a real-time pricing program with direct feedback. Due to the differences in feedback over four phases in each of our treatments, we can also measure the effectiveness of transitions between types of feedback. These transition comparisons can help determine if a certain transition will lead to more effective implementation of real-time pricing programs.

III. Methodology

In order to study efficiency patterns through changes in information feedback and pricing contracts, we designed a market structure that reflects the structure of a retail electricity market. The goal of our experiment is to determine the effect of two types of feedback on market demand in an environment simulating retail electricity markets. Direct feedback and indirect feedback are the two types of feedback examined. In our experiment, direct feedback reveals market-clearing prices which are visible at the end of the month and each day in real time as subjects purchase units. Indirect feedback is defined as feedback on real-time prices visible only at the end of each month. Feedback described as "real-time pricing feedback" reveals to participants the prices they would have been charged under a real-time pricing program, even if they are participating in a flat rate pricing program and paying flat rate prices.

We used three experimental treatments to examine the effects of feedback. Each treatment contains four phases which are summarized in Table 1 of Appendix C. Phase 2 of each treatment is the experimental phase and exhibits a flat rate pricing structure. This phase allows us to examine results occurring from different types of feedback offered to participants. Phase 2 also suggests how different types of feedback may affect the transition to real-time pricing.

We refer to the first treatment as FRP (Flat Rate Pricing), representing the flat rate pricing present without accompanying feedback in Phase 2. This treatment is the control treatment and offers participants only flat rate calculations at the end of the month during flat rate pricing phases. The second treatment, FRP-M (Flat Rate Pricing-Month), represents the treatment with indirect feedback offered during flat rate pricing in Phase 2. Feedback on prices that would occur in a real-time pricing program is offered to participants at the end of the month along with the flat rate calculations. Although real-time prices are visible, they are still charged according to the flat rate pricing structure. In the third treatment, FRP-R (Flat Rate Pricing-Real-time), feedback on real-time prices is offered both during the month (direct feedback) and at the end of the month (indirect feedback) in addition to flat rate calculations at the end of the month. In total, five sessions of each treatment were completed to sum to a total of fifteen sessions. Using calculations of total surplus to measure efficiency, we compare market efficiency achieved from different flat rate pricing phases to market efficiency and demand response achieved during real-time pricing phases. The results of these experiments will reveal more about consumer behavior in terms of the efficiencies of these markets and how participants learn and retain information.

A. Environment

In each period, called a "day," four buyers are presented with Units that they can purchase. The quantities of units available for purchase vary cyclically across different "days" that represent the demand structure found in electricity markets. There are four days in each “week,” and a total of two weeks in each “month.” At the end of each month, the buyers receive a monthly bill for the purchases made with varying information depending on the treatment. Each day represents a separate market pricing period. Day 1 is an off-peak period representing low demand (night), Days 2 and 4 are shoulder periods representing medium demand (morning and evening), and Day 3 is a peak period representing high demand (afternoon). These cycles of four pricing shoulders are designed to mimic the typical fluctuations in demand for electricity during a 24 hour period. These fluctuations in demand are reflected in deregulated day-ahead electricity markets where market-clearing prices can be determined hourly or in 30 minute intervals. Figure 1 depicts aggregate demand and supply during the 20 experimental months of the experiment. Supply remains the same throughout the duration of the 20 months so that we can more accurately measure changes resulting from the type of feedback provided to participants.

The pure-strategy Nash equilibrium outcomes for each week can be seen in Tables 3 (flat rate pricing) and 4 (real-time pricing. The supply and demand structures have been formed in such a way as to control for unilateral market power. Buyers cannot deviate profitably and unilaterally from the competitive outcome. If buyers adhere to pure-strategy Nash equilibrium outcomes for real-time pricing, the total units they purchase will equal the number of units required to achieve competitive equilibriums displayed in Figure 1.

Although the price elasticity of demand is slightly more inelastic than the price elasticity of demand found in actual retail electricity markets, we have narrowed our focus to specific points on the demand curve in order to better analyze demand response. Our demand curves for shoulder and peak demand are highly inelastic when compared specifically to retail markets found in Australia (Fan and Hyndman 2011). However, our study requires more inelastic price elasticity of demand to better examine participant response to varying contracts and feedback. Since our participants do not experience the incentives and losses they would experience outside of a laboratory setting, we must focus in on the specific points on the demand curve that would elicit reductions in demand in actual retail electricity markets.

We use two pricing contracts in our experiment, flat rate pricing and real-time pricing. Flat rate pricing represents the pricing contract found in long-term contracts formed before electricity markets were deregulated. In electricity markets that have not been deregulated, flat rate prices are determined by equally distributing all costs associated with production of the service over the total amount of produced units regardless of the daily marginal cost of producing the units. In simulation of this pricing method, uniform prices per unit are calculated as the weighted average of the market prices during the month. The market prices are determined by the matching of supply and demand. Supply in the experiment is driven by robots in the computer program; demand is determined by human subjects. At the end of each month, participants are charged the uniform price per unit for all purchases made during that month. Therefore, participants only receive a single price at the end of the month that is charged for each unit consumed. Any variations between "days" or periods in the wholesale market are not visible. Theoretically, the market efficiency under this pricing structure should be the lowest of all studied variations.

Contrary to flat rate pricing, the real-time pricing contract more accurately reflects fluctuations in the market caused by varying levels of demand. Real-time pricing fully reveals wholesale pricing signals emerging in the wholesale markets. Each consumer pays the market-clearing price determined during each day. No averages are involved; participants pay the amount determined by market supply and demand during each period.

Each experimental treatment occurs over the course of 20 experimental months. In the FRP treatment, participants make decisions in a flat rate program for the first 10 months. During these initial months, participants receive no price feedback on real-time prices. Only a flat rate calculation is visible at the end of each month. In months 11-15, they switch to a phase consisting of a real-time pricing contract with direct feedback. In months 16-20, they return to flat rate pricing without feedback on real-time prices. Weighted averages calculated during the experiment are not revealed during phases incorporating flat rate pricing contracts.

In the second experimental treatment (FRP-M), participants receive indirect feedback during Phase 2, months 6-10. Again, this experiment starts out with flat rate pricing from months 1-10, but they receive indirect real-time feedback during months 6-10. In months 11-15, participants are switched to the real-time pricing program with direct feedback. In months 16-20, they return to the flat rate program without additional real-time pricing feedback.

In the third experimental treatment (FRP-R), participants receive direct feedback during Phase 2. Prices in months 1-5 are again calculated by a flat rate structure, but in months 6-10, they receive direct feedback. Unlike in Phase 3 which uses real-time pricing, participants are not able to see costs, profits, or the Price per Unit as we are still using flat rate calculations. Participants are not able to see their flat rate Price per Unit until the end of the month when it is calculated, but they are able to see real-time prices during the months and in the monthly bills. In months 11-15, they participate in real-time pricing with direct feedback. In months 16-20, they return to flat rate pricing without additional feedback.

To review, Phase 1, Phase 3, and Phase 4 are identical in all three treatments. Phase 1, 2, and 4 offer flat-rate pricing contracts. Phase 3 features a real-time pricing contract. Phase 2 is the experimental phase in which no real-time price feedback (FRP), indirect feedback (FRP-M), and direct feedback (FRP-R) are offered during a flat rate pricing contract. Please refer to Table 1 for a visual summary of the three treatments.

B. Procedures

Participants draw a random card to be seated at one of four computers that are covered so that participants cannot view other participants' monitors. Instructions for each set of months, or phase, reveal how these numbers are calculated (Image 1-4). Instructions with an equation revealing how their Price per Unit is calculated are viewed electronically before each phase begins. Before Phases 2 and 3 begin, participants view abbreviated instructions with changes in text colored orange and bolded to signify differences. Phase 4 text viewed on the computer says only that the instructions are the same as for Phase 1. Full written instructions with changes colored orange and bolded are distributed at the beginning of each phase. The paragraph including changes is read out loud at the beginning of each phase where instructions have been altered.

On all decision screens, participants must click on "Purchase Unit" buttons consecutively in order to purchase units. If participants wish to cancel a purchase, they must click the "Undo Purchase" buttons in the opposite order from which they selected units to purchase. Subjects are given 15 seconds to decide how many units they wish to purchase. To the left of the buttons is a table revealing the units that are available to purchase and the resale value of each unit. On the decision screens for the flat rate pricing phases in FRP and FRP-M, participants are able to view their Current Balance, the number of units they have purchased, and their Resale Revenue. They are not able to see their Costs, Profit, Market Price per Unit, or their Price per Unit (see Image 5). On the decision screen for the Phase 2 of the FRP-R treatment, participants are able to view their Current Balance, Units Purchased, Resale Revenue, and Market Price per Unit (Image 6). Participants cannot view Costs, Profit, or their Price per Unit. During the real-time pricing phase, participants are able to see all the information including Current Balance, Units Purchased, Resale Revenue, Costs, Profit, Market Price per Unit, and their Price per Unit (Image 7).

At the end of each month, participants view a monthly bill. For the flat-rate pricing phases without any additional price feedback, participants view their Price per Unit, which is the weighted average of the prices during the month. They also can see Total Units Purchased, Total Resale Revenue, Total Costs, Total Profit, Total Month's Profit, and information on their Current Balance (Image 8). For Phase 2 of FRP-M and FRP-R, participants are able to see all the information they received in Phase 1 and Phase 2 of the FRP treatment in addition to the Market Price per Unit for each day (Image 9). For Phase 3, participants are able to view their Price per Unit for each day in addition to Total Resale Revenue, Total Costs, and Total Profit for each day (Image 10).

There are two questionnaires during the course of the experiment. The first questionnaire occurs after the Phase 3 instructions have been read and before Phase 3 begins. The questionnaire asks participants to rate the phases from "Dislike very much" to "Like very much." The final questionnaire asks the same question, but includes all four phases to rate instead of only three. The purpose of these questionnaires is to measure how well participants are able to relate to and understand each phase. By determining how much they like each phase, we not only determine the efficiency from the actual numbers that are produced, but we can also measure how much the participants like each phase. If participants are highly inefficient during one phase, but like that phase very much, then we might glean that they did not understand what was taking place during that phase. This information will help us better understand comprehension and preferences of our participants.

Each session lasted for approximately seventy-five minutes. Participants were undergraduate students attending Gettysburg College who were randomly recruited from the Gettysburg College email list, a list which included all current student email addresses. Participants were paid a $10 show-up fee in addition to any earnings they made during the experiment. On average, subjects made approximately $15.12 during the experiment, not including the show-up fee. Earnings were between $8 and $20, again not including show-up fee.

C. Hypotheses

The purpose of our experiment is to examine the market efficiency in flat rate pricing programs and real-time pricing programs when participants receive different forms of feedback. We will measure market efficiency over the course of the four phases in each of three treatments. We will also be observing the learning patterns of participants to see how they respond to feedback and how they respond once they no longer have the feedback after a certain amount of time has passed. Finally, the questionnaires will measure participant preference.

We predict that participants will achieve higher levels of efficiency with increasing amounts of feedback. We expect to see greater market efficiency in Phase 3 under the real-time pricing program than in all other phases. We also expect efficiency to increase overtime when participants receive additional feedback both during the month and at the end of the month. In regards to adaptation, we expect participants to achieve higher efficiency in Phase 2 of FRP-R when compared to the second phase of other treatments. We hypothesize that participants will achieve a higher efficiency in Phase 2 of FRP-M than in Phase 2 of FRP. We also expect participants to remember their purchasing patterns once they return to the flat rate structures in Phase 4 in all three experiments. However, we expect some efficiency to be lost without continuing additional real-time price feedback.

In regards to consumer comprehension, we predict that participants will have a higher preference for Phase 2 of FRP-M and FRP-R than for Phase 1 of FRP-M and FRP-R. We also hypothesize that participants will rate Phase 3 highest in all treatments after completing all four phases.

IV. Results

Data was collected from five sessions of each treatment for a total of fifteen sessions. There were a total of 160 periods in the experiment accounting for the days in 20 experimental months. We study the efficiency of each day, month, and phase in each session to compare treatments.

