The Asymmetric Effect of Uncertainty on Monetary Transmission

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Abstract

This paper discusses the asymmetric effect of uncertainty on the monetary transmission mechanism. The notion is that high uncertainty dampens the transmission of the interest rate channel, thus implying the importance of using forward guidance alongside interest rate decisions. To study this nonlinear relationship, I use a threshold VAR approach to estimate sign restricted VAR models. The results will show that at the more extreme levels of uncertainty there is considerable asymmetry in the transmission mechanism. Moreover in such instances monetary policy is less effectively able to anchor inflation and is only able to do so with a larger drop in economic activity.

Keywords: Uncertainty, Monetary transmission, Asymmetry, Sign restriction, Vector-Autoregression

Introduction

Over the recent years, uncertainty and asymmetries are two subjects that gained considerable traction in macroeconomics research. Both fields of research already have a rich literature, with there being a consensus on uncertainty shocks having an impact resembling that of a negative demand shock on economic activity (Carrière-Swallow and Céspedes (2013), Colombo (2013), Caldara et al. (2016), Cheng and Chiu (2018), Bonciani and Ricci (2020), Nilavongse, Michał, and Uddin (2020)); and several papers have shown that macroeconomic shocks can have different impacts depending on the state of the economy. Nalban and Smădu (2021), Foerster (2014), Jones and Enders (2016) and Grier et al. (2004) all take slightly different approaches, however all papers find that the impact of (negative) macroeconomic shocks is a sharper decline when uncertainty is high. Similar processes can be observed when carrying out the analysis with respect to the economy's position in the business cycle. Schüler (2014) and Colombo and Paccagnini (2020) show that uncertainty shocks have larger impact during economic contractions, and Kakes (1998) finds that monetary transmission is amplified during recessionary periods in the US and Germany. Another field of research on asymmetric dynamics is finding asymmetry in monetary policy-making itself. Lin (2021) finds that macroeconomic aggregates react asymmetrically to positive and negative monetary policy shocks. Güney (2018) links uncertainty and asymmetries in monetary policy by assuming a difference in the policy reaction function in over the business cycle.

With this paper, I aim to contribute to the pre-existing literature, by linking the effect of uncertainty to the efficacy of monetary transmission. The results could have key implications for policy making, more specifically, it could highlight the importance of forward guidance measures, especially during times, when economic uncertainty is at its peak.

The rest of the paper will be outlined as follows: Section 2 gives a brief overview of the data used, Section 3 discusses the empirical strategy, in Section 4 I discuss the results and Section 5 concludes.

Data

For the purposes of the analysis I will be estimating VAR models with three variables, the federal funds rate, consumer price index, and industrial production index. All data are monthly from ranging from January 1985 to December 2019 and all are retrieved from the federal reserve database.

```
#loading packages
#packages
suppressPackageStartupMessages({
  library(readxl)
  library(tidyverse)
  library(tseries)
  library(forecast)
  library(TSA)
  library(fpp2)
  library(lmtest)
  library(vars)
  library(mFilter)
  library(ggplot2)
  library(tsDyn)
  library(fredr)
  library(VARsignR)
  library(lubridate)
  library(cowplot)
  library(gridExtra)
  library(patchwork)
  library(data.table)
  library(tsibble)
  library(mvnfast)
})


#set api key
```

```r
fredr_set_key("cda47ae66b38ed7988c0a9c2ec80c94f")

#download data
params <- list(
  series_id = c("USEPUINDXD", "DFF", "USACPIALLMINMEI", "INDPRO"),
  frequency = "m",
  observation_start = as.Date("1950-01-01")
)



import  <- pmap_dfr(
  .l = params,
  .f = ~ fredr(series_id = .x, frequency = .y)
) %>%
  dplyr::select(date, series_id, value) %>%
  spread(key = series_id, value = value) %>%
  drop_na() %>% as_tsibble() %>% rename(epu = USEPUINDXD,
                                        ffr = DFF,
                                        cpi = USACPIALLMINMEI,
                                        indpro = INDPRO
                                        )

#select data range
data <- import %>%
  dplyr::select(date, epu, ffr, cpi, indpro) %>%
  drop_na() %>% filter(date <= as.Date("2019-12-01"))
```

```r
#plotting the data series
data %>%
  gather(key = "variable", value = "value", ffr, cpi, indpro) %>%
  mutate(variable = case_when(variable == "ffr" ~ "Federal Funds Rate",
                              variable == "cpi" ~ "Consumer Prices",
```

```
                              variable == "indpro" ~ "Industrial Production Index
        variable = factor(variable, levels = c("Federal Funds Rate", "Consumer P
  ggplot(aes(x = date, y = value)) +
  geom_line() +
  facet_wrap(~variable, scales = "free", nrow = 3) + theme_minimal() +
  labs(x = "",
       y = "")
```

