Revisiting the Intertemporal Choice Problem in the Context of Exercise Habits

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Abstract

Consumer behaviours that are difficult to reconcile with standard preferences and beliefs assumed widely in economics are found when studying gym memberships. Della Vigna and Malmendier (2006) demonstrated this, where a sample of gym members were paying, on average, more per attendance than they would otherwise pay for day passes. Using a larger sample over a longer time period, our results provide further evidence of these behaviours. First, out of 17,938 gym members sampled from a major US gym chain, 38% were found to be paying more in gym memberships than they could have paid in day passes. Second, surveyed gym members from a US university had realised gym attendances that were only half their expected gym attendance. Lastly, further analysis investigated additional behaviours of interest, such as significant time delays between final gym attendances and cancellation of memberships. These analyses provides insight into the extent of consumer naivety to their own future consumption behaviours. The wider implication of the inconsistency between the observed behaviours and those we would expect using the rational expectations hypothesis include the impact of transaction costs in causing suboptimal consumption decisions.

1 Introduction

Are we *still* paying not to go to the gym? In 2006, Della Vigna and Malmendier [1] published the paper Paying Not to Go to the Gym which demonstrated behaviours that are difficult to reconcile with standard preferences and beliefs (Della Vigna and Malmendier, 2006) using a dataset of health club members in the Boston Metropolitan Area. Their paper presented eight findings that provide insight into the behaviour of gym members (see Table 1). Two of these findings can be reasonably explained by the Standard model for rational agents, where a rational agent is assumed to exhibit rational expectations and to necessarily utility maximise according to a rational (transitive and complete) preference set.

This study, using two new datasets from a major US gym chain and from a US university gym, aims to replicate these findings and verify the robustness of the results found in the Paying Not to Go the Gym paper. Furthermore, we will discuss the interpretations of their findings in the context of our own results, discussing whether the validity of time inconsistent preferences with naivete vs. overestimation of future efficiency as theoretical explanations for observed behaviours.

Replication in the social sciences is an important exercise. As crowdsourced research studies have shown, such as the study performed by Berrar, Lopes and Dubitzky (2017) on the topic of racial bias in soccer, a given dataset can lead to different conclusions by different research teams. A number of replication studies have garnered wide attention from scholars, including Camerer et al. (2018), which finds systematic bias in published social science experiments partly due to false positives and overestimated effect sizes. Given the important findings and implications of the DVM paper providing clear examples of irrational behaviours being exhibited along with a measure of present bias in individuals, and the availability of a new gym attendance dataset, testing the robustness of these results provides further backing to the methods and theoretical findings.

In standard economic models, the assumption that agents are rational is widely used. An implication of assuming individuals are rational agents with a complete and transitive preference set is that individuals exhibit maximising behaviour, and their preferences can be inferred from the consumption decisions they make. This is the basic foundation of Revealed Preference Theory. The Weak Axiom of Revealed Preference (WARP), that must necessarily be met for an individual to have consistent preferences and in turn demonstrate maximising behaviour, is stated as follows. Given a bundle of goods x and a bundle of goods y, if an individual consumes x over y when both goods are affordable, y cannot be revealed preferred to x (Varian, 2014).

[1] Henceforth referred to as DVM

Table 1: Summary of Key Results

Finding	**Della Vigna and Malmendier (2006)**	**Our Study (2019)**
Finding 1	80% of sample pay above day pass price costs	38% of sample pay above day pass price costs
Finding 2	Average attendance in months 2-4 higher in annual than monthly contract	Replication not yet attempted
Finding 3	Ratio of gym user predicted attendance vs actual attendance is 2.3:1	Ratio of gym user predicted attendance vs actual attendance is 2.0:1
Finding 4	Mean interval between last attendance and termination 2.31 full months	Mean interval between last attendance and termination 3.17 full months
Finding 5	Survival probability after 14 months 17 percent higher for monthly than for annual contract	Replication not yet attempted
Finding 6	Average attendance 26% higher in second year for annual contract	Replication not yet attempted
Finding 7	Decreasing average attendance over time in monthly contract	Decreasing average attendance over time in monthly contract
Finding 8	Positive correlation of price per average attendance and interval between last attendance and termination	Positive correlation of price per average attendance and interval between last attendance and termination

The nature of the contracts in the gym membership data provides a means of testing the validity of standard models and whether observed consumer contract choice satisfies WARP and can be used to accurately infer consumer preferences.. Given the option of a gym membership versus paying to go the gym with day passes with every attendance, the standard model would predict that individuals would, in the absence of major temporal discounting or transaction costs, only pay for gym memberships when it is cheaper than paying per visit. This is found to not be the case, with a significant portion of our sample (37.7%) paying more in gym membership costs than what they could have paid in day pass prices. This questions the validity of the standard model assumptions, and thus demonstrates potential bias in inferring consumer preferences from consumption decisions.

2 Dataset

This study uses two datasets to replicate the findings of the DVM paper. The first is a dataset sourced from a major US gym chain, with locations in multiple states in the US. We have access to the historic attendance data of 62,818 gym members that took part in a behavioural change study in 2018, including 12 million attendances spanning between 2007 and 2019 - being censored for dates before 2007 - at 449 different clubs. While we have access to particular details about gym members, such as clubs they accessed when, the durations of their memberships, and additional services they have purchased (such as personal trainers or upgraded memberships), we do not have access to the payment plans of each gym member over time. We have estimated gym membership prices paid by each gym member by using 2019 membership prices, and inferring membership types from their attendance data. Due to lack of data on membership contract details and for simplicity, we assume that gym members all have monthly contracts with automatic renewal and no commitment to any particular contract length. It is likely that the majority of the composition of gym membership are monthly flexible contracts. The algorithm used by the author for pricing estimation can be found in Appendix A.1. The combination of monthly attendance data and estimated pricing data can be used to explore contract choice, namely the choice between paying for gym memberships or day pass prices when attending the gym. Day pass prices in 2019, although not explicitly advertised by any of the gyms in our sample, were found to be linked to the quality of gyms based on the tier of facilities they contain. The analysis performed using the collected pricing data for monthly memberships and day passes (replications of findings 1 ,4, 7, and 8) assumes the relative price between these two contracts has remained constant over the time period examined. Superficial explorations of historic data points available finds this to be approximately true, though further analysis can be done to test the robustness of this claim.

