

ECB Tests 6

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#explain what his script does and why and how to run code in readme file

Data

Main

```
# --- 1. ECB Deposit Facility Rate & Shadow Rate ---
ecb_rate_daily <- fredr(series_id = "ECBDFR", observation_start = as.Date(start_date))
ecb_rate_q <- ecb_rate_daily %>%
  mutate(quarter = as.yearqtr(date)) %>%
  group_by(quarter) %>%
  summarise(rate = last(value)) %>%
  mutate(date = as.Date(quarter))

# Wu-Xia Shadow Rate
shadow_rate_daily = as.data.frame(readMat("data/shadowrate_ECB.mat"))
colnames(shadow_rate_daily) <- c("DATE", "shadowrate")
shadow_rate_daily$DATE <- as.Date(paste0(shadow_rate_daily$DATE, "01"), format="%Y%m%d")
shadow_rate_daily$quarter <- as.yearqtr(as.Date(shadow_rate_daily$DATE))
shadow_rate_daily$month <- as.yearmon(as.Date(shadow_rate_daily$DATE))
quarterly_shadow = aggregate(shadowrate ~ quarter, data=shadow_rate_daily, FUN=mean, na.rm=T)
monthly_shadow = aggregate(shadowrate ~ month, data=shadow_rate_daily, FUN=mean, na.rm=T)

# --- 2. HICP Inflation (Euro Area) ---
inflation_data <- get_eurostat("prc_hicp_manr", filters = list(geo = "EA", coicop = "CP00"), type = "la
inflation_q <- inflation_data %>%
  filter(time >= start_date) %>%
  dplyr::select(date = time, inflation = values) %>%
  mutate(quarter = as.yearqtr(date)) %>%
  group_by(quarter) %>%
  summarise(inflation = mean(inflation, na.rm = TRUE)) %>%
  mutate(date = as.Date(quarter))

#inflation expectations
inflation_exp <- rdb(ids = "ECB/SPF/M.U2.HICP.POINT.P12M.Q.AVG")
#inflation_exp <- rdb(ids = "ECB/SPF/M.U2.HICP.POINT.P24M.Q.AVG")
inflation_exp_q <- inflation_exp %>%
  mutate(quarter = as.yearqtr(period)) %>%
  group_by(quarter) %>%
  summarise(exp_inflation = last(original_value)) %>%
  mutate(date = as.Date(quarter))

#P12M : 12-month ahead forecasts
inflation_q$exp_inflation = c(rep(NA,3),as.numeric(inflation_exp_q$exp_inflation),NA)
#P24M : 24-month ahead forecasts
#inflation_q$exp_inflation = c(rep(NA,7),as.numeric(inflation_exp_q$exp_inflation[1:101]))

# --- 3. Real GDP and Estimated Output Gap ---
# a) Real GDP for the Euro Area. The series ID is CLVMNACSCAB1GQE_A.
gdp_q <- fredr(
  series_id = "CLVMEURSCAB1GQEA19",
  observation_start = as.Date(start_date)) %>%
```

```

mutate(quarter = as.yearqtr(date)) %>%
dplyr::select(quarter, real_gdp = value) %>%
mutate(log_real_gdp = log(real_gdp))

# b) Estimate Potential GDP (the trend) using the HP Filter on the log of real GDP.
# The lambda value of 1600 is standard for quarterly data.
hp_gdp <- hpfilter(gdp_q$log_real_gdp, freq = 1600)
gdp_q$potential_gdp_log <- as.numeric(hp_gdp$trend)
ham_gdp_cycle <- filter_hamilton(gdp_q$log_real_gdp, p = 4, horizon = 8)
gdp_q$potential_gdp_log_ham <- gdp_q$log_real_gdp - ham_gdp_cycle

# Combine all data into a single data frame
data <- ecb_rate_q %>%
  dplyr::select(quarter, rate) %>%
  left_join(inflation_q, by = "quarter") %>%
  left_join(gdp_q, by = "quarter") %>%
  left_join(quarterly_shadow, by = "quarter")

# Create model variables
data <- data %>%
  mutate(
    realised_inflation_gap = inflation - 2.0,
    exp_inflation_gap = exp_inflation - 2.0,
    output_gap_hp = 100 * (log_real_gdp - potential_gdp_log),
    output_gap_ham = 100 * (log_real_gdp - potential_gdp_log_ham),
    rate_lag = lag(rate, 1),
    shadowrate = case_when(
      quarter < "2012 Q3" | quarter >= "2022 Q3" ~ rate,
      TRUE ~ shadowrate),
    shadowrate_lag = lag(shadowrate, 1))

# Remove last row since no output data
data = subset(data, quarter < "2025 Q3")

# Clean environment
rm(gdp_q, hp_gdp, ecb_rate_daily, ecb_rate_q, inflation_data, inflation_q,
  inflation_exp, inflation_exp_q, monthly_shadow, quarterly_shadow, shadow_rate_daily)

```

Data Configuration

```

# Choices in setup chunk

# ----- 1. Filter selection for output gap estimation -----

# TRUE  = Use Hamilton Filter (newer, arguably more robust)
# FALSE = Use HP Filter (classic approach)

# Applying selection
if (USE_HAMILTON_FILTER) {
  data$output_gap <- data$output_gap_ham
  message(">> CONFIGURATION: Using Hamilton Filter for output gap estimation.")
}

```

```

} else {
  data$output_gap <- data$output_gap_hp
  message(">> CONFIGURATION: Using HP Filter for output gap estimation.") }

```

```
## >> CONFIGURATION: Using Hamilton Filter for output gap estimation.
```

```

# ----- 2. Inflation expectations choice -----

# TRUE  = Use inflation expectations from ECB survey of professional forecasts
# FALSE = Use realised inflation

# Applying selection
if (USE_INFLATION_EXPECTATIONS) {
  data$inflation_gap <- data$exp_inflation_gap
  message(">> CONFIGURATION: Using inflation expectations in Taylor Rule forecasting.")
} else {
  data$inflation_gap <- data$realised_inflation_gap
  message(">> CONFIGURATION: Using realised inflation in Taylor Rule forecasting.") }

```

```
## >> CONFIGURATION: Using realised inflation in Taylor Rule forecasting.
```