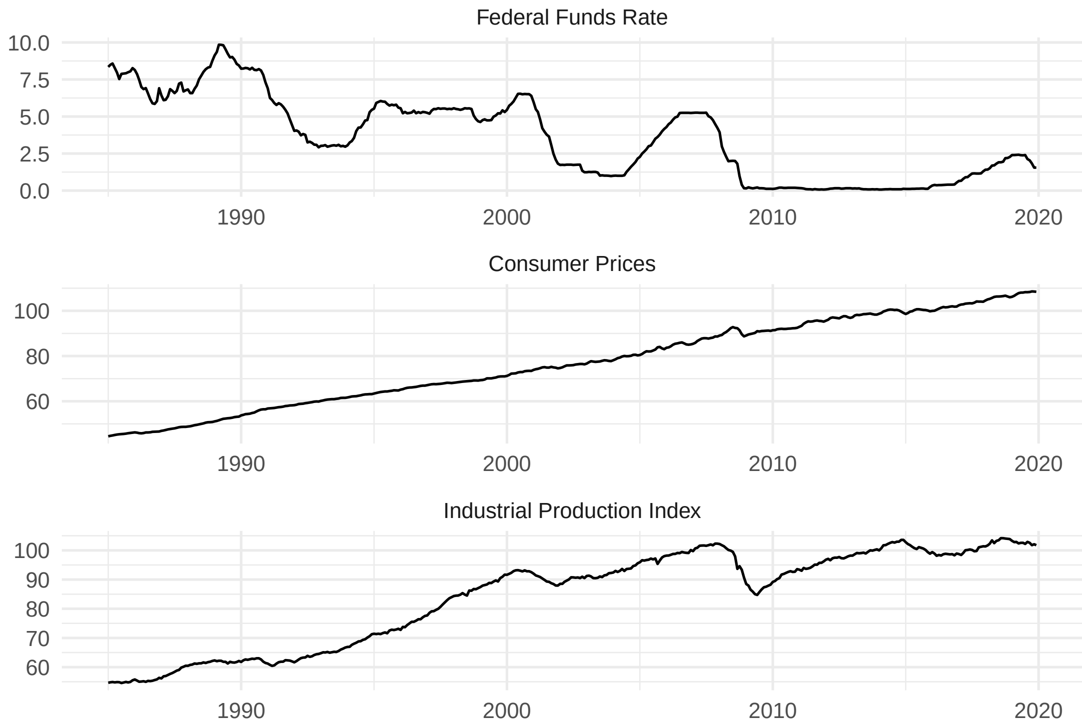

Figure 1: Time series plots of the Federal Funds Rate, Consumer Price Index and Industrial Production Index for the USA.

As most macroeconomic variables, these data series are not stationary either, which is not desirable for the stability of the VAR models. For this reason I will be using the first difference of the industrial production index and the CPI. However, I will use the FFR at its level. This way I have better stability in my models and all variables have clear economic interpretation, as the two first-differenced data series can be considered as monthly growth rates of production and inflation respectively.

Another key variable I will be using as a “quasi transition variable” is a measure of uncertainty. This however is not a trivial metric, as several data series can be interpreted as a measurement of economic turmoil. The most commonly used are among others the VIX index and the TED spread.

```r
epu <- fredr(series_id = "USEPUINDXD",
             frequency = "m") %>%
  dplyr::select(date, value) %>%
  mutate(id = "EPU index",
         id = as.factor(id))

ted <- fredr(series_id = "TEDRATE",
             frequency = "m") %>%
  dplyr::select(date, value)%>%
  mutate(id = "TED spread",
         id = as.factor(id))

vix <- fredr(series_id = "VIXCLS",
             frequency = "m") %>%
  dplyr::select(date, value)%>%
  mutate(id = "VIX index",
         id = as.factor(id))

vis <- epu %>%
  bind_rows(ted) %>%
  bind_rows(vix) %>%
  ggplot(aes(x = date, y = value, group = id, color = id)) +
  geom_line() +
  geom_smooth(method = "gam", se = FALSE, linetype = "dashed") +
  theme_classic() +
  theme(legend.title = element_blank()) +
  scale_y_log10() +
  labs(x = "",
       y = "")
vis
```

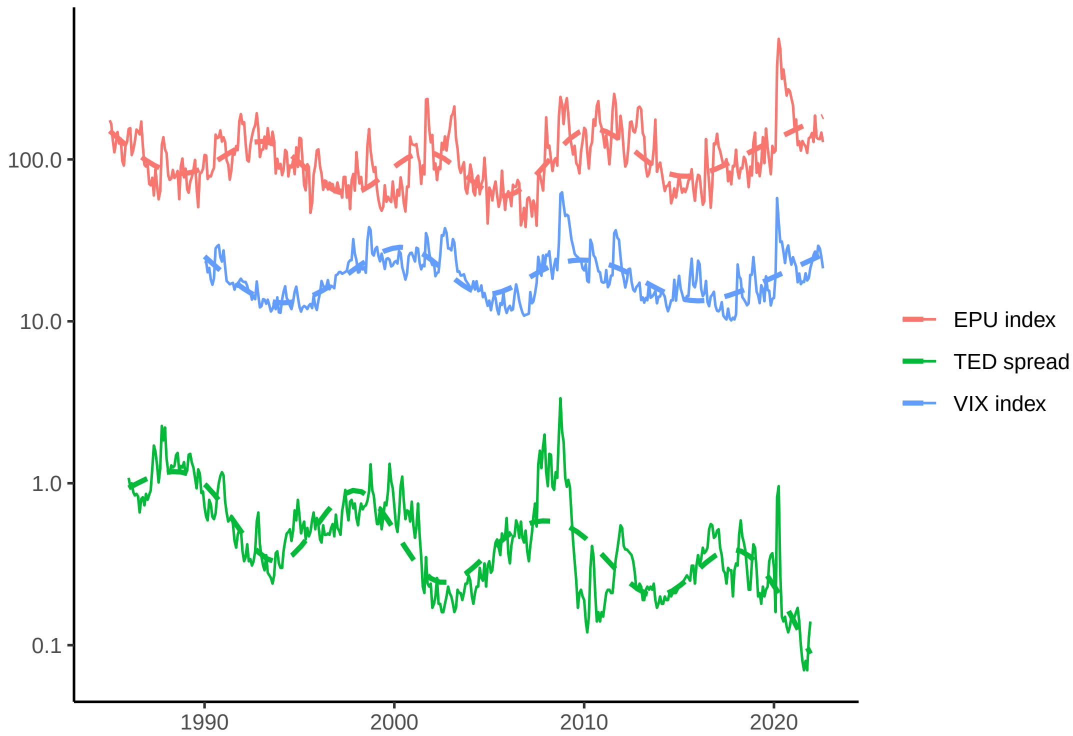

Figure 2: Time series plots of the VIX index, TED spread and the Economic Policy Uncertainty index, log scales.

