Model description and variables:

To start of, we are going to stay in line with Möller and Reichmann (2021) and we would like to see what impact only those basic sentiments on each own have on abnormal returns. This will help paint the overall starting picture of our model. Intuitively speaking, this should have minimal impact on the sentiments by them self, as some times they might be in line with an increase (decrease) in abnormal returns but in other times it might not.

Table 1:

Looking at Table 1, the intuition seems to be correct. We can see neither of those sentiment variables are significant in our baseline regression. Model fit also seems to be an issue as the R2 and adjusted R2 are no way near 1. Therefore, we can shortly conclude, that only (for example) constraining messages or uncertainty messages from the FED will not impact abnormal returns by themselves. Regressing all sentiment variables in one model also does not seam to be the correct approach, as those sentiment variables might be correlated due to their nature. Also, the authors of the original paper stayed away from such an approach.

Because the sentiments alone do not seem to have the biggest impact on abnormal returns, we start looking at different economic circumstances which could boost the impact of sentiments on abnormal returns. We know leave the comfort of Möller and Reichmann, and start moving towards our model. By adding a different variables one step at a time, we can fully grasp what impacts abnormal returns on “FED announcement days” and prevent overfitting, which could be an issue when looking at the model straight up. Firstly, a good variable to start off with is interest rates. Interest rates will paint the picture of the state of the economy at the moment. We therefore include *IR* into our models.

Table 2:

Looking at Table 2, we unfortunately can see that, unfortunately, there is still no significant impact on abnormal returns, when regressing the sentiments alongside interest rates. As interest rates are mostly rather stationary and will are not exhibit high volatility. It also can be argued that those sentiment scores and interest rates could be possibly correlated a bit. High constraining language, by theory, could easily go hand in hand with higher interest rates, and so on. Model fit, i.e. R2 and adjusted R2 seamed to have also deteriorated by adding interest rates. The latter part is to be expected, as adjusted R2 takes adding variables into account via a penalty term.

However, we still somewhat believe in our heart that interest rates might have a significant impact on abnormal returns. We therefore built upon this believe and added the lagged returns on in our model. We now regress abnormal returns on *Tone*, *Con*, *Unc* by themselves, but also now *IR* and *lagged\_return.*

Table 3:

Unfortunately, looking at the results from table 3, there are still no significant impacts on abnormal returns, which is a bit disheartening. However, model fit seams to have improved a bit. We still have a lot more variables which could help our ordeal though. We now add a special variable which could be a key contributor in the process. The other variables are self-explanatory (for the most part) – but how was the *Surprise* variable constructed? It is basically the difference between Federal Funds rate on announcement day and Fed Funds Futures as a gaugue for market expectations, i.e. the change in interest rates. This means that, this variable will account for unexpected announcement results from the fed and discounts it.

Table 4:

Analysing table 4, one can now start to understand why we think highly of this variable. By adding surprise, we can now start to see how abnormal returns react to FED Statements. In our model now, *Tone* is significant. According to the authors, this indicates that a more positive (negative) language of the FED is associated with higher (lower) intraday abnormal returns. This is in line with the findings of Schmeling and Wagner (2019), who found that negative changes in the fraction of negative words within an introductory statement of an ECB press conferences have a positive influence on stock prices and a negative influence on volatility risk premia and credit spreads. We also find that, *Surprise* is significant in every model other than *Unc*. This can be explained, intuitively, by figuring that the FED is most likely using uncertain language in times of crises, which might decrease (increase) the market expectation of interest rates.

Last but not least, we include the debt to equity ratio of firms (?) into our model. This variable tells us the rate of debt those firms (?) have in relation to their equity. The higher this ratio is the higher the leverage of its firm, the more it might react to interest rates changes. This will now complete our intended model.

Table 5:

As seen in Table 5, we still have a significant value of *tone*, but the significance of surprise has changed in some variables. Instead of our FinBERT sentiment being significant, uncertainty has now become significant. (Muss man noch erklären warum FinBERT jetzt insigniffikant sein kann)

A model which could become interesting is our model with interaction terms. The idea is that by adding interaction the effect of "Tone", "Unc", "Con", "Bert" or "Surprise" on abnormal returns is moderated by the company's leverage. In other words, the impact of these sentiment on returns may vary depending on the leverage ratio.

Table 6:

We can see in Table 6 that, the interest rate surprises are highly significant by itself but also in this interaction term. This can be explained rather intuitively. If a company has high leverage it will have a significant impact on it’s performance by a “surprise” in interest rates, as they are more vulnerable to interest rates. However, again none of the base sentiment scores are significant on their own and in combination with the debt to equity ratio. This is a bit surprising, as one could have made an argument that firms with an higher (lower) leverage could have been more (less) vulnerable to FED statements as they are at the mercy of the monetary policy in place.

BMA

After regressing everything and getting the results we do a final check via Bayesian Model Averaging ,where we can see which of the Variables from our Core data set truly are important to abnormal returns. This methodology is to check which variables have variable importance in a regression. However, we only look at the "relative importance" of the variables, as returns are difficult to predict anyway.

(Erklären warum BMA wichtig ist mit einen Paper)

BMA Table

Looking at the results from the BMA table, we can clearly see that the posterior probabilities of neither variable in our data set seams to have a high predicting power. A PIP of close to 1 would be a value to strive for in this model environment, which our model is clearly far away from. As previously stated, we are only looking for relative importance as returns are rather difficult to predict anyway, so the low PIP is quasi justified.

What we can gather though, just looking at column 4 “Cond.Pos.Sign” *Tone* and *Surprise* are at 1 which is an important fact. Generally, for example, if the variable "Cond.Pos.Sign" in a BMS plot has the value 0.7, this means that this variable is included in 70 % of the positively significant models. This indicates that this variable has a positive and significant effect on the dependent variable in many models in which it is included. This means, in our last model (without the interaction term) those two variables are highly significant in any combination.

Für conclusion müsste man beachten ob interaction term model oder standard model die bessere betrachtungsweise ist.

Add on: Schmeling and Wagner (2019) in der bibliography vom paper kopieren