	rank	number that clicked	number that did not click	total viewed	% that clicked	number of policies sold
0	1	848	763	1611	52.64	358
1	2	462	1146	1608	28.73	209
2	3	351	2050	2401	14.62	138
3	4	168	1921	2089	8.04	58
4	5	49	2242	2291	2.14	20

Fig. 1

Based on the values in **Fig. 1** we see that 783 policies were sold from a total of 10,000 ads placed. Now each ad cost ACME $10, and ACME only paid if the ad was clicked on. As there were a total of 1878 ads that were clicked on, the total cost of this advertising was $18,780.

Now the ads that received a ranking of 1 or 2 resulted in the sale of 567 policies, which accounts for about 72% of the policies that were sold. Since there were 1310 clicks needed to obtain the sale of these policies, $13,100, which accounts for nearly 70% of the total money spent on advertising. Moreover, ads with rank 1 or 2 accounted for nearly 70% of consumers that clicked to view the quote.

Ads that received a ranking of 3, 4, or 5 resulted in the sale of 216 policies, which accounts for nearly 28% of the policies that were sold. Since there were 568 clicks needed to obtain the sale of these policies, $5,680 was spent in this direction, which accounts for nearly 13. Ads with rank 3, 4, or 5 accounted for about 30% of consumers that clicked to view the quote.

To summarize, ads with rank 1 or 2 account for 70% of the total policies purchased and ads with rank 3, 4, or 5 accounted for nearly 30% of the policies purchased.

The basic idea is to create a max bid for each tier, with higher max bids for consumers in higher tiers. We can augment the max bid based on other data we receive from the consumer (e.g. whether they already have insurance or not).

If the goal is to obtain 400 policies for every 10,000 ads placed, we can make a *very* naive linear model by regressing the number of policies sold on the percentage of consumers that clicked on the ad. Though we stress this has severe limitations, as this was created using only a small number of data points, and we argue this raises the case to obtain more data to give more precise and robust recommendations. However, we also note that ads with rank 2, 3, 4, and 5 resulted in 425 policies that were bought.

Now, initially we might suggest aiming for ads with a rank of at most 2. However, there could be multiple strategies to pursue, such as targeting rank 1, 4, and 5 ads. This is where more data could be extremely useful.

Now we ask the question, which consumers do we want to pursue? Based on our modeling, and the data, we propose initially dividing consumers up by the number of vehicles they own. In terms of the data, this is because consumers with 1 vehicle purchased the largest number of policies at 439, consumers with 2 vehicles came in second with 215 policy purchases, and consumers with 3 vehicles came in last with 129 policy purchases. In this stratification, we have the following tiers:

Tier 1: This tier consists of consumers with 1 vehicle.   From the data we were given, Tier 1 consists of 3441 consumers.

Tier 2: This tier consists of consumers with 2 vehicles.   From the data we were given, Tier 2 consists of 3464 consumers.

Tier 3: This tier consists of consumers with 3 vehicles. From the data we were given, Tier 3 consists of 3095 consumers.

While we currently do not have enough data to suggest how bid price affects rank, we can offer up an example of an implementation whose aim is to reduce the number of rank 1 significantly:

Tier 1: Max bid is 10 with a decrease to 9 if 1 driver

Tier 2: Max bid is 9 with a decrease to 8 if 1 driver.

Tier 3: Max bid is 8 with an decrease to 7 if 1 driver.

In order to make a more robust and precise recommendation, we need to understand how bid price affects rank. And if possible, data on what other companies are bidding would be extremely helpful.