The former derives from the market expectations on the price changes of the S&P500 index, while the latter is the difference between the 3 month London interbank rate and the 3 month US treasury bill. Both are widely used in measuring financial stress or uncertainty, however in recent years in the literature on uncertainty, news based indices have gained a lot of traction. One such is the Economic Policy Uncertainty index created by Baker, Bloom, and Davis (2016) .

```
#generate first differences / growth rates
data <- data %>%
  mutate(cpi = cpi - lag(cpi),
         indpro = indpro - lag(indpro)) %>% drop_na()

#creating threshold values
data <- data %>%
  mutate(epu50 = median(epu),
         epu75 = quantile(epu, probs = 0.75),
```

```
        epu25 = quantile(epu, probs = 0.25))
```

```
#plot epu index with threshold values
data %>% dplyr::select(date, epu, epu50, epu25, epu75) %>%
  ggplot(aes(x = date, y = epu)) +
  geom_line() +
  geom_hline(aes(yintercept = epu50), color = "darkred") +
  geom_hline(aes(yintercept = epu25), color = "darkgreen") +
  geom_hline(aes(yintercept = epu75), color = "darkgreen") +
  theme_minimal() +
  theme(plot.title = element_text(size = 11, hjust=0.5),
        axis.title.y = element_text(size=11)) +
  labs(x = "",
       y = "",
       title = "BBD economic policy uncertainty index")
```

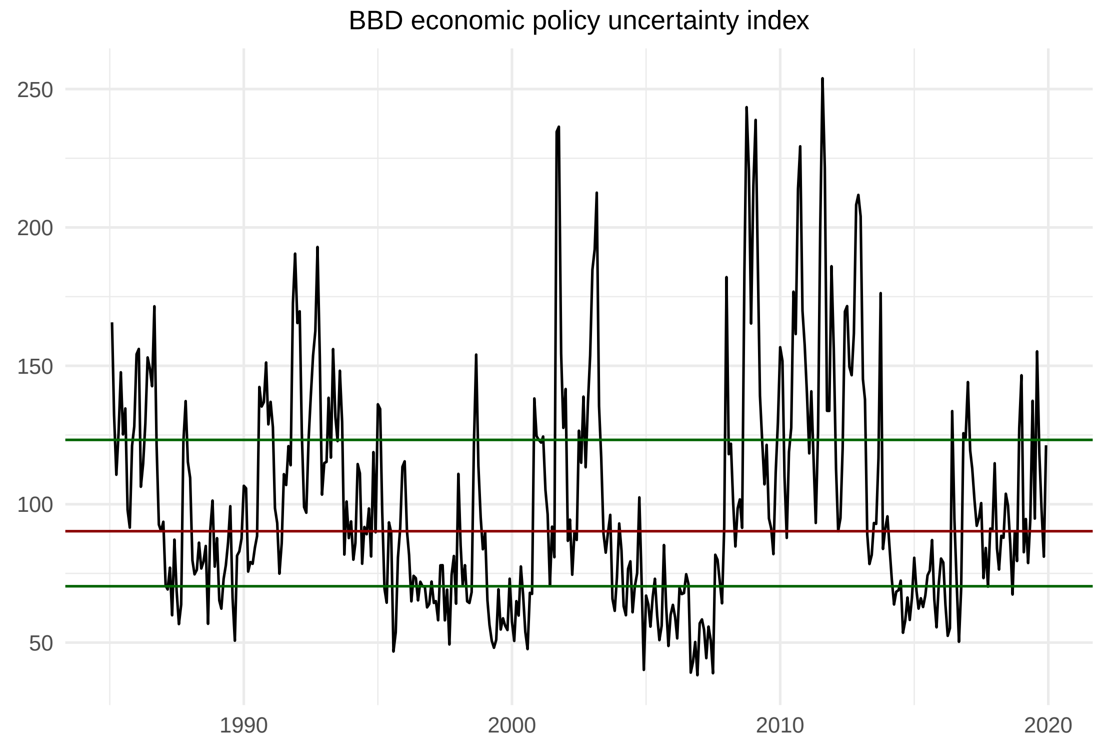

Figure 3: Time series plot of the BBD Economic Policy Uncertainty Index. The red line indicates the median value, the green lines indicate the upper and lower quartiles.

The index is primarily news based, on uncertainty related keywords in influential papers in the US. The index also takes into account temporary tax measures reported by the Congressional Budget Office and the dispersion of individual forecasts from the Federal Reserve Bank of Philadelphia's Survey of Professional Forecasters in the consumer price index and government expenditure. The index is constructed by normalizing the sub-components by their respective standard deviation and the normalized series weighted averaged (with the news based component having the highest weight of 0.5). As this index 1) covers a broader spectrum of expectations than the financial market based uncertainty counterparts, and 2) is more specific to economic policy, I believe it should serve as the most adequate measurement of uncertainty for the purposes of this study.

