Case 5: Solution

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Section 2: Basic Descriptives and Correlations

1. This question is more of a suggestion and doesn't have a specific correct answer.
2. The firm wants to know which doctors to detail. Since they are interested in the effect that detailing has on different doctors, this is a causal question. Since sending a pharma rep costs money, we want to ensure that this specific action is what causes the increase in prescriptions.

Section 3: Interpretation of a Univariate Regression

1. If a physician received three detailing visits they will on average write 3.29142 + 3 * 0.93977 = 6.11 prescriptions. Be careful that you include the intercept term!

2. Yes, it would. A detailing visit would cost 200 dollars, but generate 0.93977 * 1000 = 939.977 dollars of revenue. Since the revenue far exceeds the cost, detailing visits are worth it.
3. No. The standard error here is relatively small, and therefore the 95% confidence interval is relatively narrow. In this case, the confidence interval is 0.93977 +/- 0.0278*1.96 = [0.885,0.994]. Even on the low end of the confidence interval, revenue would far exceed the cost, and detailing would be worth it. This process is similar to a sensitivity analysis.

Section 4: Multivariate Analysis

1. In this case, some doctors might like this drug more than others. Since they like the drug, they will be more likely to prescribe it in both the past and present periods
2. No, it would not. A detailing visit would cost 200 dollars, but generate 0.0718 * 1000 = 71.81 dollars of revenue. Since the revenue is far below the cost, detailing visits are not worth it.
3. No. The standard error here is relatively small, and therefore the 95% confidence interval is relatively narrow. In this case, the confidence interval is 0.0718 +/- 0.0163*1.96 = [0.040,0.104]. Even on the high end of the confidence interval, revenue would be far below cost, and detailing would not be worth it.

4. The drop in the `detailing` coefficient can be explained by a relationship between `detailing`, `lagged_scripts`, and `mean_samples`. Suppose that doctors who tended to prescribe the drug were detailed more frequently, and received free samples more frequently. In that case, our previous analysis ascribed the effect of `lagged_scripts`, and `mean_samples` to the coefficient of `detailing`, since it was not controlled for.

Section 5: Categorical Variables

1. Interpreting this coefficient requires looking back at the summary of the data in Section 2. Looking at the values of `doctorType`, we can see that Area Specialist is the default value. Therefore, the coefficient of `factor(doctorType)General Physician` means that a General Physician will write -1.92859 fewer prescriptions than an Area Specialist.
2. Following a similar logic as the previous question, the coefficient of `factor(doctorType)Other Specialist` means that an Other Specialist will write -1.95691 fewer prescriptions than an Area Specialist
3. We do not know yet. Our analysis can tell us which doctors tend to prescribe more or less, but it does not yet tell you which doctors respond to *detailing*, which is what is actually relevant for this decision. That is, even if someone prescribes a lot, if they don't change their behavior when they are detailed, then we should not detail them.

Section 6: Interaction Effects

1. For a general physician, a detailing visit increases perscriptions by 0.3644 - 0.3197 = 0.0447, as we have to include both the `detailing` and the interaction between `detailing` and `factordoctorTypeGeneral Physician`. Area Specialist is the default value, so the effect of detailing for these doctors is just 0.3644
2. The value is so much higher because the default value happens to be `Area Specialist`, which is the type of doctor most affected by detailing. If instead `Other Specialist` was the default value, the coefficient on `detailing` would be much lower, but there would be a positive interaction between `Area Specialist` and `detailing`. Put differently, in the previous analysis had the coefficient on `detailing` was the average effect of detailing across each type of doctor. Now, with the interaction variable, it is only the effect of detailing on `Area Specialist`s.

Section 7: Fixed Effects

1. The coefficients that are NA are those that are nested by the `doctorID` fixed effect. Both `doctorType` and `mean_samples` did not vary within a doctor. Therefore, we cannot tell if a doctor is perscribing a lot because of their area of speciality, or because they liked the drug. Is this a problem? It depends on the question! If we are interested in the effect of detailing, no it does not. If we are interested in the effect of free samples, then it obviously does.
2. The standard errors have slightly increased. This is because we are estimating many more coefficients, and so have fewer degrees of freedom. However, they didn't increase that much - it is much better to deal with the potential omitted variable bias by including the fixed effect.

Section 8: Conclusion

1. The firm should target Area Specialists. Each visit to an Area Specialist costs 200 dollars but would earn 303.72 dollars of revenue. Detailing other types of doctors would lose money.
2. There are many potential variables to consider. Detailing visits in previous months, and the pharma rep all seem immediately relevant. Still, the firm did feel comfortable taking recommendations based on the provided dataset.
3. The firm should also give out more free samples, as they have a very strong relationship with scripts. Each free sample leads to almost an entire new script!