ABSTRACT

This research examines the relative effect of pricing decisions, brand perceptions, and advertising effectiveness on demand within an emerging market. This research was conducted using data from a Marketplace Business Simulations game. The simulation of interest was conducted within an undergraduate business course at the University of Tennessee, with teams of 4-5 creating companies and competing for market share by making strategic decisions within the simulation software. The simulation took place over the course of a semester within the course, and six rounds of decisions were made to reflect six business quarters. The resulting data was analyzed using Stata, a general-purpose statistical software package produced by StataCorp. This Stata analysis included the use of regression tools and data visualization commands to accurately depict and decipher the effect of product prices, consumer perceptions, and advertising effectiveness on product demand within the Marketplace Business Simulations game. Regression tools utilized included linear regression analysis and fixed-effects modeling. Data visualization was performed through Stata and Microsoft Excel, including linear regression visualization and best-fit modeling. This research concludes that, within this specific simulation, brand perceptions and advertising effectiveness were much more predictive of demand than pricing decisions. Price was found to have an inverse relationship with demand, as is expected based upon fundamental economic knowledge of demand curves. Though conclusively inverse, the strength of this relationship was inconclusive, at least as it pertains to the ability to make future decisions within the Marketplace Business Simulations software based upon estimates of this strength. Brand perceptions and advertising effectiveness were found to have much more substantial and conclusive impacts upon demand within the simulation, and the estimates gathered from this analysis could be utilized in decision-making processes for future participants in this Marketplace Business Simulations game.

Comparing Effects of Strategic Decisions on Demand in a Marketplace Simulation

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Introduction

In my undergraduate studies at the University of Tennessee, I have majored in Economics within the Haslam College of Business. As a result of this track, I have completed extensive coursework regarding pricing decisions and factors of demand in competitive markets. In addition to this major, I have minored in Public Policy Analytics. This program has provided me with experience in data analysis and visualization, specifically utilizing Stata software to analyze large datasets.

Within this project, I have made use of this prior knowledge of Economic theory and data visualization techniques gathered as a result of my coursework, and applied these skills onto analysis of data from a Marketplace Business Simulations game in which I was a participant. All of the data in this paper comes from Marketplace Business Simulation results in my specific section of Global Strategic Management, the course in which I participated in this simulation exercise. All of the data analysis and visualization is performed using Stata and Excel technology.

Background

The University of Tennessee and the Haslam College of Business place great emphasis on the practical applications of the coursework of their students. The Haslam College of Business mission statement includes the goal of "creating, sharing, and **applying** knowledge." One way the University of Tennessee pursues this mission is the required capstone sequence for all students of the College of Business - Global Strategic Management. Referred to in the course catalog as Business Administration 453, this course focuses on strategic decision-making for businesses, and features participation in a Marketplace Business Simulations game in order to provide practical application opportunities for the skills covered in previous coursework within the Haslam College of Business.

'The Marketplace platform was originally created by University of Tennessee Professor Dr. Ernest Cadotte, intended to provide a method for practical experimentation with different marketing decisions. The platform has grown since its original inception, and now allows students and educators to compete in a long-form business simulation, requiring participants to make a multitude of strategic decisions across six quarters. These decisions have direct impacts on financial performance and market share for the created companies, and provide large amounts of data to explore in determining how these different decisions factored into a group's performance.

Marketplace Business Simulations offers a variety of versions and packages for use in educational or business development settings. The particular version utilized in the Global Strategic Management course revolves around an emerging market of bicycles produced using 3-D printing technology. The BUAD 453 class is split into teams, and each team is tasked with creating a company and beginning to design bicycles for sale in this new market. In my participation in the simulation, I worked alongside four fellow Haslam College of Business students. Within these teams, participants are given specific roles and responsibilities of decision-making in their company. These roles include Sales Channel, Financial Management, Marketing, Human Resources and Production Operations. The market for these bicycles is divided into three segments: Mountain, Speed and Recreation. Each bike on the market must be categorized into one of these segments, and participants are tasked with designing products that both cater to the stated preferences of each target segment while selling at price points that maximize profitability. There are only four set locations in which companies may sell bikes: New York City, Amsterdam, Rio de Janeiro, and Bangalore. Companies may also sell to the entire world market with the creation of a web sales center.

