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Student Apartment Prices in Blacksburg, VA

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We assumed that student housing would follow a different pattern than pricing for normal apartments for rent. Considering that landlords would want to attract as many tenants as possible, it seemed reasonable to assume that the price of any given apartment would be most affected by the inclusion of laundry services, pools, and on-site fitness centers. The logic was that apartments would want to look more attractive to potential tenants by providing these luxuries, and that the maintenance of these services would force these providers to raise the prices. Thus, by modeling these desirable features against price, we would determine which of them attracted tenants and drove up the rent of an apartment.

In a research paper, Ben J. Sopranzetti (2015) outlined that hedonic models are most used in forming the consumer price index, as well as modeling the prices of electronics, clothing, and real estate. He goes on to say that, in the context of real estate, each house has its own characteristics that set it apart from others. As such, it would be much simpler to break a house down into its components rather than pricing it directly. Naturally, this can be extended to the topic of this paper, as it is difficult to compare apartment prices since the apartments themselves have their own different qualities that make them too difficult to directly compare.

II. THEORY

A hedonic model examines the demand of a certain good or service by regressing several variables, mostly categorical, on price. Historically, hedonic regression models looked at the prices of various goods using similar regression techniques as we did. Specifically, various models for housing and real estate prices also included the cost of the structures, the prices of land and the presence of various amenities as variables, treating it as a simple linear model. For most models, prices are assumed to follow a log-linear distribution. Using a log-linear regression model reduces the inherent heteroskedasticity.

The reasoning, as outlined in Sopranzetti's paper, is that the utility of a good, such as a house or apartment, is the aggregated utility of its characteristics. For example, a car's color is a characteristic of the good that can affect the utility a buyer would gain from it. If the buyer hates the color, they will derive less utility from owning the car versus another car that is identical in every way except color. This aggregated utility would be the reason why a person might rent a smaller apartment that's closer to the campus rather than one that is larger but farther away; the utility granted by the greater square footage is outweighed by the utility granted by the smaller distance from the campus. The greater utility would thereby warrant greater demand for that apartment and other apartments like it. In such situations where directly comparing two similar goods yields no real insight, it can be easier to capture the model of an object's price by examining its characteristics rather than the whole.

III. METHODS

Our work had originally started as a group project for an undergraduate economics class where we created a hedonic model while trying to model people's preferences in apartment complexes. We had chosen to create a linear model mainly consisting of multiple dummy predictors, since most of our factors were categorical variables. We chose to use them in the first place because we viewed these factors as a group of yes-no questions. For example, “Does apartment complex A have a personal bathroom in each unit?”

Our reasoning and set-up paralleled the work of Andrew Court, as detailed in Allen C. Goodman’s article (1998). Goodman (1998) described the invention of hedonic pricing analysis, crediting Court with the idea, and noted the advantages of using a hedonic model. Namely, it made it easier to deal with “nonlinearity and with changes in underlying goods bundles.” Court, and thus Goodman, stressed the fact that some goods could not be specified directly, and so one must assign weights on the various characteristics of it in terms of its importance to consumers. This sort of thinking inspired us to construct a hedonic model.

We chose to look at various amenities and features based on what we thought was important to a college student living near Virginia Tech. Considering that many off-campus students own vehicles, they would naturally need some place to park, and we presumed that they would prefer to have their own parking area. Additionally, living off-campus comes with worrying about getting to class on time, so distance would also have to play a part in the price. We included in-unit laundry services and a personal bathroom because we believed that they are both conveniences that many students would prefer having to not having. Finally, we included the presence of luxuries like an on-site gym or a pool. We did not include square footage in our model because we did not consider it an amenity that students cared about, and the square footage did not vary much between apartment complexes.

For the first part of this experiment, we used a Google form to administer the survey. Our group provided the link for the survey to participants to fill it out. Our survey included 40 students from the Virginia Tech campus, asking them to rate each amenity or feature on a scale of 1 (low importance) to 5 (high importance) based on how they would prioritize them when looking for an apartment. We took the average rating for each amenity to find what were the most important ones in the eyes of students according to their preferences. Our intention was to get an idea of what students claim to prefer and compare it to our model to see if apartment providers priced along those preferences.

To expand on the original project, I had taken it upon myself to rerun the regression under different parameters to capture the variation in rent for apartments in the Blacksburg area. More specifically, I reran it by taking the natural logarithms of the rental price and the distance from campus. Afterwards, I reran the regression but removed the statistically insignificant variables to see the changes to the regression.

Typically, a log-linear model would be preferred for modelling the price of high-tech goods, as it’s usually assumed that those prices are log-normally distributed. On the other hand, for something like housing prices, where the price is determined by the sum of the price of the lot size and the structure itself if available, a simple linear model is preferred. However, since we were unable to find the prices of the buildings and the land they were built on, a log-linear model should work just as well.