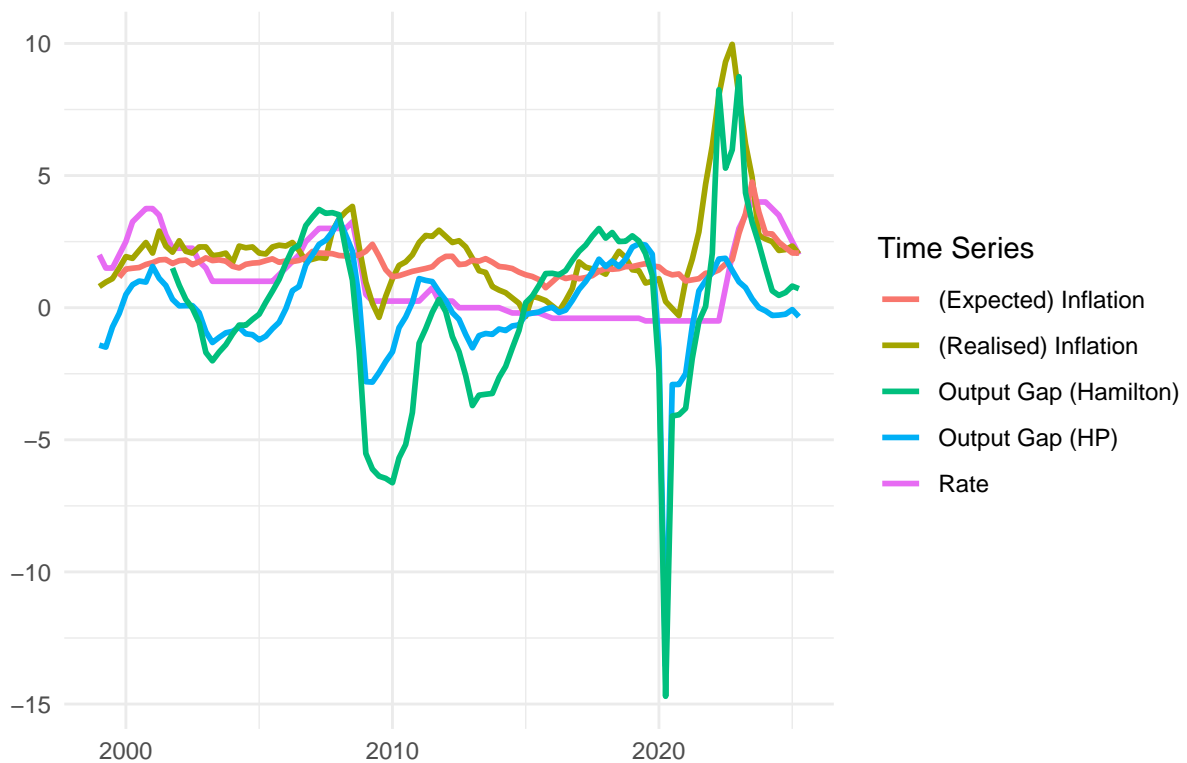
Raw Data Plots

```

ggplot(data, aes(x = date, color = series)) +
  geom_line(aes(y = rate, color = "Rate"), linewidth = 1) +
  geom_line(aes(y = inflation, color = "(Realised) Inflation"), linewidth = 1) +
  geom_line(aes(y = exp_inflation, color = "(Expected) Inflation"), linewidth = 1) +
  geom_line(aes(y = output_gap_hp, color = "Output Gap (HP)"), linewidth = 1) +
  geom_line(aes(y = output_gap_ham, color = "Output Gap (Hamilton)"), linewidth = 1) +
  labs(title = "Raw Data Plots",
       x = "",
       y = "",
       color = "Time Series") +
  theme_minimal()

```

Raw Data Plots



Data Properties

```
# Interest rate is I(1)
test1 = aTSA::adf.test(data$rate, output=F)
test1$type1
```

```
##      lag      ADF    p.value
## [1,]  0 -1.030614 0.30884518
## [2,]  1 -2.163114 0.03162811
## [3,]  2 -1.951938 0.04983296
## [4,]  3 -2.234322 0.02548950
## [5,]  4 -2.293507 0.02276643
```

```
# Inflation is I(1)
test2 = aTSA::adf.test(data$inflation, output=F)
test2$type1
```

```
##      lag      ADF    p.value
## [1,]  0 -1.125153 0.27478730
## [2,]  1 -2.251445 0.02452223
## [3,]  2 -2.472595 0.01529054
## [4,]  3 -2.263254 0.02402930
## [5,]  4 -1.490401 0.14320596
```

```
# Output gap is I(0), likely from the "gap" part
test3 = aTSA::adf.test(data$output_gap, output=F)
test3$type1
```

```
##      lag      ADF p.value
## [1,]  0 -3.177649    0.01
## [2,]  1 -2.859115    0.01
## [3,]  2 -2.843129    0.01
## [4,]  3 -3.598165    0.01
```

```
# Cleanup
rm(test1,test2,test3)

# Are interest rates and inflation co-integrated?
aTSA::coint.test(data$rate, data$inflation)
```

```
## Response: data$rate
## Input: data$inflation
## Number of inputs: 1
## Model: y ~ X + 1
## -----
## Engle-Granger Cointegration Test
## alternative: cointegrated
##
## Type 1: no trend
##      lag      EG p.value
##  4.0000 -2.9904  0.0433
## -----
## Type 2: linear trend
##      lag      EG p.value
##   4.000  -0.778  0.100
## -----
## Type 3: quadratic trend
##      lag      EG p.value
##   4.000  -0.566  0.100
## -----
## Note: p.value = 0.01 means p.value <= 0.01
##       : p.value = 0.10 means p.value >= 0.10
```

Taylor Rule Estimation

Without Lags

$$i_t = \pi^* + \gamma(y_t - \bar{y}_t) + \beta(\pi_t - \pi^*)$$

$$= (1 - \beta)\pi^* + \gamma(y_t - \bar{y}_t) + \beta\pi_t$$

```
TR <- lm(rate ~ realised_inflation_gap + output_gap, data = data)
TRsr <- lm(shadowrate ~ realised_inflation_gap + output_gap, data = data)

table1 <- export_summs(TR, TRsr, vcov = sandwich::NeweyWest,
  model.names = c("TR", "TR w/ SR"), digits = 4)
huxtable::caption(table1) <- "No Lag, No Expectations"
table1
```