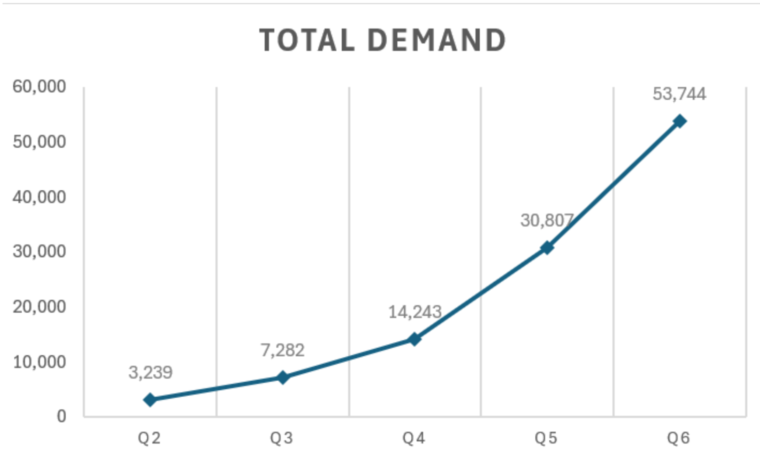
At the beginning of the simulation, participants are given an initial batch of market research data, providing group members with information regarding customers' price points, preferred product features depending on segment, and potential demand in each of the possible markets. The game takes place over six quarters, but the sale of bikes does not begin until the second quarter. In each successive quarter, there are more available decisions for groups to make, such as the design of new bikes, investment into research & development, the option to purchase more 3-D printers, and the potential to license their R&D to other groups. The sale price of bicycles may also be altered in each quarter, as well as the specific design and advertising strategies for these brands.

Throughout the simulation, participants are provided with data surrounding consumer judgment for their products. This includes brand, price and advertising judgement scores for all bikes on the market. The market share and total demand figures are provided each quarter, as well as updates to each firm's balanced scorecard and specific metrics contributing to this overall score. All of this data allows for an in-depth analysis into how decision-making affects performance and demand in a controlled simulation, foregoing all external factors that increase the complexity of data in real-world analysis. This extensive catalog of data is the basis on which this research is undertaken.

Further Marketplace Information

Created companies in this simulation are considered "demand-makers", meaning that the overall market demand for their products is not fixed. They are not consistently competing for the same consumers, but are rather intending to create demand where it did not exist before. As a result, the overall market demand within the simulation increased in each successive quarter. Each quarter's total demand numbers within my simulation are shown in **Figure 1**.

Figure 1



At the culmination of the Marketplace Simulation, each company is ranked according to their performance throughout the six quarters. These rankings are determined by a Total Performance score in a cumulative balanced scorecard. The formula for this total performance is:

Cumulative Total Performance = Cumulative Financial Performance * Cumulative Market Performance * Cumulative Marketing Effectiveness * Cumulative Investment in Future * Cumulative Wealth * Cumulative Human Resource Management * Cumulative Asset Management * Cumulative Manufacturing Productivity * Cumulative Financial Risk

Each company receives a detailed balanced scorecard at the end of each quarter, but is ultimately judged based upon this cumulative balanced scorecard which factors in performance over the whole simulation. Decisions such as R&D spending, sale prices, operating capacity and advertising choices all have an effect on this cumulative performance score. The final cumulative balanced scorecard for my section of Global Strategic Management is shown in **Figure 1.** My group, Velora, finished third with a score of 39.517.

Figure 2

Players' Standings — Velora Quarter 7

Cumulative Industry Results Ending in Quarter: 6

Company Name	Cumulative Total Performance	Cumulative Financial Performance	Cumulative Market Performance	Cumulative Marketing Effectiveness	Cumulative Investment in Future	Cumulative Wealth	Cumulative Human Resource Management	Cumulative Asset Management	Cumulative Manufacturing Productivity	Cumulative Financial Risk
Velora	39.517	68.523	0.186	0.833	3.686	1.452	0.828	1.063	0.892	0.885
Nimbus Cycling Company	49.533	76.879	0.190	0.823	3.066	1.793	0.815	1.075	0.884	0.968
Wheel Deal Warriors	19.873	52.587	0.188	0.803	3.165	1.318	0.825	0.982	0.803	0.924
Summit Cycles	132.576	115.215	0.285	0.849	2.307	2.702	0.790	1.282	0.780	0.966
InnoBike	24.851	62.280	0.175	0.798	2.840	1.614	0.815	0.931	0.822	1.000

Specific Issues

Within my research and analysis, I primarily focused on factors that affect the financial and market performance metrics in the balanced scorecard. My outcome variable of interests are demand, and subsequently market & financial performance. My explanatory variable of interest is price, as my primary goal is to analyze the importance of pricing decisions on demand and market share within the simulation results. Through this analysis, I also sought to factor in brand judgement scores to determine the relative importance of price compared to the importance of brand judgement scores in the intended market segment for a product.