Empirical Strategy

An empirical challenge for this analysis was coercing the macroeconomic aggregates to behave the way it is written in all macroeconomics textbooks, i.e. to solve the price puzzle. There have already been numerous papers on the topic of solving the price puzzle (e.g.: Hanson (2004), Giordani (2000), Demiralp, Hoover, and Perez (2014), Bishop and Tulip (2017), Cloyne and Hürtgen (2016), Romer and Romer (2004)), however with the available data series the best empirical approach would be to apply sign restrictions in the model specification. One of the most frequently used methods is the Uhlig (2005) penalty algorithm. This method however has some "hidden features" as pointed out by Arias, Rubio-Ramıérez, and Waggoner (2018). Most importantly in this paper, using the penalty function approach would artificially narrow confidence intervals for the estimates, thus giving us a false sense of robustness in the results. For this reason, I will be implementing the full bayesian rejection algorithm of Rubio-Ramirez, Waggoner, and Zha (2010). The computation is done by using the R package created by Danne (2015).

I will introduce nonlinearity by using the BBD uncertainty index to create an indicator function. Taking the interactions of the indicator with each variable, then estimating the sign restricted models will give us a set of impulse responses for each regime which can be compared. First, I will experiment with a two regime model where the high uncertainty regime is considered when the uncertainty index is above its median. Next I will also estimate a three regime version, where the threshold values will be the upper and lower quartile values of the index. Thus, a generalized mathematical representation of the model would be as follows:

$$Y_t = \sum_{k=1}^{K} \Theta_k I(X_{t-1}) Y_{t-1} + \epsilon_t, \tag{1}$$

where Y_t is the vector of endogenous variables, Θ_k is the matrix of coefficients in regime k, X_t is the regime indicator function, and ϵ_t is the error term. The ordering of the variables will be

$$Y_t = \begin{Bmatrix} FFR_t \\ CPI_t \\ INDPRO_t \end{Bmatrix} \tag{2}$$

which is only important for syntactical purposes, as the R package is only able to carry out partial identifications,and in a vector of a given set of sign restrictions, the first one is considered as the shock. As for the identification scheme, I will use a full set of sign restrictions in each regime, and repeat the simulation of the shock for each regime.

With monthly data, ideally one would try to utilize as many lagged values in a VAR model as possible. However, due to the complexity of the task, the inclusion of numerous lags will have to be sacrificed. Through experimentation, I found that for a lag length of $n = 3$ yields an adequate number of accepted IRF draws (at least 100) when a sufficiently large large simulation is run - meaning 20000 MCMC replications and 200 draws per replication. A minor caveat to mention here is that the results are somewhat sensitive to the lag length of choice. With regards to higher lags this is not as troubling, as due to a lack of accepted draws, those results are less credible, however the initial impact on inflation and economic activity can vary noticeably if we reduce the number of included lags to one or two.

In order to compare and analyze results, I find the use of impulse responses to be the best tool. As the sign restriction algorithm gives us a set of impulse responses that satisfy the restrictions, I will be taking the median of the impulse responses and an 84% confidence interval in each case. I will normalize the shocks to a one percentage point interest rate rise, so that the IRF-s are more easily compared.

```
#function to retrieve impulse responses
get_irf <- function(dim, prob, irflength, irfdata){
  prob <- prob
  x <- irfdata[ , ,dim] %>% t()
  t <- matrix(nrow = nrow(x), ncol = 1)
  med <- matrix(nrow = nrow(x), ncol = 1)
  up <- matrix(nrow = nrow(x), ncol = 1)
  dn <- matrix(nrow = nrow(x), ncol = 1)
  for(i in(1:irflength)){
    t[i] <- i-1
    med[i] <- median(x[i,])
    up[i] <- quantile(x[i,], probs = (1-prob))
    dn[i] <- quantile(x[i,], probs = prob)
  }
  irf <- bind_cols(t, med, up, dn) %>%
    rename(t = ...1,
           median = ...2,
           upper = ...3,
           lower = ...4)
  irf
}
```

Results

First let us take a look at the data series colored by the regime indicator. In the plot below, we can see that while the indicator created from the uncertainty index (especially the two regime version) is somewhat similar to a recession indicator, however I do not believe the two are to be considered interchangeable.

```r
#plot variables coloured by regime indicator - 2
p2 <- data %>%
  dplyr::select(date, ffr, cpi, indpro, epu, epu50) %>%
  mutate(indicator = ifelse(epu > epu50, 1, 2),
         indicator = case_when(indicator == 1 ~ "High uncertainty regime",
                               indicator == 2 ~ "Low uncertainty regime")) %>%
  gather(key = "variable", value = "value", ffr, cpi, indpro) %>%
  mutate(variable = case_when(variable == "ffr" ~ "Federal Funds Rate",
                              variable == "cpi" ~ "Consumer Prices",
                              variable == "indpro" ~ "Industrial Production Index
         variable = factor(variable, levels = c("Federal Funds Rate", "Consumer P
  ggplot(aes(x = date, y = value, color = indicator, group = 1)) +
  geom_line(size = .8) +
  facet_wrap(~variable, scales = "free", nrow = 3) + theme_minimal() +
  labs(x = "",
       y = "") +
  theme(legend.title = element_blank())

#plot variables coloured by regime indicator - 3
p3 <- data %>%
  dplyr::select(date, ffr, cpi, indpro, epu, epu25, epu75) %>%
  mutate(indicator_up = ifelse(epu > epu75, 1,0),
         indicator_dn = ifelse(epu < epu25, 1, 0),
         indicator_mid = ifelse(indicator_up == 0 & indicator_dn == 0, 1, 0),
         indicator = case_when(indicator_up == 1 ~ "High uncertainty regime",
                               indicator_mid == 1 ~ "Medium uncertainty regime",
                               indicator_dn == 1 ~ "Low uncertainty regime"),
         indicator = factor(indicator, levels = c("High uncertainty regime",
                                                  "Medium uncertainty regime",
                                                  "Low uncertainty regime"))) %>%
  gather(key = "variable", value = "value", ffr, cpi, indpro) %>%
  mutate(variable = case_when(variable == "ffr" ~ "Federal Funds Rate",
```

```
                              variable == "cpi" ~ "Consumer Prices",
                              variable == "indpro" ~ "Industrial Production Index
         variable = factor(variable, levels = c("Federal Funds Rate", "Consumer P
  ggplot(aes(x = date, y = value, color = indicator, group = 1)) +
  geom_line(size = .8) +
  facet_wrap(~variable, scales = "free", nrow = 3) + theme_minimal() +
  labs(x = "",
       y = "") +
  theme(legend.title = element_blank())

grid.arrange(p2, p3)
```