Table 1: No Lag, No Expectations

	TR	TR w/ SR
(Intercept)	0.8337	-0.8600
	(0.9054)	(2.6804)
realised_inflation_gap	0.1968	0.6897
	(0.4283)	(0.6086)
output_gap	0.0818	-0.0605
	(0.1636)	(0.2766)
N	95	95
R2	0.1721	0.1162

*** p < 0.001; ** p < 0.01; * p < 0.05.

```
TR_e <- lm(rate ~ exp_inflation_gap + output_gap, data = data)
TRsr_e <- lm(shadowrate ~ exp_inflation_gap + output_gap, data = data)
TR_ie <- lm(rate ~ realised_inflation_gap + exp_inflation_gap + output_gap, data = data)
TRsr_ie <- lm(shadowrate ~ realised_inflation_gap + exp_inflation_gap + output_gap, data = data)

table2 <- export_summs(TR_e, TRsr_e, TR_ie, TRsr_ie, vcov = sandwich::NeweyWest,
  model.names = c("TR", "TR w/ SR", "TR", "TR w/ SR"), digits = 4)
huxtable::caption(table2) <- "No Lag, with Inflation Expectations"
table2
```

Lagged Models

$$= \phi i_{t-1} + (1 - \beta)\pi^* + \gamma(y_t - \bar{y}_t) + \beta\pi_t$$

Table 2: No Lag, with Inflation Expectations

	TR	TR w/ SR	TR	TR w/ SR
(Intercept)	1.3435 *** (0.3182)	0.2878 (1.5599)	1.3374 *** (0.3711)	0.1721 (1.5916)
exp_inflation_gap	1.7244 *** (0.3525)	3.7621 ** (1.3734)	1.7108 *** (0.3468)	3.5056 ** (1.1661)
output_gap	0.0702 (0.0469)	-0.0054 (0.1864)	0.0655 (0.0812)	-0.0938 (0.2132)
realised_inflation_gap			0.0170 (0.1281)	0.3211 (0.3442)
N	95	95	95	95
R2	0.6172	0.3904	0.6176	0.4091

*** p < 0.001; ** p < 0.01; * p < 0.05.

```
lTR <- lm(rate ~ rate_lag + realised_inflation_gap + output_gap, data = data)
lTRsr <- lm(shadowrate ~ shadowrate_lag + realised_inflation_gap + output_gap, data = data)

table3 <- export_summs(lTR, lTRsr, vcov = sandwich::NeweyWest,
  model.names = c("TR", "TR w/ SR"), digits = 4)
huxtable::caption(table3) <- "Interest Rate Lag, No Expectations"
table3
```

```
lTR_e <- lm(rate ~ rate_lag + exp_inflation_gap + output_gap, data = data)
lTRsr_e <- lm(shadowrate ~ shadowrate_lag + exp_inflation_gap + output_gap, data = data)
lTR_ie <- lm(rate ~ rate_lag + realised_inflation_gap + exp_inflation_gap + output_gap, data = data)
lTRsr_ie <- lm(shadowrate ~ shadowrate_lag + realised_inflation_gap + exp_inflation_gap + output_gap, data = data)

table4 <- export_summs(lTR_e, lTRsr_e, lTR_ie, lTRsr_ie, vcov = sandwich::NeweyWest,
  model.names = c("TR", "TR w/ SR", "TR", "TR w/ SR"), digits = 4)
huxtable::caption(table4) <- "Interest Rate Lag, with Inflation Expectations"
table4
```

Checking for structural breaks

```
# Start of ZLB in 2012 Q3
breakpoint1 <- 55 #R = 55 in evaluation chunk

# Covid
breakpoint2 <- 85 #R = 85 in evaluation chunk
```


Table 3: Interest Rate Lag, No Expectations

	TR	TR w/ SR
(Intercept)	0.0505 (0.0411)	-0.0776 (0.0618)
rate_lag	0.9190 *** (0.0390)	
realised_inflation_gap	0.0879 * (0.0350)	0.2499 *** (0.0344)
output_gap	0.0218 (0.0163)	-0.0117 (0.0185)
shadowrate_lag		0.9530 *** (0.0176)
N	95	95
R2	0.9594	0.9828

*** p < 0.001; ** p < 0.01; * p < 0.05.

```
# Chow test (rejecting the null means there are structural breaks)
chow_test1 <- sctest(rate ~ rate_lag + inflation_gap + output_gap, type = "Chow", point = breakpoint1, c
chow_test2 <- sctest(rate ~ rate_lag + inflation_gap + output_gap, type = "Chow", point = breakpoint2, c

chow_df <- data.frame(
  "2012 Q3" = round(chow_test1$p.value, 4),
  "2020 Q1" = round(chow_test2$p.value, 4),
  check.names = FALSE)

kable(chow_df, digits = 4, format = format)%>%
  kable_styling(bootstrap_options = "striped", full_width = FALSE)
```

Rolling Estimation (for structural breaks)

```
# This function automatically plots the output from the rolling estimation loop
plot_rolling_coefs <- function(data, var_name, var_name_title=var_name) {

  # 1. Dynamically create the column names for CIs
  lower_col <- paste0(var_name, "_lower")
  upper_col <- paste0(var_name, "_upper")
```

Table 4: Interest Rate Lag, with Inflation Expectations

	TR	TR w/ SR	TR	TR w/ SR
(Intercept)	0.1795 *	0.0002	0.1336 ***	-0.0895
	(0.0794)	(0.0866)	(0.0378)	(0.0621)
rate_lag	0.8610 ***		0.8744 ***	
	(0.0437)		(0.0392)	
exp_inflation_gap	0.2380 **	0.1284	0.1532 ***	-0.0543
	(0.0731)	(0.1043)	(0.0435)	(0.0623)
output_gap	0.0449 *	0.0592	0.0232	-0.0109
	(0.0218)	(0.0475)	(0.0164)	(0.0182)
shadowrate_lag		0.9632 ***		0.9581 ***
		(0.0286)		(0.0190)
realised_inflation_gap			0.0771 *	0.2533 ***
			(0.0378)	(0.0347)
N	95	95	95	95
R2	0.9543	0.9712	0.9611	0.9828