Methodology

In performing this analysis, I collected data for each product sold in each specific quarter throughout the simulation. Though the design of a bicycle, or its price, may not have changed between quarters, each bicycle listed for sale in a certain quarter is treated as a unique data point. Across the simulation, there were a total of 132 unique data points according to this methodology. Each data point includes the name of the specific product, the quarter it was sold in, the demand in that quarter, the price point it was sold at in that quarter (after rebates), and the brand judgement of that product for its intended segment in that quarter.

Variables

Demand - This is a numeric variable, denoting the total demand for each specific product (brand) in each specific quarter.

PriceAfterRebate - This is a numeric variable, denoting the price each product (brand) was sold at, subtracting rebates, in each specific quarter

Brand - This is a string variable, denoting the name of each specific product (brand). Brand in this case refers to individual bikes offered, not the company offering them.

BrandID **-** This is the encoded value of Brand as a numeric variable in Stata, allowing for regression analysis to be run that accounts for differences in brands (advertising spending, etc.) when determining the relationship between price and demand.

Quarter **-** This is a string variable, denoting the specific quarter each product (brand) was sold in.

QuarterID **-** This is the encoded value of Quarter as a numeric variable in Stata, allowing for regression analysis to be run that accounts for demand differences between quarters when determining the relationship between price and demand.

BrandJudgement **-** This is a numeric variable, denoting the Brand Judgement score for a particular product (brand) in its intended market segment for a specific quarter. Brand Judgement scores are consumers ratings of brand quality for specific products.

AdJudgement – This is a numeric variable, denoting the Ad Judgement score for a particular product (brand) in its intended market segment for a specific quarter. Ad Judgement scores are consumers ratings of advertisements for specific products.

Findings

The initial analysis was a simple OLS regressions to determine the direction and strength of the relationship between *demand and PriceAfterRebate*. This first involved running a simple regression between these two variables. The result of this regression is shown in **Figure 3**

Figure 3

```
. regress demand priceafterrebate

      Source |       SS           df       MS      Number of obs   =       132
-------------+----------------------------------   F(1, 130)       =      2.88
       Model |  1390846.93         1  1390846.93   Prob > F        =    0.0918
    Residual |  62686092.6       130  482200.712   R-squared       =    0.0217
-------------+----------------------------------   Adj R-squared   =    0.0142
       Total |  64076939.5       131  489136.943   Root MSE        =    694.41

------------------------------------------------------------------------------
          demand | Coefficient  Std. err.      t    P>|t|     [95% conf. interval]
-----------------+------------------------------------------------------------
priceafterrebate |   .5117697   .3013345     1.70   0.092    -.0843845    1.107924
           _cons |   142.0507   394.1907     0.36   0.719    -637.8085    921.9099
------------------------------------------------------------------------------
```

This output indicates that, without any controlling factors, the relationship between demand and price is extremely low. The R-Squared for this data is .0217, meaning that just 2.17% of the variation in demand can be explained by variations in price after rebate in the model. Furthermore, p-value for the coefficient on demand is not statistically significant at the 5% level (.092>.05). This demonstrates the need for further regression that takes external factors into consideration, specifically the rise in overall demand for each quarter, and the brand specific differences that contributed to varying demand numbers.

The next regression uses QuarterID as a dummy variable to estimate the effects of specific quarters on the expected demand for a product. The output is shown in **Figure 4.**

Figure 4

```
. regress demand i.QuarterID

      Source |       SS           df       MS      Number of obs   =       132
-------------+----------------------------------   F(3, 128)       =     13.27
       Model |  15197086.6         3  5065695.52   Prob > F        =    0.0000
    Residual |  48879852.9       128  381873.851   R-squared       =    0.2372
-------------+----------------------------------   Adj R-squared   =    0.2193
       Total |  64076939.5       131  489136.943   Root MSE        =    617.96

------------------------------------------------------------------------------
      demand | Coefficient  Std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
   QuarterID |
         Q4  |   210.9098   175.3473     1.20   0.231    -136.0448    557.8645
         Q5  |   494.1018    163.256     3.03   0.003     171.0719    817.1317
         Q6  |   904.8458   159.0037     5.69   0.000       590.23    1219.462
             |
       _cons |   316.6087   128.8534     2.46   0.015     61.65014    571.5673
------------------------------------------------------------------------------
```

This model, with quarters as a dummy variable, explains 23.72% of the variation in demand in the data. The coefficient on each quarter represents the expected difference in demand from the baseline quarter (Q3). This regression indicates that differences in total demand between quarters accounts for about 25% of the variation in demand by product in the data, an expected number considering there are four quarters of data and substantial changes in overall demand numbers in each quarter.

