

Nils Baker Case Study

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1 Executive Summary

This section is to be written last and contains a short (approx 250 words) summary of the case study as a whole.

2 Background

Summarizes the case study prompt. Contains any basic term definitions and prepares reader for discussion. Should propose basic question so that the Models section can dive right in.

3 Models

3.1 Initial Considerations

The data that we have received to pursue Nils Baker's hypothesis includes four columns. Initially, they are *ID*, *Total.Households.in.Area*, *Households.with.Account*, and *Inside.Outside.Footprint*. First, we drop the last two rows of the data set because they are empty and change the column names to *ID*, *Total.Households*, *Accounts*, and *Footprint*, respectively. Next, further preprocessing of the data is performed so that we have numeric data (see **Additional Codeblock 1** in the *Appendix* for the code used to do this).

The first column, *ID*, is identical to the row number and, thus, will not be considered in this case study. Each row itself is a separate Metropolitan Statistical Area (MSA). For our purposes, we need only understand that each row contains a different geographic region. The next two columns, *Total.Households* and *Accounts*, contain the number of total households and the number of those households that have a checking account with the bank. The last column, *Footprint*, was originally coded with either “Inside” or “Outside.” A region was considered “Inside” if there was both a physical bank location and an ATM in the region. This was recoded as 1 for easier analysis of the data. A region was considered “Outside” if there was not a physical bank location and only an ATM in the region. This was recoded as 0.

Finally, we will add a column called *Accts.Hsehld* that takes the *Accounts* column and divides it by the *Total.Households* column. We may want to choose this as the response variable since this allows us to get closer to evaluating Nils Baker’s hypothesis without as much interpretation of the model.

With the data in a usable form, we can now view the correlation matrix to get an initial feel for the relationships amongst the variables.

Figure 1

##	ID	Total.Households	Accounts	Footprint
## ID	1.0000000	-0.67957529	-0.66181262	0.3030236
## Total.Households	-0.6795753	1.00000000	0.91121152	-0.3004534
## Accounts	-0.6618126	0.91121152	1.00000000	-0.2171381
## Footprint	0.3030236	-0.30045335	-0.21713807	1.0000000
## Accts.Hsehld	0.1732239	-0.08685308	0.07169036	0.1523331
##	Accts.Hsehld			
## ID	0.17322388			
## Total.Households	-0.08685308			
## Accounts	0.07169036			
## Footprint	0.15233308			
## Accts.Hsehld	1.00000000			

We can ignore the values involving ID since this is basically just a running counter of which number region we see. Its correlation with *Total.Households* is based on the fact that the data set’s observations are organized by the number of households in the region with the largest first. We see that *Accounts* has a strong correlation with *Total.Households*, which is reasonable since we expect that regions with more households will have more accounts, just based on volume. Also, this explains the negative correlation between *Accounts* and ID. The numbers indicate what we would expect for *Footprint*; the correlations with the households and accounts do not show anything. That is, the locations of physical banks were not chosen based on the number of households or accounts in a region. This correlation matrix ends up showing us that trying to predict *Accts.Hsehld* may be difficult, but hopefully combining a few features will help. Please see **Additional Figure 1** in the *Appendix* for the pairs plot that shows these relationships graphically.

3.2 Procedure

The goal in this case study, as stated by Nils Baker, is to ascertain whether or not the presence of a physical bank in a region increases the likelihood of a given household possessing a checking account. We will start with Simple Linear Regression (SLR) models, before considering more complex Multiple Linear Regression (MLR) models.

3.3 SLR Models

3.3.1 Predicting Number of Accounts

We will start by evaluating SLR models for *Accounts*. Even though these models may be more difficult to interpret in terms of Nils Baker’s hypothesis, if we find an especially good model, then we may make an

exception. The summaries of these three models are below.