*** p < 0.001; ** p < 0.01; * p < 0.05.

	2012 Q3	2020 Q1
F	0.0019	0.0364

```
# 2. Create the plot, using the .data[[ ]] pronoun to find the
# columns based on the variable names (modularity)

plot <- ggplot(data, aes(x = date)) +

  # Add a dashed line at y=0 for reference
  geom_hline(yintercept = 0, linetype = "dashed", color = "grey40", linewidth = 0.5) +

  # Add the 95% confidence interval ribbon
  geom_ribbon(aes(ymin = .data[[lower_col]], ymax = .data[[upper_col]]),
    fill = "dodgerblue", alpha = 0.3) +

  # Add the coefficient estimate line
  geom_line(aes(y = .data[[var_name]]),
    color = "dodgerblue4", linewidth = 1) +

  # Aesthetic
  labs(title = paste("Rolling Coefficient Estimate:", var_name_title),
```

```

    subtitle = "with 95% confidence interval",
    x = "",
    y = "Coefficient Value") +
  theme_minimal() +
  theme(plot.title = element_text(face = "bold", size = 14, margin = margin(b=5)),
        plot.subtitle = element_text(size = 12, color = "grey30", margin = margin(b=10)),
        axis.title = element_text(size = 12),
        axis.text = element_text(size = 10))
  return(plot) }

```

```

# Set rolling window (in quarters) & Looping Parameter
W = 30
L = nrow(data) - W + 1
formula = rate ~ rate_lag + inflation_gap + output_gap

# Preparation of result data, dates, var names, and confidence intervals
var_names <- attr(terms(formula), "term.labels")
window_end_dates <- data$quarter[W:nrow(data)] # First window [1:W] ends at data$date[W]
TR_roll <- data.frame(date = window_end_dates)
TR_roll[var_names] <- NA
lower_col_names <- paste0(var_names, "_lower")
upper_col_names <- paste0(var_names, "_upper")

# Looped estimation of TR, outputs coefficients and CIs
for (l in 1:L) {
  # 1. Define splits (with rolling scheme)
  rolled_data <- data[1:(W + l - 1), ]

  # 2. Estimate TR on split data, using whatever formula is desired
  TR_estimate <- lm(formula, data = rolled_data)

  # 3. Pull out coefficients & compute confidence intervals
  all_coefs <- coef(TR_estimate)
  all_cis <- confint(TR_estimate)

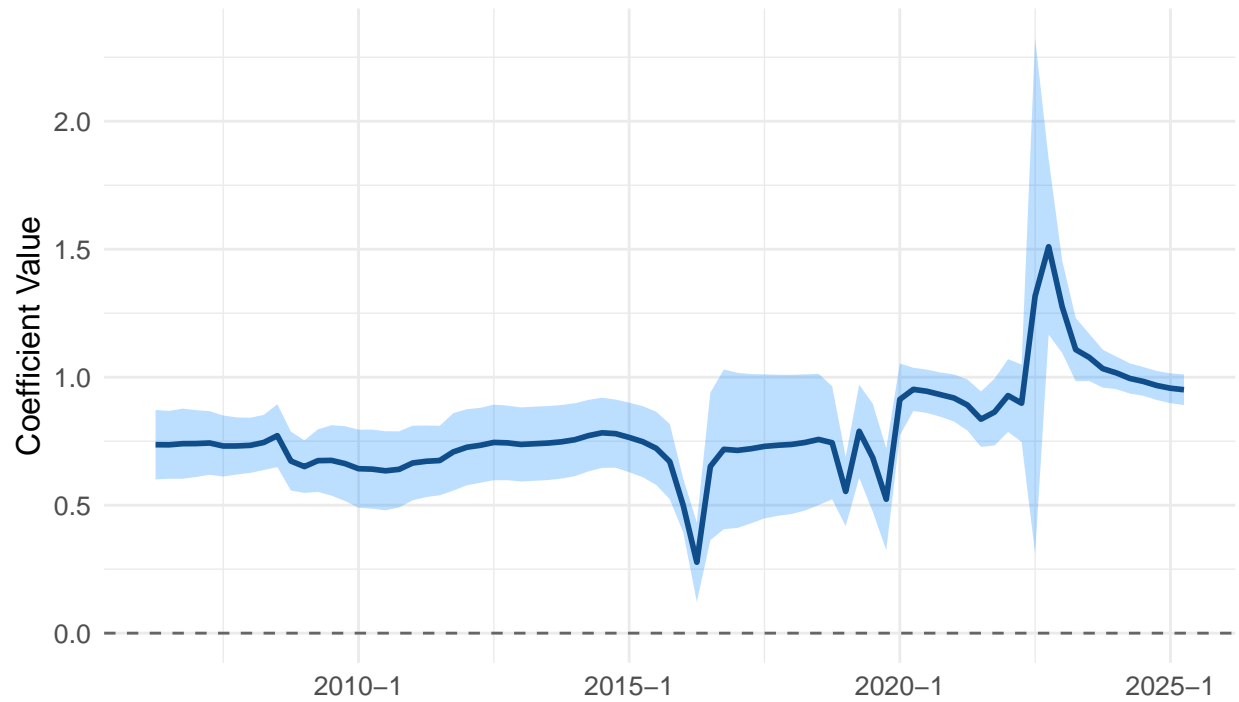
  TR_roll[l, var_names] <- all_coefs[var_names]
  TR_roll[l, lower_col_names] <- all_cis[var_names, 1]
  TR_roll[l, upper_col_names] <- all_cis[var_names, 2] }

# Plotting (note: this part is not modular, obviously)
plot_rolling_coefs(TR_roll, "rate_lag", var_name_title="Rate Lag")