In the regression using BrandID as a dummy explanatory variable, 97% of the variation in demand was explained by the model. This demonstrates that, above differences in price and between quarters, it was differences in brands that was the primary determinant in demand. This output is shown in **Figure 5.**

Figure 5

```
. regress demand i.BrandID
```

Source	SS	df	MS			
				Number of obs	=	132
				F(75, 56)	=	29.87
Model	62514500.6	75	833526.675	Prob > F	=	0.0000
Residual	1562438.92	56	27900.6949	R-squared	=	0.9756
				Adj R-squared	=	0.9430
Total	64076939.5	131	489136.943	Root MSE	=	167.04

demand	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
BrandID						
Aero Arrow 3	1238.5	204.5753	6.05	0.000	828.6865	1648.314
Aero Arrow X	2235.5	204.5753	10.93	0.000	1825.686	2645.314
AeroRider	-239.5	167.035	-1.43	0.157	-574.1113	95.11134
AeroRider 2.0	-104.1667	152.4814	-0.68	0.497	-409.6236	201.2903
AeroRider 3.0	175.5	167.035	1.05	0.298	-159.1113	510.1113
AeroRider 4.0	1723.5	204.5753	8.42	0.000	1313.686	2133.314
Climb-on 3	1988.5	204.5753	9.72	0.000	1578.686	2398.314
ComfortBike 2.0	-421.5	167.035	-2.52	0.014	-756.1113	-86.88866
ComfortBike 3.0	44.5	167.035	0.27	0.791	-290.1113	379.1113
CruiseRider	-463.1667	152.4814	-3.04	0.004	-768.6236	-157.7097
CruiseRider 2.0	-237.25	144.6566	-1.64	0.107	-527.0319	52.53192
CruiseRider 3.0	407.5	167.035	2.44	0.018	72.88866	742.1113
CruiseRider 4.0	1751.5	204.5753	8.56	0.000	1341.686	2161.314
FalconBike	175.5	204.5753	0.86	0.395	-234.3135	585.3135
FalconBike 2.0	367.5	204.5753	1.80	0.078	-42.31352	777.3135
Limit Breaker	-572.5	204.5753	-2.80	0.007	-982.3135	-162.6865
Limit Breaker 2	-30.5	204.5753	-0.15	0.882	-440.3135	379.3135
Limit Breaker 3	734.5	204.5753	3.59	0.001	324.6865	1144.314
Limit Breaker 4	1816.5	204.5753	8.88	0.000	1406.686	2226.314
Mount Warrior	-452.5	167.035	-2.71	0.009	-787.1113	-117.8887
Mount Warrior 2	101	167.035	0.60	0.548	-233.6113	435.6113
Race1	-277.25	144.6566	-1.92	0.060	-567.0319	12.53192
Really Rugged 2	-275	167.035	-1.65	0.105	-609.6113	59.61134
Relax 3	281	167.035	1.68	0.098	-53.61134	615.6113
RelaxBike 2.0	-293.5	167.035	-1.76	0.084	-628.1113	41.11134
RelaxBike 3.0	-55.5	204.5753	-0.27	0.787	-465.3135	354.3135
RelaxBike 4.0	-50.5	204.5753	-0.25	0.806	-460.3135	359.3135
Ridge Rider 2	-575.5	204.5753	-2.81	0.007	-985.3135	-165.6865
Ridge Rider 3	1742.5	204.5753	8.52	0.000	1332.686	2152.314
Ridge Rider X	2636.5	204.5753	12.89	0.000	2226.686	3046.314
Rlly Rugged 2.1	1394.5	204.5753	6.82	0.000	984.6865	1804.314
RockyBike	79.5	152.4814	0.52	0.604	-225.957	384.957
