Energy Conservation Contests as Field Experiments on Strategic Allocation of Effort

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Abstract

Data from campus energy reduction contests carried out over a two-year period are described and analysed. A key feature of the contests is that feedback on daily energy consumption, and ranking relative to other contestants, is available to each contestant through a dedicated website. The 'Tullock Contest' format is applied and we consider and formally test where possible for optimal effort allocation, incentive compatibility, and the impact of asymmetric information. We find that prizes are not incentive compatible, but that position in the ranking is a strong motivator: being ranked in the top five brings about a reduction in consumption of 7.7% in the subsequent period; being in the bottom ten brings about an increase of 6.5%. Change in ranking has a mixed effect on competitors: an improvement brings about a further reduction in consumption of 5.1%; whilst a decline induces an increase of 4.8%. More general results relating to energy consumption are also found, for example: females consume more energy than males; there are economies of scale in energy use within campus flats; and there are time trends in energy use within semesters. We find an interesting result for males whose ranking has worsened, not only are they *not* motivated to reduce energy they actually increase their consumption under such circumstances.

JEL classification: Q41; D12; C33

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1 Introduction

Following the UK becoming a signatory to the Kyoto Protocol, the Government passed The Climate Change Act, in 2008 committing the UK to a 34% cut in Greenhouse Gas (GHG) emissions by 2020 against a 1990 baseline, with further targets set for 2050 of up to 80%. Initially, only applicable to large polluters these targets are becoming more important for a wider sector of the economy with detailed compulsory targets being fed down to universities through HEFCE. In order to meet the target, guidance from HEFCE to universities requires them to publish carbon management plans that provide details of how reduction targets will be met. These targets currently relate to 'Scope 1 and 2 emissions'[1] only, with additional guidelines expected soon, for 'Scope 3 emissions'. Scope 3 emissions will include energy used in student residences, student transport to university and carbon emissions associated with all waste generated by residential students. As an initiative to start to understand and control energy costs smart metering is being installed in residences at the flat level in many universities, this provides data for economic and social analysis.

Smart metering and advanced communication technology now play an increasingly important role in the information process helping consumers to understand their patterns of energy use to enable the adjustment of demand. In the domestic setting there is a natural economic case for energy conservation, since energy is a normal good, and households can benefit financially from any savings they are prepared to make. Evidence also exists however that despite significant financial incentives, households are *not* necessarily motivated economically to conserve energy (Costanzo et al. (1986), Dennis et al. (1990), Harrigan (1991), Stern and Aronson (1984)). For the average consumer budget constraints allow limited discretionary choice, for example: renting a DVD increases energy consumption but reduces expenditure on out-of-home entertainment. Nielsen (1993) find evidence of heterogeneity in households' energy consumption related to socioeconomic and lifestyle characteristics, Wilhite and Ling (1995) also find evidence that households with younger adults, and with higher income were more likely to reduce energy consumption in response to feedback. Whereas Mountain (2006) and Brandon and Lewis (1999) find no evidence to support energy conservation associated with socioeconomic factors.

Rent payable on university accommodation often incorporates energy costs, thereby absorbing the risk associated with excessive use by student residents. An ability to establish long term ac-

[1]These comprise of emissions from vehicle fleets, in-house boilers from sources owned or controlled by the institution, and emissions from purchased electricity

curate forecasts of energy demand, will in part, help providers to pass on the savings to students, but more importantly enable supply to be better tailored to demand in a concerted effort to meet carbon reduction targets.

Students are unaccustomed to being motivated by economic means to conserve energy, particularly if they reside in campus accommodation. Energy Conservation Tournaments (ECT), first introduced into UK University campuses in the early Nineties, are regarded as a viable tool to engage students at little cost and have widespread appeal to universities keen to save expenditure on energy, and to boost their 'Green credentials'. Their effectiveness in reducing energy and engendering conservation habits however, is unknown, some focus on environmental aspects, whilst others treat them as entertainment[2]. The limited number and magnitude of the prizes generally offered are incentive compatible only, for those few who stand a chance of winning a prize. Hetrogeniety in 'desire to conserve' energy, the role of feedback and the duration of such tournaments makes this an interesting area to research.

The main purpose of this research is to evaluate the incentive compatibility of using a tournament structure in such competitions. We do this by empirically modelling data obtained from a number of tournaments that took place over two years for six colleges on campus in a British university in the North West of England. The theoretical underpinnings are taken from the Tullock Contest Tullock (1980) and modelling follows the methodology of Lazear and Rosen (1981) and Ederer (2010).

This paper is set out as follows: In Section 2 we review the literature, in Section 3 we present the theoretical model and in Section 4 we describe the econometric methodology used for analysis. In Section 5 we describe the data and the collection process. In Section 6 we present and discuss the results and in Section 7 we conclude with recommendations for the future.

2 Review of the literature

2.1 Energy reduction

Scant attention has been given in the economics literature to the unusual situation where individuals are asked to conserve energy in a situation where there is no connection between benefit and cost. A contribution in the field of social-psychology is McMakin et al. (2002) who study

[2]See for example:'Student Switchoff' at http://www.studentswitchoff.org/unis.

the impact of energy conservation initiatives in military residences. They find that a combination of motivators, including appeal to environmental and social responsibility, and lifestyle benefits, weakly contribute to behavioural change. However, they conclude that altruism is more likely to be an effective motivator when residents feel a sufficient degree of personal control over their wider environment. Other work associated with behavioural analysis is Hayes and Cone (1977). They study post-graduate student housing on a university campus where energy and water charges are combined with the rent. Household metering is combined with daily feedback and varying monetary incentives randomly withdrawn over the monitoring period. Despite the magnitude of the incentive the impact due to this was immediate, and substantial reductions followed, however, long term reductions associated with feedback alone were found to be modest.

Work on sustainability and feedback such as Petersen et al. (2007) also reviews campus activity. Non-intrusive Wi-Fi technology is used to monitor energy consumption for 1600 student residences. Feedback was given in two treatments: ‘high resolution’ being daily; and ‘low resolution’ being weekly. The two types of feedback consist of actual and aggregated data for their own residence and for their competitors. Over the five week monitoring period, reductions in consumption for daily feedback were found to be greater.

Literature associated with environmental aspects such as energy and buildings is Wilhite and Ling (1995). Their work describes a three-year field experiment into the impact of feedback on energy consumption at the household level, in Norway. The households concerned derived direct economic benefit from savings they made. Feedback varied with the detail it offered and for some households included energy saving tips. They found that energy savings from feedback declined over time. Another example is from the field of environmental psychology. Brandon and Lewis (1999) examine the effects of different levels of enhanced feedback on energy consumption for ninety-eight UK households over nine months. They find that relative household consumption is positively associated with conservation from feedback citing ‘environmental beliefs’, as being a good predictor of personal conservation behaviour.

Further work on the role of feedback in energy conservation such as, Neenan (2009) and Darby (2006) review a number of publications on energy monitoring and feedback methodology. The main findings are that feedback should be immediate, clearly presented, household specific, relative to a meaningful standard, and given for a prolonged period, to effect sustainable behavioural change. Darby (2006) also comments in detail about the different electronic devices used to provide feedback.

2.2 Tournament theory

Tournament theory is usually associated with labour economics or sports competitions as an incentive scheme, than to campus energy conservation. Tournament refers to the relative performance of individuals rather than the absolute performance, where ranking is purely ordinal. The seminal paper in the field is by Lazear and Rosen (1981) together with Rosen (1986) the association of using tournament to increase effort has become popular in numerous of fields. Several interactions between different aspects interplay in this area, such as context, cost, prize structure, externalities, alliances and feedback. The role of prizes features strongly in the Tullock contest (Tullock, 1980), empirical work is ambiguous whether the size, or the spread of prizes is effective in raising effort levels. For example, (Ehrenberg and Bognanno, 1990*a*,*b*, Lynch and Zax, 2000) find prize money *is* incentive compatible whilst for others (Orszag, 1994, Lynch, 2005) it *is not*. Although, there are prizes associated with the ECT which we examine, these are relatively small, and preliminary work has found them to be redundant in determining effort. Unlike typical contests where there is heterogeneity in ability, there is no pre-tournament entry threshold in our ECT, theory would therefore suggest (Lazear and Rosen, 1981) that tournament may be inefficient, although it requires minimal monitoring at minimal cost, because only the rank matters in deciding the winner.

3 Model and Methodology

3.1 Theoretical model

In this section we introduce a simple tournament model with information feedback that captures the essential features of the energy conservation tournament. This model closely follows the structure of Ederer (2010) and has the following features. First, there are players with heterogeneous ability; second, it is a multi-stage game with performance feedback between stages; and finally both own effort and some randomness determine the winner.

There are two risk-neutral players (1 and 2) engaged in a two-stage tournament (stage 1 and stage 2) for one prize. The common winning prize value is v and the loser gets 0. Each stage follows a Lazear and Rosen (1981) type of format, in which the players may expend costly effort, the effort is added with a noise and the total is the output of that period. The players get feedback about both their output and ranking after the first stage, and then choose their effort level in the second stage. The player with the highest total output (combined from both stages) wins the tournament. This is an abstract specification of the ECT in which the tournament can broadly be divided into two parts, in the first part ranking is unknown and in the second there is symmetric information regarding performance and ranking.