Figure 2

```
##
## Call:
## lm(formula = Accounts ~ Total.Households, data = d)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -4645.8  -358.6  -223.9    77.7   7823.8
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)   2.260e+02  1.447e+02   1.562   0.121
## Total.Households 1.086e-02  4.521e-04  24.029 <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1366 on 118 degrees of freedom
## Multiple R-squared:  0.8303, Adjusted R-squared:  0.8289
## F-statistic: 577.4 on 1 and 118 DF, p-value: < 2.2e-16

##
## Call:
## lm(formula = Accounts ~ Footprint, data = d)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -2540.2  -1778.4  -819.1   -40.1  16943.4
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)   2627.2     395.4   6.645 9.86e-10 ***
## Footprint    -1437.6     594.9  -2.416  0.0172 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 3236 on 118 degrees of freedom
## Multiple R-squared:  0.04715, Adjusted R-squared:  0.03907
## F-statistic: 5.839 on 1 and 118 DF, p-value: 0.01721

##
## Call:
## lm(formula = Accounts ~ Accts.Hsehld, data = d)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -2671.2  -1594.0  -1433.4   143.6  16047.8
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)   1742.8     439.6   3.965 0.000126 ***
```

```
## Accts.Hsehld 17527.1    22448.6    0.781 0.436504
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 3307 on 118 degrees of freedom
## Multiple R-squared:  0.00514,    Adjusted R-squared:  -0.003292
## F-statistic: 0.6096 on 1 and 118 DF,  p-value: 0.4365
```

Considering the results of the correlation matrix above, none of these results are particularly surprising. The total number of households in a region proves to be a good predictor of the number of accounts in the region. The coefficient of determination, denoted R^2 , is high, so we know that a significant amount of the variation in **Accounts** is explained by **Total.Households**. Additionally, the p-value for the coefficient and the model are significant. However, this model only serves to highlight the drawbacks of choosing **Accounts** as the response variable since we can only determine that regions with more households have more accounts. We can say nothing about how likely a given household is to have an account.

The other two models, which use **Footprint** and **Accts.Hsehld**, are exceptionally poor. **Footprint** is the feature that most interests us since it tells us if a physical bank is in the region. While we would have been surprised to see the presence of a physical bank be a good predictor of the gross number of accounts, seeing that it is not fits in with what we would expect. Now we will look at SLR models predicting the number of accounts per household in a region.

3.3.2 Predicting Accounts per Household

Now we look at how each of the individual potential predictors does with **Accts.Hsehld** as the response variable. By using this response variable, we can easily understand which potential predictors are involved in determining the likelihood of a given household having an account with the bank. The summaries of these three models are below.

Figure 3

```
##
## Call:
## lm(formula = Accts.Hsehld ~ Total.Households, data = d)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.010135 -0.006645 -0.003025  0.001904  0.121737
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)   1.492e-02  1.432e-03  10.423  <2e-16 ***
## Total.Households -4.235e-09  4.472e-09  -0.947    0.346
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.01351 on 118 degrees of freedom
## Multiple R-squared:  0.007543,    Adjusted R-squared:  -0.0008672
## F-statistic: 0.8969 on 1 and 118 DF,  p-value: 0.3456

##
## Call:
## lm(formula = Accts.Hsehld ~ Accounts, data = d)
```

```
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.009282 -0.006456 -0.003580  0.002018  0.122535
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 1.365e-02  1.444e-03   9.454 3.94e-16 ***
## Accounts    2.932e-07  3.756e-07   0.781  0.437
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.01353 on 118 degrees of freedom
## Multiple R-squared:  0.00514,    Adjusted R-squared:  -0.003292
## F-statistic: 0.6096 on 1 and 118 DF,  p-value: 0.4365

##
## Call:
## lm(formula = Accts.Hsehld ~ Footprint, data = d)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.011787 -0.006085 -0.003160  0.002384  0.120077
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 0.012411   0.001637   7.580 8.62e-12 ***
## Footprint    0.004125   0.002464   1.674  0.0967 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.0134 on 118 degrees of freedom
## Multiple R-squared:  0.02321,    Adjusted R-squared:  0.01493
## F-statistic: 2.803 on 1 and 118 DF,  p-value: 0.09672
```

Once again, these results are aligned with those from the correlation matrix. All three SLR models are quite poor. Their respective R^2 values are very low, and their respective p-values are high. With a higher p-value we cannot reject the null hypothesis these models are just as good as the average at predicting `Accts.Hsehld`. Interestingly, the R^2 and p-values are best, albeit still terrible, for the SLR that used `Footprint`. Depending on what we find when looking at MLR models, Nils Baker's hypothesis still has a chance at being correct. Now we will turn our attention to MLR models to try to find one that does a decent job at predicting `Accts.Hsehld`.