RockyBike 2.0	180.5	204.5753	0.88	0.381	-229.3135	590.3135
Roll-on	-483	167.035	-2.89	0.005	-817.6113	-148.3887
Roll-on 2	21.5	167.035	0.13	0.898	-313.1113	356.1113
S.F.A.M.Bike	678.5	204.5753	3.32	0.002	268.6865	1088.314
S.F.A.M.Bike 2	751.5	204.5753	3.67	0.001	341.6865	1161.314
Smooth Roller	-258.5	204.5753	-1.26	0.212	-668.3135	151.3135
Smooth Roller 2	-52.5	204.5753	-0.26	0.798	-462.3135	357.3135
Smooth Roller 3	620.5	204.5753	3.03	0.004	210.6865	1030.314
Smooth Roller X	1508.5	204.5753	7.37	0.000	1098.686	1918.314
SonicBike	-520.5	204.5753	-2.54	0.014	-930.3135	-110.6865
Speed Racer 2	-451	167.035	-2.70	0.009	-785.6113	-116.3887
Speed Racer 2.1	502.5	204.5753	2.46	0.017	92.68648	912.3135
Speedy Quik 3.1	781.5	204.5753	3.82	0.000	371.6865	1191.314
Speedy quick 3	811.5	204.5753	3.97	0.000	401.6865	1221.314
SummitRider	-447.8333	152.4814	-2.94	0.005	-753.2903	-142.3764
SummitRider 2.0	-52.5	144.6566	-0.36	0.718	-342.2819	237.2819
SummitRider 3	-73.5	204.5753	-0.36	0.721	-483.3135	336.3135
SummitRider 3.0	-174.5	204.5753	-0.85	0.397	-584.3135	235.3135
SummitRider 4.0	2259.5	204.5753	11.04	0.000	1849.686	2669.314
SuperSonicBike	-190	167.035	-1.14	0.260	-524.6113	144.6113
SuperSonicBike2	-124.5	204.5753	-0.61	0.545	-534.3135	285.3135
Too Fast 4 U	198.5	204.5753	0.97	0.336	-211.3135	608.3135
TurboBike	-245.8333	152.4814	-1.61	0.113	-551.2903	59.62363
TurboBike 2.0	-306.5	204.5753	-1.50	0.140	-716.3135	103.3135
Urban Cruiser 2	-21	167.035	-0.13	0.900	-355.6113	313.6113
Urban Cruiser 3	331.5	204.5753	1.62	0.111	-78.31352	741.3135
Urban Cruiser 4	900.5	204.5753	4.40	0.000	490.6865	1310.314
VeloBlaze	-35.5	167.035	-0.21	0.832	-370.1113	299.1113
VeloBlaze Pro	1225.5	204.5753	5.99	0.000	815.6865	1635.314
VeloDelight	-95.5	167.035	-0.57	0.570	-430.1113	239.1113
VeloDelight Pro	1050.5	204.5753	5.14	0.000	640.6865	1460.314
VeloEverest	331.5	167.035	1.98	0.052	-3.111336	666.1113
VeloEverest Pro	2165.5	204.5753	10.59	0.000	1755.686	2575.314
Veloclimb Pro 2	-291.25	144.6566	-2.01	0.049	-581.0319	-1.468083
Veloclimb X	-306	144.6566	-2.12	0.039	-595.7819	-16.21808
Veloease	-141.5	152.4814	-0.93	0.357	-446.957	163.957
Velospeed Pro	-254	144.6566	-1.76	0.085	-543.7819	35.78192
Velospeed X	-400.25	144.6566	-2.77	0.008	-690.0319	-110.4681
Wayfinder 2	462	167.035	2.77	0.008	127.3887	796.6113
Wayfinder 3	795.5	204.5753	3.89	0.000	385.6865	1205.314
Wayfinder 4	1952.5	204.5753	9.54	0.000	1542.686	2362.314
Wheely Smooth 1	-178.75	144.6566	-1.24	0.222	-468.5319	111.0319
xtreme smooth 3	1126.5	204.5753	5.51	0.000	716.6865	1536.314
_cons	662.5	118.1116	5.61	0.000	425.8941	899.1059