To formalize the model, we assume that player i expends effort e_{it} in period t. The output in period t is x_{it}=e_{it}+ϵ_{it} where ϵ_{it} is the additive noise term. Thus, the probability that player i wins the tournament is:

$$P_i = \begin{cases} 1 & \text{if} \quad (x_{i1} + x_{i2}) > (x_{j1} + x_{j2}) \\ 0 & \text{otherwise} \end{cases}$$

And the payoff for player i is:

$$\pi_i = \begin{cases} v \quad -c(e_{i1} - c(e_{i2}) & \text{if} \quad (x_{i1} + x_{i2}) > (x_{j1} + x_{j2}) \\ \quad\;\; -c(e_{i1} - c(e_{i2}) & \text{otherwise} \end{cases}$$

Where $c(.)$ is the effort cost function with the standard properties $c^{'}(.) > 0, c^{''}(.) > 0, c^{'}(0) = 0$ and $\lim_{y\to\infty} c^{'}(y) = \infty$. Following Lazear and Rosen (1981) and Ederer (2010), we assume the cost function to be sufficiently convex such that an interior equilibrium exists and the first order condition is sufficient for characterizing optima.

The probability that player i wins can be rewritten as:

$$\begin{aligned} P_i &= P((x_{i1} + x_{i2}) > (x_{j1} + x_{j2})) \\ &= P(e_{i1} + e_{i2}) - (e_{j1} + e_{j2}) > (\epsilon_{i1} + \epsilon_{i2}) - (\epsilon_{j1} + \epsilon_{j2}) \\ &= F((e_{i1} + e_{i2}) - (e_{j1} + e_{j2})) \end{aligned}$$

(1)

Where $F(.)$ is the CDF of $(\epsilon_{j1} + \epsilon_{j2}) - (\epsilon_{i1} + \epsilon_{i2})$ with PDF $f(.)$ which, is uni-modal at 0 and is twice continuously differentiable.

In the context of our ECT this suggests that after an initial no-feedback period, feedback is given to the students about their effort and ranking, they then make a decision about their second period effort depending on the outcome from the first period. We assume students to be rational (or at least to be intrinsically motivated by environmental concern, if the prize is not sufficient) and use backwards induction following the analyses of Ederer (2010, pp. 742) and expect that if in the first period, the output difference ($|x_{i1} - x_{j1}|$) is high, then the effort chosen will be low in the second period. Conversely, if it is low, then the effort chosen will be relatively higher. We split the duration of the tournament into two periods, the first week, and the remaining seven weeks, this enables us to to establish what a stable routine might be for each flat and the initial ranking for the first stage of the model. Flats ranked in the top five by rank after the first stage are classified as 'high performers,' flats ranked in the bottom ten at the end of the first stage are classified as 'poor performers.'

3.1.1 Hypothesis testing

H(1) High performers will exert extra effort to reduce energy consumption, in the second stage of the tournament.
H(2) Poor performers will exert less effort to reduce energy consumption in the second stage of the tournament.

4 Econometric Model

To test the theoretical model given in Section 3.1 we develop three econometric models in the first we use a simple structure to test the effect on consumption of being in the top or bottom of the rankings at the end of the first week. In the second we go further by deriving a model of effort and find the factors that determine this for our two identified groups. In the third, we estimate a pooled model of effort.

4.1 Test for the effect of prior ranking on consumption

To test Equation 1. Let i index flats, ($i = 1 \cdots, n$) and t index time in days, ($t = 1 \cdots, T$). Let y_{it} be the daily cumulative consumption of energy of flat i in period t defined by:

$$\sum_{t=1}^{T} y_i$$

Let x be a dummy variable to denote a ranking in the top five, (High performers) at any time during the first week. Let z be a dummy variable to denote a ranking in the bottom ten, (Poor performers),[3] at any time during the first week. We discard the data for the first week and estimate the following models for each college for each semester:

$$y_{it} = \beta_0 + x_i\beta_1 + v_i + \epsilon_{it} \tag{2}$$

$$y_{it} = \alpha_0 + z_i\alpha_1 + v_i + \epsilon_{it} \tag{3}$$

Where: i=1, ⋯, n, t=1,⋯ T, $v_i + \epsilon_i$ is the residual. v_i and x_i; v_i and z_i are uncorrelated.

4.1.1 Hypothesis testing

We test:

H(1) in Equation 2 $H_0 : \beta_1 < 0$, a reduction in consumption.

H(2) in Equation 3 $H_0 : \alpha_1 > 0$, an increase in consumption.

The results for these are given by college in Tables 1 to 6 and discussed in Section 6.

4.2 Testing for strategic allocation of effort

Let Y_{it} be the normalized effort score of flat i in period t, defined by:

$$Y_{it} = P\left(\ 1 - \Phi\left(\ \frac{(x_{it} - \bar{x}_{i,1})}{\sigma_t}\ \right)\ \right)$$

Where:

$0 < Y < 1$, i=1, ⋯, n, t=1,⋯ T.

x_{it} is the natural log of per person consumption for flat i at t.

$\bar{x}_i$ is mean log of per person consumption over the first week for flat i.

σ_t is the standard deviation of per person consumption over all flats at t.

Note that a low consumption level results in a high value of Y, indicating a high effort level. We assume that Y is determined as follows:

[3] Except for college 2, where the number of flats is small and only the ranking of the bottom 5 is used instead

(4) $$Y_{it} = \gamma_0 + \gamma_1 \Delta Y_{it-1} + \gamma_2 \mathrm{D}_{it} + \gamma_3 \mathrm{R}_{1,it-1} + \gamma_4 \mathrm{R}_{2,it-7} + \gamma_5 \mathrm{T} + v_i + \epsilon_{it}$$

Where:

ΔY_{it-1}, 'difference in effort' ($Y_{it-1} - Y_{it-2}$).
D, 'distance to winning' ($y_{it} - y_{jt}$), where flat j is the best performing flat.
R is the cumulative rank of consumption per flat at t defined as:

$$\sum_{i=1}^{n} \sum_{t=1}^{T} r_{it}$$

Where r=1 denotes best performance.
$R_{1,it-1}$ is the first period lag of *r*
$R_{1,it-7}$ is the weekly period lag of *r*
T, time in days.
v_i is the unit specific residual.
ϵ_{it} is the error term (mean 0, uncorrelated with itself, 'D', 'R', 'T' or *v*, and homoskedastic).

4.2.1 Hypothesis testing

We test for the effect of feedback on effort with the following hypotheses using Equation 4:

- H(3) Strategic allocation of effort. If students are naturally inclined to conserve energy they will neither increase or decrease effort. $H_0 : \gamma_1 = 0$.
- H(4) The effect of the 'distance to winning' on effort, if $(y_{it} - y_{jt})$ is large, effort is expected to be reduced $H_0 : \gamma_2 < 0$.
- H(5) The effect of 'lagged rank' on effort $R_{1,it-1} > 0$, $H_0 : \gamma_3 > 0$, if ranking is high in the first stage. $H_0 : \gamma_3 = 0$ otherwise .
- H(6) The effect of 'weekly lagged rank' on effort, $R_{1,it-7} > 0$, $H_0 : \gamma_4 > 0$ if ranking is high in the first stage. $H_0 : \gamma_3 = 0$ otherwise.
- H(7) If the ECT is effective at engendering energy conservation behaviour we expect to see $H_0 : \gamma_5 > 0$.

H(3) to H(7) are tested on four samples of the data separately:

- Model (1), is estimated for the 'High performers' only.
- Model (2), is an estimate that includes all flats not in Model (1).
- Model (3), estimated for the 'Poor performers' only.
- Model (4) is an estimate that includes all flats not in Model (3).

The results from Models (1) and (2) are compared as a further test of H(1), whilst the results from Models (3 and (4) are compared as a further test of H(2). The results for these are given by college in Tables 7 to 12 and discussed in Section 6.

Equation 4 is estimated using a fixed-effects estimator and our panel data, which we discuss in Section 5, it is estimated for each college for each semester using flat level clustering.

4.3 Pooled level estimates of effort allocation

In this treatment we pool the data from all colleges over semesters 4, 5 and 6 and include demographic variables as well as data obtained for a control group of flats (discussed in Section 5). Again we let i index flats, ($i = 1 \cdots, n$) and t index time in days, ($t = 1 \cdots, T$). Here we let Y_{it} be the log of daily flat level consumption of energy of flat i in period t defined by:

$$Y_{it} = \alpha_0 + \alpha_1 \bar{Y}_{it-7} + \alpha_2' X_{it} + \alpha_3' W_{it} + \alpha_4' Z_{it} + \beta t + \epsilon_{it} \tag{5}$$

$$i = 1, \cdots, N \; t = 1, \cdots, T.$$

Where:

$\bar{Y}_{it-7}$ is the mean natural log of daily consumption by flat i in the previous week t. this acts as the cultural norm in this model.

X_{it} is a vector of variables related to the characteristics of the flat. These include: the percentage of males; the average year of study (yos); the number in the flat; and the number in the flat squared.

$W_{i,t}$ is a vector of rank related variables. These include a dummy for being in the top five (Top); a dummy for being in the bottom ten (Bottom); a dummy to denote an improvement in rank (rank improve); a dummy to denote a worsening in rank (rank worsen), (both of these dummy variables are derived from the difference in rank between $t - 1$ and $t - 2$).

$Z_{i,t}$ is a vector of flat characteristics. These include: males and year of study; and rent payable per flat.

t represents time in days in each semester, this is approximately 56 days.

ϵ_{it} is the error term.

4.3.1 Hypothesis testing

We test for the effect of individual and flat level characteristics on consumption with the following hypotheses using Equation 5:

- H(8) Gender. Do males consume more?
- H(9) Longevity at university. Do students collect more kit over time?
- The ECT, we use control data for non-competition flats.
- Ranking, being in the top or bottom of the ranking as well as a change in ranking.