The second dataset is sourced from a US university located in southern California. We used survey data from 60 students collected in June 2019, in conjunction with a year of gym attendance data for 1412 students from the university gym collected during 2018. The analysis performed comparing survey data and attendance data (replication of finding 3) assumes that the surveyed students are representative of the students in the attendance data, despite being pulled from a different (though overlapping) population.

It is important to note that the US university gym attendance data was attached to cafeteria data on the university site, such that in order to identify individuals in the gym data they must have attended the cafeteria at some point during 2018. It is also important to note that students do not need to purchase a gym membership, as they are automatically enrolled through their tuition fees. Therefore their attendance durations have been estimated by the time between their first and last gym attendance during 2018 in order to find their average monthly attendance. Students with no gym attendances, or an attendance duration that is less than a month, were removed from the sample. We assume that those with no gym attendances during 2018 had no intention of going to the gym. Those with attendance durations with less than a month are removed to prevent inflation of average monthly attendance figures.

2.1 Contractural Menu

The contractual menu we are exploiting to demonstrate irrational behaviour includes the price of monthly memberships and day pass prices.

The menu of monthly membership prices at the major US gym chain is vast. The price a gym member pays for a membership depends on a number of factors including the gym type, location and membership structure. Gyms are grouped into four tiers. With each increase in the tier, the size and the number of amenities a gym offers increases, therefore the price of memberships increases with each tier. The location of a gym may lead to a small premium being attached to the membership prices (an additional $5 a month compared to gyms in the same tier in terms of amenities offered). This is possibly linked to the income levels in each location, with higher price memberships usually being offered in dense urban areas.

There are two main membership structures offered: all monthly EFT transfer/automatic renewal contracts, being 12-month commitment contracts with reduced monthly dues (by $5 a month) and no initiation fee, and basic contracts with higher monthly dues, no commitment and an initiation fee. Regularly throughout the year, the gym chain offers discounts where the basic contract has no initiation fee. In addition to these contracts, there are upfront payments that can be made for various periods of time such as 7-day, 30-day, 90-day and 1 year memberships. These come at a price premium, with the 1 year memberships paid upfront generally having parity with 12-month commitment monthly contracts. Additionally, members can pay for a membership either at a single club, or pay for memberships that access all clubs of a particular quality level. Our dataset does not provide information on which specific contract has been chosen, so we assume basic monthly contracts make up a majority of the sample memberships.

2.2 Sample Construction

Appendix A.2 shows the sample construction. The clean sub-sample has been cut from the original dataset in order to for analysis to be performed.

Since the sample was drawn from those participating in a behavioural change study in 2018, to remove any influence of this study on attendance we are censoring memberships after the end of 2016. In order to reduce the possibilities of errors in earlier attendance entries and membership data, the dataset is also censoring memberships from before 2010. The censoring causes the most significant reduction in sample size compared to the rest of the exclusion criteria, reducing the sample size of individuals by 58%.

A small number of gyms did not have pricing data available, due to their closure before the time of writing. Therefore members that attended these clubs have been excluded. A small number of gym members were excluded due to not registering a single attendance. Membership agreements, by default, should last at least 2 months since first and last month dues are paid at registration therefore entries with a shorter membership duration than this are assumed to be anomalous. Finally some attendances are logged at Unknown clubs. Members logging attendances at unknown clubs have been removed since a comparison cannot be made with the clubs specific day pass price.

The iterative exclusions made should not lead to any selection bias since there is no apparent link between those with missing data and gym attendance. One area which could present bias is excluding those without pricing data for all clubs they attend. This affects clubs that have been closed before July 2019. The reasons for closure may be linked to the quality of service and facilities at these locations, which may have an impact on attendance. However due to the number of gyms in this chain (449 total in our sample), members usually have the option to attend another location that is close by. The assumption must be made that this does not have a significant effect on attendance, which is reasonable since the portion of closed clubs in the dataset is low. The determinants of why some attendances are listed to unknown clubs is not known.

2.2.1 Formation of Pricing Data

Membership pricing estimation is based on current pricing and the duration of upgraded memberships. In addition to a monthly membership payment, contracted members have to pay an annual fee every 12 months, starting after 3 months into their memberships. When members upgrade their contracts, they pay the difference in price between the two contracts which is roughly \$10 between any two contracts. See Appendix A.2 for the precise algorithm.

2.3 Additional Descriptive Statistics

The final sample is composed of 17,938 individuals, including 11,786 females (65.7%), 5,980 males (33.3%) and 172 (1.0%) indeterminant. The mean age of gym members, when signing up to the behaviour change program, is 42.7 years with a standard deviation of 13.0. The mean age when signing up for a gym membership is 35.5 years with a standard deviation of 12.5. The median ages, respectively, are 41 years and 33.2 years. This reflects a longer right tail in the age distributions, with the modal groups being 27-28 years and 25-26 years respectively.

3 Contract Choice at Enrollment

Result 1 37.7% of the sample are paying more in membership fees than they could have paid in day passes.

Descriptive statistics for a selected sub-sample of the data have been collected, presented in Table 2.

There are some striking similarities in the results found here and in DVM. The current estimate for the median average monthly gym attendance is 3.7, while in DVM it is 3.5. The mean average monthly attendance here is 5.6, while in DVM their sample mean (from the portion of their sample with monthly memberships) is 4.3. This appears to be related to the nature of the distribution. Our sample has a higher proportion of gym members at the extremes with high attenders pulling up the mean, but the medians remain similar. This may be due to the sample of gym goers. The sample had all signed up for a behavioural change fitness program that rewarded gym attendance, which may have appealed to dedicated gym goers that self-selected into the fitness program and also to those who have very low attendance seeking incentives to go more. The distributions of the data is presented in Figure 1.