```

Rolling Coefficient Estimate: Rate Lag

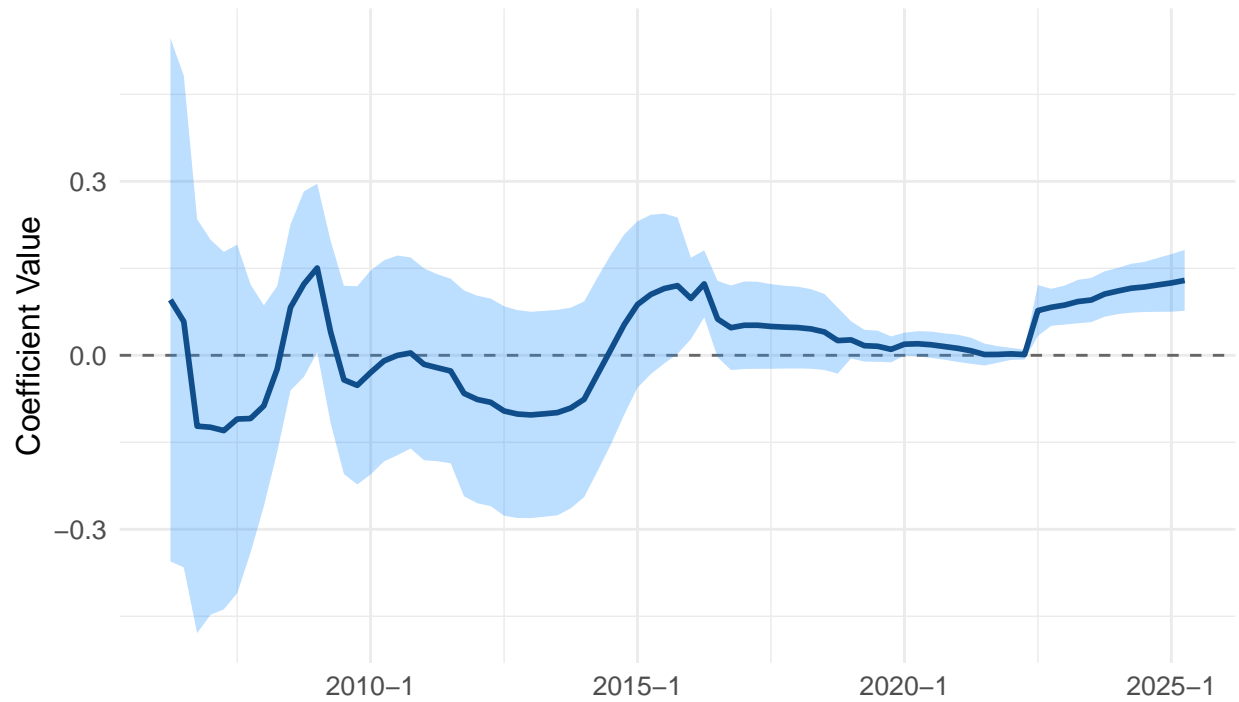
with 95% confidence interval



```
plot_rolling_coefs(TR_roll, "inflation_gap", var_name_title="Inflation (Gap)")
```

Rolling Coefficient Estimate: Inflation (Gap)

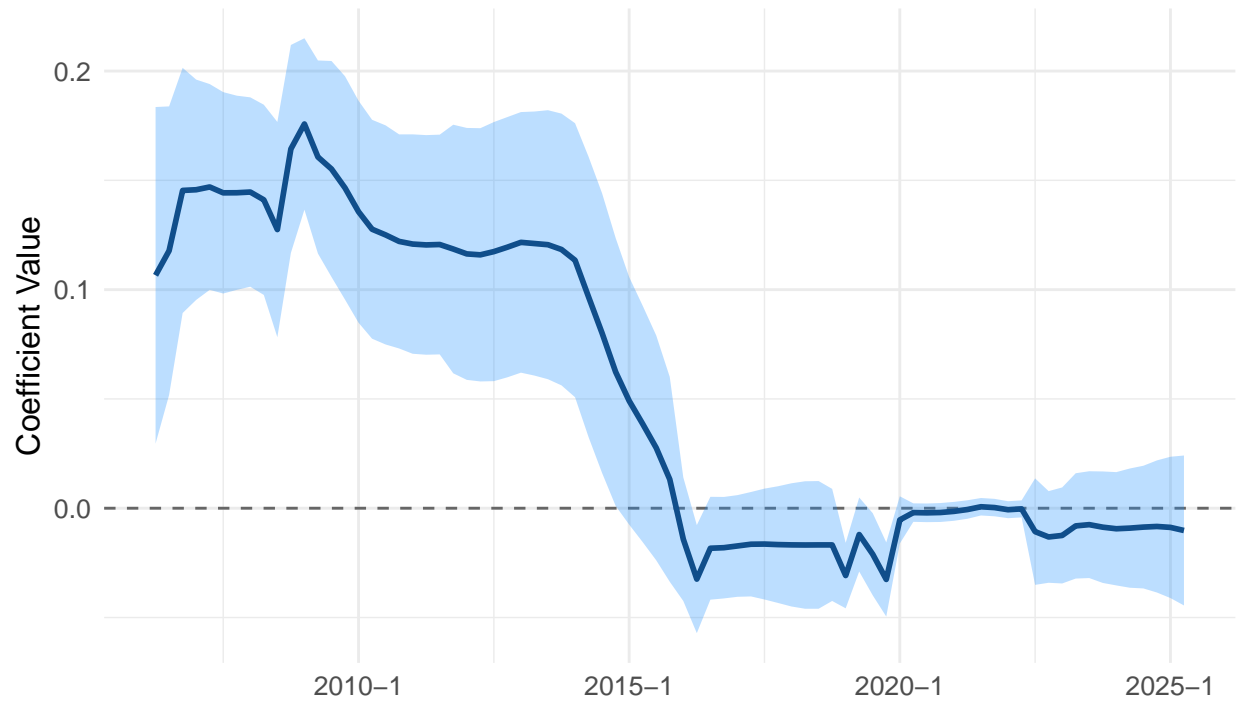
with 95% confidence interval



```
plot_rolling_coefs(TR_roll, "output_gap", var_name_title="Output Gap")
```