Next, taking a look at the impulse responses of the two regime model, we can see mostly a lack of evidence for nonlinearity. The simulated path of the FFR shock and the response of inflation is rather similar in both regimes. The major difference in the two regimes is in the response of economic activity, as in the low uncertainty case the drop in output is much less persistent compared to the high regime. This could be explained by low uncertainty periods generally being characterized by stable GDP growth as seen in the previous graphs.

```
#some parameters for estimation and irfs
nlag <- 3
seed <- 2022
prob <- 0.16
irflength <- 21
draw <- 20000
subdraw <- 200

# fit 2 regime model
data_2regime <- data %>%
  dplyr::select(date, ffr, cpi, indpro, epu, epu50) %>%
  mutate(indicator = ifelse(epu > epu50, 1, 0),
         indicator_inv = ifelse(indicator == 1, 0, 1),
```

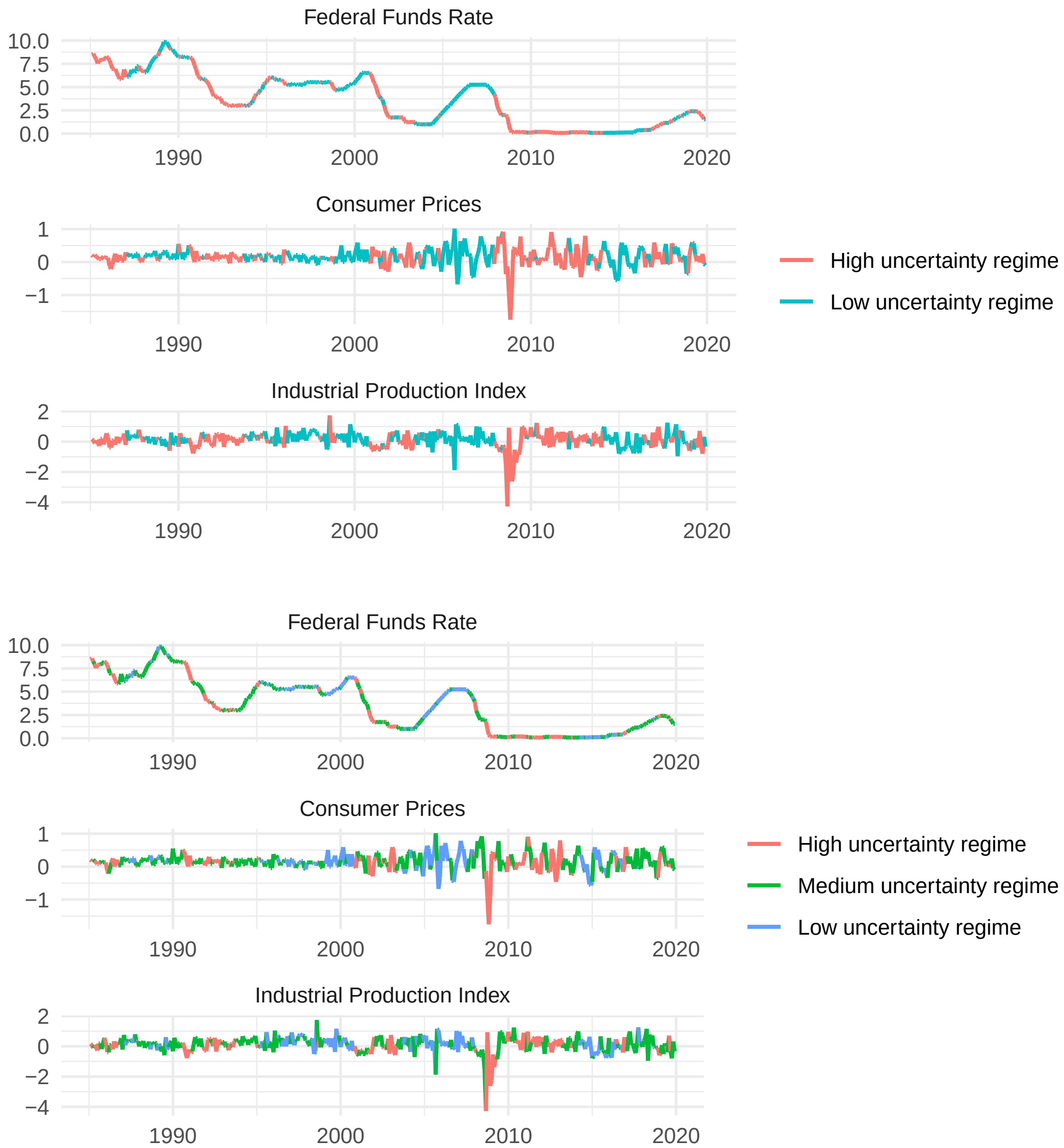

Figure 4: Time series plots of the endogenous variables colored by the regime indicators.

```
         ffr_up = ffr*indicator,
         cpi_up = cpi*indicator,
         indpro_up = indpro*indicator,
         ffr_dn = ffr*indicator_inv,
         cpi_dn = cpi*indicator_inv,
         indpro_dn = indpro*indicator_inv) %>% as_tibble() %>%
  dplyr::select(ffr_up, cpi_up, indpro_up, ffr_dn, cpi_dn, indpro_dn) %>% ts()


set.seed(seed)
constr_up <- c(+1, -2, -3)
model_up <- rwz.reject(Y=data_2regime, nlags=nlag, draws=draw, subdraws=subdraw,
                        KMAX=6, constrained=constr_up, constant=TRUE, steps=21)
irfs1 <- model_up$IRFS

set.seed(seed)
constr_dn <- c(+4, -5, -6)
model_dn <- rwz.reject(Y=data_2regime, nlags=nlag, draws=draw, subdraws=subdraw,
                       KMAX=6, constrained=constr_dn, constant=TRUE, steps=21)
irfs2 <- model_dn$IRFS



ffr_up <- get_irf(1, prob, irflength, irfs1) %>% mutate(label = "FFR",
                                                        regime = "High uncertaint
cpi_up <- get_irf(2, prob, irflength, irfs1) %>% mutate(label = "CPI",
                                                        regime = "High uncertaint
indpro_up <- get_irf(3, prob, irflength, irfs1) %>% mutate(label = "INDPRO",