To decide the significance, we used the statistical software R to measure the significance level of each attribute in the model, and we decided our significance threshold to be at 5 percent. Those that met the requirement were considered significant according to the hedonic model, and the factor in question did determine the rent, at least in part, of an apartment. Those that didn't meet it were considered insignificant. Typically, in statistics, the significance of a categorical variable is unreliable, but in econometric analysis we often only have categorical variables to examine, so we will not discount these factors. Afterwards we compared our regression results to our survey results to match up consumer preferences in both datasets.

IV. EMPIRICAL RESULTS

Our survey asked subjects to rate the features or amenities according to how important they were in selecting an apartment. The features were: Distance from campus, in-unit laundry services, pool access, gym services, enforced private parking, a personal bathroom, and square footage of the unit. After gathering our data, we collected them into a table, taking the average rating for each attribute. Following this paragraph is the table.

Table 1:

Factor	**Mean Rating**
Permit Parking	4.49
Distance from Campus	4.19
Laundry Services	4.03
Personal Bathroom	3.69
Square Footage	3.53
Gym/Fitness Center	3.23
Pool Access	2.60

About apartments, we gathered information on various student housing complexes around Virginia Tech. In total, we researched 15 different complexes, prioritizing the most advertised complexes near the campus. For each complex, we looked at the average rent per room, as different units may have different rates, and we tabulated these results below.

Apartment Prices

Table 2:

Complex	**Average Rent Per Room**
The Edge	$809.00
The Village	$659.00
The Retreat	$813.90
Foxridge	$558.90
Terrace View	$736.25
Hunters Ridge	$425.00
Maple Ridge	$515.00
Uptown Village	$675.00
Sturbridge Square	$538.33
Chasewood Downs	$600.22
Windsor Hill	$658.00
Ridgewood Village	$580.00
Lantern Ridge Village	$375.00
Mill at Blacksburg	$533.00
Jefferson	$549.00

Next, we found what amenities and features each complex offered, as well as the average square footage of an apartment. We compiled them into a table for side-by-side comparison and to get a clear picture of which complex offered what.

Table 3:

Complex	**Community Pool**	**Parking**	**Laundry Services**	**Fitness Center**	**Common Areas**
The Edge	Present	Permit Only	In-unit	Present	Present
The Village	Present	Free	In-unit	Present	Present
The Retreat	Present	Permit Only	In-unit	Present	Present
Foxridge	Present	Free	Optional	Present	Present
Terrace View	Present	Permit Only	In-unit	Present	Present
Hunters Ridge	Not Present	Permit Only	In-unit	Present	Present
Maple Ridge	Present	Permit Only	In-unit	Present	Present
Uptown Village	Not Present	Free	In-unit	Not Present	Present
Windsor Hills	Present	Free	In-unit	Present	Present
Ridgewood Village	Not Present	Permit Only	In-unit	Not Present	Present
Lantern Ridge	Present	Permit Only	In-unit	Not Present	Present
Mill at Blacksburg	Present	Free	Communal	Present	Present
Jefferson	Not Present	Permit Only	Optional	Not Present	Not Present
Sturbridge Square	Present	Permit Only	Optional	Present	Present
Chasewood Downs	Present	Permit Only	Communal	Present	Present

We compiled all our data into a table, listing the prices of rooms in different complexes and the values assigned to each amenity to neatly fit our predictors into our models. Because many of the features are categorical, we had treated them as dummy variables, assigning a 1 if the feature was present and a 0 if it was not or communal for laundry services. The full table is listed in the Appendix.

Model 1:

After running our regression in R, we generated a table of coefficients as displayed below.

Variable	Estimate	Significance	Standard Error
Distance in Miles	-168.86	0.000123	41.01
Number of Rooms	-41.72	0.038996	19.75
Bathrooms per Room	186.32	0.032002	84.79
Community Pool	144.89	0.429528	182.12
Parking Privileges	114.61	0.038807	54.21
In-unit Laundry Services	12.43	0.830278	57.74
On-site Gym	-252.09	0.209414	198.61
Common Areas	431.33	0.015867	173.58

We used a simple linear regression model, using estimated price as the response variable while using the various features as predictor variables. Our adjusted R-squared value was 0.3348, meaning this model captures 33.48% of the rent prices' variability.

Model 2:

Next, I believed that our model could be improved if we used a logarithmic regression instead of a simple linear model. Thus, I created such a model in R, applying natural logarithmic transformations to both price and distance, with its table of coefficients following this paragraph..