Equation 5 is estimated using a fixed effects pooled GLS estimator, using two models (5) and (6) where model (6) includes additional interaction variables. The results for these models are given in Table 13.

5 Data Collection and Descriptive Statistics

As a policy decision to raise culture awareness in environmental issues, an ECT was set up by the students' union, involving three colleges of student accommodation in the autumn semester of 2009 (Semester 1). The competition entailed the monitoring of overall electricity consumption via digital sensing equipment known as smart metering on a daily basis per flat, for eight weeks of the semester, for six semesters. We claim this to be a *field experiment* as defined by Harrison and List (2004) as students were aware that monitoring was taking place and that they were in a competition. Only electricity usage, which excludes hot water and central heating is monitored. The flats involved comprise of one college of 52 older flats (College 3). These have between 5 and 8 bedrooms sharing two bathrooms and a kitchen, (the energy monitors for these flats are retro-fitted OWLS). And two further colleges, College 1 (25 flats) and College 2 (18 flats), these are new-build 'eco-town houses' comprising of between ten and twelve en-suite bedrooms sharing three kitchens and a large lounge. Monitoring of these houses is via in-built monitoring equipment. Students in all colleges can view how well they are performing relative to others in their college, on the student's union website on a daily basis. Feedback is available in kWh and in terms of CO_2 emissions. Students in College 3 also receive enhanced feedback in the form of instantaneous usage from a display linked to their OWL monitor, in their kitchens. In all 915 undergraduate students of mixed gender, academic year (these demographics are also collected) and degree major, are involved in the competition in each year.

Further data was also collected from a further 340 flats for 1000 students for semesters 4 to 6. This is used as a control to help assess the effectiveness of the competition.

Unlike traditional tournaments, the students do not self-select into the ECT, instead they are allocated to it by virtue of the accommodation to which they are assigned. The students occupying the flats do so for one academic year and are included in three competitions over that time. Some may also be included in the following year but would not occupy the same flat. The monitoring period in this study exceeds that of many smaller university competitions reported on the web[4] and in the literature cited in Section 2.1. It also meets the specification for monitoring as suggested by Neenan (2009), and we believe offers a higher degree of credibility and accuracy than other self-reported examples. A prize is awarded to each of the top three performing flats in each college at the end of the eight week monitoring period in each semester. These prizes are tiered and comprise of two monetary packages paid to all individuals in the winning flat (approximately £15 to £50 per person), or as a group prize awarded to the whole flat such as a 'trolley dash' around the Union supermarket. Again, unlike other tournaments, such as in the case of sports tournaments, personalities gain economic benefit through the betterment of their rating/ranking, and sponsorship, the students in these tournaments receive no other additional benefits, economic or otherwise, to reward effort.

An interesting feature of this tournament is that as a dynamic contest there is full availability of data on own and opponents energy consumption and ranking on a lagged daily basis. Although, we cannot verify if the students actually make use of this information, this contrasts with most sports contests, such as golf and horse racing, where information is asymmetric. This allows us to model the informational impact of public information (feedback) on energy consumption in a

[4]There are many websites that claim to be running carbon competitions similar to this posted on the web. But it has not been possible to interact them any of the organizers to verify their methodology or claims.

dynamic context.

As described in Section 4, two variables of interest are the 'effort score' and the 'distance to winning'. Figures 1, 3 and 5 depict the distribution of 'distance to winning' variable together with a normal distribution for each semester for each college. The spread varies greatly and in most cases the distribution is multi-modal.

The distribution of the 'effort score' is give in Figures 2, 4 and 6, these more closely follow the normal distribution although the spread also varies with semester and college. We have truncated the effort score to 0.99 if greater than this in the empirical work we describe. Effort is measured on the scale $0 <$effort< 1, an effort level of 0.5 is in fact no change in effort, a score > 0.5 is higher effort and a score < 0.5 is reduced effort. For colleges 1 and 2 there is a greater population below 0.5 in the first semester of the academic year (semesters 1 and 4) which shifts slightly towards the centre in the second semesters (semesters 2 and 5). But for college 3 the distribution is more symmetric, with the exception of semester 2. There is a slight weight in the upper section of the distribution in the pattern for the summer semesters, 3 and 6, particularly evident for college 1. An explanation for this is that in the summer students take their exams and return home at different times, thus spending less time in their flats. Consumption can therefore fall and effort appears to have dramatically improved.

6 Results

6.1 Interpretation of results: Hypothesis (1)

Let us be reminded of this hypothesis:
H (1) High performers will exert extra effort to reduce energy consumption, in the second stage of the tournament. The results for this are given in Tables 1, 3 and 5. We estimated Equation 2 testing for $\beta_1 < 0$, this is the variable 'In top 5 in wk1' shown in the tables. We find that the coefficient for this is negative in every semester for each college. This confirms that being a 'high performer' in the first stage, has a strongly significant effect of reducing consumption in the second stage.

We also set out to test further H(1) with respect to allocation of effort estimating Equation 4. The results from these estimates are given in Tables 7, 9 and 11. These results are set out in pairs with Model (1) estimated on the 'high performer' sample appearing on the left for each semester and Model (2) on the right estimated on the remaining sample, for each of the six semesters by college.

The results for these are mixed across the colleges and semesters, starting with allocation of effort H(3), shown as $\Delta Y_{i,t-1}$ in the tables. This hypothesis is not rejected in the majority of cases, however, it is either significantly negative or significantly positive in some cases. A significantly positive coefficient indicates that an increase in effort is followed by a further increase; a negative coefficient would indicate that an increase is followed by a decrease. This reveals evidence of cultural norms. Nielsen (1993) claims that these are dependent on a number of factors such as the time spent in the home, norms and habits, and the proportion of electricity consumption that can be influenced by external activities, such that students can choose to work/eat/relax from/at home or in other locations on campus. We find a wide variance in student energy consumption for all colleges. We also find that high effort followed by high effort, occurred less frequently that high effort followed by low effort, possibly suggesting a lack of application or strong heterogeneity in consumption/ attitudes/desire towards energy conservation.

H(4), tests the effect of the 'distance to winning' on effort we find that this is negative in the majority of cases. There is no evidence that the 'high performers' are more discouraged than the rest.

H(5) and H(6) test for the effect of knowledge of recent ranking and weekly ranking on effort. We test positive coefficients in for the variables 'Lag Rank' and 'Weekly lag Rank' for the 'high performers'. These results are inconclusive, for the lag of rank (7/18) are significantly positive for the 'high performers', and (11/18) for the others. However, there are mostly not significant values for the weekly lag. This suggests that the first lag is more important in effort determination but not for the 'high performers'.

For H(7) we test for sustained effort over the semester, this is shown as 'Time' in the tables. The results are again mixed, this tends to be negative or not significant in the autumn semesters and positive in the spring (semesters 2 and 5) and summer (semesters 3 and 6) ones. This we attribute to students using additional heating during cold spells, and returning home in warm spells. There does not appear to be any difference in the magnitude of this coefficient for the two samples of flats. We cannot confirm or deny that students are developing a greater commitment to energy conservation.

6.2 Interpretation of results: Hypothesis (2)

Again let us be reminded of this hypothesis:

H(2) Poor performers will exert less effort to reduce energy consumption in the second stage of the tournament. We are testing H(2) in Equation 3 $\quad H_0 : \alpha_1 > 0$. The results for this are given in Tables 2, 4 and 6 and it is shown as the variable 'In the bottom 10 in wk1' or bottom 5 wk1 for college 2. We find that the sign on this coefficient is significant or strongly significantly positive in every case, confirming that ranking in the first week is a strong predictor of future performance regardless of position.

We also set out to test further H(2) with respect to allocation of effort estimating Equation 4. The results from these estimates are given in Tables 8, 10 and 12. Again these results are set out in pairs with Model (3) estimated on the 'poor performer' sample appearing on the left for each semester.

Again the results for these are mixed, starting with allocation of effort H(3), shown as $\Delta Y_{i,t-1}$ in the tables. These results are not too different from the ones discussed above, with little difference between the two samples of flats.

H(4), tests the effect of the 'distance to winning' on effort. As discussed above this coefficient is also significantly negative in every case, no seasonal bias is evident in these samples.

H(5) and H(6) test for the effect of knowledge of recent ranking and weekly ranking on effort. Again little difference in the lag rank, however, there is a population of significant values for the weekly lag (5/18) for the 'poor performers'. This suggests that the weekly lag has greater value and is more important in effort determination to this group.

6.3 Interpretation of results: Hypothesis (5) and (6)

With reference to the results presented in Table 13, we interpret the hypotheses mention in Section 4.3.

Do males consume more energy than females? The negative coefficient for the percentage of males in the flat is an indication that males *do* in fact consume less than females. An explanation for this is that female students typically use hair driers and heating tongs which are energy intensive, so in flats with fewer females we find lower consumption of energy. Males might also be more involved in sports, which reduces the time they spend in the flat.

Does longevity at university mean students consume more energy? This myth was brought about by college residential officers noticing what they believed was, *more electronic equipment and televisions*, in flats after the Christmas period. We cannot find evidence to support this, with a negative but not significant coefficient on the year of study variable.

Is there evidence of economies of scale in energy consumption? Kandel and Lazear (1992) find in the firm setting that effort falls as firm size rises due to free-riding, but that peer pressure can exert positive influence on smaller groups where all stand to benefit from group effort. The strongly significant, positive /negative coefficients for the‘ number in the flat’ and it’s square (the function is therefore quadratic as expected) do reflect evidence that economies of scale exist. We can think of three benefits from this, an opportunity to cooperate amongst flat-mates to share cooking, an absence of free-riding and positive externalities from peer pressure. The turning point[5] tells us that energy consumption rises as the number of students increases to 4.7 then falls off. This might also be interpreted as generating utility up to four students and dis-utility when the fifth joins the flat.