Rolling Coefficient Estimate: Output Gap

with 95% confidence interval



Forecasting Model Evaluation

Helpers

```
#-----
# Helper function for adding p-value significance stars
#-----

format_p_values_with_stars <- function(p) {
  stars <- case_when(
    p < 0.01 ~ "***",
    p < 0.05 ~ "**",
    p < 0.10 ~ "*",
    TRUE    ~ ""
  )
  paste0(format(round(p, 4), nsmall = 3), " ", stars)}

#-----
# HELPER FUNCTION FOR MINCER-ZARNOWITZ REPORTING
#-----
# This function runs the Mincer-Zarnowitz regression (Actuals ~ Forecasts)
# for each horizon h and tests the joint null hypothesis H0: (alpha, beta) = (0, 1).
#-----

generate_mincer_zarnowitz_report <- function(F_model,
                                             Actual_values,
                                             H,
                                             model_caption,
                                             format = "html") {

  # Pre-allocate storage for results
  mz_results <- data.frame(
    Horizon = 1:H,
    Alpha = numeric(H),
    Beta = numeric(H),
    P_Value_Joint_Test = numeric(H))

  for (h in 1:H) {
    # 1. Create a clean data frame for this horizon
    # This pairs the forecasts and actual values and removes any NAs,
    # ensuring they remain perfectly aligned.
    df_h <- data.frame(
      actuals = Actual_values[[h]],
      forecasts = F_model[[h]] ) %>%
      na.omit()

    # Check if we have enough data to run the regression (at least 2 obs)
    if (nrow(df_h) > 2) {
      # 2. Run MZ regression
      mz_reg <- lm(actuals ~ forecasts, data = df_h)

      # 3. Get coefficients
      coeffs <- summary(mz_reg)$coefficients
      mz_results$Alpha[h] <- coeffs[1, 1]
      mz_results$Beta[h] <- coeffs[2, 1]
    }
  }
}
```

```

# Using NW errors as seen in class, with lag selection h-1
v_matrix <-
  if (h == 1) {
    # h=1: No autocorrelation, use standard "White" (HC) errors
    sandwich::vcovHC(mz_reg, type = "HC3")
  } else {
    # h>1: Use Newey-West, manually setting lag = h-1
    sandwich::NeweyWest(mz_reg, lag = h - 1)}

# 4. Test Joint Hypothesis H0: Alpha = 0 AND Beta = 1 and store pvalues
test_joint <- linearHypothesis(mz_reg,
                               c("(Intercept) = 0", "forecasts = 1"), vcov. = v_matrix)
mz_results$P_Value_Joint_Test[h] <- test_joint$"Pr(>F)"[2]

} else {
  # Not enough data to run regression for this horizon
  mz_results$Alpha[h] <- NA_real_
  mz_results$Beta[h] <- NA_real_
  mz_results$P_Value_Joint_Test[h] <- NA_real_ } }

# Format the results for the table
mz_results <- mz_results %>%
  mutate(Alpha = round(Alpha, 4),
         Beta = round(Beta, 4),
         P_Value_Joint_Test = format_p_values_with_stars(P_Value_Joint_Test))

# Create the table
table_output <- kable(
  mz_results,
  format = format,
  booktabs = TRUE,
  caption = model_caption,
  digits = 4,
  col.names = c("h", "Alpha", "Beta", "pv(Joint)"),
  escape = FALSE ) %>%
  kable_styling(
    latex_options = c("striped", "scale_down"),
    position = "center" ) %>%
  column_spec(1, bold = TRUE, border_right = TRUE) %>%
  column_spec(4, monospace = TRUE) %>%
  footnote(
    general = "pv(Joint) is the p-value for the joint hypothesis H_0: (Alpha, Beta) = (0, 1). A high p",
    symbol = c(
      "Signif. codes:  '***' 0.01,  '**' 0.05,  '*' 0.1"),
    general_title = "Note:",
    symbol_title = "",
    footnote_as_chunk = TRUE,
    threeparttable = TRUE)
return(table_output) }

```

#-----


```

# HELPER FUNCTION FOR REPORTING DM tests
#-----

# This function creates the DM tests and kable output
generate_report_table <- function(FE_TR_model, FE_BM_model, H, model_caption, format = "html") { MSFE_TR =
  MSFE_BM = numeric(H)

  # Calculate MSFEs
  for (h in 1:H) {
    # Ensure errors are cleaned of NAs
    fe1 <- na.omit(FE_TR_model[[h]])
    fe2 <- na.omit(FE_BM_model[[h]])

    MSFE_TR[h] = mean((fe1)^2)
    MSFE_BM[h] = mean((fe2)^2)}

  # Run DM Tests
  Dmpvalues = matrix(), nrow = H, ncol = 3)
  colnames(Dmpvalues) <- c("DM_Two_Sided", "DM_Greater", "DM_Lesser")
  for (h in 1:H){
    # Note: dm.test needs the *full* (un-omitted) error vectors
    # to align them properly, hence using the original list inputs
    x1 = dm.test(e1 = FE_BM_model[[h]], e2 = FE_TR_model[[h]], h = h)
    x2 = dm.test(e1 = FE_BM_model[[h]], e2 = FE_TR_model[[h]], h = h, alternative = "greater")
    x3 = dm.test(e1 = FE_BM_model[[h]], e2 = FE_TR_model[[h]], h = h, alternative = "less")
    Dmpvalues[h, 1] = round(x1$p.value, digits = 4)
    Dmpvalues[h, 2] = round(x2$p.value, digits = 4)
    Dmpvalues[h, 3] = round(x3$p.value, digits = 4)}

  # Create final table data
  forecast_comparison <- data.frame(
    Horizon = 1:H,
    MSFE_TR = MSFE_TR,
    MSFE_BM = MSFE_BM) %>%
    mutate(Ratio_TR_vs_BM = MSFE_TR / MSFE_BM)

  forecast_comparison <- bind_cols(forecast_comparison, as.data.frame(Dmpvalues))

  final_data_formatted <- forecast_comparison %>%
    mutate(across(starts_with("DM_"), format_p_values_with_stars))

  # Create the kable table
  table_output <- kable(
    final_data_formatted,
    format = format,
    booktabs = TRUE,
    caption = model_caption,
    digits = 4,
    col.names = c("h", "MSFE TR", "MSFE BM", "Ratio", "DM Two-Sided", "DM Greater", "DM Lesser"),
    escape = FALSE) %>%
    kable_styling(
      latex_options = c("striped", "scale_down"),
      position = "center") %>%

```

```

column_spec(1, bold = TRUE, border_right = TRUE) %>%
column_spec(5:7, monospace = TRUE) %>%
footnote(
  general = "TR refers to the forecast made with an estimated Taylor Rule. BM refers to a benchmark",
  symbol = c(
    "'DM Greater' tests if the TR model is significantly more accurate than the BM model.",
    "'DM Lesser' tests if the TR model is significantly less accurate than the BM model."),
  general_title = "Note:",
  symbol_title = "DM Test Alternative Hypotheses (H_A):",
  footnote_as_chunk = TRUE,
  threeparttable = TRUE)

return(table_output)}

```

Estimation

```

#parameters
R = 85 #notes: structural breaks at R=55 and R=85
cat("Evaluation sample starts after", as.character(data$quarter[R]))