3.4 MLR Models

3.4.1 Initial Considerations

MLR models can get quite complicated. We can look at how different terms interact with each other, quadratic terms, etc. It is imperative that we keep Nils Barker's hypothesis in mind as we look at MLR models. We want to see how well `Footprint` predicts `Accts.Hsehld`. Thus, we will focus on generating models that will help us answer that question.

3.4.2 Ramsey RESET Test

The Ramsey RESET Test attempts to determine if quadratic terms add value to a model. It does not take into consideration the interaction between quadratic terms and other variables, so this will only help to give us an intuition. The results of the test are below.

Figure 4

```
##
## RESET test
##
## data:  lm(Accts.Hsehd ~ Accounts + Total.Households, data = d)
## RESET = 1.9605e-05, df1 = 1, df2 = 116, p-value = 0.9965
```

We see that the p-value is about as bad as is possible at 0.9965. This test was run for just possible quadratic terms. We will not evaluate any higher order terms with such a poor value. We did not run the test with `Footprint` in the model because a qualitative variable cannot be squared. Thus, we expect that quadratic terms will be most valuable for their interactions, if at all. Now we turn our attention to actual MLR models.

3.4.3 Footprint with one other term

In the correlation matrix (**Figure 1** above) we saw that `Accounts` and `Total.Households` have a very high correlation (0.911). Thus, we will explore models with only one or the other.

The code and summaries for each of the models explored can be found in **Additional Codeblock 2** in the *Appendix*. However, they will not be displayed here because none offered promising results. R^2 only goes up to 0.02741. When R^2 is adjusted to account for the number of predictors, R_a^2 only gets up to a miniscule 0.008395. With these dispiriting results we turn our attention to MLR models with both `Accounts` and `Total.Households`.

3.4.4 Using all potential predictors

We know that error cannot be unexplained. Thus, we can look at the R^2 value with all possible quadratic and interaction terms to get a sense of just how high we can hope to get that value when building our model. Additionally, we can compare R_a^2 to make sure that our chosen model improves on this. See below.

Figure 5

```
##
## Call:
## lm(formula = Accts.Hsehd ~ (. - ID + I(Accounts^2) + I(Total.Households^2))^2,
##     data = d)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.023668 -0.002990 -0.000442  0.002224  0.067033
##
## Coefficients:
##              Estimate Std. Error t value
## (Intercept)    1.421e-02  2.309e-03   6.155
## Total.Households -2.303e-07  6.991e-08  -3.294
## Accounts        1.649e-05  5.187e-06   3.179
```

```
## Footprint                4.773e-03  3.204e-03  1.490
## I(Accounts^2)            -1.645e-09  1.657e-09 -0.992
## I(Total.Households^2)    4.947e-13  1.847e-13  2.678
## Total.Households:Accounts -8.893e-12  2.363e-11 -0.376
## Total.Households:Footprint -5.193e-07  1.193e-07 -4.353
## Total.Households:I(Accounts^2) -8.068e-15  5.562e-15 -1.451
## Total.Households:I(Total.Households^2) -5.887e-19  2.365e-19 -2.490
## Accounts:Footprint       3.012e-05  5.980e-06  5.037
## Accounts:I(Accounts^2)    2.793e-13  1.975e-13  1.415
## Accounts:I(Total.Households^2) 8.509e-17  5.784e-17  1.471
## Footprint:I(Accounts^2)   -3.212e-09  7.623e-10 -4.213
## Footprint:I(Total.Households^2) 1.009e-12  3.746e-13  2.693
## I(Accounts^2):I(Total.Households^2) 8.509e-22  6.355e-22  1.339
## Pr(>|t|)
## (Intercept)              1.43e-08 ***
## Total.Households          0.00135 **
## Accounts                   0.00195 **
## Footprint                  0.13937
## I(Accounts^2)              0.32332
## I(Total.Households^2)      0.00860 **
## Total.Households:Accounts  0.70747
## Total.Households:Footprint 3.15e-05 ***
## Total.Households:I(Accounts^2) 0.14990
## Total.Households:I(Total.Households^2) 0.01438 *
## Accounts:Footprint         2.00e-06 ***
## Accounts:I(Accounts^2)      0.16018
## Accounts:I(Total.Households^2) 0.14428
## Footprint:I(Accounts^2)     5.38e-05 ***
## Footprint:I(Total.Households^2) 0.00825 **
## I(Accounts^2):I(Total.Households^2) 0.18352
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.008973 on 104 degrees of freedom
## Multiple R-squared:  0.6141, Adjusted R-squared:  0.5585
## F-statistic: 11.03 on 15 and 104 DF,  p-value: 1.699e-15
```