What effect is there on consumption from a change in ranking? The two variables to denote a recent change in ranking, are signed as expected with strongly significant coefficients: negatively for an improvement in ranking; and positively for a worsening in ranking. These lagged variables reflect additional effort for an improvement of 5.1% and a slackening in effort of 4.8% when a fall in ranking occurs. In Model (6), we include two additional variables, where the change in ranking is also interacted with the percentage of males variable to further understand if there is a significant difference in attitude between the sexes to good/poor performance indicators. Our positive but not significant coefficient for an improvement in ranking suggests no difference in effect between the sexes when news is good. However, the mildly significant and positive coefficient for a decline in ranking suggests that males are not only *not* motivated to reduce energy they actually increase their consumption under such circumstances. This has strong resonance with the observations of Kagel (1995) whose finding of tacit collusion gives rise to under (over) compensation strategies in response to performance evaluations. Our result collaborates research by Barankay (n.d.), who finds that ranking has a negative effect on the performance of salesmen, when dis-associated with financial rewards. It also collaborates research by Kuhnen and Tymula

[5] coefficient for ‘no in flat’/(2 × coefficient on ‘no in flat squared’)

(2012), who describe a 'productivity hierarchy effect' associated with information on performance ranking. In their research experimental subjects engaged in maths solving tasks appear to react to rank related feedback depending both on their expectations and on the actual ranking. They report that productivity is subsequently, reduced when they find that their rank was better than expected. Other research termed 'Joy of winning' obtained from brain scans of subjects involved in tournaments Dohmen et al. (2011) indicate a strong effect from winning for both males and females.

What effect does 'being in the competition' have on performance? The two pairs of interaction terms: 'year of study' and 'percentage of males', combined with being (not being) in the competition, separately estimate the effects of being the competition. We are interested in the difference in the magnitude of these coefficients and their respective significance. Surprisingly, the coefficient for the competition flats is more than double that of the non-competition flats and is strongly significant, indicating a significantly higher level of consumption for males who have been at university longer and are in the competition compared with their non-competition peers. This might be an artifact Kagel's tacit collusion theory, where they collude to raise levels of utility through higher consumption, after all making an effort for *eight weeks* is a huge sacrifice for some. Or it may be a signal that the effort level of these individuals to reduce consumption, exceeds that of their valuation of the reward. Alternatively, this is an example of contestants knowing their value of the prize with certainty but, they have high discount rates which reduces its value over time. In which case their behaviour is consistent with a rational consumer and not self-sabotage.

7 Conclusion

The main objective of this research is to evaluate the incentive compatibility of the tournament in reducing energy consumption. Preliminary work indicated that the prizes offered were not incentive compatible in this tournament scenario for any semester or for any college. We therefore tested theory with respect to effort allocation. We divided the period of data collection into two stages, in the first we measured the consumption levels and established a ranking list allocating any flat that appeared in the top five positions in the first week into a 'high performer' set. We then tested their consumption over the second period with respect to the first week's ranking. We found overwhelming evidence that initial ranking predicts future behaviour for good or ill.

We then proceeded to examine effort allocation by deriving an effort variable and using explanatory variables related to feedback to estimate models. Here we found that both the distance from winning was overwhelmingly significant in driving down effort levels.

Finally, we estimated a pooled model using individual and flat level characteristics. Here we busted myths about gender bias, longevity at university and dis-utility amongst flat-mates. Overall this work contributes some interesting insights into the world of student living and empirical models of tournament theory.

7.1 Suggestions for future campus tournaments

We draw on the lessons inherent in tournament theory (Moldovanu and Sela, 2001, Fu and Lu, 2009, Konrad, 2009) and Sheremeta (2010) and suggest that future tournaments incorporate an initial threshold set on the basis of a target reductions. Qualifiers are then entered into a prize draw. This will remove the lack of incentive compatibility and raise effort levels across the board.

Table 1: College 1 Testing H(1)

	Semester (1)	Semester (2)	Semester (3)	Semester (4)	Semester (5)	Semester (6)
In top 5 in wk1	-0.227***	-0.290***	-0.300***	-0.177***	-0.235***	-0.301***
	(0.0392)	(0.0633)	(0.0575)	(0.0513)	(0.0434)	(0.0429)
Constant	4.510***	4.564***	4.451***	4.433***	4.414***	3.496***
	(0.0222)	(0.0358)	(0.0282)	(0.0290)	(0.0213)	(0.0257)
N	1200	1250	1275	1225	1150	300
Number of flats	25	25	25	25	25	25
Mean obs per flat	48	50	51	49	46	12
σ_u	0.0473	0.125	0.0918	0.0908	0.0538	0.0672
σ_e	0.541	0.560	0.582	0.546	0.512	0.270
ρ	6.66e-09	0.00000464	0.000000174	0.000568	6.48e-08	2.27e-12

Dependent variable: Log of per person cumulative consumption. Over observation in weeks 2 to 8. Random-effects GLS regression.

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2: College 1 Testing H(2)

	Semester (1)	Semester (2)	Semester (3)	Semester (4)	Semester (5)	Semester (6)
In bottom 10 wk1	0.202***	0.267***	0.271***	0.244***	0.241***	0.289***
	(0.0394)	(0.0598)	(0.0458)	(0.0314)	(0.0307)	(0.0413)
Constant	4.324***	4.343***	4.238***	4.240***	4.213***	3.238***
	(0.0295)	(0.0415)	(0.0330)	(0.0235)	(0.0238)	(0.0298)
N	1200	1250	1275	1225	1150	300
Number of flats	25	25	25	25	25	25
Mean obs per flat	48	50	51	49	46	12
σ_u	0.0589	0.127	0.0802	0	0	0.0676
σ_e	0.541	0.560	0.582	0.546	0.512	0.270
ρ	0.000000284	0.00000808	3.27e-09	7.80e-15	4.20e-15	2.64e-12

Dependent variable: Log of per person cumulative consumption. Over observation in weeks 2 to 8. Random-effects GLS regression.

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3: College 2 Testing H(1)

	Semester (1)	Semester (2)	Semester (3)	Semester (4)	Semester (5)	Semester (6)
In top 5 in wk1	-0.194***	-0.195***	-0.718**	-0.363**	-0.326***	-0.351***
	(0.0425)	(0.0523)	(0.241)	(0.113)	(0.0483)	(0.0619)
Constant	4.495***	4.531***	4.401***	4.419***	4.456***	3.573***
	(0.0265)	(0.0348)	(0.139)	(0.0755)	(0.0279)	(0.0462)
N	864	900	918	882	828	216
Number of flats	18	18	18	18	18	18
Mean obs per flat	48	50	51	49	46	12
σ_u	0.0417	0.0763	0.475	0.222	0.0594	0.106
σ_e	0.536	0.562	0.568	0.608	0.517	0.265
ρ	0.00000508	0.000184	0.00285	0.00136	1.44e-11	1.49e-08

Dependent variable: Log of per person cumulative consumption. Over observation in weeks 2 to 8. Random-effects GLS regression.

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4: College 2 Testing H(2)

	Semester (1)	Semester (2)	Semester (3)	Semester (4)	Semester (5)	Semester (6)
In bottom 5 wk1	0.169***	0.252***	0.537*	0.346**	0.270***	0.326***
	(0.0487)	(0.0415)	(0.257)	(0.116)	(0.0620)	(0.0731)
Constant	4.354***	4.360***	3.953***	4.104***	4.242***	3.251***
	(0.0303)	(0.0240)	(0.161)	(0.0777)	(0.0386)	(0.0456)
N	864	900	918	882	828	216
Number of flats	18	18	18	18	18	18
Mean obs per flat	48	50	51	49	46	12
σ_u	0.0644	0.0238	0.526	0.230	0.103	0.130
σ_e	0.536	0.562	0.568	0.608	0.517	0.265
ρ	0.000518	1.30e-09	0.0370	0.00297	0.0000129	0.00000820

Dependent variable: Log of per person cumulative consumption. Over observation in weeks 2 to 8. Random-effects GLS regression.

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5: College 3 Testing H(1)

	Semester (1)	Semester (2)	Semester (3)	Semester (4)	Semester (5)	Semester (6)
In top 5 in wk 1	-0.365***	-0.581***	-0.568***	-0.340***	-0.491***	-0.415***
	(0.109)	(0.123)	(0.0995)	(0.0705)	(0.0930)	(0.114)
Constant	4.332***	4.748***	4.523***	4.573***	4.681***	3.513***
	(0.0337)	(0.0451)	(0.0390)	(0.0293)	(0.0351)	(0.0472)
N	2444	2548	2548	2548	2401	492
Number of flats	52	52	52	52	49	41
Mean obs per flat	47	49	49	49	49	12
σ_u	0.206	0.294	0.248	0.175	0.215	0.261
σ_e	0.724	0.494	0.522	0.550	0.521	0.298
ρ	0.000774	0.00000224	1.13e-08	0.00000139	0.000000131	0.000281

Dependent variable: Log of per person cumulative consumption. Over observation in weeks 2 to 8. Random-effects GLS regression.