Variable	Estimate	Significance	Standard Error
Log (Distance in Miles)	-0.417434	$8.09 * 10^{-5}$	0.098416
Number of Rooms	-0.052217	0.0621	0.027449
Bathrooms per Room	0.300557	0.0137	0.118221
Community Pool	0.247684	0.3335	0.253951
Parking Privileges	0.170626	0.0279	0.075634
In-unit Laundry Services	0.009698	0.9055	0.081334
On-site Gym	-0.360681	0.1927	0.273670
Common Areas	0.594951	0.0158	0.239264

This model used the natural logarithm of the estimated price and the distance from campus, as they were the only continuous variables in the model. I had an adjusted R-squared of 0.3526 with this logarithmic model, which means this second model explains 35.26% of the rent prices' variability.

Model 3:

Afterwards, I removed the insignificant variables and ran the logarithmic regression again to see what changes happened. Again, our table of coefficients is below.

Variable	Estimate	Significance	Standard Error
Log (Distance in Miles)	5.96567	$3.42 * 10^{-5}$	0.08612
Number of Rooms	-0.38520	0.0314	0.02483
Bathrooms per Room	0.33135	0.0032	0.10794
Parking Privileges	0.15488	0.0267	0.06823
Common Areas	0.48832	0.0081	0.17839

This model gave us an adjusted R-squared of 0.3624. By removing the statistically insignificant variables, I had raised the correlation coefficient between the dependent variable and the independent variables, meaning this final model captures 36.24% of the prices' variation.

V. CONCLUSION

Based on our threshold, we found that the most significant factors, according to each model, are the number of rooms per unit, bathrooms, the distance from campus, the presence of common areas, and the enforcement of private parking. On the other hand, we can say that the presence of in-unit laundry services, an on-site gym, and a community pool are insignificant. A possible explanation could be that in-unit laundry services are standard, especially for newer and renovated buildings in the Blacksburg area. As for gyms and pools, the cost for them is shared by all tenants in the entire complex, so their inclusion would only increase the price of a given unit by a negligible amount. Additionally, these three factors are more akin to luxuries that students don't take into consideration when searching for housing.

Our standard error for the variables in the final model suggests that our estimate for distance is well within acceptable parameters. However, our other estimates have standard errors that range up to half their value, suggesting that these estimates are heavily biased. This bias could have come through specification errors or due to a low sample size. We might have been able to reduce the size of our standard errors by using a purely linear model or by increasing our sample size. Ultimately, this bias is unimportant because the final model most of the biased estimators and respecified as a logarithmic model, reducing the standard errors greatly. As such, the bias in our final model is negligible.

Our survey mostly corresponds with the results of our models, concurring that pool access and gym access are unimportant to students. However, our survey implies that the presence of in-unit laundry services should be more important while our models imply that it is insignificant. Such a mismatch could be due to how we modeled the presence of laundry services or how we asked the question in the survey, as many complexes have a communal service, and the survey question could be interpreted as "Do you think it's important for a complex to have laundry services at all?".

Additionally, the models indicated that the number of bathrooms was significant, while the survey seemed to imply that tenants didn't view having a personal bathroom as especially important. Again, this may be due to how we asked the question in the survey, as we modeled the number of bathrooms, not whether each tenant had a personal bathroom, and we modeled it as a discrete variable as opposed to a dummy variable. This sort of specification error may have led to some bias in our model.

Finally, all three models and the survey agree that the enforcement of parking privileges and the distance from campus are significant factors in deciding the price of an apartment. The further an apartment complex is from campus, the cheaper the rent, as most students want something close by to get to class in a timely manner. And seeing as many students as possible who live off campus have cars, parking is a major issue around the university, and any chance at having reserved parking is treasured, to say the least.

VI. REFERENCES

Sopranzetti, Ben J. "Hedonic Regression Models." *Handbook of Financial Econometrics and Statistics*, 2014, 2119–34. https://doi.org/10.1007/978-1-4614-7750-1_78.

Goodman, A., 1998. Andrew Court and the Invention of Hedonic Price Analysis. *Journal of Urban Economics*, 44(2), pp.291-298.