                                                           regime = "High uncerta

ffr_dn <- get_irf(4, prob, irflength, irfs2) %>% mutate(label = "FFR",
                                                        regime = "Low uncertainty
```

```
cpi_dn <- get_irf(5, prob, irflength, irfs2) %>% mutate(label = "CPI",
                                                     regime = "Low uncertainty
indpro_dn <- get_irf(6, prob, irflength, irfs2) %>% mutate(label = "INDPRO",
                                                     regime = "Low uncertai

bind_rows(ffr_up, cpi_up, indpro_up,
          ffr_dn, cpi_dn, indpro_dn) %>%
  mutate(label = factor(label, levels = c("FFR", "CPI", "INDPRO")),
         regime = factor(regime, levels = c("High uncertainty", "Low uncertainty"
  left_join(bind_rows(ffr_up, cpi_up, indpro_up,
                      ffr_dn, cpi_dn, indpro_dn) %>%
              mutate(label = factor(label, levels = c("FFR", "CPI", "INDPRO")),
                     regime = factor(regime, levels = c("High uncertainty", "Low
              filter(t == 0) %>%
              mutate(mult = 1/median) %>%
              mutate(mult = ifelse(mult < 0, NA, mult)) %>%
              group_by(regime) %>%
              mutate(mult = min(mult, na.rm = TRUE)) %>%
              ungroup() %>%
              mutate(median = median * mult,
                     upper = upper * mult,
                     lower = lower * mult) %>%
              dplyr::select(label, regime, mult),
            by = c("regime", 'label')) %>%
  mutate(median = median * mult,
         upper = upper * mult,
         lower = lower * mult) %>%
  ggplot(aes(x = t, y = median, ymin = lower, ymax = upper)) +
  geom_line() +
  geom_hline(yintercept = 0, color = "red") +
  geom_ribbon(fill="grey", alpha=.2, color="grey50", linetype="dashed") +
  facet_wrap(regime~label, scales = "free")+
```

```
  theme_minimal() +
  theme(plot.title = element_text(size = 11, hjust=0.5),
        axis.title.y = element_text(size=11)) +
  labs(x = "",
       y ="")
```

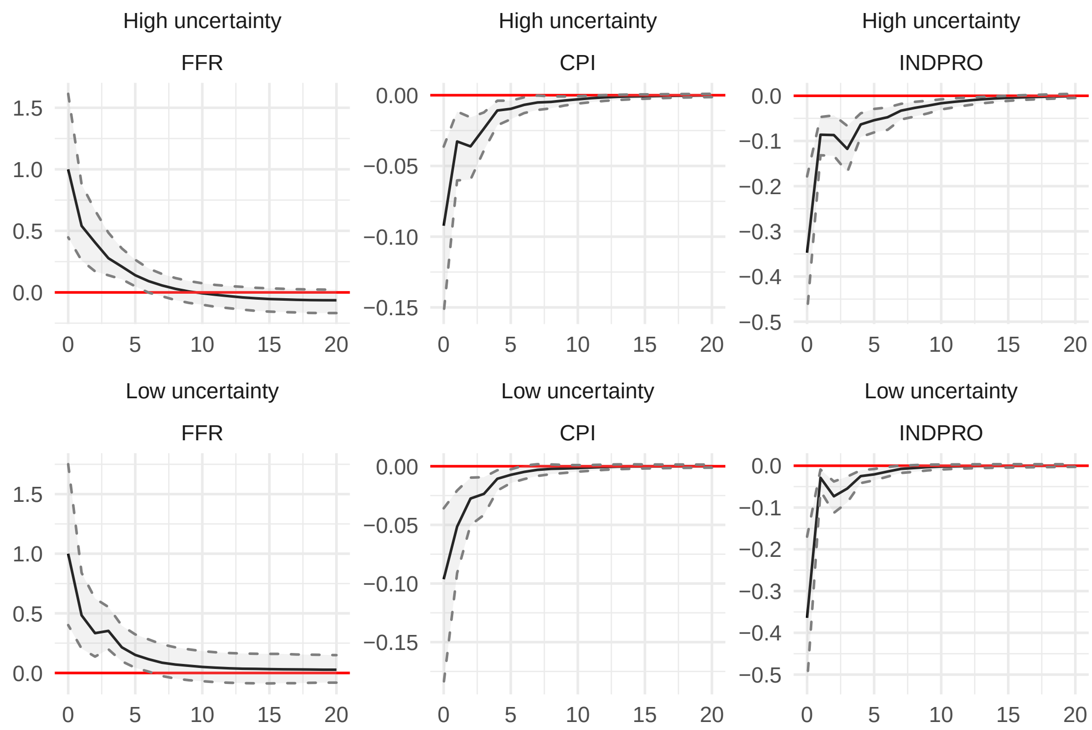

Figure 5: Impulse responses from two regime model.