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6: College 3 Testing H(2)

	Semester (1)	Semester (2)	Semester (3)	Semester (4)	Semester (5)	Semester (6)
In bottom 10 wk1	0.393***	0.638***	0.575***	0.338***	0.464***	0
	(0.0633)	(0.0692)	(0.0689)	(0.0572)	(0.0881)	(0)
Constant	4.206***	4.498***	4.292***	4.430***	4.535***	3.442***
	(0.0304)	(0.0359)	(0.0345)	(0.0286)	(0.0356)	(0.0491)
N	2444	2548	2548	2548	2401	492
Number of flats	52	52	52	52	49	41
Mean obs per flat	47	49	49	49	49	12
σ_u	0.161	0.210	0.202	0.160	0.215	0.302
σ_e	0.724	0.494	0.522	0.550	0.521	0.298
ρ	5.28e-10	3.26e-20	7.74e-17	3.46e-09	0.000000143	.

Dependent variable: Log of per person cumulative consumption. Over observation in weeks 2 to 8. Random-effects GLS regression.

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7: College 1 Results for Equation (4) also Testing H(1)

	Semester 1 Model 1	Semester 1 Model 2	Semester 2 Model 1	Semester 2 Model 2	Semester 3 Model 1	Semester 3 Model 2
$\Delta Y_{i,t-1}$	0.0311	-0.0461	-0.0528	0.00533	-0.312***	-0.112
	(0.0433)	(0.0494)	(0.0418)	(0.0280)	(0.0408)	(0.0800)
Distance to win	-1.877**	-1.663**	-0.279	-1.043***	-0.963	-2.053***
	(0.526)	(0.435)	(0.284)	(0.205)	(0.615)	(0.446)
Lag Rank	0.0222	0.0185*	0.000749	0.00692	0.0221	0.00778*
	(0.0104)	(0.00789)	(0.00926)	(0.00473)	(0.0106)	(0.00325)
Weekly lag Rank	-0.00232	0.00745	-0.00655	0.00420	0.0109	0.00659
	(0.00589)	(0.00731)	(0.00624)	(0.00423)	(0.0225)	(0.00473)
Time	-0.000269	-0.00106	-5.54e-08	0.00186*	0.00552	0.0101***
	(0.000931)	(0.000769)	(0.000982)	(0.000667)	(0.00217)	(0.00135)
Constant	0.669***	0.672**	0.569***	0.696***	-0.324	-0.161
	(0.0786)	(0.182)	(0.100)	(0.131)	(0.249)	(0.111)
N	384	816	400	850	306	969
Number of flats	8	17	8	17	6	19
Mean obs per flat	48	48	50	50	51	51
R^2 adj	0.0459	0.0632	-0.00197	0.0221	0.293	0.305
Corr(u_i, xb)	-0.303	0.0855	0.0522	-0.764	0.504	-0.719
F Stat	4.747	6.869	0.904	6.026	24060.0	119.0
DF	5	5	5	5	5	5
σ_u	0.132	0.0895	0.120	0.149	0.114	0.150
σ_e	0.186	0.189	0.163	0.162	0.139	0.150
ρ	0.0239	0.000135	0.582	0.000306	4.62e-11	2.55e-15

	Semester 4 Model 1	Semester 4 Model 2	Semester 5 Model 1	Semester 5 Model 2	Semester 6 Model 1	Semester 6 Model 2
$\Delta Y_{i,t-1}$	0.198*	0.132**	0.0667	-0.00665	0.248	0.0655
	(0.0627)	(0.0339)	(0.0746)	(0.0254)	(0.118)	(0.0583)
Distance to win	-5.059***	-4.348***	-3.869**	-4.284***	-3.709**	-3.434***
	(0.626)	(0.244)	(0.774)	(0.713)	(0.909)	(0.590)
Lag Rank	0.0413**	0.0296**	0.0160	0.0297***	0.0838*	0.0530***
	(0.0102)	(0.00845)	(0.0236)	(0.00682)	(0.0305)	(0.0129)
Weekly lag Rank	0.0146	0.0164*	0.0166	0.0104	0.0130	0.0169*
	(0.00930)	(0.00694)	(0.0129)	(0.00495)	(0.0156)	(0.00692)
Time	-0.00710***	-0.00633***	0.00244*	0.00215**	0.00417	0.00936*
	(0.000793)	(0.000874)	(0.000629)	(0.000661)	(0.0100)	(0.00399)
Constant	0.971***	1.325***	0.611**	1.219***	0.400	-0.148
	(0.114)	(0.152)	(0.119)	(0.176)	(1.324)	(0.455)
N	392	833	276	874	108	192
Number of flats	8	17	6	19	9	16
Mean obs per flat	49	49	46	46	12	12
R^2 adj	0.138	0.130	0.0324	0.105	0.237	0.227
Corr(u_i, xb)	-0.939	-0.883	-0.886	-0.840	-0.332	0.274
F Stat	27.34	100.9	21892.9	33.08	16.55	22.97
DF	5	5	5	5	5	5
σ_u	0.361	0.242	0.202	0.212	0.185	0.125
σ_e	0.210	0.193	0.205	0.196	0.165	0.135
ρ	0.000104	3.07e-13	5.85e-11	1.89e-10	0.000231	7.32e-08

Standard errors in parentheses, adjusted for flat clusters * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 8: College 1 Results for Equation (4) also Testing H(2)

	Semester 1 Model 3	Semester 1 Model 4	Semester 2 Model 3	Semester 2 Model 4	Semester 3 Model 3	Semester 3 Model 4
$\Delta Y_{i,t-1}$	-0.0486	0.0134	0.00872	-0.0364	-0.147	-0.189**
	(0.0568)	(0.0349)	(0.0255)	(0.0405)	(0.104)	(0.0553)
Distance to win	-1.660**	-1.937**	-0.891**	-0.616*	-1.874**	-1.341*
	(0.488)	(0.435)	(0.276)	(0.242)	(0.550)	(0.476)
Lag Rank	0.0207*	0.0172	0.00830	0.00247	0.00715	0.0116*
	(0.00929)	(0.00922)	(0.00715)	(0.00531)	(0.00551)	(0.00464)
Weekly lag Rank	0.00633	0.00326	0.00327	-0.000773	0.00510	0.0136
	(0.00825)	(0.00682)	(0.00537)	(0.00650)	(0.00576)	(0.0102)
Time	-0.000792	-0.000670	0.00185*	0.000735	0.00941***	0.00787**
	(0.000976)	(0.000775)	(0.000821)	(0.000881)	(0.00174)	(0.00182)
Constant	0.649*	0.710***	0.656**	0.568***	-0.0723	-0.430
	(0.235)	(0.0687)	(0.193)	(0.0824)	(0.150)	(0.204)
N	672	528	600	650	663	612
Number of flats	14	11	12	13	13	12
Mean obs per flat	48	48	50	50	51	51
R^2 adj	0.0594	0.0509	0.0158	0.00503	0.278	0.310
Corr(u_i, xb)	0.00487	-0.465	-0.709	-0.192	-0.551	-0.0433
F Stat	5.434	6.279	3.256	2.422	113.5	19.98
DF	5	5	5	5	5	5
σ_u	0.0951	0.122	0.127	0.102	0.116	0.108
σ_e	0.194	0.182	0.164	0.162	0.158	0.138
ρ	0.00169	0.00290	0.0264	0.0621	1.23e-10	0.00000717

	Semester 4 Model 3	Semester 4 Model 4	Semester 5 Model 3	Semester 5 Model 4	Model 3	Model 4
$\Delta Y_{i,t-1}$	0.126**	0.183**	0.00795	0.0489	0.0582	0.198
	(0.0312)	(0.0522)	(0.0273)	(0.0473)	(0.0558)	(0.100)
Distance to win	-4.509***	-4.822***	-3.521***	-5.317***	-3.174***	-3.800**
	(0.270)	(0.489)	(0.605)	(1.099)	(0.648)	(0.868)
Lag Rank	0.0257**	0.0525**	0.0216**	0.0278	0.0459**	0.102**
	(0.00715)	(0.0137)	(0.00530)	(0.0180)	(0.0137)	(0.0279)
Weekly lag Rank	0.0181*	0.0115	0.00450	0.0355*	0.0161	0.0174
	(0.00633)	(0.0111)	(0.00287)	(0.0114)	(0.00758)	(0.0144)
Time	-0.00604***	-0.00747***	0.00244**	0.00230*	0.00865	0.00581
	(0.000878)	(0.000695)	(0.000645)	(0.000920)	(0.00425)	(0.00817)
Constant	1.504***	0.902***	1.240***	0.770***	-0.0396	0.0293
	(0.148)	(0.0801)	(0.198)	(0.153)	(0.465)	(1.073)
N	686	539	690	460	156	144
Number of flats	14	11	15	10	13	12
Mean obs per flat	49	49	46	46	12	12
R^2 adj	0.141	0.133	0.0741	0.130	0.184	0.287
Corr(u_i, xb)	-0.836	-0.828	-0.531	-0.894	0.324	-0.0532
F Stat	103.1	47.78	33.62	10.67	13.71	12.56
DF	5	5	5	5	5	5
σ_u	0.212	0.217	0.133	0.261	0.137	0.155
σ_e	0.185	0.215	0.193	0.204	0.133	0.157
ρ	4.00e-11	0.000000279	1.54e-08	0.000590	0.0000228	0.0000740

Standard errors in parentheses, adjusted for flat clusters * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 9: College 2 Results for Equation (4) also Testing H(1)