The average costs per month for individuals is similar in both our and DVMs sample. The median cost per attendance in our sample, however, is much lower at \$12.41 compared to \$21.89 in DVM. Yet despite this much lower median cost per attendance, we still find that 6,771 (37.7% of) gym members pay a higher price per month than they would otherwise pay if they simply paid day pass prices. The main driver of the difference in the proportion of gym members paying more in membership fees than day pass prices between our study and in DVM is likely the ratio of membership prices to day pass prices. While the ratio of mean monthly membership fees to mean day pass prices is 7:1 in DVM, in our sample it is 5:2. Therefore individuals in our sample, on average, only need to attend the gym 2-3 times a month before their memberships are cost effective which is much less than for individuals in the DVM sample.

Table 2: Descriptive Statistics of Attendance Data

Descriptive Statistic	**Average Monthly Attendance**	**Average Monthly Costs ($)**	**Average Cost of Attendance ($)**	**Average Day Pass Price ($)**
Mean	5.33	49.86	74.71	21.21
Median	3.73	50.32	13.38	20.03
Variance	27.58	57.89	90235.27	9.55
Standard Deviation	5.25	7.61	266.04	3.10
Range	0.01-47.11	29.72-88.94	1.00 - 5075.25	15-30
Sample Size	17938	17938	17938	17938

Result 2 Average expected gym attendance (14.15) is twice that of the average actual gym attendance (6.94).

Despite using major gym chain attendance data for most of this study, we did not have practical means of surveying expectations from a representative population for the major gym chain dataset. However we did have access to university students, and their university gym attendance data in order to replicate this result. During July 2019, university students were asked to fill out an online survey regarding their gym attendance. Of the 60 individuals sampled, 36 attended the university gym, 5 had gym memberships at a gym outside the university, and 18 did not have a gym membership.

The university gym attendance data had an original sample of 1412 undergraduates and visiting undergraduate students. Due to the sample being collected from those who had attended the Caltech cafeteria, it is possible that many of the 1412 had no intention of attending the gym despite being automatically enrolled. Therefore the sample was reduced by excluding those with 0 attendances. Since there is no data for when an individual signed up for a membership, I am calculating the length of membership using the time between first and last gym attendance by an individual. I also excluded those whose time between first and last attendance was less than one month, since this affected individual mean monthly attendance figures making them unreasonably high. For instance, in the case where the first

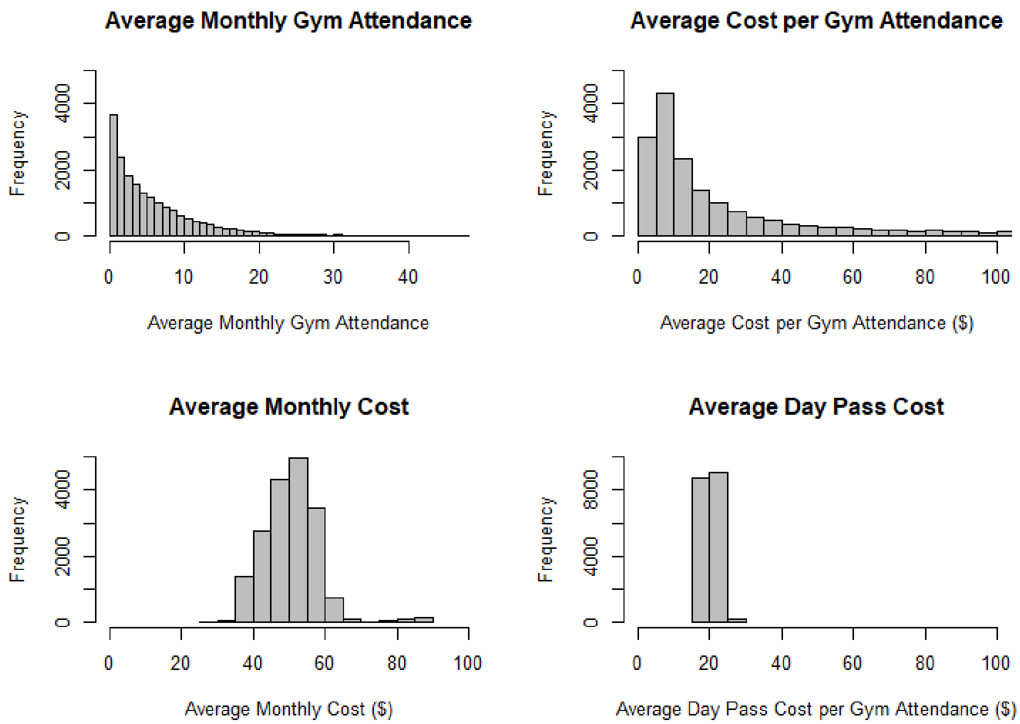

Figure 1: Distributions of Attendance Data

and last attendance of an individual are only one day apart.

The descriptive statistics for the survey data and gym attendance data are presented in Table 3. The sample distribution of the expected average monthly gym attendance, and the realised average monthly gym attendance, can be seen as follows in Figure 2.