If differences between brands are theorized to be the primary determinant of demand, it is important to understand which facet of these brand differences is crucial in predicting demand. The next regression analyzes the relationship between Demand and Brand Judgement, specifically the Brand Judgement score (0-100) for a product in its target segment. This output is shown in **Figure 6.**

Figure 6

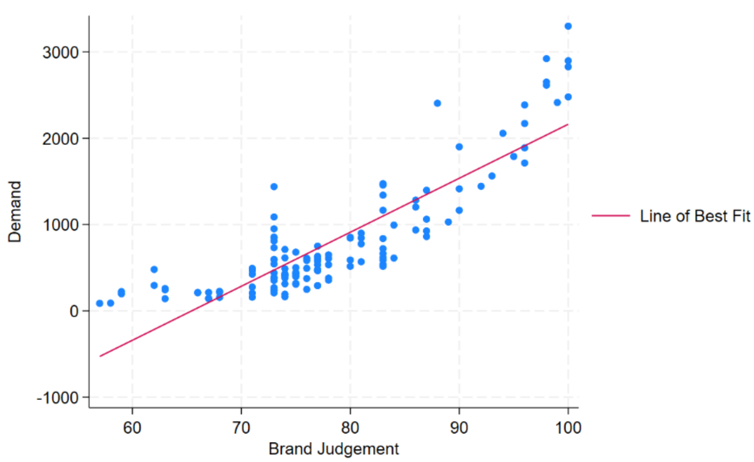
```
. regress demand brandjudgement

      Source |       SS           df       MS      Number of obs   =       132
-------------+----------------------------------   F(1, 130)       =    373.21
       Model |  47523223.8         1  47523223.8   Prob > F        =    0.0000
    Residual |  16553715.7       130  127336.275   R-squared       =    0.7417
-------------+----------------------------------   Adj R-squared   =    0.7397
       Total |  64076939.5       131  489136.943   Root MSE        =    356.84

--------------------------------------------------------------------------------
        demand | Coefficient  Std. err.      t    P>|t|     [95% conf. interval]
---------------+----------------------------------------------------------------
brandjudgement |   62.56917   3.238796    19.32   0.000     56.1616    68.97674
         _cons |  -4094.802   255.4536   -16.03   0.000   -4600.186   -3589.417
--------------------------------------------------------------------------------
```

This regression indicates a strong linear relationship between brand judgement scores and expected demand for a product, even without controlling for differences between quarters. 74.17% percent of the variation in demand amongst products can be explained by variations among brand judgement scores. This indicates that a product's brand judgement score is a major factor in the explanatory power of *BrandID* on demand. The linear relationship between *brandjudgement* and *demand* is shown in **Figure 7**.

Figure 7



Another factor in the variations among brands that may be critical to differences in demand is the ad judgement scores for the marketing efforts of these brands. The value of ad judgement for each specific brand is the ad judgement score (0-100) within the target segment of the product for that quarter. The regression of *adjudgement* on *demand* indicates that 58.51% of the variation in demand can be explained by differences in ad judgement scores. This R-Squared value is less than that of brand judgement's effect on demand, telling us that brand judgement scores have a more substantial impact on expected demand for a product, more so than the advertisements placed on these products. Nevertheless, this regression indicates a moderately strong linear relationship between ad judgement scores and demand. The regression output and linear model are shown below in **Figure 8** and **Figure 9**, respectively.

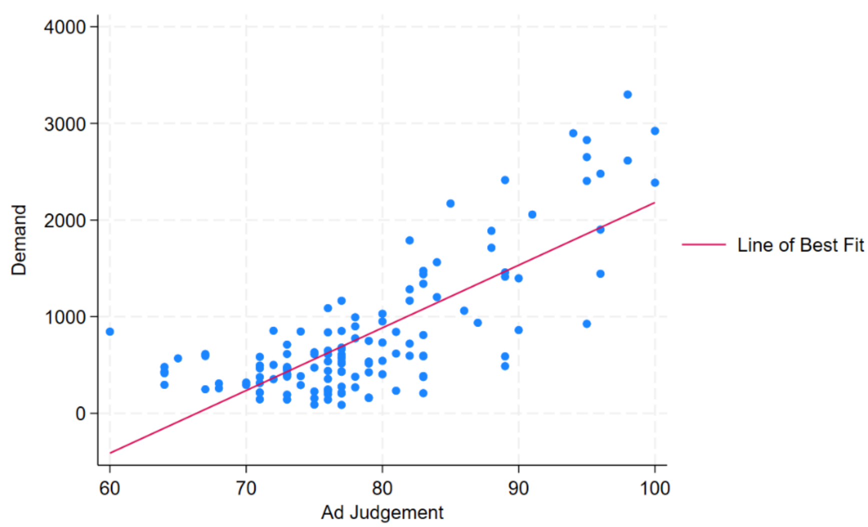
Figure 8

```
. regress demand adjudgement

      Source |       SS           df       MS      Number of obs   =       132
-------------+----------------------------------   F(1, 130)       =    183.30
       Model |  37488970.5         1  37488970.5   Prob > F        =    0.0000
    Residual |    26587969       130  204522.839   R-squared       =    0.5851
-------------+----------------------------------   Adj R-squared   =    0.5819
       Total |  64076939.5       131  489136.943   Root MSE        =    452.24

------------------------------------------------------------------------------
      demand | Coefficient  Std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
 adjudgement |   64.82628   4.788177    13.54   0.000     55.35344    74.29911
       _cons |  -4301.463   379.1179   -11.35   0.000    -5051.503   -3551.424
------------------------------------------------------------------------------
```

Figure 9



So far, we have established that *BrandID* is the primary predictor of demand for a product, even compared to its price. This means that everything associated with a brand (product quality, advertisement quality, company reputation) is the primary predictor of demand for a product. However, we have still yet to establish that, when controlling for other factors, the price of a product has a statistically significant effect on its expected demand.