We find that $R^2 = 0.6141$ and $R_a^2 = 0.5585$. Now we can evaluate how less bloated models compare.

```
##
## Call:
## lm(formula = Accts.Hsehlld ~ . - ID + Footprint:Accounts + Total.Households:Footprint +
##      I(Accounts^2) + I(Total.Households^2) + Footprint:I(Accounts^2) +
##      Footprint:I(Total.Households^2), data = d)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.024939 -0.003457 -0.001472  0.002135  0.068849
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    1.182e-02  1.653e-03   7.150 1.01e-10 ***
## Total.Households -9.749e-08  2.366e-08  -4.121 7.32e-05 ***
## Accounts        9.509e-06  2.362e-06   4.026 0.000104 ***
```

```
## Footprint          7.859e-03  2.680e-03  2.932 0.004096 **
## I(Accounts^2)      -5.234e-10  1.846e-10 -2.836 0.005439 **
## I(Total.Households^2) 5.402e-14  1.860e-14  2.904 0.004450 **
## Accounts:Footprint  3.403e-05  4.873e-06  6.984 2.30e-10 ***
## Total.Households:Footprint -6.379e-07  7.951e-08 -8.023 1.22e-12 ***
## Footprint:I(Accounts^2) -3.203e-09  5.120e-10 -6.255 7.78e-09 ***
## Footprint:I(Total.Households^2) 1.244e-12  1.672e-13  7.443 2.33e-11 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.009204 on 110 degrees of freedom
## Multiple R-squared:  0.5706, Adjusted R-squared:  0.5354
## F-statistic: 16.24 on 9 and 110 DF,  p-value: < 2.2e-16
```

Here we find all coefficients are significant at the $\alpha = 0.05$ level. That is, we can be at least 95% confident in the significance of these coefficients. $R^2 = 0.5706$ and $R_a^2 = 0.5354$. These values are close to the obese one above. Also, the interaction terms with **Footprint** are all the most significant ones.

Details how we arrived at the models that we tried and how they worked. Include details about both the processes and the model to which they led. Our thought processes should be detailed so that there is no question how we got to our models. This needs to do all of the leg work so that the Conclusions section can focus on the actual meaning of the model. *This section should include subsections for each model with two hashes and then further subsectioning using three hashes for each part of the model discussion.*

4 Conclusions

The goal is that everything is built up to this point so that little we can just plow right into the meaning of the model. Other general conclusions can be included.

5 Appendix

5.1 Additional Codeblocks

Additional Codeblock 1

```
d <- read.csv("41330723.csv", header = TRUE, stringsAsFactors = FALSE)
d <- d[1:120, ] # last two rows contain no data
names(d) <- c("ID", "Total.Households", "Accounts", "Footprint")

for (i in 2:3) {
  d[[i]] <- gsub(",", "", d[[i]])
  d[[i]] <- as.numeric(d[[i]])
}

d[["Footprint"]][d[["Footprint"]] == "Outside"] <- 0
d[["Footprint"]][d[["Footprint"]] == "Inside"] <- 1
d[["Footprint"]] <- as.numeric(d[["Footprint"]])
d[["ID"]] <- as.numeric(d[["ID"]])
d[["Accts.Hsehold"]] <- d[["Accounts"]] / d[["Total.Households"]]
```



```
head(d)
```

```
##      ID Total.Households Accounts Footprint Accts.Hsehld
## 1  1      1772960      17563         0 0.009906033
## 2  2      1345209      14547         0 0.010813933
## 3  3       960434      10847         0 0.011293853
## 4  4       928274      18133         1 0.019534103
## 5  5       893995       5291         0 0.005918378
## 6  6       812137       6297         0 0.007753618
```