Table 3: Descriptive Statistics of University Gym Survey and University Gym Attendance Data

Descriptive Statistics	**Expected Attendance**	**Realised Attendance**
Mean	14.15	6.94
Median	12.50	5.71
Variance	45.34	27.88
Standard Deviation	6.73	5.28
Range	0.50-30.50	0.19-29.68
Sample Size	36	815

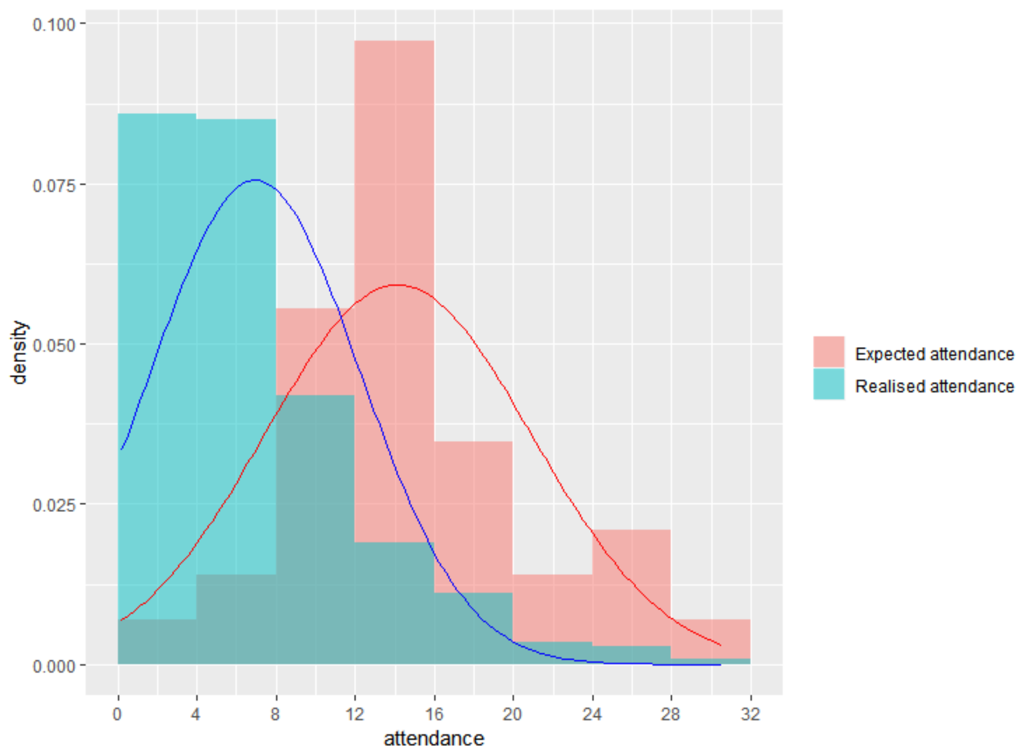

Figure 2: Expected and Realised Gym Attendance by University Students

The results show that expected gym attendance is much greater than the observed gym attendance over twice that of both average measures (mean and median). The difference between the two means is statistically significant with a t-value of 5.58. This result is similar to that observed in DVM, where their survey found gym members expected to attend 9.5 times per month, over twice what was observed in the data with an average monthly attendance of 4.17. The differences in magnitude in the data can likely be explained by the population sampled, with the university student population being of a younger and more active demographic, while the DVM sample had an average age of around 32 years old. Selection bias in the survey sample towards those who are active gym goers is not apparent, due to the high proportion of responses that were registered by those who do not attend the gym or exercise at all.

The modal group of realised monthly attendances is less than once per week (0-4 a month), while the modal group of expected attendance is three-four times a week (12-15 a month). It is intuitive that those who intend to go to the gym will expect their attendance to be above zero, hence a more bell curved shape distribution, while in realised attendance data we see a rapid decline as gym attendances increase above an average of two times per week.

Performing a simple linear transformation, reducing expected monthly attendance by seven (roughly attendances two per week) and mapping negative transformed points to zero, the transformed expected attendance and actual attendance begin to align as shown in Table 4 and Figure 3. This is not a perfect mapping, which is possibly caused by heterogeneity in the optimism of those in the sample. That is, as the number of attendances increase, the overestimation of attendance in absolute values may increase.

Table 4: Transformed Expected Attendance and Realised Attendance

Descriptive Statistics	**Transformed Expected Attendance**	**Realised Attendance**
Mean	7.47	6.94
Median	5.50	5.71
Variance	38.97	27.88
Standard Deviation	6.24	5.28
Range	0.5-23.5	0.19-29.68
Sample Size	36	815

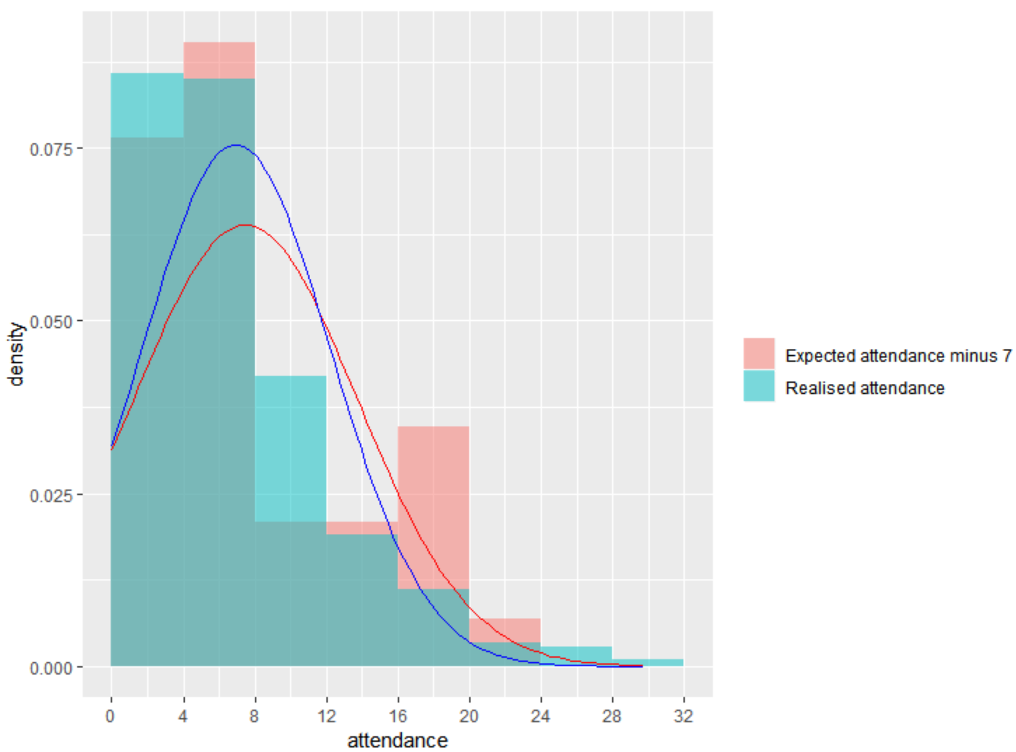

Figure 3: Transformed Expected and Realised Gym Attendance by University Students