To establish if this is the case, we must run a Fixed-Effects regression, controlling for brand identity as the panel variable and the quarter of sale as the time variable. By doing so, we are able to isolate the effect of price on demand without the (substantial) confounding factors of brand characteristics and variations in overall demand between quarters. The output of this Fixed-Effects model is shown in **Figure 10** below.

Figure 10

```
. xtset BrandID QuarterID

Panel variable: BrandID (unbalanced)
 Time variable: QuarterID, 1 to 4
         Delta: 1 unit

. xtreg demand priceafterrebate i.QuarterID, fe

Fixed-effects (within) regression               Number of obs     =        132
Group variable: BrandID                         Number of groups  =         76

R-squared:                                      Obs per group:
     Within  = 0.6100                                         min =          1
     Between = 0.1463                                         avg =        1.7
     Overall = 0.0846                                         max =          4

                                                F(4, 52)          =      20.33
corr(u_i, Xb) = -0.5405                         Prob > F          =     0.0000

------------------------------------------------------------------------------------
          demand | Coefficient  Std. err.      t    P>|t|     [95% conf. interval]
-----------------+------------------------------------------------------------------
priceafterrebate |  -.8910343   .3247325    -2.74   0.008    -1.542658   -.2394109
                 |
       QuarterID |
              Q4 |   205.7566   34.42161     5.98   0.000     136.6846    274.8286
              Q5 |   160.8097   37.67977     4.27   0.000     85.19968    236.4197
              Q6 |  -112.2122   46.73282    -2.40   0.020    -205.9884   -18.43589
                 |
           _cons |   1904.454   426.9125     4.46   0.000     1047.791    2761.116
-----------------+------------------------------------------------------------------
         sigma_u |  925.38248
         sigma_e |  108.25251
             rho |   .9865001   (fraction of variance due to u_i)
------------------------------------------------------------------------------------
F test that all u_i=0: F(75, 52) = 54.00                    Prob > F = 0.0000
```

With this output, we will break down what the data shows us about the relative effect of price on demand within this simulation.

- The coefficient on *priceafterrebate* is **-0.89**, indicating that a 1 dollar increase in price decreases expected demand for a product by 0.89 units. This coefficient is statistically negative at the 5% level, proving that price does have a (weak) inverse relationship with demand.
- The within R-Squared value of **0.61** indicates that **61%** of the variation in demand **within** a particular brand across quarters can be explained by changes in price of this product.

This shows a price change does have a significant effect on expected demand for a particular product.

- The between R-Squared value of .1463 indicates that 14.63% of the variation **between** brands can be explained by differences in price for these products. While less substantial than the explanatory power of price on demand within brands, this still demonstrates that price plays a factor in expected demand for a product when brand-specific and quarter-specific effects are controlled for.
- The rho value of .9865 indicates that 98.65% of the variation in demand in the simulation is explained by brand-specific effects. These effects include brand judgement scores, ad judgement scores, and other factors un-accounted for in the model. This underscores the importance of decision-making in the simulation, and the relative unimportance of price relative to these other characteristics of a product.

Further Analysis of Findings

A crucial data point here, found in **Figure 10**, is the coefficient on *priceafterrebate*: **-0.89**. This means that, for each additional dollar in the price of a product, its expected demand decreases by 0.89. The inverse is also true. For each dollar that the price of a product is reduced, its expected demand increases by **0.89.** This is important in considering the economic benefits of cutting or increasing costs within the simulation.

If this coefficient was less than -1 (e.g. -1.2), then expected demand would **increase** by **more than 1** for every 1-dollar reduction in price. The revenue from this increased demand would always outweigh the loss of revenue from the price reduction. Conversely, for every 1-dollar increase in price, expected demand would **fall** by **more than 1**. Thus, cutting prices would be the better strategy for revenue growth, obviously considering internal factors such as profit margin maximization, production costs, and desired cash balances.

However, this value is not less than -1. This means that with each 1-dollar reduction in price, expected demand **only increases** by **0.89**. The lost revenue from the price reduction is not covered by the increased revenue from additional demand, and price reduction is likely not the correct strategy, all else equal. Conversely, with a 1-dollar increase in price, expected demand **only decreases** by **0.89.** The loss in revenue from the decrease in expected demand is more than covered by the additional revenue from the price increase, and raising prices is the correct strategy, all else equal.