In order to calculate efficiency of each day, we divide total surplus achieved by total surplus possible. In order to obtain total surplus for each day, we must calculate consumer and producer surplus for each day. Consumer surplus is equal to the following, with resale revenue being the buyer's value of the units purchased:

(1)

$$
\begin{aligned}
&\mathit{Consumer\ Surplus} \\
&\qquad = \left(\mathit{Resale\ Revenue\ Buyer}\ 1 - (\mathit{Total\ Units\ Purchased} * \mathit{Price\ per\ Unit})\right) \\
&\qquad + \left(\mathit{Resale\ Revenue\ Buyer}\ 2 - (\mathit{Total\ Units\ Purchased} * \mathit{Price\ per\ Unit})\right) \\
&\qquad + \left(\mathit{Resale\ Revenue\ Buyer}\ 3 - (\mathit{Total\ Units\ Purchased} * \mathit{Price\ per\ Unit})\right) \\
&\qquad + \left(\mathit{Resale\ Revenue\ Buyer}\ 4 - (\mathit{Total\ Units\ Purchased} * \mathit{Price\ per\ Unit})\right)
\end{aligned}
$$

Price per Unit differs depending on the phase. In the flat rate phases, Price per Unit equals:

(2)

$$Flat\ Rate\ Price\ per\ Unit =$$

$$\frac{(Total\ Units\ Purchased\ Day\ 1 * Cost\ per\ Unit\ Day\ 1) + \cdots + (Total\ Units\ Purchased\ Day\ 8 * Cost\ per\ Unit\ Day\ 8)}{(Total\ Units\ Purchased\ Day\ 1 + \cdots + Total\ Units\ Purchased\ Day\ 8)}$$

In the flat rate phases, Price per Unit is calculated as the weighted average cost for units purchased over the eight days of the month. For real-time phases, Price per Unit is as follows:

(3)

$$Real - time\ Price\ Per\ Unit\ Day\ X = Cost\ per\ Unit\ Day\ X$$

While Price per Unit in the flat rate pricing phases is calculated as the weighted average price of the month, the Price per Unit during real-time phases is equal to the Cost per Unit for each day.

Producer surplus is calculated as follows:

(4)

$$Producer\ Surplus = (Price\ per\ Unit * Total\ Units\ Purshased) - Producer\ Cost$$

Producer Costs are listed in Table 2. The Producer Cost for each day is determined by the number of units purchased that day. Producer surplus calculated during real-time pricing uses the real-time Price per Unit instead of weighted average calculations.

Once consumer and producer surplus have been determined for each day, they can be added together to create total surplus, using the appropriate real-time or flat rate calculation, depending on the phase in which the efficiency is being calculated. For monthly efficiency calculations, the following calculation is used:

(5)

$$Monthly\ Efficiency = \frac{Total\ Surplus\ Day\ 1 + \cdots + Total\ Surplus\ Day\ 8}{Maximum\ Possible\ Surplus\ Day\ 1 + \cdots + Maximum\ Possible\ Surplus\ Day\ 8}$$

Phase efficiency is calculated as the average of the monthly efficiencies.

The average phase efficiencies of all sessions of each treatment are displayed in Table 5. The average change in efficiency between phases is presented in Table 6. In descriptive statistical analysis, we find that on average, Phase 3 had the highest efficiency in all three treatments. On average, all three treatments experienced an increase in efficiency in each phase leading up to Phase 3. FRP-M and FRP-R treatments experienced the highest increase in efficiency from Phase 2 to Phase 3 suggesting that feedback might play an important role here. Efficiency rose by 12 percent on average in FRP-M and by 8 percent in FRP-R while efficiency rose by 7 percent in the FRP treatment. Efficiency fell in all treatments in Phase 4, decreasing by 4 percent in FRP and FRP-R and by 3 percent in FRP-M.

Figure 2 and Figure 3 track the average changes between sessions that take place over the course of months and phases in each treatment. From these graphical representations, we can see the FRP treatment increases by the least significance over the 20 months. However, we see that both FRP-M and FRP-R treatments increase in efficiency with greater magnitude leading up to month 15, the end of Phase 3. Although the differences in efficiency decreases in Phase 4 are slight, we can see that FRP-M and FRP-R appear to decrease a little more gradually than FRP.

Questionnaire results can be found in Tables 6 and 7. Figures 4 and 5 also show a visual representation of the differences between ratings entered by subjects. In the first questionnaire, Phase 2 received the highest ratings and Phase 3, before participation, received the lowest. Of the three treatments, Phase 2 and Phase 3 were rated the highest in the FRP-R treatment. From the final questionnaire, we can see that Phase 3 was rated the highest in all three treatments. Out of the three treatments, Phase 2 was rated the highest in FRP-R.

In order to compare our results to those of other studies, we also calculated savings gained through each treatment. We add total cost for all units purchased each day in a phase in order to calculate savings. To compare phases, we calculate total cost for a phase and then subtract aggregate cost from the aggregate cost of the previous phase. The difference in cost amounts to savings. From our results, we find that direct feedback in Phase 2 generated the greatest savings. The savings from indirect feedback was less than no feedback in the transition from Phase 1 to Phase 2. Savings represented in terms of the difference in average total cost between phases of each treatment is presented in Table 19. We compare the percentage of savings calculated for Phase 2 in our study to those summarized by Darby (2006) in Table 21.

V. Findings

A. Efficiencies

The efficiencies in the FRP-R treatment with direct feedback in Phase 2 did exhibit higher efficiencies in Phases 2, 3, and 4. Using Ordinary Least Squares regression analysis, we examined differences between phases in each treatment. Our analysis, summarized in Table 9, suggests that direct feedback does increase efficiencies. This finding is in accordance with our initial hypothesis that higher efficiencies would be produced in Phase 2 of FRP-R.

Our OLS regression models measure the differences between efficiencies in phases more accurately than basic descriptive analysis depicted in the results. We generate three models using monthly efficiencies for each treatment as our dependent variables. To explore differences between phases in a treatment as a whole, we first take the monthly efficiencies calculated from each session of one treatment and average them to produce the average monthly efficiencies for a single treatment. Thus, for example, monthly efficiencies for Month 1 for Session 1-5 of the FRP treatment are first added, and then the total is divided by the number of sessions to produce the average FRP efficiency for Month 1. This technique is applied to all months of all treatments which produces three independent variables: FRP, FRP-M, and FRP-R. We then generate three dummy variables for each model with the constant in our model acting as our base phase, Phase 1. We also add a time trend (*PERIOD*) since our data is time series occurring over the course of 20 months to measure learning and the change over the course of the entire treatment.

Model 1

$$FRP_t = \beta_1 + \beta_2\, PHASE\ 2 + \beta_3\, PHASE\ 3 + \beta_4\, PHASE\ 4 + \beta_5\, PERIOD + \mu_t$$

Model 2

$$FRP\text{-}M_t = \beta_1 + \beta_2\, PHASE\ 2 + \beta_3\, PHASE\ 3 + \beta_4\, PHASE\ 4 + \beta_5\, PERIOD + \mu_t$$

Model 3

$$FRP\text{-}R_t = \beta_1 + \beta_2\, PHASE\ 2 + \beta_3\, PHASE\ 3 + \beta_4\, PHASE\ 4 + \beta_5\, PERIOD + \mu_t$$

We do not find autocorrelation to be a problem in our models. However, we do encounter heteroskedasticity in our FRP-M and FRP-R models. Since our experiment does rely on individual choice, the error learning does reduce the variability of decisions, thus leading to the problem of unequal variance. Thus, we do not achieve minimum variance in our class of unbiased estimators. In order to correct for this issue, we use robust standard errors in Model 2 and Model 3.

Although using averages of the months in each session of each treatment dilutes the visible differences and changes between phases due to the varied starting efficiencies, we can still use these three models to analyze any noticeable changes across sessions in each treatment. As suspected with the diluted averages, the coefficients for efficiencies of Phase 2, 3 and 4 in the FRP and FRP-M models are not found to be statistically significant, thus showing that the efficiencies in these phases were not statistically higher than efficiencies in Phase 1. However, statistically significant differences are clearly visible in our third model. In our FRP-R model, holding other variables constant, coefficients for Phase 2 and Phase 3 were found to be statistically significant at the 1 percent level of significance while the coefficient for Phase 4 was found to be statistically significant at the 5 percent level of significance. This result shows that efficiencies in Phase 2, 3, and 4 were higher than efficiencies in Phase 1 and that these differences were constant enough through sessions to appear in the regression results. Thus, the increases in efficiency were more significant in the FRP-R treatment than in the FRP and FRP-M treatments.

Even though coefficients for Phase 2, 3 and 4 of the FRP and FRP-M models were not found to be statistically significant when holding other variables constant in each case, the coefficient for the time trend variable was found to be significant. The significance of the coefficient for the time trend reveals that both treatments experienced a positive increase in efficiency over the course of the 20 months suggesting that learning does take place in these environments. The coefficient for the time trend variable for the FRP model was found to be statistically significant at the 10 percent level of significance while the coefficient for the FRP-M model was statistically significant at the 5 percent level of significance, holding other variables constant. This significance contrasts with the significance of our time trend variable in our third model. Even though phase coefficients were statistically significant, the overall increase in efficiency was not captured by the time trend in the FRP-R model.

While regression analysis revealed results that were consistent with our hypothesis concerning phase efficiencies in FRP-R, we still cannot make clear assumptions about our data. Upon further analysis of phase comparisons, the results become more difficult to interpret due to limitations in sample size. Also, although Phase 1 should not be different between treatments, we find a statistically significant difference between FRP and FRP-M and again between FRP-M and FRP-R. Results from all comparisons can be found in Tables 10 and 11.

The inconclusiveness of our results was pinpointed in comparisons between phases and transitions using the Two-Sample Fligner-Policello Robust Rank-Order Test. The robust rank-order test is a non-parametric test similar to the more common Wilcoxon rank-sum test. However, while the Wilcoxon rank-sum test allows for non-normal distributions, it does not allow for unequal variances. We use the robust rank-order test in this case because it allows for both non-normal distributions and unequal variance. The efficiency data for each treatment is not equally distributed nor does it exhibit equal variance. We will return to the Wilcoxon rank-sum test for our questionnaire data later on as its constraints are more appropriate for that data.

In this case, we use the robust rank-order test to compare a single phase in two treatments to determine if efficiencies in one phase of one treatment are greater or less than efficiencies in the same phase of another treatment. Results of these tests for all phases of all treatments are visible in Table 10. Monthly efficiencies from all sessions of each treatment for each phase are used for comparison. For example, when comparing Phase 1 of FRP to FRP-M, all monthly efficiencies of Phase 1 from all five sessions of FRP are compared to all monthly efficiencies of Phase 1 from all five sessions of FRP-M.

We could not identify clear findings from the results of the robust rank-order test. Although Phase 1 should not be different between treatments, we find a statistically significant difference between FRP and FRP-M and FRP-M and FRP-R. The difference between treatments in Phase 1 raises questions as to whether or not the differences between the remaining phases are affected by the different starting points of each treatment. From the results, we can also determine a statistically significant difference between FRP and FRP-M in Phase 2, FRP-M and FRP-R in Phase 2, and FRP and FRP-M in Phase 4. However, the differences in Phase 1 make conclusions from these results impossible. Although we include this data as it is important to note these differences that appear in Phase 1 that may affect other data analysis, this method of analysis does not seem useful in interpreting results. Aside from these differences, we can also conjecture that the small sample sizes do influence critical values, another complication that makes interpretation difficult.

In addition to comparing efficiencies in phases, we also use the robust rank-order test to examine transitions. First, we calculate the difference in efficiency between phases for each session. Using these differences, we then can compare the transitions between two treatments. The results of these tests are summarized in Table 11. We find statistically significant differences in the transition from Phase 2 to Phase 3 between FRP and FRP-M and also between FRP-M and FRP-R. However, for the same reasons as for the previous set of tests, inferences from these results may also be impossible to ascertain.

B. Questionnaires

Consumer preference in data collected from the two questionnaires allows us to gather information about how participants perceive information presented on demand-side management programs. While we cannot make concrete assumptions about differences in efficiencies between phases and treatments, the questionnaire data revealed clearer findings. Results show that prior to implementation of real-time pricing, participants were averse to the change in contract even with feedback offered in the preceding phase. However, this aversion was the least in the FRP-R treatment when direct feedback preceded the transition. Phase 2 of FRP received lower ratings on average than the other two treatments. These results suggest that participants did prefer direct feedback over other types of feedback in accordance with our hypothesis, but were averse to real-time pricing before implementation. In order to test significance of these differences, we use the Wilcoxon Rank-Sum Test. Tables 12-17 summarize the results of these tests.