```

Evaluation sample starts after 2020 Q1

```

P = nrow(data) - R #but will effectively be: P = T-h-R
H = 10 #number of different horizons (takes 10 to go until 2027 Q4)

#note: we are doing a recursive estimation scheme for out-of-sample tests
#note: we are doing direct forecasts

#-----
# 1. DEFINE THE TAYLOR RULE (TR) MODEL FORMULAS
#-----

# TR based on current inflation
formula_1 <- rate ~ inflation_gap + output_gap
formula_2 <- shadowrate ~ inflation_gap + output_gap
formula_3 <- rate ~ rate_lag + inflation_gap + output_gap
formula_4 <- shadowrate ~ shadowrate_lag + inflation_gap + output_gap

#-----
# 2. PRE-ALLOCATE STORAGE FOR ALL RESULTS
#-----

# We need 4 lists for the TR models, 1 list for the shared benchmark
init_storage_list <- function(H, P) {
  storage <- vector("list", length = H)
  for (h in 1:H) {
    storage[[h]] <- rep(NA_real_, P)}
  return(storage)}

# Storage for realised values
Actuals <- init_storage_list(H, P)

```

```

# Storage for Forecasts
F_TR_1 <- init_storage_list(H, P) # Model 1: shadowrate, no lag
F_TR_2 <- init_storage_list(H, P) # Model 2: rate, no lag
F_TR_3 <- init_storage_list(H, P) # Model 3: shadowrate, with lag
F_TR_4 <- init_storage_list(H, P) # Model 4: rate, with lag
F_BM   <- init_storage_list(H, P) # Benchmark: ARIMA

# Storage for Forecast Errors
FE_TR_1 <- init_storage_list(H, P) # Model 1: shadowrate, no lag
FE_TR_2 <- init_storage_list(H, P) # Model 2: rate, no lag
FE_TR_3 <- init_storage_list(H, P) # Model 3: shadowrate, with lag
FE_TR_4 <- init_storage_list(H, P) # Model 4: rate, with lag
FE_BM   <- init_storage_list(H, P) # Benchmark: ARIMA

#-----
# 3. SETUP & RUN THE PARALLEL BACKTESTING LOOP
#-----

num_cores <- detectCores() - 1
cl <- makeCluster(num_cores)
registerDoParallel(cl)

# .export sends read-only objects to each core
# .packages loads libraries on each core
worker_results <- foreach(
  p = P:1,
  .packages = c("forecast", "stats", "dplyr"),
  .export = c("data", "H", "formula_1", "formula_2", "formula_3", "formula_4")
) %dopar% {

  # 1. Define splits (with rolling scheme)
  training <- data[(1 + nrow(data) - R - p):(nrow(data) - p), ]
  testing <- data[(nrow(data) - (p - 1)):nrow(data), ]

  # --- 2. Fit common models only once ---
  # note: d=1 for interest and inflation as non-stationary
  inflation_arma <- my.auto.arima(training$inflation_gap, max.p=4, max.q=4, d=1)
  outputgap_arma <- my.auto.arima(training$output_gap, max.p=4, max.q=4, d=0)
  interest_arma <- my.auto.arima(training$rate, max.p=4, max.q=4, d=1) # Benchmark

  # --- 3. Get common forecasts only once (all H horizons) ---
  inflation_forecasts <- my.forecast(inflation_arma, h = H)
  outputgap_forecasts <- my.forecast(outputgap_arma, h = H)
  BMpredicted_rates <- my.forecast(interest_arma, h = H)

  # --- 4. Fit the 4 TR models ---
  TR_model_1 <- lm(formula_1, data = training)
  TR_model_2 <- lm(formula_2, data = training)
  TR_model_3 <- lm(formula_3, data = training)
  TR_model_4 <- lm(formula_4, data = training)

  # --- 5. Build forecast input data & get forecasts for non-lagged models ---
  # These are direct forecasts

```

```

new_data_base <- data.frame(
  inflation_gap = inflation_forecasts,
  output_gap = outputgap_forecasts)

TR_preds_1 <- round(pmax(predict(TR_model_1, new_data_base), min(data$rate)) / 0.25) * 0.25
TR_preds_2 <- round(pmax(predict(TR_model_2, new_data_base), min(data$rate)) / 0.25) * 0.25
BM_preds <- round(pmax(BMpredicted_rates, min(data$rate)) / 0.25) * 0.25

# --- 6. Get forecasts for lagged models via iteration ---
# We must loop 1 step at a time, feeding forecasts back in.

# a) Pre-allocate storage for H forecasts
TR_preds_3 <- numeric(H)
TR_preds_4 <- numeric(H)

# b) Get the last known lag from the training set (lag for h=1 forecast)
current_rate_lag <- last(training$rate)
current_shadowrate_lag <- last(training$shadowrate)

# Loop for iterative forecasting
for (h in 1:H) {
  # --- Prepare dataset for predictions ---
  new_data_3_h <- data.frame(
    inflation_gap = inflation_forecasts[h],
    output_gap = outputgap_forecasts[h],
    rate_lag = current_rate_lag)
  new_data_4_h <- data.frame(
    inflation_gap = inflation_forecasts[h],
    output_gap = outputgap_forecasts[h],
    shadowrate_lag = current_shadowrate_lag )

  # Get the forecast values (keep for lag, and then round for actual prediction)
  pred_3_h <- predict(TR_model_3, new_data_3_h)
  TR_preds_3[h] <- round(pmax(pred_3_h, min(data$rate)) / 0.25) * 0.25
  pred_4_h <- predict(TR_model_4, new_data_4_h)
  TR_preds_4[h] <- round(pmax(pred_4_h, min(data$rate)) / 0.25) * 0.25

  # Update lag for h+1
  current_shadowrate_lag <- pred_4_h
  current_rate_lag <- pred_3_h }

# --- 7. Get actual values in evaluation sample ---
actual_rates <- testing$rate[1:H]

# --- 8. Return all FORECASTS and ACTUALS from the worker ---
list(f_tr1 = TR_preds_1,
     f_tr2 = TR_preds_2,
     f_tr3 = TR_preds_3,
     f_tr4 = TR_preds_4,
     f_bm = BM_preds,
     actuals = actual_rates) }

# --- Stop the Cluster ---