Obviously, there are a variety of confounding factors that go into this type of decision-making. This coefficient essentially represents the price elasticity of demand for a product, and the value of this elasticity usually changes at different price levels. Previously mentioned considerations of profit margins and production costs are also important factors in pricing decisions. Furthermore, the 95% confidence interval for this coefficient in our data is **[-1.54, -.24]**. This interval includes values on both sides of this crucial **-1** mark, and therefore no reliable conclusions can be drawn regarding the relatively optimal pricing strategies demonstrated by the data from this particular Marketplace Simulation.

An important facet of pricing decisions revolves around costs and benefits. Previous data analysis in this study demonstrates that, in the confines of the marketplace simulation, brand judgement and ad judgement scores have a more substantial effect on demand for a product than its price. This is shown by the R-Squared values in **Figures 3, 6, and 8**, as well as demonstrated in the rho-value in **Figure 10.** Within the marketplace simulation, and in the real world, corporations must decide whether the increased costs associated with improving brand judgement and ad judgement are made worth it by the associated increases in demand with these improvements. The coefficients in **Figures 6 and 8** give us some insight into this. The linear regression analysis of the effect of brand judgement on demand, shown in **Figure 6**, finds that each 1-score increase in brand judgement for a product increases its expected demand by 62.56. Similarly, the linear regression analysis of the effect of ad judgement on demand, shown in **Figure 8**, finds that each 1-score increase in ad judgement for a product increases its expected demand by 64.82. Both values are statistically significant.

To find the economic benefit of this increase in demand, I found the average price (after rebate) of all bikes sold in this simulation: $1293.68. Therefore, the increase in revenue from a 1-score increase in brand judgement or ad judgement is the coefficient on these variables from the linear regression multiplied by this average price.

- Brand Judgement: 62.56 x $1293.68 = **$80,932.62**
- Ad Judgement: 64.82 x $1293.68 = **$83,856.34**

These values can be extremely useful in considering the benefits of spending money on improvements to products or advertisements and can be weighed against the costs of these improvements to determine if they are economically viable.

Furthermore, this data can be used to put a mathematical value comparative effects on demand from changes in price and judgement scores that we have previously established. We previously discussed the value of -0.89 for the coefficient on *priceafterdemand* from the Fixed-Effects regression shown in **Figure 10.** We can use this coefficient to estimate the reduction in price necessary to increase demand the same amount as a 1-unit increase in brand judgement and ad judgement.

- Brand Judgement: 62.56/0.89 = **$70.29**
- Ad Judgement: 64.82/0.89 = **$72.83**

In the case of a price decrease, this matching demand increase is coupled with a decrease in overall revenue with this coefficient on *priceafterrebate* of **0.89**, as we established earlier in this findings section. Therefore, it is not economically feasible to decrease price to the extent that would match the revenue increases found by 1-unit increases in brand or ad judgement scores. However, revenue is not indicative of profitability nor financial success. To adequately weigh the comparative costs and benefits of attempting to increase demand through either a price-cutting strategy or investments in improving judgement scores, one must have the full array of information regarding production costs, investment costs, and price elasticity in their particular market.

These calculations, to the extent that they are beneficial at all, merely provide a baseline estimate of the marginal demand changes associated with changes in price, brand judgement, and ad judgement. These marginal values can be useful, when considered among a variety of other factors available to the participants of this simulation.

Conclusion

In this simulation, the data did not indicate a particularly strong relationship between price and demand. Even when controlling for confounding factors such as variability in demand across quarters and brand-specific fixed effects, the certainty of the effect of price on demand was difficult to establish. The existence of an inverse relationship between these was found in our analysis, but the confidence interval on the coefficient of price showed that we could not conclusively determine the strength of this relationship effectively enough to be utilized in economic analysis. For this to be the case, we would have needed the interval range to not include -1, that crucial value of price elasticity of demand on which any economic analysis of pricing decisions must be based upon.

We did find conclusive evidence that brand judgement and ad judgement scores have substantial effects upon the expected demand of a product. I was shocked at the increase in demand that occurs at the marginal level, specifically the value of 62.56 for the marginal increase in expected demand with a 1-unit increase in the brand judgement score of a product. This provides strong evidence that much attention must be paid to the design of products and the design of their advertisements. With everyone in the simulation receiving the same design options and investment capabilities, the decisions that succeed in separating a company from the pack in terms of consumer perceptions are likely the most important in terms of determining their market share and total performance in the simulation. In this Marketplace simulation game with an emerging industry, market size is theoretically unbounded. In this scenario, providing a clearly superior product and advertising it well appears to be the most effective way in guaranteeing high levels of demand. Pricing decisions are important on the margins, but I believe this data analysis clearly shows the superior importance of brand identity in ensuring success in Marketplace Simulations.