Referring to Table 12, we can observe preference for phases in each treatment when participants assign ratings at the end of the session. Phase 1 was not preferred in one treatment over another treatment in any of the three comparisons which tells us that Phase 1 was not perceived differently in different treatments. This lack of statistically significant difference in preference allows us to better examine differences that appear in other phases. For example, when examining Phase 2, negative, statistically significant critical values reveal that ratings for Phase 2 were higher in FRP-R when compared to FRP and FRP-M. Thus, participants preferred Phase 2 of FRP-R over FRP and FRP-M treatments, even though we did not find statistically significant differences in efficiencies for Phase 2 between treatments. Phase 3 was also rated higher in FRP-R than in the FRP treatment by a statistically significant amount, again showing an inclination by the participants toward FRP-R.

The Phase 3 questionnaire data can help us to better understand how consumers might respond to changes in pricing programs before they are implemented. The results from the phase comparisons between treatments in the Phase 3 questionnaire are shown in Table 13. Here, we see that there are no statistically significant critical values, thus indicating that difference in ratings was not great enough to achieve statistically significant differences between means. Even though efficiency in Phase 3 ended up being higher than in Phase 1 and Phase 2, participants revealed an aversion to the new phase. However, in the final questionnaire after having participated in Phase 3, participants show a clear preference for Phase 3. If we refer to Table 16, we can see how ratings of phases change before and after the Phase is completed. The difference in ratings of Phase 3 before and after completion is dramatic. The critical values for comparing ratings of Phase 3 in the Phase 3 questionnaire and end questionnaire are statistically significant at or above the 1 percent level of significance. Thus dramatic transition in ratings gives us insight into consumer response to the implementation of new programs. Before participants had participated in Phase 3, they were averse to Phase 3 and the change. However, after completing the phase, they rated Phase 3 higher than the other phases, showing a clear preference for Phase 3. In addition to a strong preference for Phase 3 and an aversion to Phase 4, the critical value for the end questionnaire ratings comparison between Phase 1 and Phase 2 of FRP-R was found to be statistically significant at the 10 percent level of significance. This statistically significant value shows that Phase 2 was preferred to Phase 1 in FRP-R, a preference that was not observed in the other two treatments.

The difference between ratings submitted in the final questionnaire and in the questionnaire administered at Phase 3 reveals that consumers are clearer in their preferences after they have participated in Phase 3. Even though instructions administered before the Phase 3 questionnaire state they will be offered more feedback, consumers do not respond positively with ratings that are statistically significant. We are observing this same phenomenon in field implementation of demand-side management programs (Structure Consulting Group, LLC 2010). Although field experiments have proven that there are efficiency gains to be made from demand-side management programs for both utilities and consumers, consumers show aversion to smart meters and resist the new programs being offered to them.

We find negative correlations between initial ratings of Phase 3 prior to implementation and efficiencies achieved in Phase 3 with real-time pricing and direct feedback. This negative correlation was not found to be statistically significant for FRP-R or FRP-M, suggesting that the ratings were not low enough to create statistically significant results. Thus, indirect and direct feedback in the preceding phase may have caused subjects to be less averse to participating in real-time pricing. The p-value for the coefficient for ratings of Phase 3 prior to implementation in FRP-R is higher than that of FRP-M, suggesting direct feedback may be more effective in lessening aversion to real-time pricing implementation.

In order to measure the relationship between efficiencies and participants' ratings, we looked at correlations between the efficiencies and questionnaire results for each treatment. This correlation data can be viewed in Table 18. As we might expect, we observe negative correlation between questionnaire ratings and efficiencies when using ratings from the Phase 3 questionnaire. However, this correlation is the least in FRP-R by a considerable and non-statistically significant amount: -8 percent (not statistically significant) compared to -47 percent (significant at 10 percent level of significance) for FRP. In line with the observations we have already made, these relationships change dramatically when using results from the final questionnaire. In the final questionnaire, ratings are positively correlated with efficiencies. This result suggests that participants, even without having knowledge of the actual efficiency calculations, rated the phases in line with efficiencies. Thus, phases with lower efficiencies received lower ratings and phases with higher efficiencies received higher ratings.

The absence of statistical significance for FRP-R in the correlation matrix indicates that the ratings for that treatment do not coincide with efficiencies to a statistically significant degree. However, from our rank-sum tests, we have already determined preferences for phases that are higher than in other treatments. The lack of statistically significant relationships for the Phase 3 questionnaire for both FRP-M and FRP-R suggests not only that participants were not accurate in determining future efficiencies, but also suggests that their aversion was not so much in contrast of future efficiencies achieved as to create statistically significant coefficients. While the relationships are still negative, suggesting a negative relationship between ratings and efficiencies, feedback may have had an impact on lessening aversion to Phase 3 prior to participation.

Since implementation and success of demand-side management programs seems to have been slowed by consumer aversion (Fehrenbacker 2009), the results of our questionnaires can help us better understand consumer preferences before and after they are presented with a real-time pricing program. Direct feedback may be useful in lessening initial aversion to real-time pricing implementation. Also, we see that participants do seem to select higher ratings for phases with higher efficiencies after participation, suggesting they have a better understanding of benefits after they have experienced a certain contract.

C. Savings

Since most analyses of both demand-side management programs and feedback are presented in the forms of potential savings, we have also calculated savings for comparison (Table 19, 20). From our savings calculations, we observe that the highest savings in Phase 2 are achieved with direct feedback. The savings in the transition to direct feedback were 10% higher than the savings achieved through the transition to Phase 2 in the control treatment. However, the savings from indirect feedback were not higher than the savings from the control treatment. A visual representation of these differences in savings in Phase 2 can be viewed in Figure 6. These findings are in accordance with our previous conclusions. While direct feedback does seem to be successful in increasing efficiency and savings, indirect feedback is not as effective.

VI. Conclusion

From our findings, we can determine that highest market efficiency was achieved with real-time pricing and direct feedback. However, indirect feedback was not as effective in increasing market efficiency as predicted. Data limitations made differences in efficiencies between treatments difficult, but we can glean that direct real-time pricing feedback during a flat rate pricing contract did seem to have a positive impact on efficiencies. Efficiency was retained more in the direct feedback treatment after transitioning from a real-time pricing contract back to a flat rate pricing contract based on descriptive analysis. More sessions of all treatments would need to be performed in order to make more definite claims about differences in efficiencies. However, from basic analysis, we can conclude that direct feedback was useful in implementation of real-time pricing.

In the final questionnaire, participants did show clear preferences that were in line with our expectations. Participants preferred the real-time pricing contract after participation in all three treatments. Participants also expressed higher ratings for direct feedback over no feedback in the FRP-R treatment involving direct feedback in implementation of real-time pricing. While direct feedback was preferred, the preference for indirect feedback was not found to be statistically significant after participants had completed the experiment. In the first questionnaire, we observed results similar to those that are occurring outside of the lab. Participants showed an aversion to real-time pricing before participation, although this aversion was least in the direct feedback treatment. This finding also suggests that direct feedback would be useful in increasing consumer receptiveness to new demand-side management programs.

This experiment is the first study on the effect of feedback in retail electricity markets during a transition to real-time pricing. Although differences in efficiency between treatments were convoluted and not as clean as expected, participants' preferences do provide useful information about how consumers might respond to implementation of real-time pricing programs and changes in feedback. Although presently, we are observing an aversion to emerging smart meters and the associated demand-side management programs, the information collected here suggests that better information could assist in consumer acceptance of new programs. Also, with efficiency rising after implementation of these programs with feedback, consumer aversion also decreases such that they prefer the new programs.

As determined by the California Public Utilities Commission, utilities do need to communicate more effectively with consumers. Our results show that after implementation, consumers may feel more positively about real-time pricing programs or programs offering additional feedback. We cannot deduce whether they have an understanding of the efficiencies or their consumer surpluses, but we can claim that there is a positive correlation between higher efficiencies and higher ratings.

From data collected in field experiments and this laboratory experiment, real-time pricing programs do lead to greater efficiency gains. However, if consumers are averse to these programs and opt out of participation, then these efficiency gains cannot be realized. Although indirect feedback did not prove to be greatly influential in increasing efficiency of participant consumption, direct feedback did have an impact on consumer preferences and did lead to higher efficiency in descriptive and regression analysis. Thus, direct feedback could be beneficial as the grid transitions through deregulation to encompass real-time pricing programs.