Figure 4 presents the results of a hypothetical question posed in the survey. The question asked was as follows:

> *Consider the following hypothetical scenario. Answer what you would do in the following scenario. Suppose that, based on your previous experience, you expect to attend the gym on average 5 times per month (about once a week), if you enroll in a monthly membership at a nearby gym. You plan to attend the gym throughout the next year. Would you choose...*
>
> - *A monthly membership with a monthly fee of $70*
> - *Daily visit passes for $10 (each visit to the gym costs $10)*

This question had 52 responses. When provided a scenario with a realised average monthly attendance, most respondents made the rational choice of using day pass prices. The results are surprisingly similar to those from the original survey performed in DVM with a notable portion of responses choosing the monthly membership option.

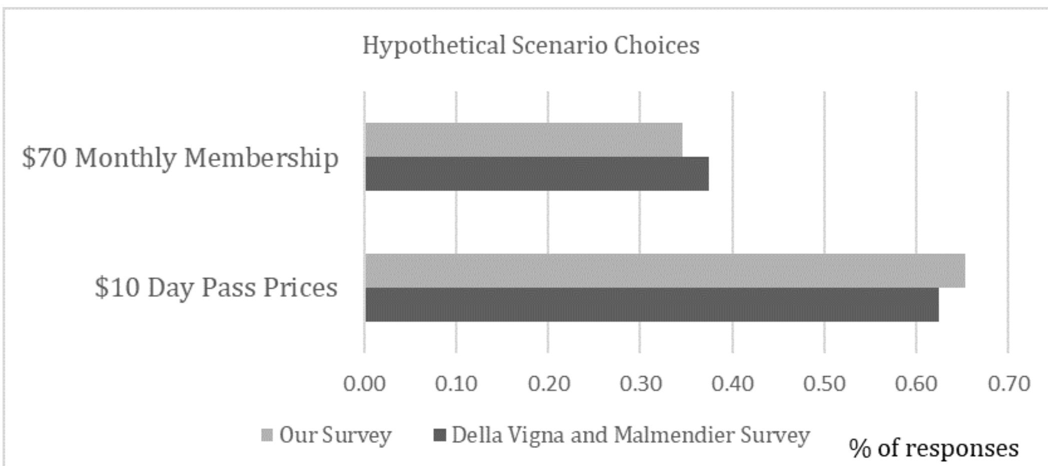

Figure 4: Results of Hypothetical Question from Survey

The results from the survey and university gym attendance analysis suggests individuals have unrealistic expectations about their future attendance, to a significant degree. The survey results also suggest that, when provided with realistic expectations, individuals would generally choose to pay the cheaper day pass options. However the significant portion of respondents still choosing the monthly membership option points to optimism even with updated information about past gym attendance. Both surveys should be interpreted with caution, however, since the survey samples are not the same as the samples used to find realised gym attendance.

4 Contract Choice Over Time

Result 3 - The mean lag between an individuals final attendance and the cancellation of their gym membership is 3.17 months, with 36.0% of gym members having a lag of at least a month between final attendance and cancellation.

Descriptive statistics of cancellation lags in our sample can be found in Table 5, and the distribution (censored at 2 months) in Figure 5. In our sample, the modal group of individuals was those with minimal cancellation lags. Since individuals pay for their final month of attendance when signing up for a membership, individuals always have the option to attend the gym for the next month when they cancel their memberships. This shows that a majority of individuals cancelled their memberships and attended the gym right up to the point where their memberships terminated. However a large proportion of the sample had a lag of over a month when cancelling their memberships. Therefore these individuals lost the cost of one month of membership by not cancelling earlier. In some cases, the cancelations lags are severe with one individual having a lag of almost 6 years (almost the entire span of our sample period). This points to behaviours of some individuals that do not fall in line with the standard model predictions since the standard model, calibrated in DVM, predicts cancellation lags that last at most a couple of days[2].

Table 5: Descriptive Statistics of Cancellation Lags

Descriptive Statistics	**Delay (Months)**	**Cost of Lag ($)**
Mean	3.17	142.33
Median	0.25	0
Variance	51.124	119630.7
Standard Deviation	7.15	345.88
Range	0.02-68.52	0-3451.28
Sample Size	585	585
Interquartile Range	0.06-3.31	0-151.38

[2] Although further calibrations can be done using data from our dataset to further confirm this.