VII. APPENDIX

Survey link: https://virginiatech.qualtrics.com/jfe/form/SV_aXofOZfQDvY1909

Full Version of Table 4:

Price	Location	Distance (miles)	Rooms	Bathrooms per room	Community Pool	Parking Privileges	In-unit Laundry Services	On-site Gym	Common Areas
809.00	Edge	0.8	4	1	1	1	1	1	1
639.00	Village	0.8	4	1	1	0	1	1	1
639.00	Village	0.8	4	0.75	1	0	1	1	1
674.00	Village	0.8	2	0.5	1	0	1	1	1
684.00	Village	0.8	2	0.5	1	0	1	1	1
929.00	Retreat	1.6	2	1	1	1	1	1	1
850.00	Retreat	1.6	3	1	1	1	1	1	1
810.00	Retreat	1.6	4	1	1	1	1	1	1
810.00	Retreat	1.6	4	1.125	1	1	1	1	1
800.00	Retreat	1.6	4	1	1	1	1	1	1
815.00	Retreat	1.6	4	1.125	1	1	1	1	1
775.00	Retreat	1.6	5	1	1	1	1	1	1
790.00	Retreat	1.6	5	1	1	1	1	1	1
785.00	Retreat	1.6	5	1.1	1	1	1	1	1
775.00	Retreat	1.6	5	1.1	1	1	1	1	1
947.50	Foxridge	2.2	1	1	1	0	0	1	1
530.75	Foxridge	2.2	2	0.75	1	0	0	1	1
528.75	Foxridge	2.2	2	0.5	1	0	0	1	1
405.50	Foxridge	2.2	3	0.5	1	0	0	1	1
432.83	Foxridge	2.2	3	0.75	1	0	0	1	1
545.50	Foxridge	2.2	4	0.75	1	0	0	1	1
521.50	Foxridge	2.2	5	0.6	1	0	0	1	1
1112.50	Terrace View	1.5	1	1	1	1	1	1	1

1205.00	Terrace View	1.5	1	1.5	1	1	1	1	1
615.00	Terrace View	1.5	2	1	1	1	1	1	1
722.50	Terrace View	1.5	2	1.25	1	1	1	1	1
705.50	Terrace View	1.5	2	0.75	1	1	1	1	1
543.00	Terrace View	1.5	3	1	1	1	1	1	1
614.50	Terrace View	1.5	3	0.667	1	1	1	1	1
614.00	Terrace View	1.5	3	0.833	1	1	1	1	1
695.50	Terrace View	1.5	4	0.625	1	1	1	1	1
535.00	Terrace View	1.5	4	1	1	1	1	1	1
425.00	Hunters Ridge	2	4	0.5	0	1	1	1	1
700.00	Uptown Village	2.2	2	1.25	0	0	1	0	1
675.00	Uptown Village	2.2	3	1.5	0	0	1	0	1
650.00	Uptown Village	2.2	4	1	0	0	1	0	1
600.00	Sturbridge	1.1	2	0.75	1	1	0	1	1
525.00	Sturbridge	1.1	3	0.333	1	1	0	1	1
625.00	Sturbridge	1.1	4	1	1	1	0	1	1
640.00	Chasewood Downs	1.5	1	1	1	1	0	1	1

720.00	Chasewood Downs	1.5	1	1	1	1	0	1	1
750.00	Chasewood Downs	1.5	1	1	1	1	0	1	1
760.00	Chasewood Downs	1.5	1	1	1	1	0	1	1
790.00	Chasewood Downs	1.5	1	1	1	1	0	1	1
860.00	Chasewood Downs	1.5	2	0.5	1	1	0	1	1
860.00	Chasewood Downs	1.5	2	0.5	1	1	0	1	1
970.00	Chasewood Downs	1.5	2	0.5	1	1	0	1	1
1191.00	Chasewood Downs	1.5	3	0.333	1	1	0	1	1
990.00	Windsor Hill	1.4	1	1	1	1	1	1	1
1030.00	Windsor Hill	1.4	2	1	1	1	1	1	1
1405.00	Windsor Hill	1.4	3	1.5	1	1	1	1	1
375.00	Lantern Ridge	2.9	2	1	1	1	0	1	1
800.00	Mill at Blacksburg	2.4	1	1	1	0	0	1	1
435.00	Mill at Blacksburg	2.4	2	1	1	0	0	1	1
365.00	Mill at Blacksburg	2.4	3	1	1	0	0	1	1
700.00	Jefferson	1.3	1	1	0	1	0	0	0
398.00	Jefferson	1.3	2	1	0	1	0	0	0

885.00	Ridgewood Village	3.4	1	1	0	1	1	0	1
483.00	Ridgewood Village	3.4	2	0.5	0	1	1	0	1
372.00	Ridgewood Village	3.4	3	0.3333	0	1	1	0	1
495.00	Maple Ridge	2.6	2	0.75	1	1	1	1	1
525.00	Maple Ridge	2.6	2	1.25	1	1	1	1	1
540.00	Maple Ridge	2.6	2	1.25	1	1	1	1	1
500.00	Maple Ridge	2.6	3	0.666	1	1	1	1	1
530.00	Maple Ridge	2.6	3	1	1	1	1	1	1
500.00	Maple Ridge	2.6	4	0.5	1	1	1	1	1
515.00	Maple Ridge	2.6	4	1	1	1	1	1	1