With the results of the two regime model in mind, I believe there is room for further developing the model to investigate the relationship between uncertainty and monetary policy. A problem of the two regime model could be that the transmission is very similar when uncertainty is just above or just below the median - i.e. not being able to grasp the two extreme sides. Thus, a three regime variant where the threshold points are at the upper and lower quartiles could yield us a clearer picture. The impulse responses of the three regime model can be seen below:

```
#fit 3 regime model
data_3regime <- data %>%
  dplyr::select(date, ffr, cpi, indpro, epu, epu25, epu75) %>%
```

```
  mutate(indicator_up = ifelse(epu > epu75, 1,0),
         indicator_dn = ifelse(epu < epu25, 1, 0),
         indicator_mid = ifelse(indicator_up == 0 & indicator_dn == 0, 1, 0),
         ffr_up = ffr*indicator_up,
         cpi_up = cpi*indicator_up,
         indpro_up = indpro*indicator_up,
         ffr_mid = ffr*indicator_mid,
         cpi_mid = cpi*indicator_mid,
         indpro_mid = indpro*indicator_mid,
         ffr_dn = ffr*indicator_dn,
         cpi_dn = cpi*indicator_dn,
         indpro_dn = indpro*indicator_dn) %>%
  as_tibble() %>%
  dplyr::select(ffr_up, cpi_up, indpro_up, ffr_mid, cpi_mid, indpro_mid, ffr_dn,


set.seed(seed)
constr_up <- c(+1, -2, -3)
model_up <- rwz.reject(Y=data_3regime, nlags=nlag, draws=draw, subdraws=subdraw,
                         KMAX=6, constrained=constr_up, constant=TRUE, steps=21)
irfs1 <- model_up$IRFS

set.seed(seed)
constr_mid <- c(+4, -5, -6)
model_mid <- rwz.reject(Y=data_3regime, nlags=nlag, draws=draw, subdraws=subdraw,
                         KMAX=6, constrained=constr_mid, constant=TRUE, steps=21)
irfs2 <- model_mid$IRFS

set.seed(seed)
constr_dn <- c(+7, -8, -9)
model_dn <- rwz.reject(Y=data_3regime, nlags=nlag, draws=draw, subdraws=subdraw,
                         KMAX=6, constrained=constr_dn, constant=TRUE, steps=21)
```

```
irfs3 <- model_dn$IRFS



prob <- 0.16
irflength <- 21

ffr_up <- get_irf(1, prob, irflength, irfs1) %>% mutate(label = "FFR",
                                                       regime = "High uncertaint
cpi_up <- get_irf(2, prob, irflength, irfs1) %>% mutate(label = "CPI",
                                                       regime = "High uncertaint
indpro_up <- get_irf(3, prob, irflength, irfs1) %>% mutate(label = "INDPRO",
                                                          regime = "High uncerta

ffr_mid <- get_irf(4, prob, irflength, irfs2) %>% mutate(label = "FFR",
                                                       regime = "Medium uncertai
cpi_mid <- get_irf(5, prob, irflength, irfs2) %>% mutate(label = "CPI",
                                                       regime = "Medium uncertai
indpro_mid <- get_irf(6, prob, irflength, irfs2) %>% mutate(label = "INDPRO",
                                                          regime = "Medium uncer

ffr_dn <- get_irf(7, prob, irflength, irfs3) %>% mutate(label = "FFR",
                                                       regime = "Low uncertainty
cpi_dn <- get_irf(8, prob, irflength, irfs3) %>% mutate(label = "CPI",
                                                       regime = "Low uncertainty
indpro_dn <- get_irf(9, prob, irflength, irfs3) %>% mutate(label = "INDPRO",
                                                          regime = "Low uncertai



bind_rows(ffr_up, cpi_up, indpro_up,
          ffr_mid, cpi_mid, indpro_mid,
          ffr_dn, cpi_dn, indpro_dn) %>%
  mutate(label = factor(label, levels = c("FFR", "CPI", "INDPRO")),
```

```
       regime = factor(regime, levels = c("High uncertainty", "Medium uncertain
  left_join(bind_rows(ffr_up, cpi_up, indpro_up,
                      ffr_mid, cpi_mid, indpro_mid,
                      ffr_dn, cpi_dn, indpro_dn) %>%
              mutate(label = factor(label, levels = c("FFR", "CPI", "INDPRO")),
                     regime = factor(regime, levels = c("High uncertainty", "Medi
              filter(t == 0) %>%
              mutate(mult = 1/median) %>%
              mutate(mult = ifelse(mult < 0, NA, mult)) %>%
              group_by(regime) %>%
              mutate(mult = min(mult, na.rm = TRUE)) %>%
              ungroup() %>%
              mutate(median = median * mult,
                     upper = upper * mult,
                     lower = lower * mult) %>%
              dplyr::select(label, regime, mult),
            by = c("regime", 'label')) %>%
  mutate(median = median * mult,
         upper = upper * mult,
         lower = lower * mult) %>%
  ggplot(aes(x = t, y = median, ymin = lower, ymax = upper)) +
  geom_line() +
  geom_hline(yintercept = 0, color = "red") +
  geom_ribbon(fill="grey", alpha=.2, color="grey50", linetype="dashed") +
  facet_wrap(regime~label, scales = "free")+
  theme_minimal() +
  theme(plot.title = element_text(size = 11, hjust=0.5),
        axis.title.y = element_text(size=11)) +
  labs(x = "",
       y ="")
```