Appendix A

Figure 1: Supply and Demand Structure for 1 Week

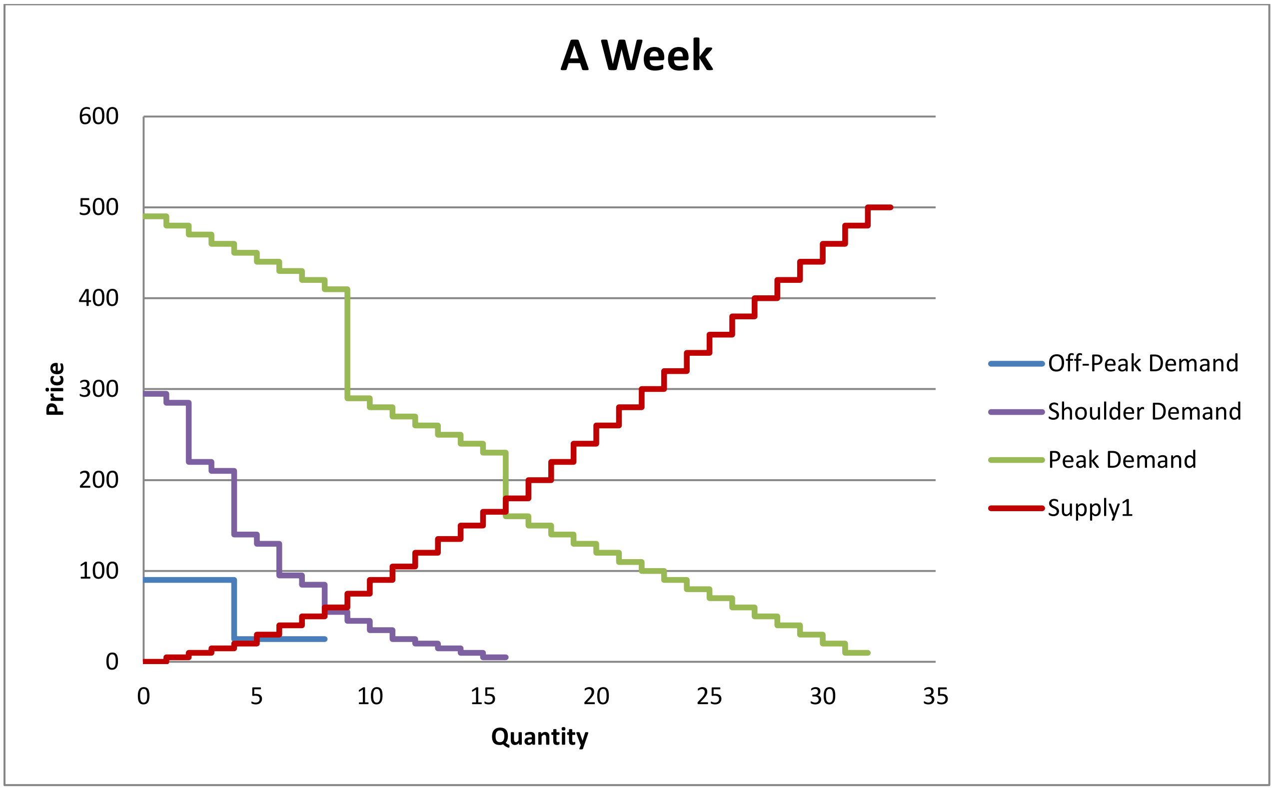


Figure 2: Average Monthly Efficiencies

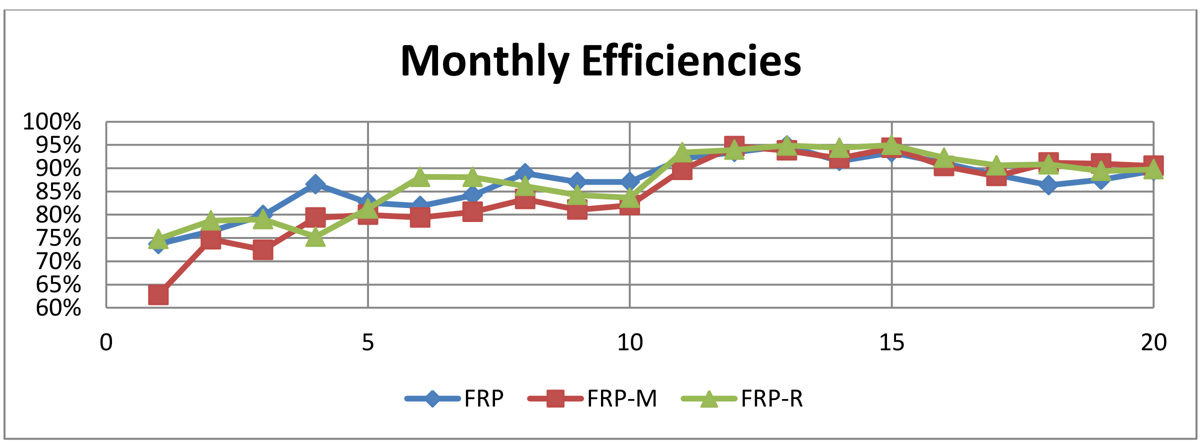


Figure 3: Average Phase Efficiencies

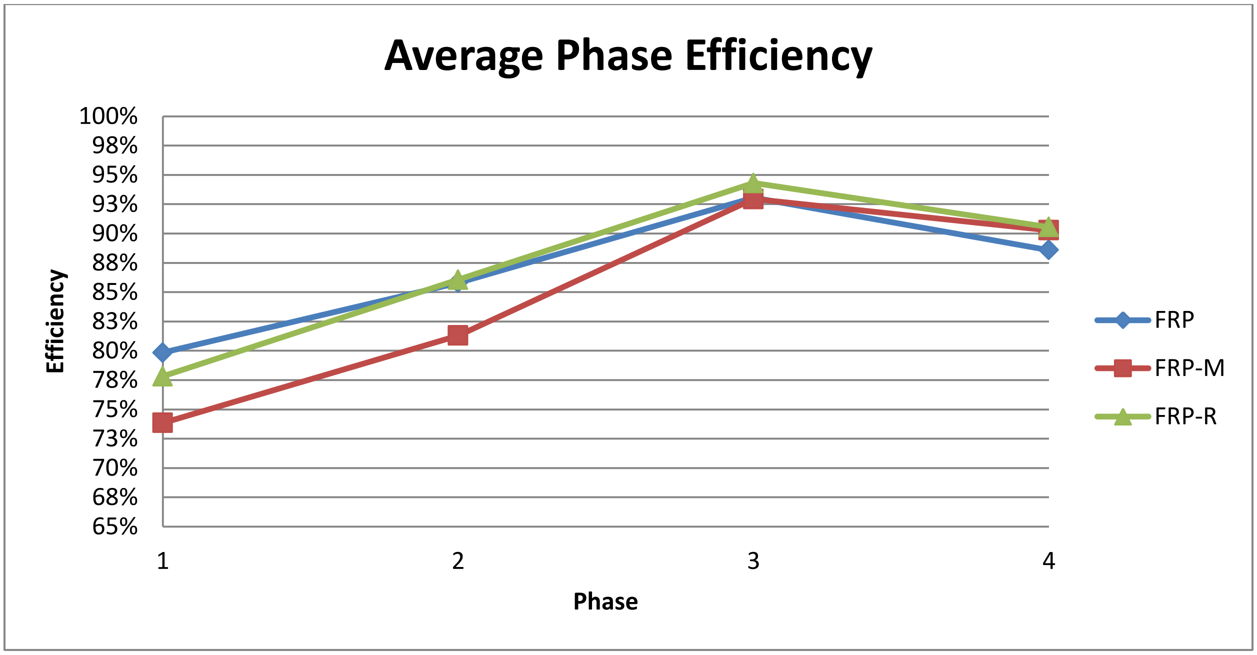


Figure 4: First Questionnaire Ratings

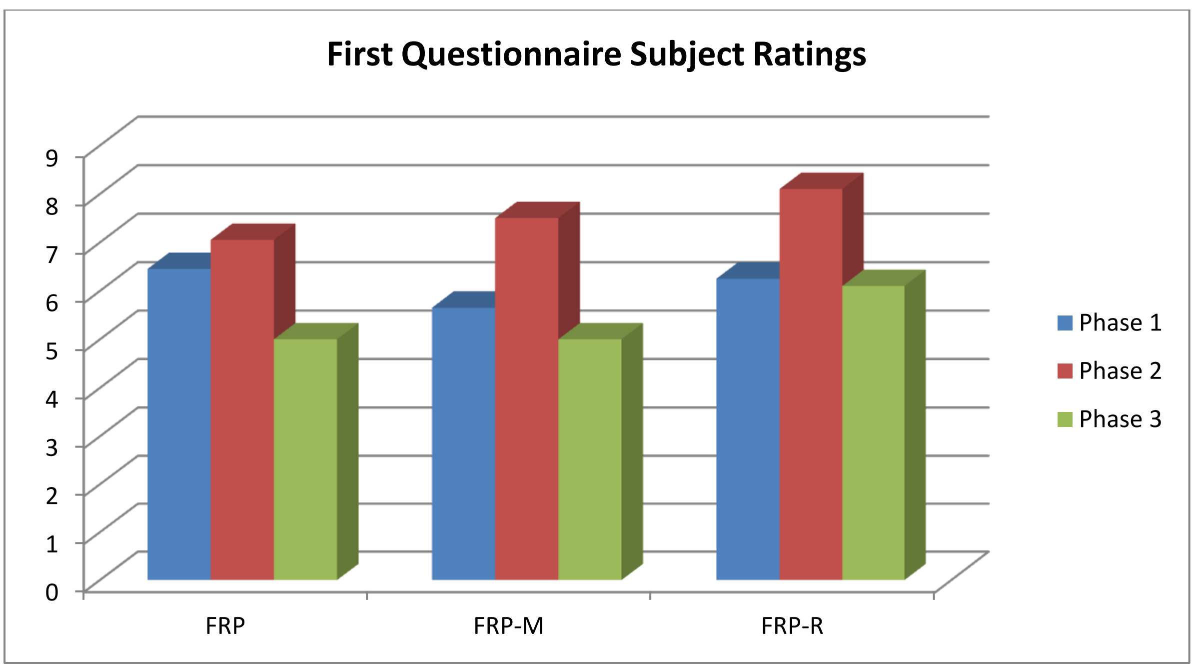


Figure 5: Final Questionnaire Ratings

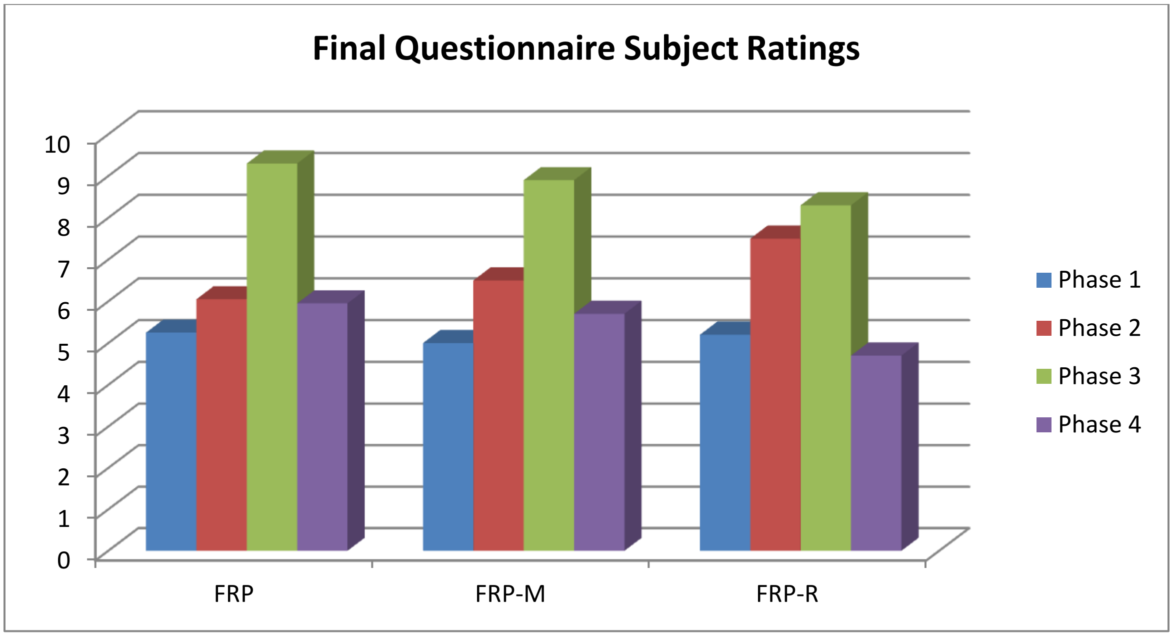
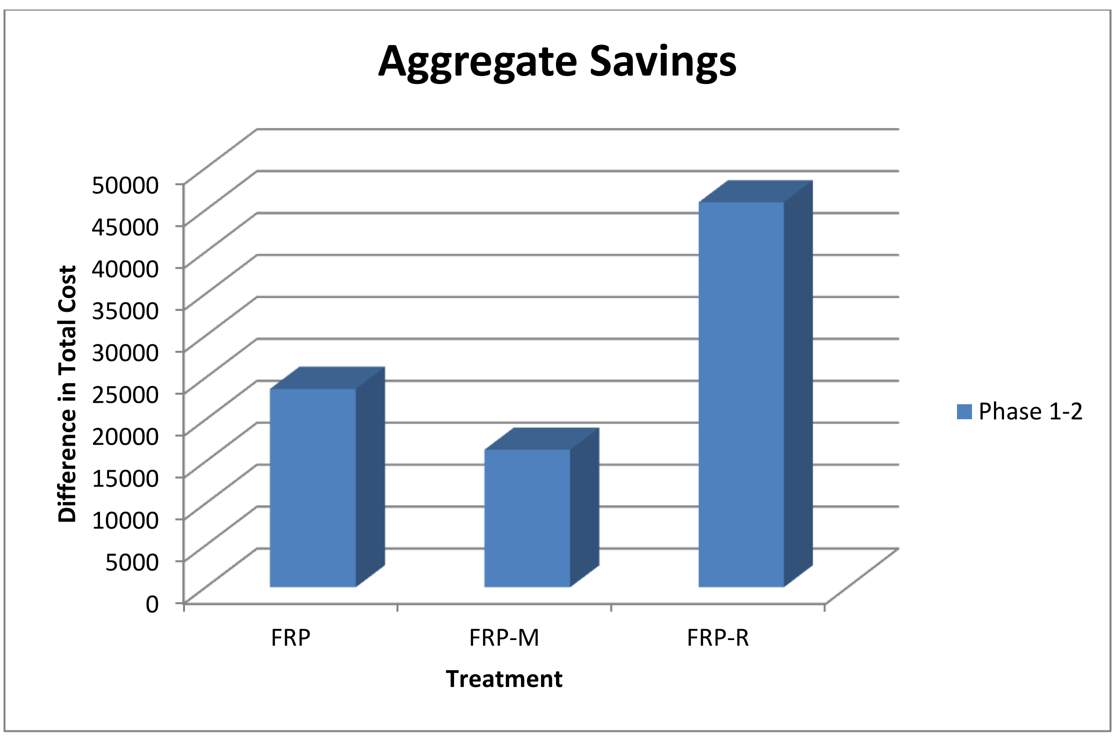
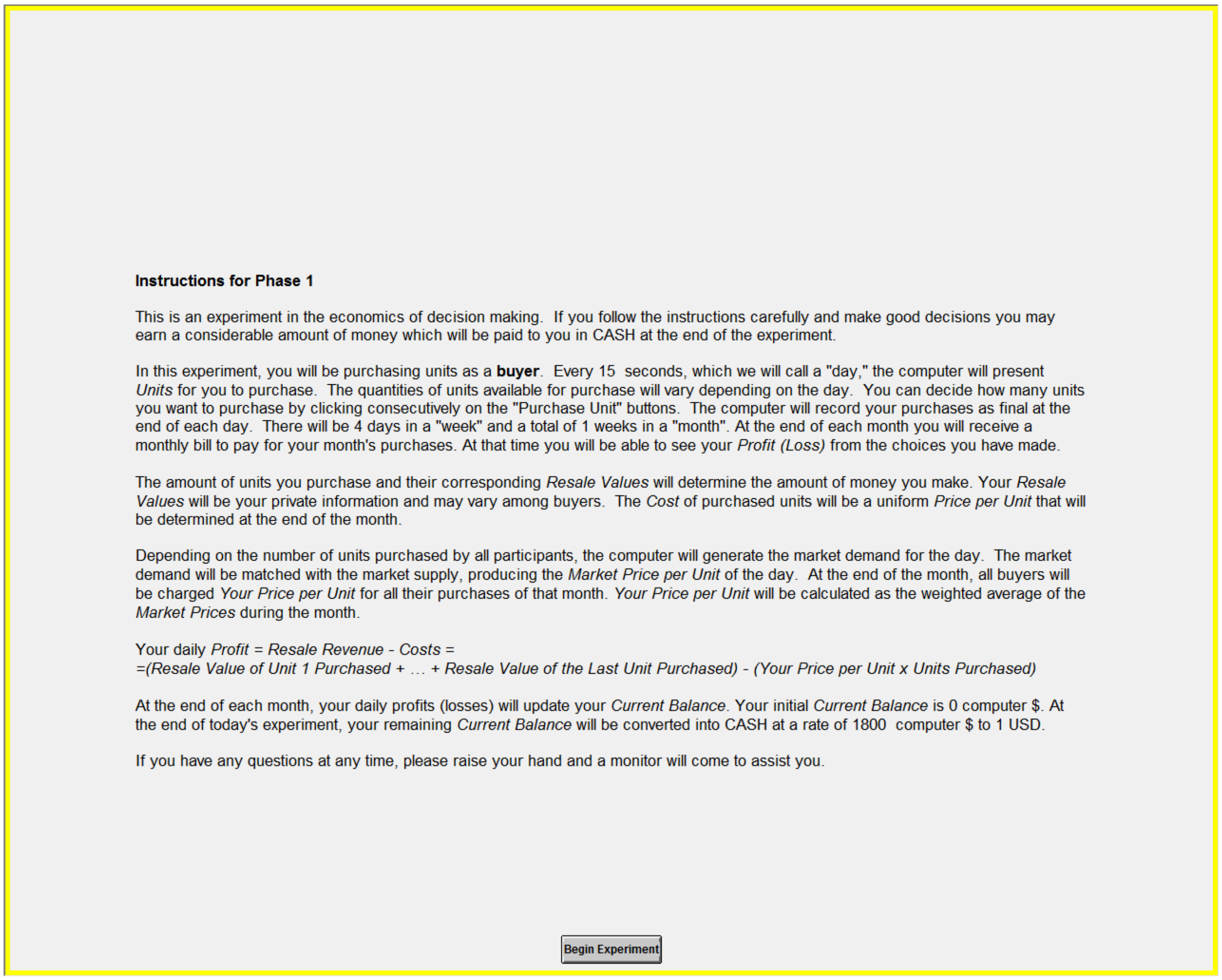