	Semester 1 Model 1	Semester 1 Model 2	Semester 2 Model 1	Semester 2 Model 2	Semester 3 Model 1	Semester 3 Model 2
$\Delta Y_{i,t-1}$	0.0725	0.0642*	0.000229	-0.00965	-0.320**	-0.355**
	(0.0651)	(0.0263)	(0.0726)	(0.0465)	(0.0480)	(0.0970)
Distance to win	-2.615**	-1.770**	-1.662	-2.030*	-0.601***	-0.197
	(0.646)	(0.470)	(0.905)	(0.642)	(0.0705)	(0.112)
Lag Rank	0.00636	0.0180	0.0246	0.0390*	0.0117	0.00332
	(0.0132)	(0.0111)	(0.0232)	(0.0144)	(0.00624)	(0.00362)
Weekly lag Rank	0.0168	0.0119	0.00736	-0.00407	-0.00319	-0.00284
	(0.0265)	(0.00760)	(0.0115)	(0.00782)	(0.00522)	(0.00238)
Time	0.0000113	-0.00227*	0.000205	-0.000755	0.00768***	0.00343**
	(0.00160)	(0.000796)	(0.000859)	(0.000795)	(0.000711)	(0.000910)
Constant	0.546***	0.759***	0.477*	0.752*	-0.0311	0.245*
	(0.0838)	(0.0919)	(0.137)	(0.235)	(0.0408)	(0.0904)
N	336	528	400	500	306	612
Number of flats	7	11	8	10	6	12
Mean obs per flat	48	48	50	50	51	51
R^2 adj	0.0430	0.0465	0.00268	0.0326	0.592	0.333
Corr(u_i, xb)	-0.709	-0.181	0.0266	-0.645	-0.972	-0.146
F Stat	34.36	5.302	2.667	6.954	64.76	19.79
DF	5	5	5	5	5	5
σ_u	0.154	0.187	0.0437	0.110	0.433	0.0554
σ_e	0.205	0.189	0.222	0.181	0.0857	0.0725
ρ	0.000162	0.00564	0.100	0.00307	0.000118	0.00000754

	Semester 4 Model 1	Semester 4 Model 2	Semester 5 Model 1	Semester 5 Model 2	Semester 6 Model 1	Semester 6 Model 2
$\Delta Y_{i,t-1}$	-0.152	-0.0360	0.0895	0.0942*	0.108	0.0637
	(0.0973)	(0.0726)	(0.0736)	(0.0396)	(0.0903)	(0.0887)
Distance to win	-0.235*	-0.136**	-3.655*	-4.617***	-5.287*	-4.206***
	(0.0812)	(0.0411)	(0.937)	(0.639)	(1.704)	(0.461)
Lag Rank	-0.0185	-0.0180	0.0786	0.0566*	0.112**	0.0802*
	(0.0255)	(0.0127)	(0.0541)	(0.0199)	(0.0311)	(0.0236)
Weekly lag Rank	0.00357	-0.00560	0.0431	0.0193	0.0206	0.0367***
	(0.0323)	(0.00937)	(0.0197)	(0.0115)	(0.0133)	(0.00663)
Time	-0.0100**	-0.00555**	-0.00235	-0.00191	0.0413*	0.0182***
	(0.00190)	(0.00119)	(0.00152)	(0.00104)	(0.0163)	(0.00288)
Constant	0.894**	1.129***	1.063**	2.200***	-3.008	-0.0336
	(0.170)	(0.122)	(0.182)	(0.264)	(1.487)	(0.421)
N	392	490	276	552	120	96
Number of flats	8	10	6	12	10	8
Mean obs per flat	49	49	46	46	12	12
R^2 adj	0.278	0.0592	0.0504	0.0804	0.269	0.518
Corr(u_i, xb)	-0.593	-0.650	-0.878	-0.826	-0.966	-0.123
F Stat	27.81	38.60	154.3	20.25	3.848	757.8
DF	5	5	5	5	5	5
σ_u	0.172	0.104	0.276	0.155	0.507	0.151
σ_e	0.164	0.137	0.175	0.168	0.143	0.112
ρ	0.0000980	0.00000268	0.0000138	0.00000670	0.0240	1.08e-09

Standard errors in parentheses, adjusted for flat clusters * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 10: College 2 Results for Equation (4) also Testing H(2)

	Semester 1 Model 3	Semester 1 Model 4	Semester 2 Model 3	Semester 2 Model 4	Semester 3 Model 3	Semester 3 Model 4
$\Delta Y_{i,t-1}$	0.0358	0.0766	-0.0178	0.00205	-0.372*	-0.367***
	(0.0357)	(0.0401)	(0.0711)	(0.0554)	(0.112)	(0.0530)
Distance to win	-1.139*	-2.907***	-2.048*	-1.907*	-0.330*	-0.455**
	(0.435)	(0.422)	(0.655)	(0.665)	(0.0939)	(0.132)
Lag Rank	0.00975	0.0198*	0.0635	0.0283	0.0105	0.00495
	(0.0128)	(0.00882)	(0.0251)	(0.0152)	(0.00483)	(0.00394)
Weekly lag Rank	0.0101	0.0140	0.0244	0.00213	-0.00314	-0.00437
	(0.00948)	(0.0145)	(0.0201)	(0.00825)	(0.00363)	(0.00321)
Time	-0.00217	-0.000584	-0.000144	-0.000384	0.00479***	0.00584***
	(0.00104)	(0.00112)	(0.000860)	(0.000681)	(0.000633)	(0.00123)
Constant	0.754***	0.641***	-0.0653	0.596***	0.231	0.177**
	(0.0891)	(0.0790)	(0.196)	(0.118)	(0.134)	(0.0553)
N	336	528	300	600	357	561
Number of flats	7	11	6	12	7	11
Mean obs per flat	48	48	50	50	51	51
R^2 adj	0.0376	0.0516	0.0339	0.0116	0.419	0.481
Corr(u_i, xb)	0.240	-0.784	0.307	-0.400	-0.213	-0.956
F Stat	19.64	27.13	5.382	3.520	340.7	58.12
DF	5	5	5	5	5	5
σ_u	0.183	0.182	0.0965	0.0680	0.0582	0.268
σ_e	0.169	0.210	0.178	0.210	0.0745	0.0800
ρ	0.000804	0.00000424	0.0386	0.0199	0.000000181	0.000000107

	Semester 4 Model 3	Semester 4 Model 4	Semester 5 Model 3	Semester 5 Model 4	Semester 6 Model 3	Semester 6 Model 4
$\Delta Y_{i,t-1}$	-0.0722	-0.114	0.0686	0.0967*	0.119	0.0859
	(0.0852)	(0.0881)	(0.0593)	(0.0429)	(0.0893)	(0.0887)
Distance to win	-0.140*	-0.233**	-4.843**	-3.649**	-3.996***	-4.838***
	(0.0468)	(0.0691)	(0.845)	(0.803)	(0.559)	(0.920)
Lag Rank	-0.0178	-0.0200	0.0616	0.0650*	0.0659	0.109**
	(0.0119)	(0.0239)	(0.0328)	(0.0257)	(0.0270)	(0.0240)
Weekly lag Rank	-0.00753	0.00386	0.0217	0.0223	0.0356**	0.0190
	(0.0113)	(0.0262)	(0.0125)	(0.0223)	(0.00674)	(0.0127)
Time	-0.00533**	-0.0100***	-0.00241	-0.00169	0.0152*	0.0371**
	(0.00150)	(0.00183)	(0.00162)	(0.000839)	(0.00413)	(0.00881)
Constant	1.152***	0.966***	2.337**	1.308***	0.416	-2.598*
	(0.150)	(0.132)	(0.401)	(0.221)	(0.486)	(0.826)
N	392	490	322	506	84	132
Number of flats	8	10	7	11	7	11
Mean obs per flat	49	49	46	46	12	12
R^2 adj	0.0781	0.237	0.0801	0.0559	0.474	0.332
Corr(u_i, xb)	-0.550	-0.669	-0.718	-0.932	-0.179	-0.948
F Stat	132.4	25.62	9.388	4.415	1225.2	5.981
DF	5	5	5	5	5	5
σ_u	0.104	0.194	0.130	0.308	0.163	0.485
σ_e	0.132	0.162	0.165	0.175	0.110	0.141
ρ	0.000000469	0.0000157	0.00613	0.0112	3.93e-09	0.00352

Standard errors in parentheses, adjusted for flat clusters * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 11: College 3 Results for Equation (4) also Testing H(1)

	Semester 1 Model 1	Semester 1 Model 2	Semester 2 Model 1	Semester 2 Model 2	Semester 3 Model 1	Semester 3 Model 2
$\Delta Y_{i,t-1}$	-0.0269	0.00445	-0.330**	-0.283***	-0.292***	-0.239***
	(0.0827)	(0.0257)	(0.0702)	(0.0230)	(0.0282)	(0.0239)
Distance to win	-1.376*	-3.091***	-0.882**	-1.177***	-2.184***	-1.576***
	(0.449)	(0.287)	(0.176)	(0.150)	(0.350)	(0.197)
Lag Rank	0.0305**	0.0235***	0.00414	0.0179***	0.0447*	0.0161***
	(0.00479)	(0.00308)	(0.00858)	(0.00297)	(0.0132)	(0.00360)
Weekly lag Rank	0.00408	0.00656**	0.00799	0.00568**	0.00819	0.00637***
	(0.00790)	(0.00213)	(0.00944)	(0.00186)	(0.00539)	(0.00162)
Time	-0.00632*	-0.00959***	0.00646***	0.00903***	-0.00107	-0.00137
	(0.00185)	(0.000889)	(0.00105)	(0.000746)	(0.000704)	(0.000754)
Constant	0.581**	1.756***	0.0787	-0.0227	0.980***	1.350***
	(0.106)	(0.158)	(0.0552)	(0.0864)	(0.147)	(0.212)
N	210	1974	343	2205	392	2156
Number of flats	5	47	7	45	8	44
Mean obs per flat	42	42	49	49	49	49
R^2 adj	0.108	0.137	0.362	0.281	0.240	0.297
Corr(u_i, xb)	-0.356	-0.941	-0.478	-0.538	-0.908	-0.778
F Stat	.	30.40	113.9	124.4	69.33	115.3
DF	4	5	5	5	5	5
σ_u	0.182	0.349	0.0776	0.0925	0.282	0.184
σ_e	0.150	0.163	0.150	0.164	0.169	0.162
ρ	.	4.20e-23	0.00000476	3.19e-35	0.00000439	9.12e-34