As a contrast to the two regime version, here we can see some sharper differences,

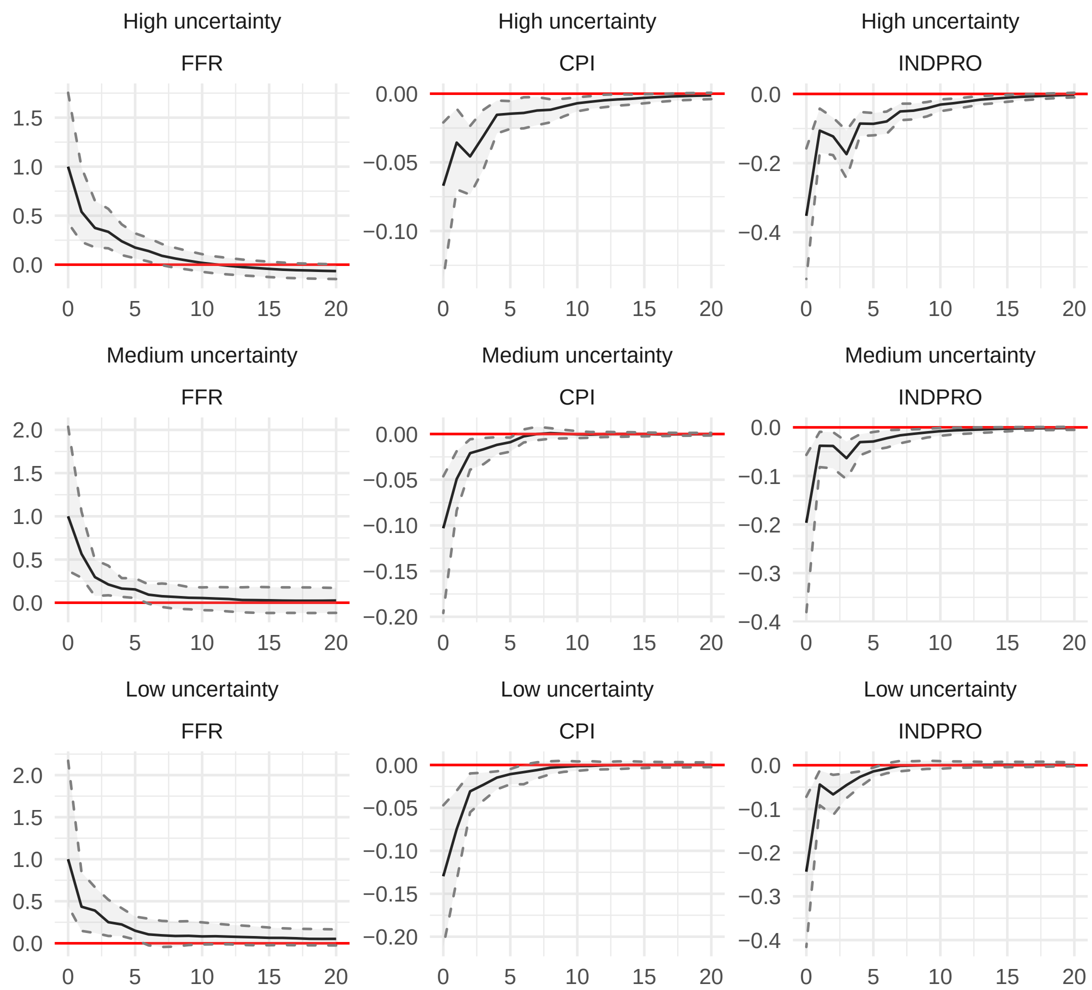

Figure 6: Impulse responses from three regime model.

hinting at the existence of the nonlinear relationship. In terms of the persistence of the FFR shock we see close to no differences, however differences in the responses of inflation and economic activity between the regimes is quite curious. The first thing we can notice is the persistence of the shock especially on output is considerably stronger when uncertainty is high compared to the other two regimes. Rising the interest rate is also considerably less effective at anchoring inflation as in the high uncertainty regime the impact nearly halves compared to the other two regimes. The drop in output is similar in all cases, however in the high uncertainty regime it is mildly amplified - hinting at a moderately larger trade-off in output drop versus inflation anchoring capability. These results suggest that interest rate decisions alone might not be solely sufficient at effectively reducing inflation, thus implying the importance of utilizing additional measures such as forward guidance in order to moderate economic uncertainty. An important caveat here is that the BBD Economic Policy uncertainty index by construction would likely be higher around the time of important policy actions such as interst rate rises. This could imply that the true impact of an interest rate decision is closer to what we see from the impulse responses of the high uncertainty regime as opposed to the other two set of impulse responses.

Conclusion

This paper attempts at quantifying the impact of uncertainty on the monetary transmission mechanism. To study this asymmetric relationship I fit a two and three regime VAR model with sign restrictions using an indicator function created from the BBD Economic Policy Uncertainty Index. While in the two regime case there seems to be close to no asymmetry in the interest rate channel, in the more extreme sides of the distribution we can observe that high levels of uncertainty above its upper quartile seems to dampen the inflation anchoring capability of interest rate shocks at a mildly larger output drop trade-off. This would imply two conclusions: 1) as the index measuring uncertainty tracks news coverage - taking higher values around important policy decisions - it is likely the true impact of the interest rate channel is quantitatively more similar to the impact observed in high uncertainty times; and 2) interest rate decisions alone are less effective at anchoring inflation

- pointing to the neccessity of combining it with alternative measures like forward guidance. Quantifying the impact of such measures is however beyond the scopes of this paper.

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