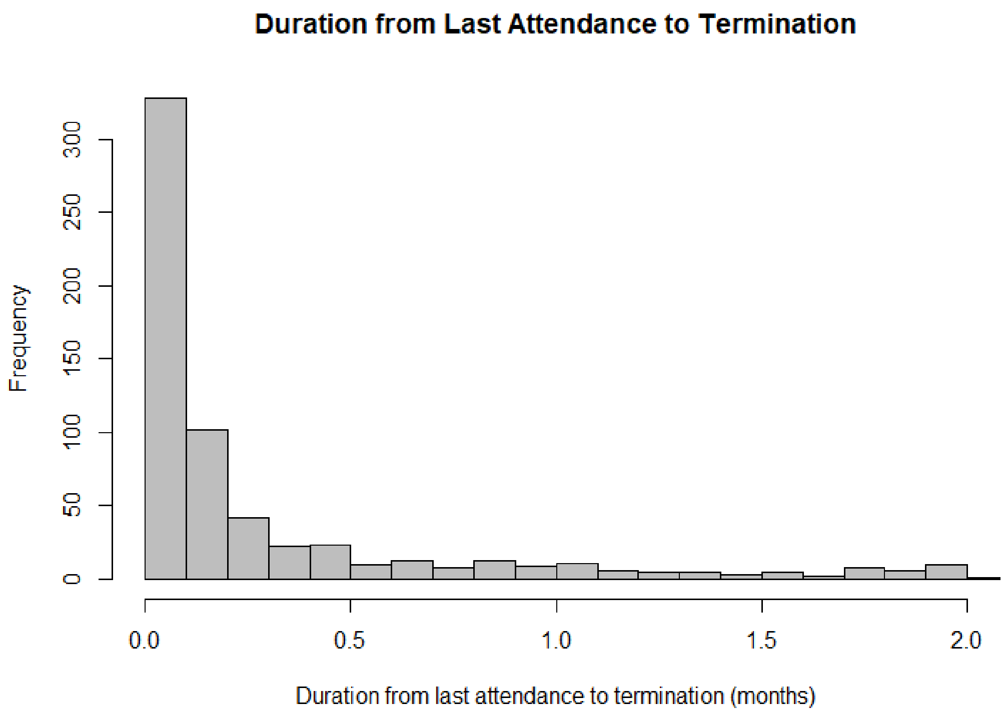

Figure 5: Distribution of Cancellation Lags (cencsored at 2 months)

Result 4 - The average attendance of gym members is falling over time.

Table 6 and Figure 6 provide a summary of the attendance and attendance costs over time. We would expect that the lowest attenders in the sample, who have the highest average cost per attendance, would be the first the cancel their gym memberships in favour of paying day pass prices. However we find that the mean and median attendance of the sample, with attrition as individuals cancel their gym memberships over time after sign-up, declines significantly. Those remaining in the sample after twelve months have a mean attendance that is less than half the mean attendance in the first month of their gym memberships. Even more damning is the median attendance, showing that by month eleven and twelve over half of gym members in the sample did not register a single attendance. This points to more active members actively cancelling their memberships, while low attenders are remaining in the sample for longer periods of time.

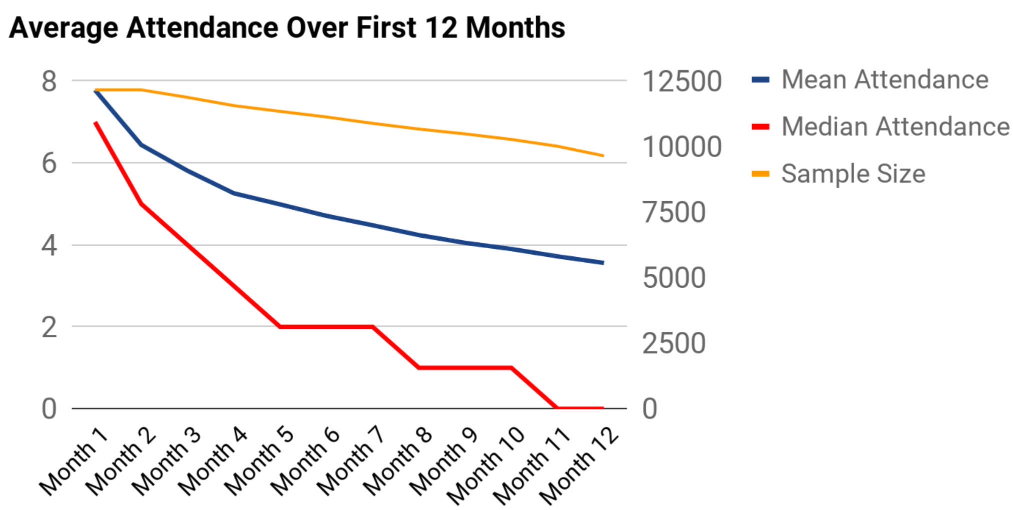

Figure 6: Average Attendance Over Time After Signup

Table 6: Average Monthly Attendance Over Time After Signup

Month	**Mean Monthly Cost ($)**	**Mean Attendance**	**Median Attendance**	**Mean Price per Attendance ($)**
Month 1	49.55 (7.62) N = 12163	7.78 (6.44) N = 12163	7 N = 12163	6.37 N = 12163
Month 2	49.55 (7.62) N = 12163	6.44 (6.44) N = 12163	5 N = 12163	7.69 N = 12163
Month 3	49.55 (7.63) N = 11877	5.81 (6.37) N = 11877	4 N = 11877	8.53 N = 11877
Month 4	49.54 (7.61) N = 11562	5.26 (6.23) N = 11562	3 N = 11562	9.42 N = 11562
Month 5	49.52 (7.63) N = 11342	4.99 (6.23) N = 11342	2 N = 11342	9.93 N = 11342
Month 6	49.51 (7.63) N = 11129	4.71 (6.19) N = 11129	2 N = 11129	10.50 N = 11129
Month 7	49.51 (7.63) N = 10886	4.48 (6.15) N = 10886	2 N = 10886	11.06 N = 10886
Month 8	49.51 (7.63) N = 10668	4.24 (6.07) N = 10668	1 N = 10668	11.67 N = 10668
Month 9	49.50 (7.64) N = 10483	4.05 (6.01) N = 10483	1 N = 10483	12.21 N = 10483
Month 10	49.50 (7.62) N = 10272	3.90 (5.93) N = 10272	1 N = 10272	12.71 N = 10272
Month 11	49.54 (7.64) N = 10011	3.72 (5.85) N = 10011	0 N = 10011	13.30 N = 10011
Month 12	49.52 (7.65) N = 9646	3.56 (5.79) N = 9646	0 N = 9646	13.84 N = 9646

The standard deviations of mean monthly cost and mean attendance are in parentheses. Mean price per attendance is calculated simply as mean monthly cost over mean attendance.

Result 5 - Users who pay a high price per attendance is correlated with a longer cancellation lag (time between final attendance and contract termination).

After transforming cancellation lags and price per attendance, by adding one and taking logs, in order to make them more linear, we find a positive and greater correlation between price per attendance and cancellation lags relative to the correlation found in DVM. This result suggests heterogeneity, to a more significant degree, in our sample. This supports the hypothesis that a single unique mechanisms such as overestimation of future efficiency or self-control drives both the high price per attendance and cancellation lags. I.e. those exhibiting one behaviour is likely to exhibit the latter behaviour.