Figure 6: Phase 2 Savings



Appendix B

Image 1: Phase 1 Instructions for FRP, FRP-M, and FRP-R



Instructions for Phase 1

This is an experiment in the economics of decision making. If you follow the instructions carefully and make good decisions you may earn a considerable amount of money which will be paid to you in CASH at the end of the experiment.

In this experiment, you will be purchasing units as a **buyer**. Every 15 seconds, which we will call a "day," the computer will present *Units* for you to purchase. The quantities of units available for purchase will vary depending on the day. You can decide how many units you want to purchase by clicking consecutively on the "Purchase Unit" buttons. The computer will record your purchases as final at the end of each day. There will be 4 days in a "week" and a total of 1 weeks in a "month". At the end of each month you will receive a monthly bill to pay for your month's purchases. At that time you will be able to see your *Profit (Loss)* from the choices you have made.

The amount of units you purchase and their corresponding *Resale Values* will determine the amount of money you make. Your *Resale Values* will be your private information and may vary among buyers. The *Cost* of purchased units will be a uniform *Price per Unit* that will be determined at the end of the month.

Depending on the number of units purchased by all participants, the computer will generate the market demand for the day. The market demand will be matched with the market supply, producing the *Market Price per Unit* of the day. At the end of the month, all buyers will be charged *Your Price per Unit* for all their purchases of that month. *Your Price per Unit* will be calculated as the weighted average of the *Market Prices* during the month.

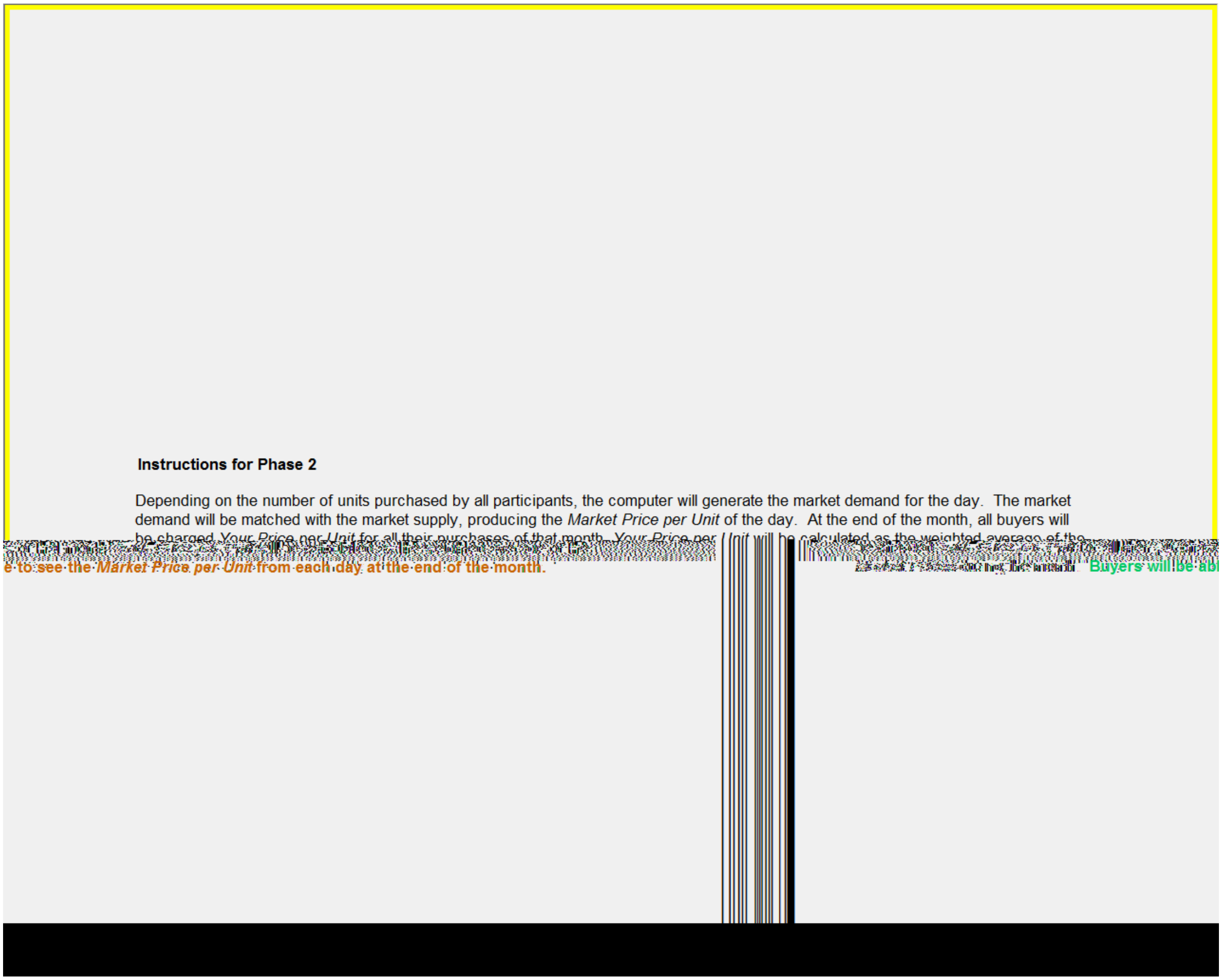
Your daily *Profit = Resale Revenue - Costs =*
=(Resale Value of Unit 1 Purchased + … + Resale Value of the Last Unit Purchased) - (Your Price per Unit x Units Purchased)

At the end of each month, your daily profits (losses) will update your *Current Balance*. Your initial *Current Balance* is 0 computer $. At the end of today's experiment, your remaining *Current Balance* will be converted into CASH at a rate of 1800 computer $ to 1 USD.

If you have any questions at any time, please raise your hand and a monitor will come to assist you.

Begin Experiment

Image 2: Phase 2 FRP-R Instructions


Instructions for Phase 2

Depending on the number of units purchased by all participants, the computer will generate the market demand for the day. The market demand will be matched with the market supply, producing the *Market Price per Unit* of the day. At the end of the month, all buyers will be charged *Your Price per Unit* for all their purchases of that month. *Your Price per Unit* will be calculated as the weighted average of the

e to see the *Market Price per Unit* from each day at the end of the month.