	Semester 4 Model 1	Semester 4 Model 2	Semester 5 Model 1	Semester 5 Model 2	Semester 6 Model 1	Semester 6 Model 2
$\Delta Y_{i,t-1}$	0.0599	0.0228	-0.0433	-0.0491	-0.0708	-0.119
	(0.0559)	(0.0207)	(0.0634)	(0.0328)	(0.144)	(0.0728)
Distance to win	-2.109	-1.745***	-0.647	-1.614***	-0.137	-0.731**
	(0.970)	(0.390)	(0.338)	(0.225)	(0.438)	(0.209)
Lag Rank	0.0170	0.00489	-0.00645	0.0151**	0.0496	0.0170**
	(0.00968)	(0.00378)	(0.00920)	(0.00454)	(0.0307)	(0.00523)
Weekly lag Rank	0.00506	0.00481***	0.00447	0.00377	-0.00351	0.00117
	(0.00242)	(0.00132)	(0.00338)	(0.00308)	(0.00324)	(0.00252)
Time	0.00157	0.000284	0.00262*	0.00448***	-0.0276	-0.0214*
	(0.000811)	(0.000801)	(0.00100)	(0.000561)	(0.0146)	(0.00904)
Constant	1.105**	1.504***	0.479***	0.987***	3.564	3.249*
	(0.322)	(0.186)	(0.0646)	(0.157)	(1.719)	(1.256)
N	441	2107	343	2056	82	401
Number of flats	9	43	7	42	7	34
Mean obs per flat	49	49	49	48.95	11.71	11.79
R^2 adj	0.0387	0.104	0.0217	0.0691	0.132	0.0728
Corr(u_i, xb)	-0.956	-0.789	-0.664	-0.802	-0.792	-0.188
F Stat	2.880	17.10	8.688	29.94	60.69	5.822
DF	5	5	5	5	5	5
σ_u	0.392	0.203	0.114	0.190	0.189	0.151
σ_e	0.188	0.169	0.152	0.162	0.151	0.165
ρ	0.0694	2.03e-16	0.00752	1.13e-20	0.0000307	0.000000715

Standard errors in parentheses, adjusted for flat clusters * p < 0.05, ** p < 0.01, *** p < 0.001

Table 12: College 3 Results for Equation (4) also Testing H(2)

	Semester 1 Model 3	Semester 1 Model 4	Semester 2 Model 3	Semester 2 Model 4	Semester 3 Model 3	Semester 3 Model 4
$\Delta Y_{i,t-1}$	-0.00639	0.00215	-0.211***	-0.305***	-0.237***	-0.259***
	(0.0421)	(0.0308)	(0.0482)	(0.0235)	(0.0370)	(0.0232)
Distance to win	-2.581***	-2.770***	-1.857***	-1.134***	-1.076**	-2.145***
	(0.368)	(0.392)	(0.140)	(0.173)	(0.254)	(0.211)
Lag Rank	0.0176**	0.0233***	0.0371***	0.0169***	0.0263***	0.0229***
	(0.00522)	(0.00411)	(0.00797)	(0.00300)	(0.00535)	(0.00313)
Weekly lag Rank	0.00344	0.00663**	0.0167**	0.00406*	0.0135**	0.00526**
	(0.00552)	(0.00219)	(0.00415)	(0.00198)	(0.00372)	(0.00157)
Time	-0.00956***	-0.00859***	0.0147***	0.00801***	0.00102	-0.00239***
	(0.00141)	(0.00108)	(0.00109)	(0.000687)	(0.00153)	(0.000547)
Constant	2.104***	1.377***	-0.888*	0.0394	-0.149	1.590***
	(0.320)	(0.156)	(0.396)	(0.0615)	(0.456)	(0.156)
N	504	1680	686	1862	637	1911
Number of flats	12	40	14	38	13	39
Mean obs per flat	42	42	49	49	49	49
R^2 adj	0.196	0.100	0.303	0.297	0.376	0.274
Corr(u_i, xb)	-0.944	-0.750	-0.352	-0.338	-0.0951	-0.861
F Stat	14.27	14.44	126.4	137.6	48.33	66.44
DF	5	5	5	5	5	5
σ_u	0.403	0.186	0.0831	0.0692	0.0854	0.220
σ_e	0.179	0.157	0.162	0.161	0.166	0.159
ρ	0.0000393	4.17e-14	1.08e-11	9.97e-31	1.85e-08	1.30e-25

	Semester 4 Model 3	Semester 4 Model 4	Semester 5 Model 3	Semester 5 Model 4	Semester 6 Model 3	Semester 6 Model 4
$\Delta Y_{i,t-1}$	0.00559	0.0365	-0.00511	-0.0401	–	-0.133*
	(0.0410)	(0.0239)	(0.0872)	(0.0294)	–	(0.0637)
Distance to win	-1.155**	-2.042***	-3.119**	-1.399***	–	-0.636**
	(0.325)	(0.516)	(0.623)	(0.228)	–	(0.197)
Lag Rankk	0.000787	0.00778	0.0419*	0.0106*	–	0.0187**
	(0.00662)	(0.00473)	(0.0146)	(0.00407)	–	(0.00567)
Weekly lag Rank	0.00640	0.00543***	0.0205*	0.00234	–	-0.0000241
	(0.00378)	(0.00127)	(0.00648)	(0.00220)	–	(0.00212)
Time	-0.000470	0.00101	0.00477*	0.00444***	–	-0.0182*
	(0.000943)	(0.000941)	(0.00147)	(0.000530)	–	(0.00790)
Constant	1.272**	1.436***	1.154*	0.823***	–	2.756*
	(0.318)	(0.217)	(0.414)	(0.110)	–	(1.098)
N	637	1911	392	2007	–	483
Number of flats	13	39	8	41	–	41
Mean obs per flat	49	49	49	48.95	–	11.78
R^2 adj	0.0329	0.108	0.221	0.0428	–	0.0696
Corr(u_i, xb)	-0.854	-0.866	-0.880	-0.865	–	-0.0546
F Stat	5.311	12.22	226.9	16.08	–	6.113
DF	5	5	5	5	–	5
σ_u	0.161	0.259	0.247	0.203	–	0.150
σ_e	0.175	0.172	0.153	0.161	–	0.164
ρ	0.00271	1.39e-12	7.22e-08	3.01e-15	–	2.79e-08

Standard errors in parentheses, adjusted for flat clusters * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 13: Pooled Estimate of Effort Allocation

	Model (5)	Model (6)
	$y_{i,t}$	$y_{i,t}$
$\bar{y}_{i,t-7}$	0.729***	0.728***
	(0.0153)	(0.0153)
% males	-0.0274*	-0.0537**
	(0.0111)	(0.0193)
Average year of study (yos)	-0.00545	-0.00566
	(0.00290)	(0.00292)
# in flat	0.0486***	0.0467***
	(0.00976)	(0.00972)
# in flat squared	-0.00144***	-0.00139***
	(0.000353)	(0.000351)
Competition: males*yos	0.0260***	0.0288***
	(0.00569)	(0.00637)
Non-competition: males*yos	0.0109*	0.00905
	(0.00503)	(0.00488)
Competition: flat rent	0.0189	0.0234
	(0.0219)	(0.0219)
Non-competition: flat rent	0.0253	0.0305
	(0.0205)	(0.0205)
Ranked in Top 5_{t-7}	-0.0771***	-0.0771***
	(0.00600)	(0.00600)
Ranked in Bottom 10_{t-7}	0.0649***	0.0651***
	(0.00559)	(0.00560)
Δ_{t-1} rank improve	-0.0515***	-0.0770***
	(0.00547)	(0.0164)
Δ_{t-1} rank worsen	0.0476***	0.0298**
	(0.00485)	(0.00943)
Δ_{t-1} rank improve*males		0.0498
		(0.0307)
Δ_{t-1} rank worsen*males		0.0347*
		(0.0162)
Time	-0.000288***	-0.000288***
	(0.0000356)	(0.0000356)
Constant	0.518***	0.523***
	(0.0553)	(0.0557)
N	34,477	34,477
No of groups	334	334
R^2 Within	.1451	.1450
R^2 Between	.9817	.9817
R^2 Overall	.6597	.6596

Standard errors in parentheses.* p < 0.05, ** p < 0.01, *** p < 0.001

Dependent variable weekly average consumption, estimated using pooled OLS with flat level clustering

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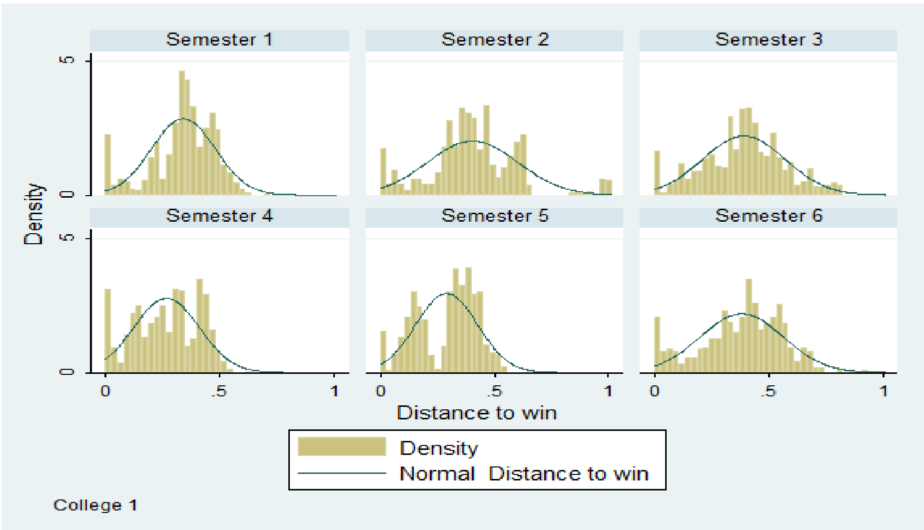