The heterogeneity in our sample may be more evident due to the sample composition, as explained earlier, as our sample may be composed of more dedicated gym goers as well as those who struggle greatly with gym attendance.

Table 7: Correlation Between Average Price per Attendance and Cancellation Lags

Month	**Correlation Coefficient (DVM)**	**Correlation Coefficient (Our Sample)**	**OLS Regression Coefficient (Our Sample)**
Month 1	0.192	0.475 N = 429	0.464 N = 429
Month 4	0.182	0.461 N = 411	0.387 N = 411

5 Interpretations

The interpretation of these findings is summarised in Table 1[3] in DVM. Our replication also provides sufficient backing for their leading explanations for the observed behaviours. Namely, time inconsistent preferences with naivete and overestimation of future efficiency.

The two interpretations in DVM can be summarised as follows:

Time Inconsistent Preferences with Naivete.

Individuals display present bias, being a preference for present over future payoffs, or alter-

[3]Page 695

natively a distaste for present costs over deferring them into the future. In economic models, this is shown using (β, δ) preferences (O'Donoghue and Rabin, 1999), being discounting future time periods by δ with an additional β discount term for all future time periods, with β demonstrating present bias. Since attending the gym is a present cost with long run payoffs, present-biased individuals will attend the gym less than they would like at the time of enrolment. As a commitment device, individuals may purchase a gym membership to increase future attendance. These individuals will also delay one-time cost tasks, such as the act of cancelling a gym membership when they update their expectations of their attendance. However simulations of present-bias performed in DVM still do not explain why cancellation lags are so large. Additionally, it is theorised that individuals are nave as to their future present-bias. That is, they underestimate how present-biased they will be in the future, where their expected β discount factor, $\tilde{\beta}$, is such that $\beta < \tilde{\beta} \leq 1$ (O'Donoghue and Rabin, 2001). This leads to substantial delays in membership cancellation, since this leads to a greater tendency for individuals to delay cancelling till a future time where they think they will be likely to incur the cost of cancelling their gym membership.

Overestimation of future efficiency

Alternatively, individuals may be overestimating the benefits of going to the gym, or underestimate the costs. But they do not only overestimate their gym attendance, they also underestimate the costs of cancellation. Anecdotal examples of this can be found reading review sites for various gyms, where individuals are exasperated with the efforts required to cancel a gym membership (usually requiring a formal letter or a visit to the gym in order to cancel memberships at US gyms). Therefore the overestimation of gym attendance, along with underestimation of the cost of cancelling a gym membership, may lead to individuals keeping their memberships for extended periods with low attendance.

6 Discussion

The results we have reproduced support the results of the original DVM study. We have shown that a significant proportion of our sample have chosen to pay for a monthly membership contract that is more costly than simply paying for day passes. Our sample also exhibits other interesting behaviours found in DVM, such as long cancellation lags, decreasing average attendance over time, and positive correlation of price per average attendance. Therefore the main findings of the DVM appear robust to scrutiny using a new updated. However, more work needs to be done to test the remaining three findings. We have also not provided any significant backing to the interpretation of their results, namely calibrating a model of time inconsistent preferences and finding an estimate of that is equal to 0.7.

Our survey results combined with the university gym data, in addition to results found in Acland and Levy (2012), may promote stronger backing for theoretical explanation provided by overestimation of future efficiency.

While we see an optimism in future gym attendance that leads to a prior belief that average gym attendance costs will be lower with a gym membership than paying day pass prices, we see persistent optimism even with updated attendance information. This is eluded to by the hypothetical question posed to our survey sample, but this persistent optimism is also found in Acland and Levys post-treatment sample of individuals who took part in an experimental intervention that attempts to invoke exercise habits. Post-treatment groups overpredicted their actual attendance by a factor in the range 2-4, although this is less optimistic than the pre-treatment group who overpredicted by a factor in the range 2.5-5.5.

We would like to perform our own calibrations of the model of time-inconsistent preferences presented in DVM using our pricing and attendance data before we can provide a strong backing for this theoretical explanation. In theory, it is possible that individuals have overly optimistic expectations of their gym attendance, even if they are non-attenders. If this is the case, there may be significant lags between a final attendance and the point where an individual even considers cancelling a gym membership due to their optimism. This could then explain a significant portion of the lags observed, rather than lags caused procrastination in making the costly action of cancelling a gym membership.

This would have interesting policy implications since the positive welfare effects of legislation that attempts to reduce the cost of cancelling, such as regulations making memberships as easy to cancel as they are to sign up to, may be minimal in gym markets. Rather it may be individuals optimism for gym attendance that generate the majority of welfare loss in paying for services they do not utilise cost effectively.

7 Conclusion

Our replication of the DVM findings has shown their results to be robust, with our data exhibiting similar behaviours. Our test of rational expectations provided behaviours of similar direction and magnitude in the optimism of our survey subjects. Our sample from the major US gym chain also exhibited similar behaviours to the DVM sample, though the nature of our sample selection may have lead to the disparity in the magnitude of our results versus those found in DVM. Despite the absence of precise pricing data in our sample that may mean our results lack precision in the measurement, the sample still displays behaviours that are irreconcilable with the assumptions imposed on economic agents in standard models.

There is still further work required to provide support for DVMs interpretations of their results, namely running simulations of time inconsistent preference models that have been calibrated for our sample.

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8 Acknowledgements

Many thanks to Anastasia Buyalskaya for her on-going support with this analysis, and to Colin Camerer for both his support and for providing the opportunity to work on this project and with his lab group. I would also like to thank the Camerer lab group for their support and helpful feedback on this analysis.

Many thanks to the Behaviour Change for Good team at the University of Pennsylvania for providing the dataset used for this analysis.