Additional Codeblock 2

```
summary(lm(Accts.Hsehld ~ Footprint + Total.Households, data = d))
```

```
##
## Call:
## lm(formula = Accts.Hsehld ~ Footprint + Total.Households, data = d)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.011920 -0.006122 -0.003293  0.002291  0.119948
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)   1.293e-02  1.979e-03   6.536 1.72e-09 ***
## Footprint      3.758e-03  2.592e-03   1.450   0.150
## Total.Households -2.202e-09  4.667e-09  -0.472   0.638
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.01345 on 117 degrees of freedom
## Multiple R-squared:  0.02506,    Adjusted R-squared:  0.008395
## F-statistic: 1.504 on 2 and 117 DF,  p-value: 0.2266
```

```
summary(lm(Accts.Hsehld ~ Footprint + Total.Households +
           Footprint:Total.Households, data = d))
```

```
##
## Call:
## lm(formula = Accts.Hsehld ~ Footprint + Total.Households + Footprint:Total.Households,
##     data = d)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.011634 -0.006183 -0.003389  0.002127  0.120225
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)   1.306e-02  2.022e-03   6.461 2.54e-09 ***
## Footprint      3.299e-03  2.922e-03   1.129   0.261
## Total.Households -2.754e-09  4.950e-09  -0.556   0.579
```

```
## Footprint:Total.Households  5.284e-09  1.532e-08  0.345  0.731
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.0135 on 116 degrees of freedom
## Multiple R-squared:  0.02606,    Adjusted R-squared:  0.0008719
## F-statistic: 1.035 on 3 and 116 DF,  p-value: 0.38
```

```
summary(lm(Accts.Hsehld ~ Footprint + Total.Households +
           Footprint:Total.Households + I(Total.Households^2),
           data = d))
```

```
##
## Call:
## lm(formula = Accts.Hsehld ~ Footprint + Total.Households + Footprint:Total.Households +
##     I(Total.Households^2), data = d)
##
## Residuals:
```

	Min	1Q	Median	3Q	Max
	-0.011703	-0.006198	-0.003313	0.002467	0.120160

```
##
## Coefficients:
```

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	1.336e-02	2.363e-03	5.652	1.17e-07 ***
Footprint	3.091e-03	3.056e-03	1.011	0.314
Total.Households	-5.533e-09	1.246e-08	-0.444	0.658
I(Total.Households^2)	2.172e-15	8.934e-15	0.243	0.808
Footprint:Total.Households	6.161e-09	1.580e-08	0.390	0.697

```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.01355 on 115 degrees of freedom
## Multiple R-squared:  0.02656,    Adjusted R-squared:  -0.007298
## F-statistic: 0.7844 on 4 and 115 DF,  p-value: 0.5375
```

```
summary(lm(Accts.Hsehld ~ Footprint + Total.Households +
           Footprint:Total.Households + I(Total.Households^2) +
           Footprint:I(Total.Households^2),
           data = d))
```

```
##
## Call:
## lm(formula = Accts.Hsehld ~ Footprint + Total.Households + Footprint:Total.Households +
##     I(Total.Households^2) + Footprint:I(Total.Households^2),
##     data = d)
##
## Residuals:
```

	Min	1Q	Median	3Q	Max
	-0.012253	-0.006095	-0.003269	0.002092	0.119637

```
##
## Coefficients:
```

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	1.329e-02	2.381e-03	5.583	1.62e-07 ***

```
## Footprint          3.836e-03  3.870e-03  0.991  0.324
## Total.Households  -4.936e-09  1.265e-08 -0.390  0.697
## I(Total.Households^2)  1.706e-15  9.090e-15  0.188  0.851
## Footprint:Total.Households  -9.514e-09  5.207e-08 -0.183  0.855
## Footprint:I(Total.Households^2)  1.769e-14  5.597e-14  0.316  0.753
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.01361 on 114 degrees of freedom
## Multiple R-squared:  0.02741,    Adjusted R-squared:  -0.01524
## F-statistic: 0.6426 on 5 and 114 DF,  p-value: 0.6676
```

5.2 Additional Figures

Additional Figure 1