Figure 1: College 1 Distribution of The Distance to Winning Values
Source: Source: Green Lancaster 2010-2011

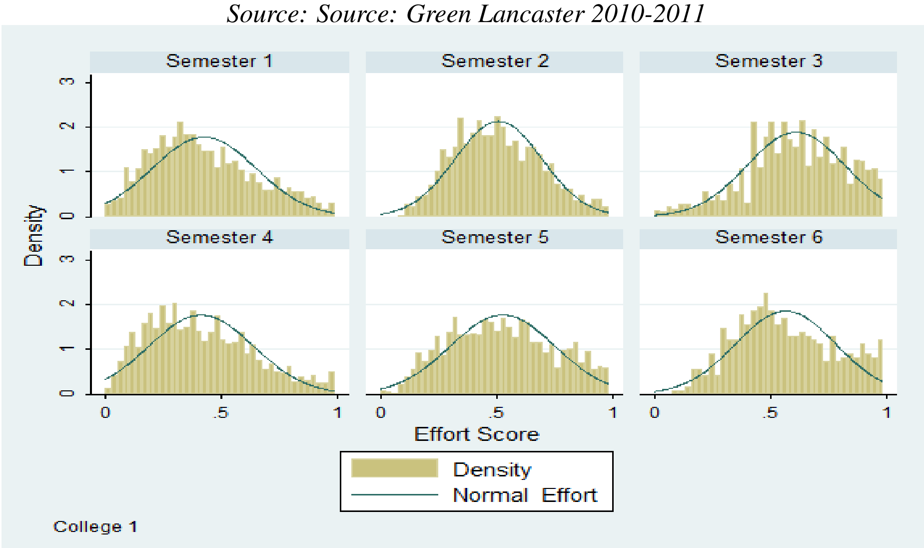

Figure 2: College 1 Distribution of Effort Scores
Source: Source: Green Lancaster 2010-2011

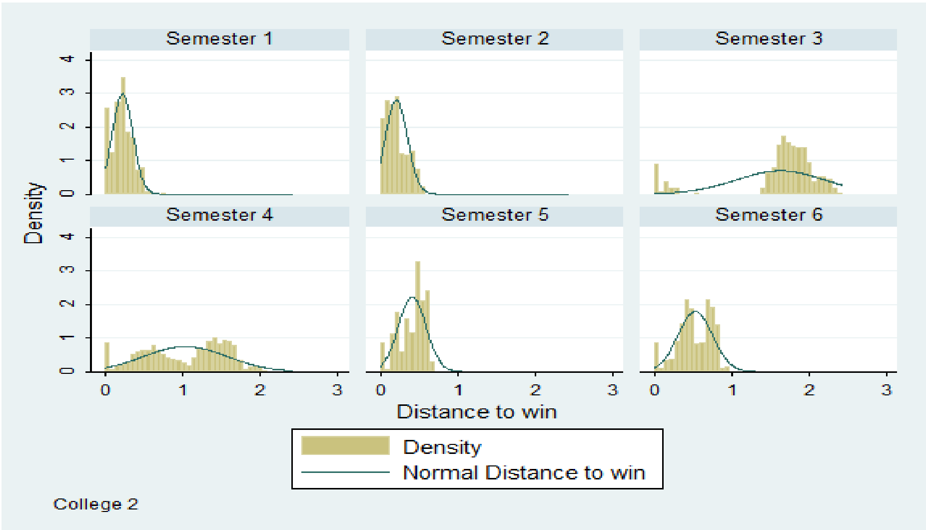

Figure 3: College 2 Distribution of The Distance to Winning Values.
Source: Source: Green Lancaster 2010-2011

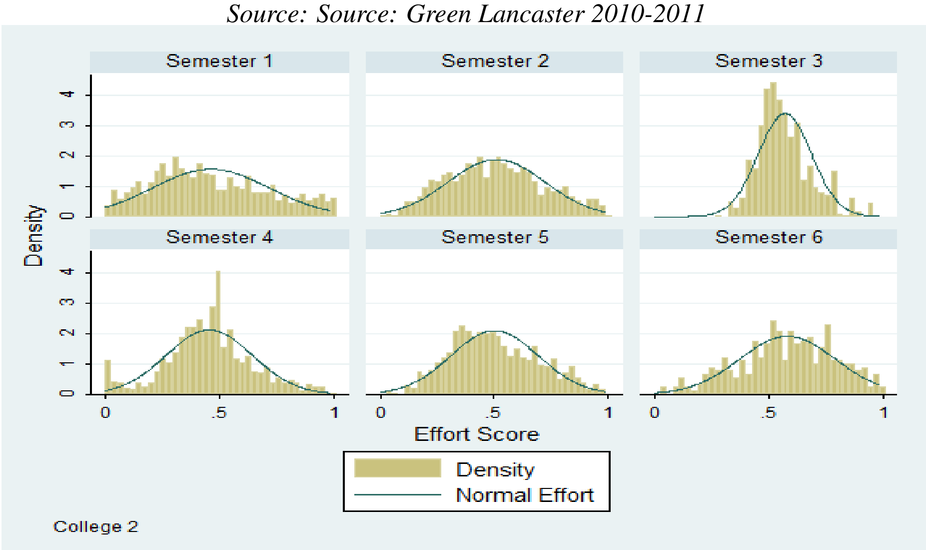

Figure 4: College 2 Distribution of Effort Scores.
Source: Source: Green Lancaster 2010-2011

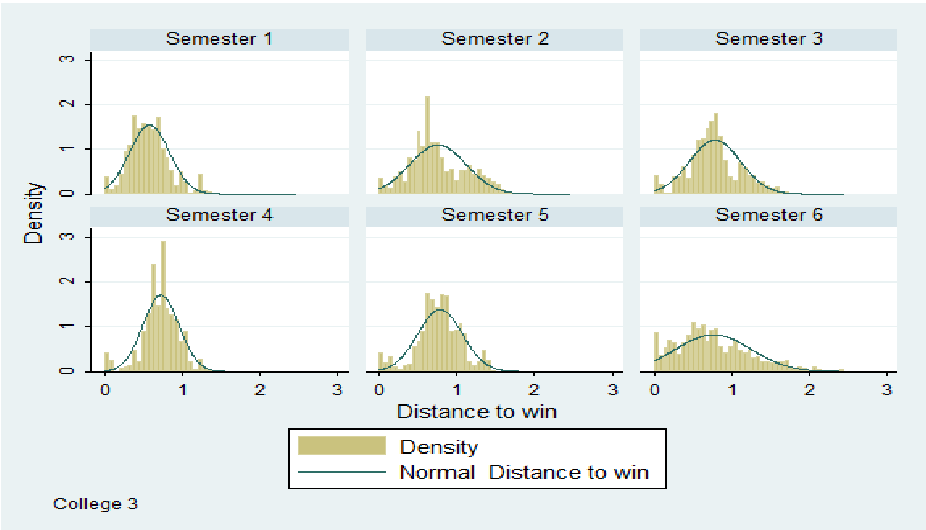

Figure 5: College 3 Distribution of The Distance to Winning Values.
Source: Source: Green Lancaster 2010-2011

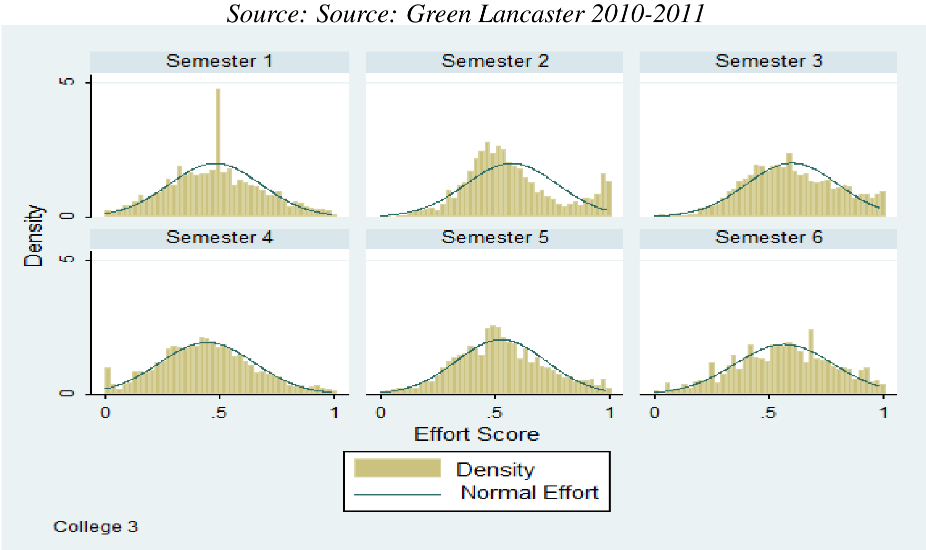

Figure 6: College 3 Distribution of Effort Scores.
Source: Green Lancaster 2010-2011