A Appendix

A.1 Pricing Estimation Algorithm

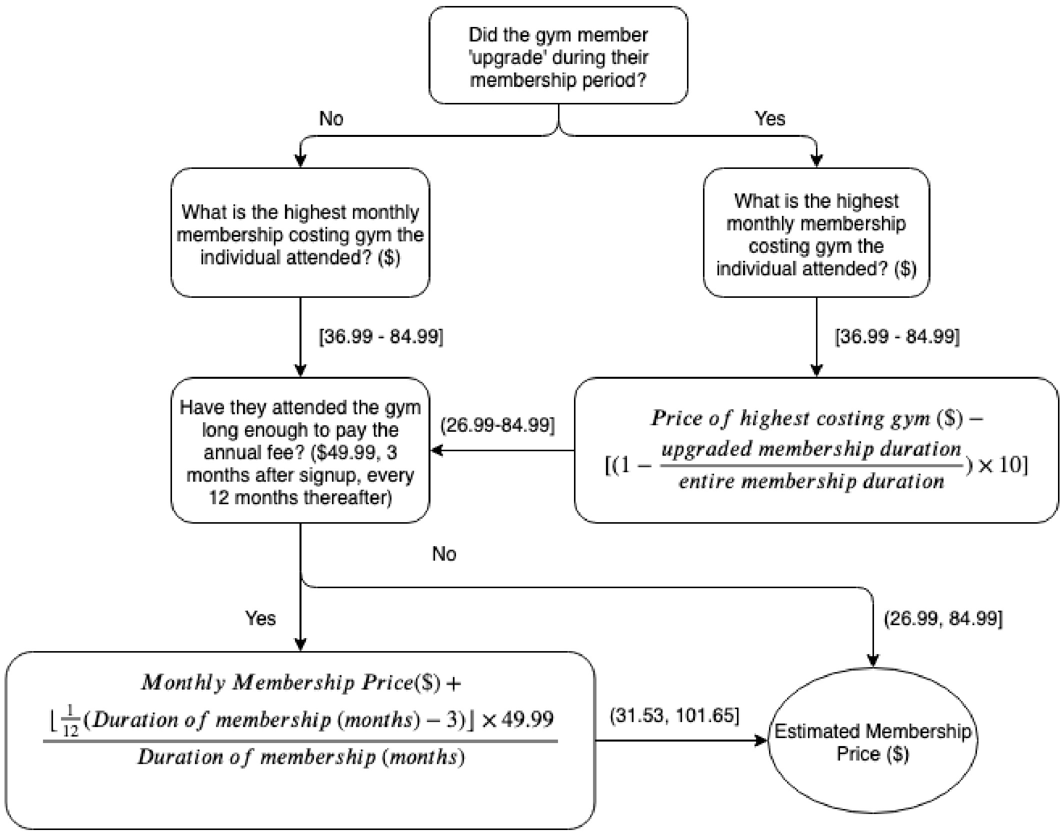

Figure 7: Pricing Estimation Algorithm

A.2 Exclusion Criteria Generating Sample

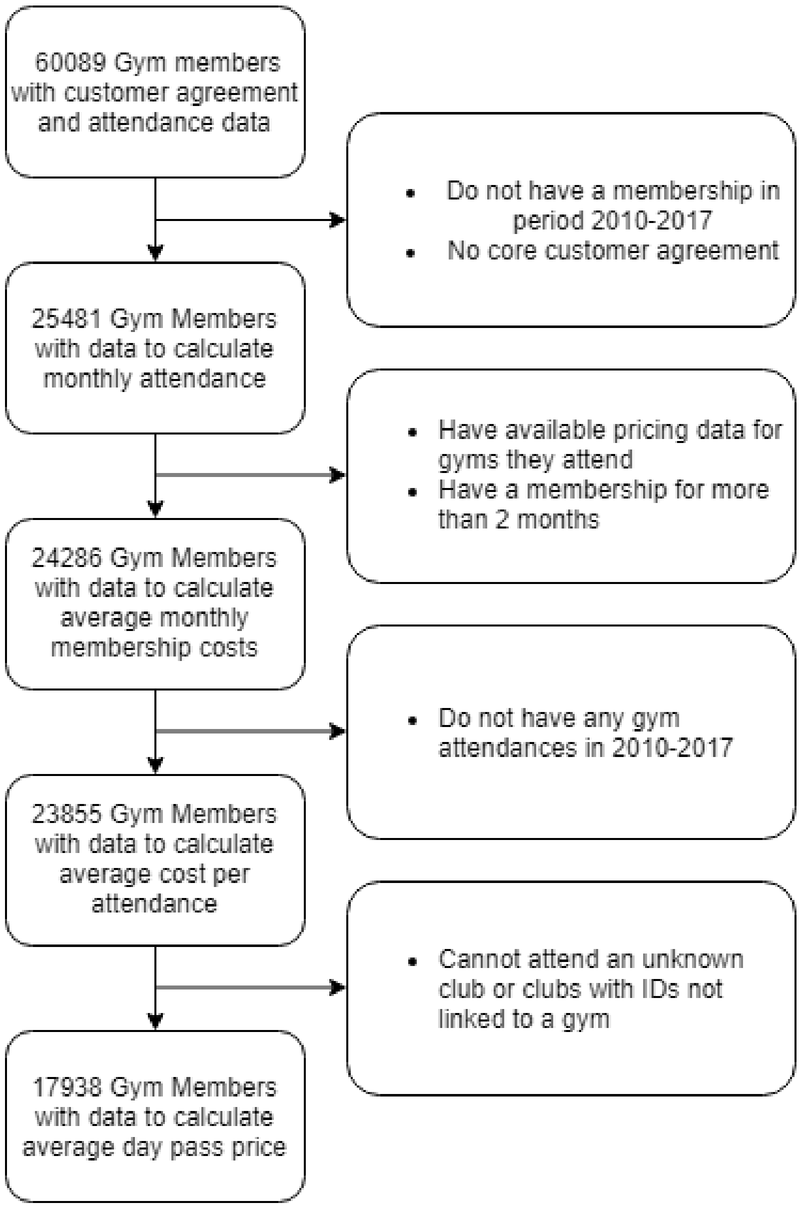

Figure 8: Exclusion Criteria for Constructing Sample