Buyers will be abl

Image 3: Phase 2 FRP-R Instructions

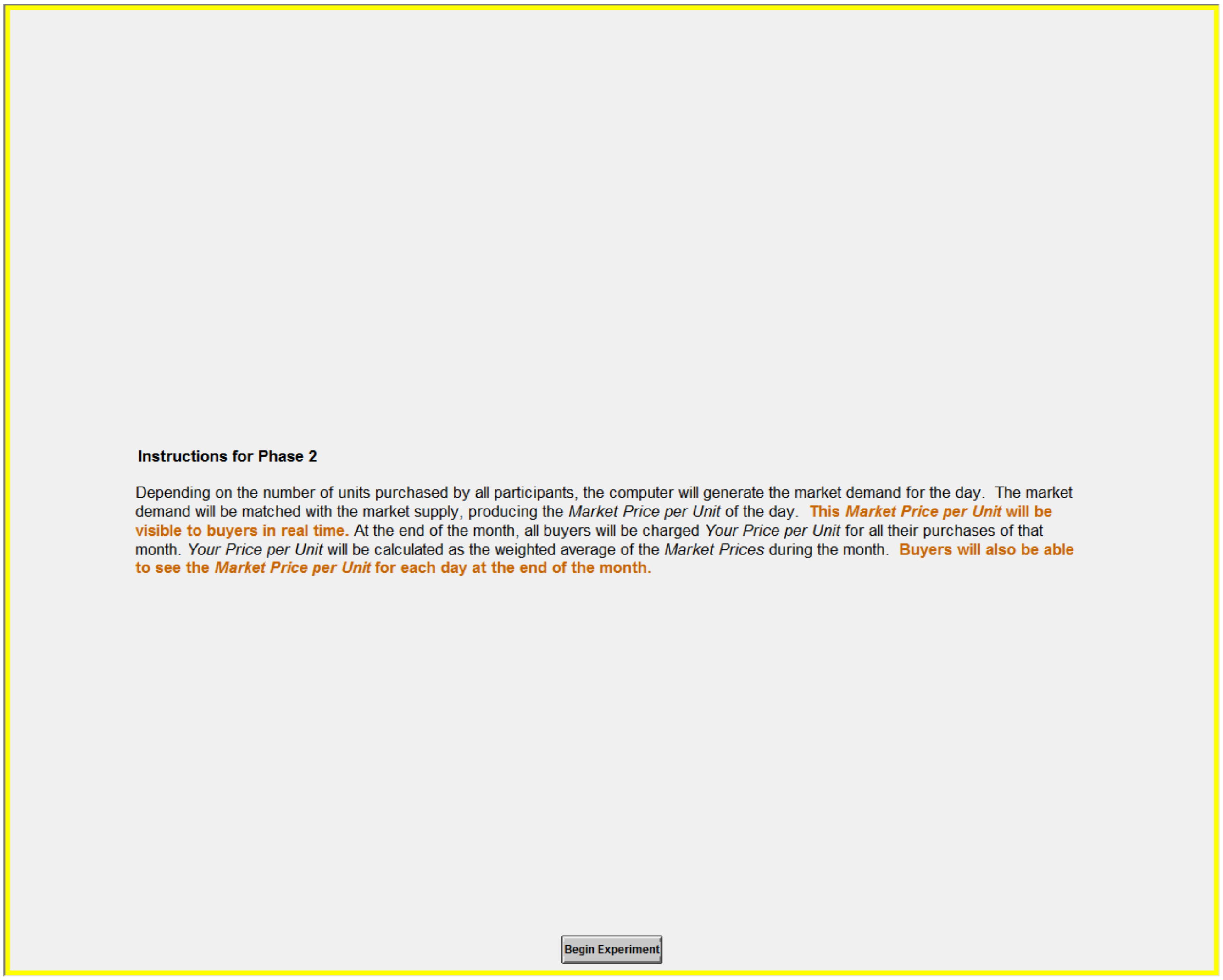


Image 4: Phase 3 Instructions

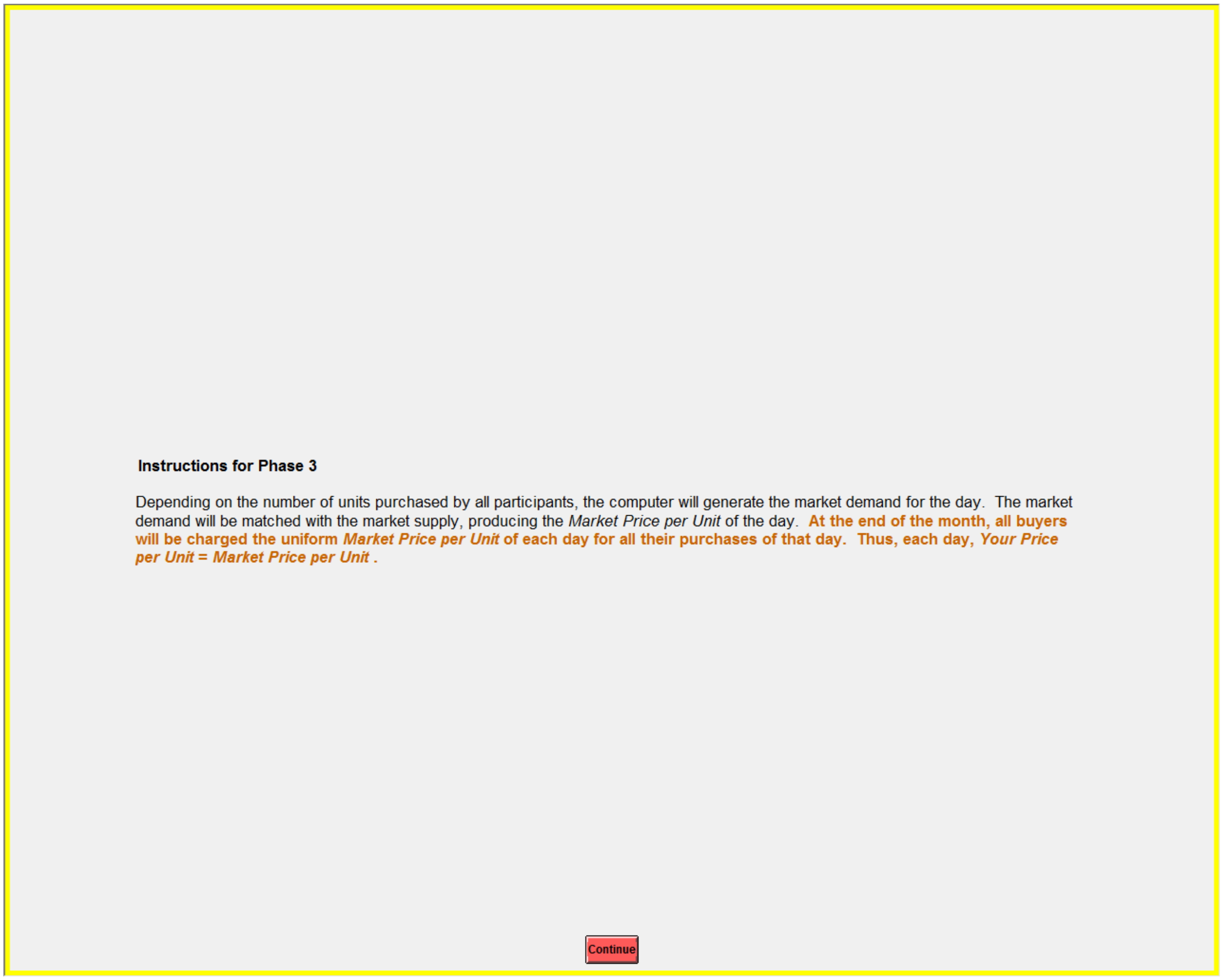


Image 5: Phase 2 Decision Screen for FRP and FRP-M

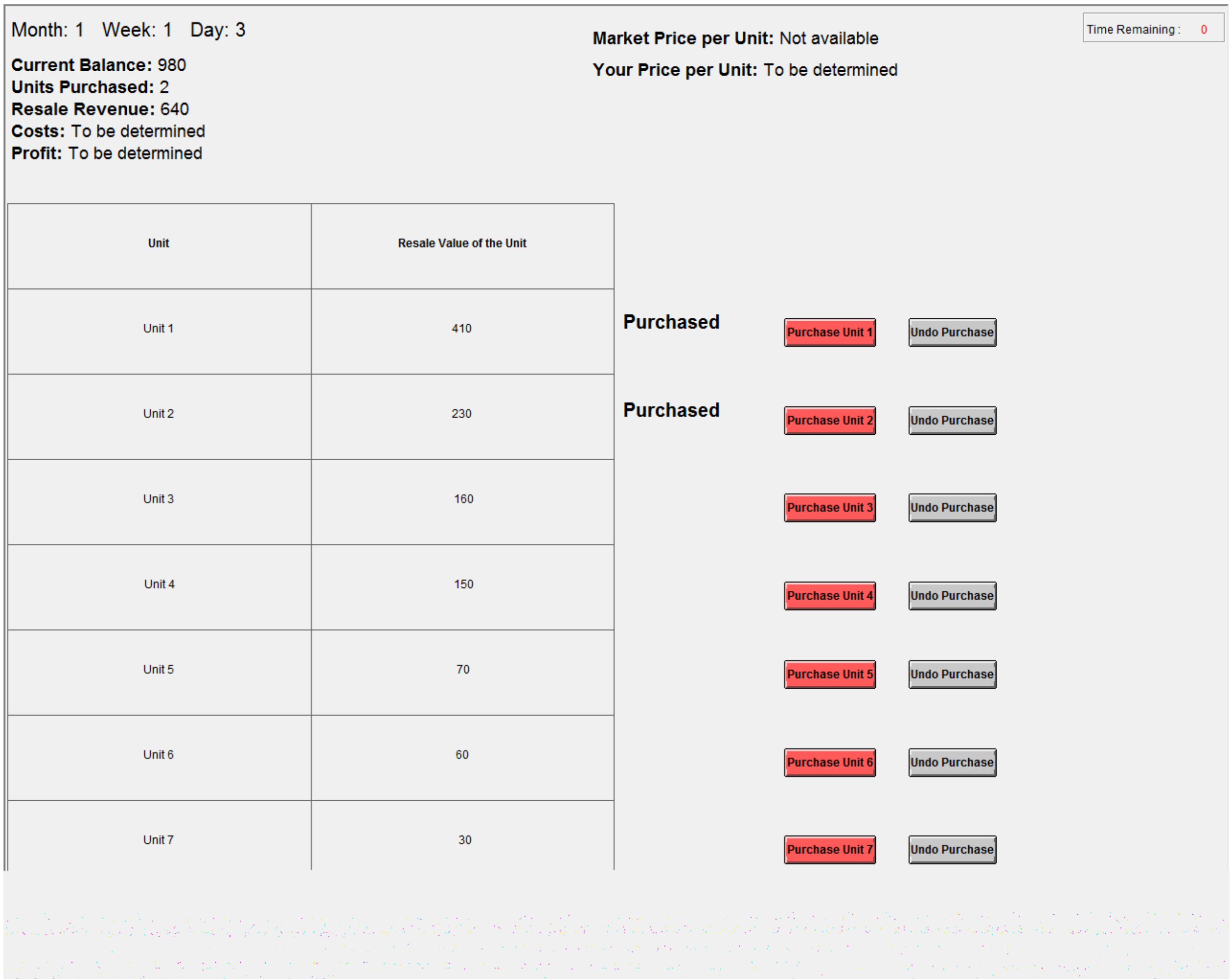


Image 6: Phase 2 Decision Screen for FRP-R

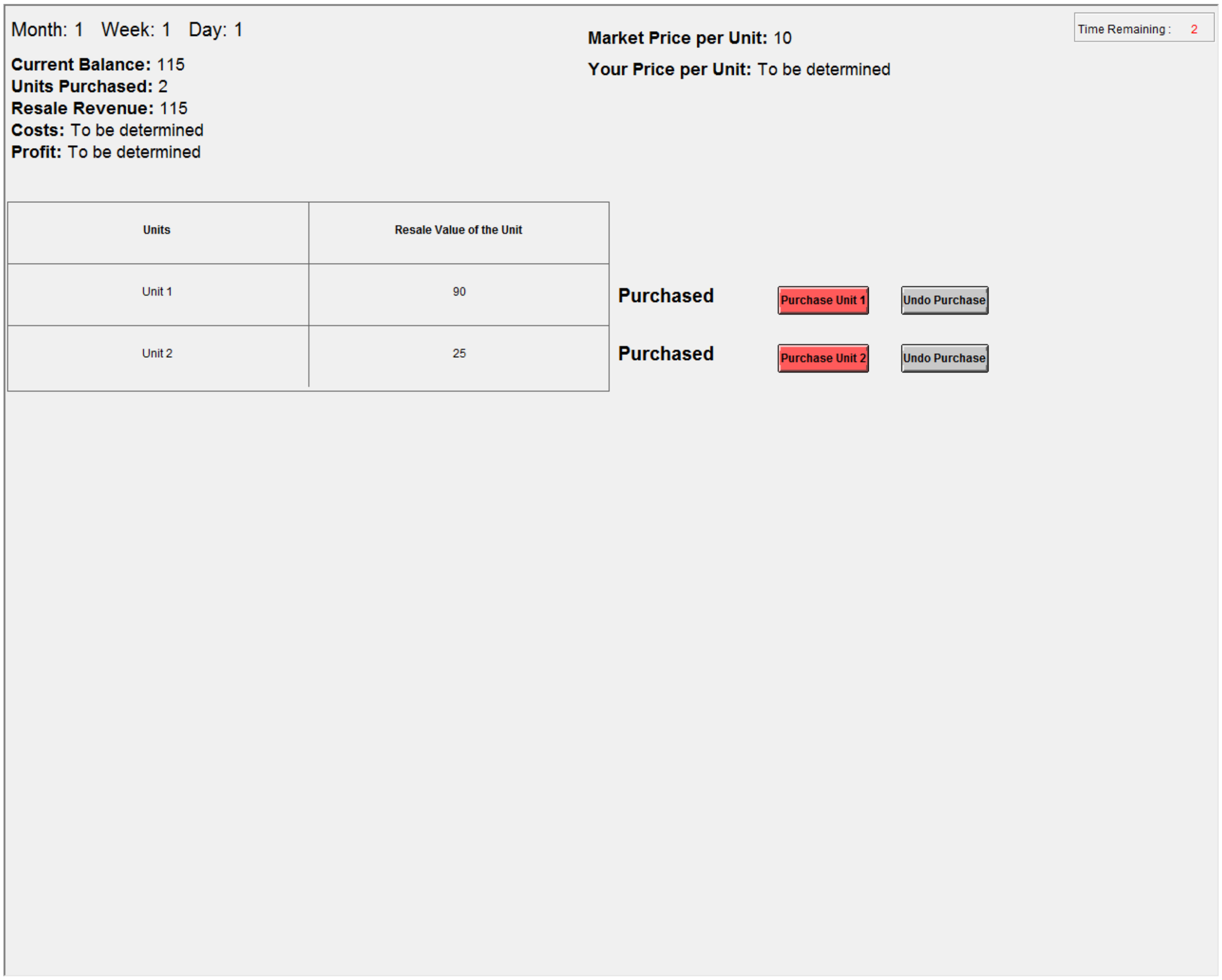


Image 7: Phase 3 Decision Screen for FRP, FRP-M, and FRP-R

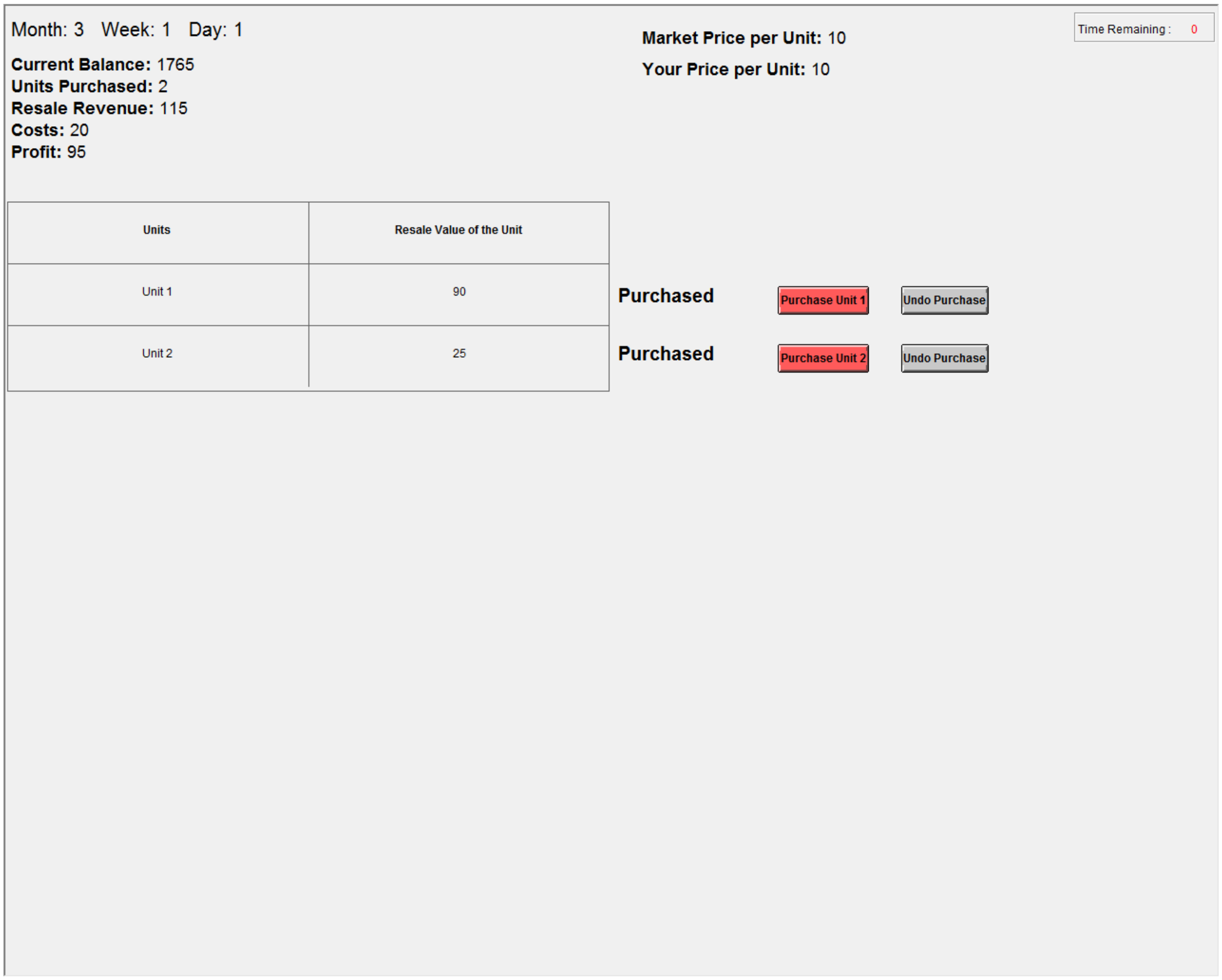


Image 8: Phase 2 Monthly Bill for FRP and Phase 4 Monthly Bill for FRP, FRP-M, and FRP-R

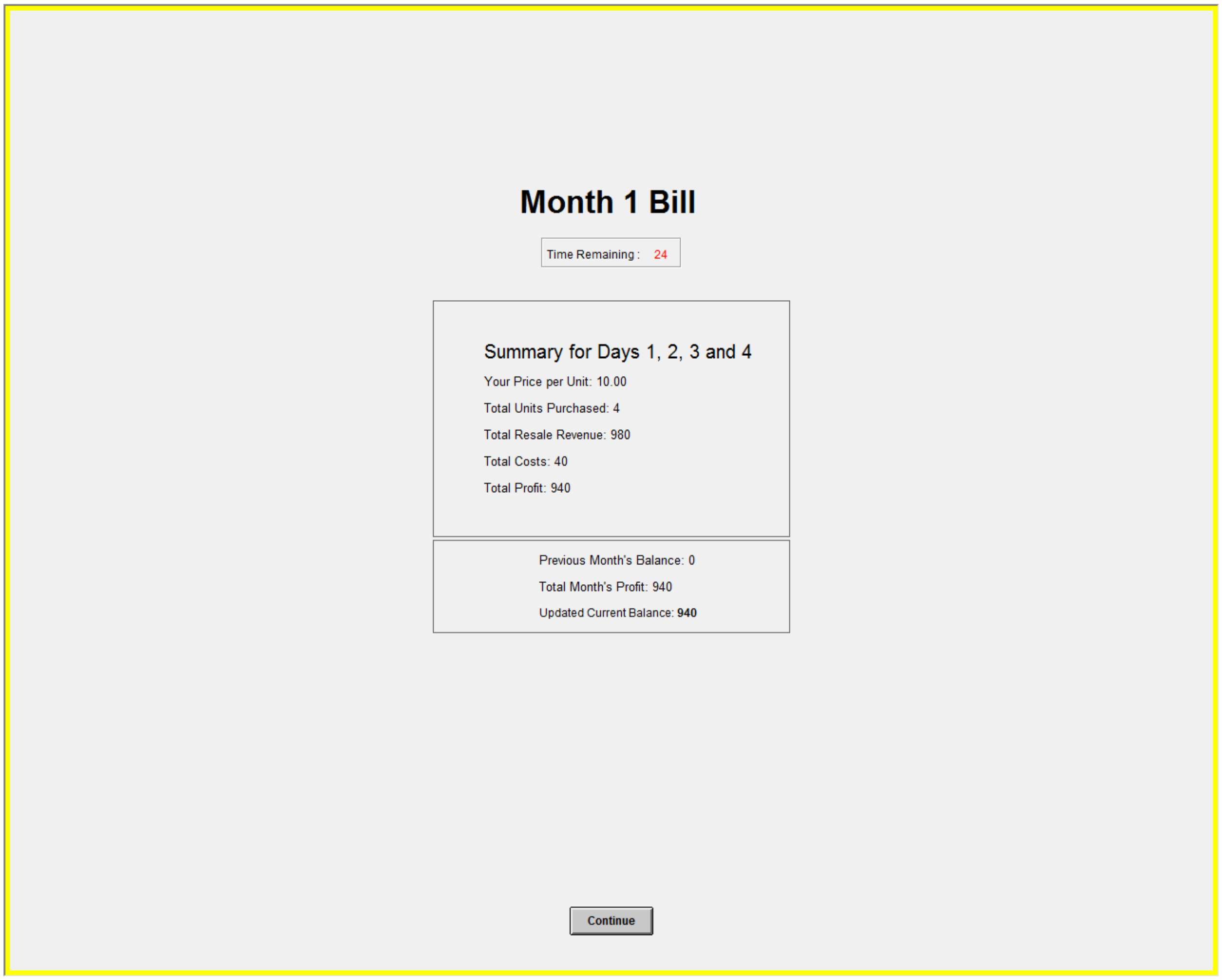


Image 9: Phase 2 Monthly Bill for FRP-M and FRP-R

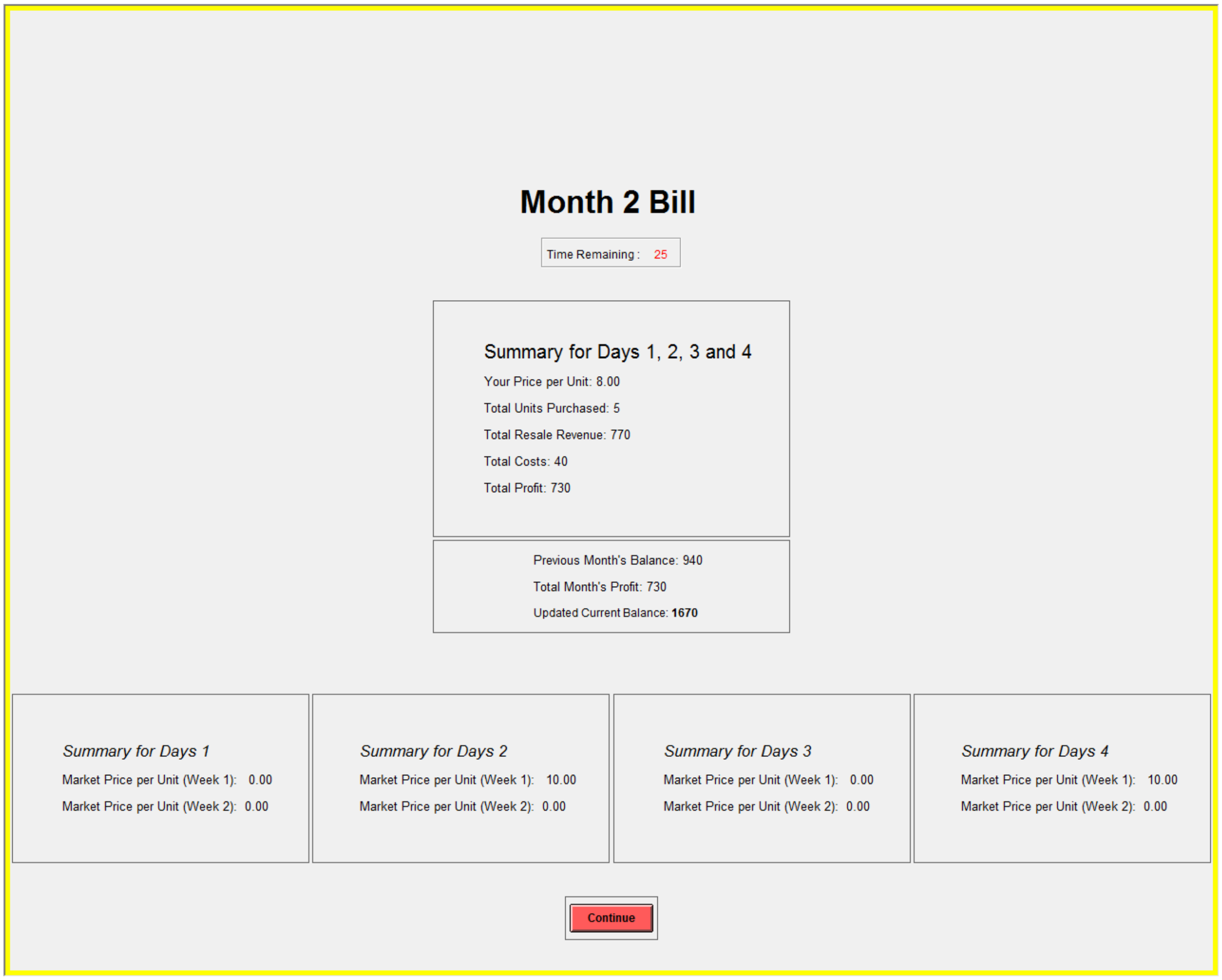
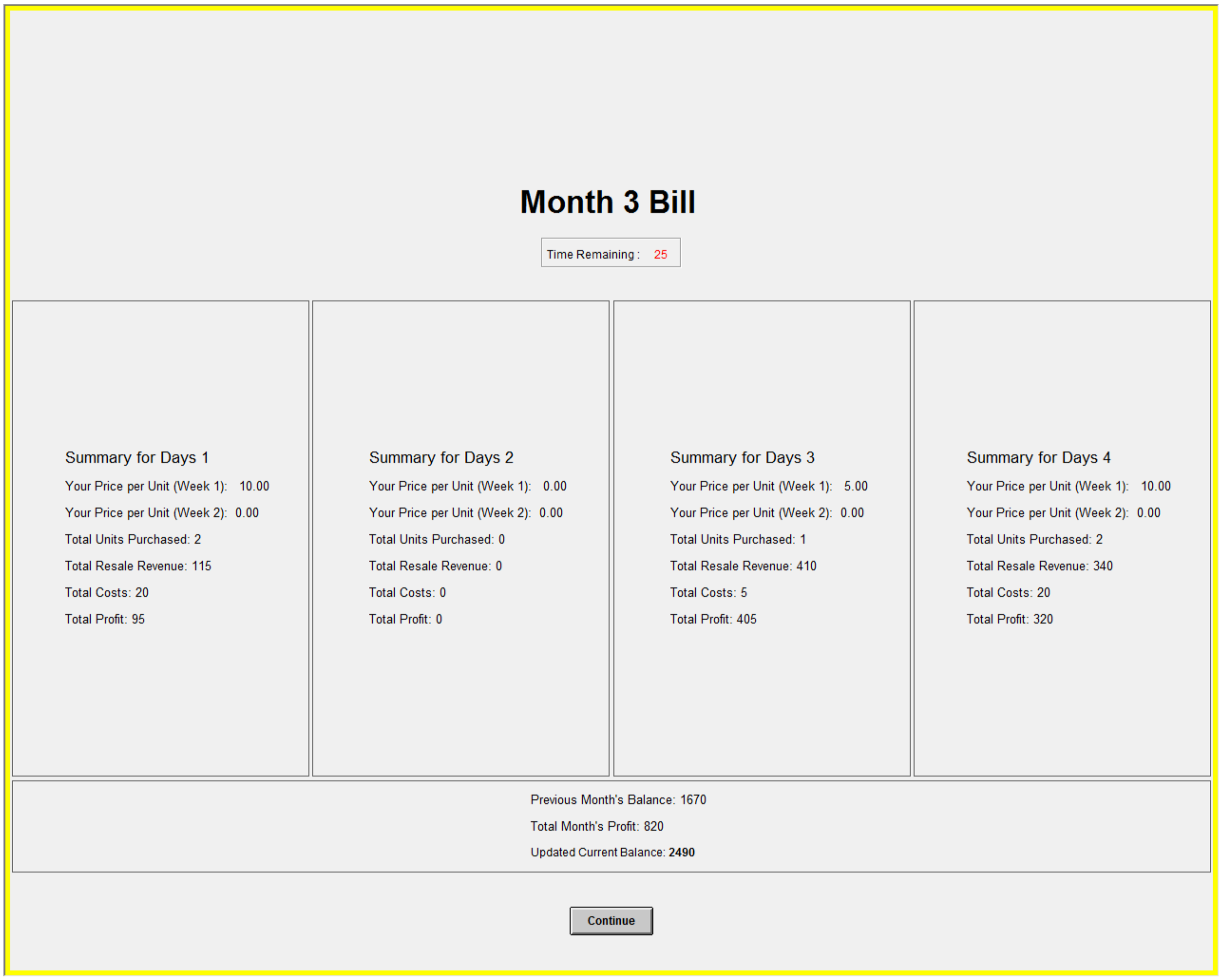


Image 10: Phase 3 Monthly Bill for FRP, FRP-M, and FRP-R



Appendix C

Table 1: Summary of Treatments

Treatment	Phase 1		Phase 2		Phase 3		Phase 4	
	Pricing Program	Type of Additional Feedback	Pricing Program	Type of Additional Feedback	Pricing Program	Type of Additional Feedback	Pricing Program	Type of Additional Feedback
FRP	Flat rate	None	Flat rate	None	Real-time	Direct	Flat rate	None
FRP-M	Flat rate	None	Flat rate	Indirect	Real-time	Direct	Flat rate	None
FRP-R	Flat rate	None	Flat rate	Direct	Real-time	Direct	Flat rate	None

Table 2: Producer Surplus Calculations

Producer Surplus Table		
Units	Cost per Unit	Producer Cost
0	0	0
1	5	5
2	10	15
3	15	30
4	20	50
5	30	80
6	40	120
7	50	170
8	60	230
9	75	305
10	90	395
11	105	500
12	120	620
13	135	755
14	150	905
15	165	1070
16	180	1250
17	200	1450
18	220	1670
19	240	1910
20	260	2170
21	280	2450
22	300	2750
23	320	3070
24	340	3410
25	360	3770
26	380	4150
27	400	4550
28	420	4970
29	440	5410
30	460	5870
31	480	6350
32	500	6850

Table 3: Flat Rate Pricing Pure-Strategy Nash Equilibrium Outcomes

	Units Purchased				
	Subject 1	Subject 2	Subject 3	Subject 4	**Total**
Day1	0	0	0	0	**0**
Day2	2	2	2	2	**8**
Day3	3	3	5	5	**16**
Day4	1	1	2	2	**6**
total	6	6	9	9	**30**

Table 4: Real-Time Pricing Pure-Strategy Nash Equilibrium Outcomes

	Units Purchased				
	Subject 1	Subject 2	Subject 3	Subject 4	**Total**
Day1	1	1	1	1	**4**
Day2	2	2	2	2	**8**
Day3	3	3	5	5	**16**
Day4	1	1	3	3	**8**
total	7	7	11	11	**36**

Table 5: Average Phase Efficiencies

	Phase 1	Phase 2	Phase 3	Phase 4
FRP	80%	86%	93%	89%
FRP-M	74%	81%	93%	90%
FRP-R	78%	86%	94%	91%

Table 6: Average Change in Efficiencies

	Phase 1-2	Phase 2-3	Phase 3-4
FRP	6%	7%	-4%
FRP-M	7%	12%	-3%
FRP-R	8%	8%	-4%

Table 7: First Questionnaire Ratings

	FRP	FRP-M	FRP-R
Phase 1	6.45	5.65	6.25
Phase 2	7.05	7.5	8.1
Phase 3	5	5	6.1

Table 8: Final Questionnaire Ratings

	FRP	FRP-M	FRP-R
Phase 1	5.25	5	5.2
Phase 2	6.05	6.5	7.5
Phase 3	9.3	8.9	8.3
Phase 4	5.95	5.7	4.7

Table 9: Model 1-3 Regression Results

Independent Variables	FRP	FRP-M	FRP-R
Constant	0.77	0.698	0.783
	(0.018)	(0.036)	(0.016)
Phase 2	0.013	0.006	0.09***
	(0.028)	(0.029)	(0.026)
Phase 3	0.038	0.055	0.18***
	(0.048)	(0.055)	(0.042)
Phase 4	-0.053	-0.04	0.149**
	(0.069)	(0.084)	(0.06)
Period (time trend)	0.009*	0.014**	-0.002
	(.004)	(0.006)	(0.004)
R-squared	0.808	0.889	0.934
No. observations	20	20	20

FRP-M and FRP-R models use robust standard errors. Dependent variables are the average of each day's efficiencies of all sessions of designated treatment. Coefficients reported with standard errors and robust standard errors in parentheses.

*, **, *** indicates significance at the 90%, 95%, and 99% level, respectively

Table 10: Critical Values for Two-Sample Fligner-Policello Robust Rank Order Test Phase Comparison

	FRP vs. FRP-M	FRP vs. FRP-R	FRP-M vs. FRP-R
Phase 1	2.32 (0.01)***	0.939 (0.174)	-1.321 (0.093)*
Phase 2	2.936 (0.002)***	-0.609 (0.271)	-3.361 (0.000)***
Phase 3	0.975 (0.165)	-0.898 (0.185)	-1.224 (0.11)
Phase 4	-1.42 (0.078)*	-1.189 (0.117)	-0.32 (0.375)

p values represented in parentheses; *, **, *** indicates significance at the 90%, 95%, and 99% level, respectively

Table 11: Critical Values for Two-Sample Fligner-Policello Robust Rank Order Transition Comparison

	FRP vs. FRP-M	FRP vs. FRP-R	FRP-M vs. FRP-R
Phase 1 to Phase 2	-0.18 (0.429)	-0.853 (0.197)	0.09 (0.464)
Phase 2 to Phase 3	-1.664 (0.048)**	0.093 (0.463)	1.448 (0.074)*
Phase 3 to Phase 4	-0.375 (0.354)	0.093 (0.463)	0.472 (0.318)

p values represented in parentheses; *, **, *** indicates significance at the 90%, 95%, and 99% level, respectively

Table 12: Wilcoxon Rank Sum Test Critical Values for End Questionnaire Treatment Comparisons

	FRP vs. FRP-M	FRP vs. FRP-R	FRP-M vs. FRP-R
Phase 1	0.191 (0.849)	-0.259 (0.796)	-0.259 (0.796)
Phase 2	-0.246 (0.805)	-1.818 (0.069)*	-1.761 (0.078)*
Phase 3	0.537 (0.591)	1.883 (0.06)*	1.390 (0.165)
Phase 4	0.286 (0.775)	0.835 (0.404)	0.668 (0.505)

p values represented in parentheses; *, **, *** indicates significance at the 90%, 95%, and 99% level, respectively

Table 13: Wilcoxon Rank Sum Test Critical Values for Phase 3 Questionnaire Treatment Comparisons

	FRP vs. FRP-M	FRP vs. FRP-R	FRP-M vs. FRP-R
Phase 1	0.853 (0.394)	-0.151 (0.88)	-0.751 (0.453)
Phase 2	-0.551 (0.582)	-1.312 (0.189)	-0.814 (0.416)
Phase 3	0.316 (0.752)	-1.216 (0.224)	-1.216 (0.224)

p values represented in parentheses; *, **, *** indicates significance at the 90%, 95%, and 99% level, respectively

Table 14: Wilcoxon Rank Sum Test Critical Values for End Questionnaire Phase Comparisons

	Phase 1 to Phase 2	Phase 2 to Phase 3	Phase 3 to Phase 4
FRP	-1.228 (0.219)	-4.763 (0.000)***	4.507 (0.000)***
FRP-M	-1.454 (0.146)	-3.202 (0.001)***	3.245 (0.001)***
FRP-R	-1.860 (0.063)*	-2.173 (0.03)**	3.263 (0.001)***

p values represented in parentheses; *, **, *** indicates significance at the 90%, 95%, and 99% level, respectively

Table 15: Wilcoxon Rank Sum Test Critical Values for Phase 3 Questionnaire Phase Comparisons

	Phase 1 to Phase 2	Phase 2 to Phase 3
FRP	-1.240 (0.215)	2.821 (0.005)***
FRP-M	-2.105 (0.035)**	2.926 (0.003)***
FRP-R	-1.998 (0.046)*	2.219 (0.027)**

p values represented in parentheses; *, **, *** indicates significance at the 90%, 95%, and 99% level, respectively

Table 16: Wilcoxon Rank Sum Test Critical Values for Difference in Preference between Phase 3 and End Questionnaires

	Phase 1	Phase 2	Phase 3
FRP	1.785 (0.074)*	1.584 (0.113)	-5.185 (0.00)***
FRP-M	0.708 (0.479)	1.483 (0.138)	-4.216 (0.00)***
FRP-R	0.873 (0.383)	1.319 (0.187)	-2.470 (0.014)***

p values represented in parentheses; *, **, *** indicates significance at the 90%, 95%, and 99% level, respectively

Table 17: Wilcoxon Rank Sum Test Critical Values for End Questionnaire Preference for Phase 1 vs. Phase 4

	FRP	FRP-M	FRP-R
Phase 1 vs. Phase 4	-1.092 (0.275)	-0.667 (0.505)	0.191 (0.848)

p values represented in parentheses; *, **, *** indicates significance at the 90%, 95%, and 99% level, respectively

Table 18: Correlation between Phase Efficiencies and Subjects' Ratings of Phases

Questionnaire	Efficiencies		
	FRP	FRP-M	FRP-R
Phase 3	-0.473*	-0.166	-0.078
	(0.075)	(0.555)	(0.782)
Final	0.613***	0.444**	0.335
	(0.004)	(0.05)	(0.149)

p values represented in parentheses; *, **, *** indicates significance at the 90%, 95%, and 99% level, respectively

Table 20: Total Cost Savings

	FRP	FRP-M	FRP-R
Phase 1-2	23650	16390	45910
Phase 2-3	35430	15210	4575
Phase 3-4	-7845	5665	-15765

Table 21: Savings Comparison

	Type of Feedback		
	None	Indirect	Direct
Darby 2006	-	0-10%	5-15%
Weisz 2012	11%	9%	21%

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