```

```

stopCluster(cl)
rm(cl)

#-----
# 4. UNPACK PARALLEL RESULTS INTO STORAGE LISTS
#-----

# 'worker_results' is a list of P lists. We need to re-organize it.
for (i in 1:P) {
  # i=1 corresponds to p=P, i=2 to p=P-1, ... i=P to p=1
  # This 'storage_index' matches the loop order
  storage_index <- i
  p_results <- worker_results[[i]]

  for (h in 1:H) {
    # Get the raw values for this h
    actual_val <- p_results$actuals[h]
    f_tr1_val <- p_results$f_tr1[h]
    f_tr2_val <- p_results$f_tr2[h]
    f_tr3_val <- p_results$f_tr3[h]
    f_tr4_val <- p_results$f_tr4[h]
    f_bm_val <- p_results$f_bm[h]

    # Store Actuals (for MZ)
    Actuals[[h]][storage_index] <- actual_val

    # Store Forecasts (for MZ)
    F_TR_1[[h]][storage_index] <- f_tr1_val
    F_TR_2[[h]][storage_index] <- f_tr2_val
    F_TR_3[[h]][storage_index] <- f_tr3_val
    F_TR_4[[h]][storage_index] <- f_tr4_val
    F_BM[[h]][storage_index] <- f_bm_val

    # Calculate and Store Errors (for MSFE/DM)
    FE_TR_1[[h]][storage_index] <- f_tr1_val - actual_val
    FE_TR_2[[h]][storage_index] <- f_tr2_val - actual_val
    FE_TR_3[[h]][storage_index] <- f_tr3_val - actual_val
    FE_TR_4[[h]][storage_index] <- f_tr4_val - actual_val
    FE_BM[[h]][storage_index] <- f_bm_val - actual_val } }

#-----
# 5. RENDER RESULTS MORE INTUITIVE FOR FURTHER ANALYSIS
#-----

# Convert the forecast lists (F_TR_x) into single dataframes
forecast_to_df <- function(forecast_list, period) {
  # Convert each element to numeric (benchmark is ts object, which is bad)
  numeric_list <- lapply(forecast_list, function(x) as.numeric(x)) #just make each list inside numeric
  df <- as.data.frame(numeric_list)
  # Add period and horizon
  df$period <- period #first list is all horizon 1 forecasts, gives this to all observations
  df$horizon <- 1:nrow(df) #counts rows and gives each the horizon corresponding to it
  df}

```

```

# Apply to all forecasting models
df_all <- do.call(rbind, lapply(seq_along(worker_results), function(i) {
  forecast_to_df(worker_results[[i]], period = i) })))
df_all[] <- lapply(df_all, function(x) as.numeric(x))

```

Spaghetti Plots

```

# Select the model to plot
model <- "f_tr3"

# period = date the forecast was made
# date_of_forecast = the future date we are predicting
df_all$date_of_forecast <- df_all$period + df_all$horizon

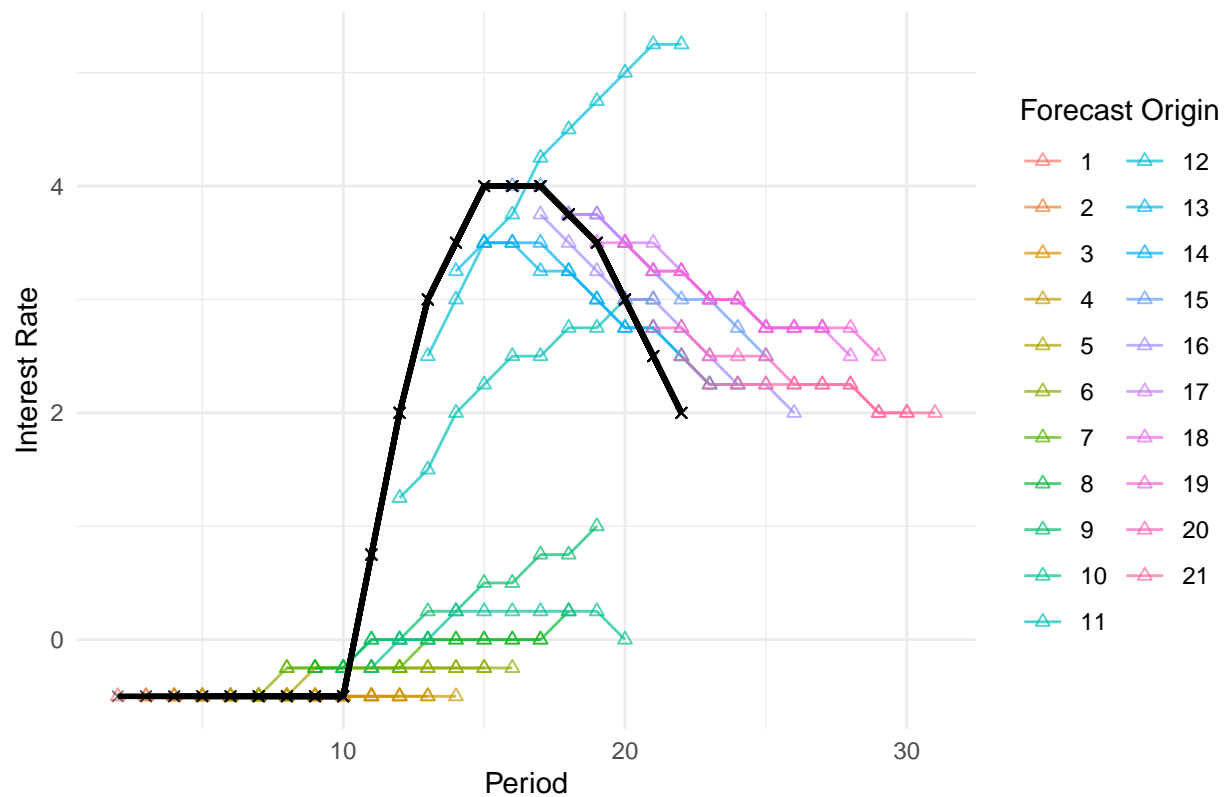
# Spaghetti plot with color per period
ggplot(df_all, aes(x = date_of_forecast, y = .data[[model]], group = period, color = factor(period))) +
  geom_line(alpha = 0.7) +      # forecast lines
  geom_point(shape = 2, alpha = 0.7) +

  # Actuals as black baseline
  geom_line(aes(y = actuals), color = "black", size = 1) +
  geom_point(aes(y = actuals), color = "black", shape = 4, alpha = 0.5) +

  labs(title = paste("Forecast of", model, "vs Actual Rate"),
       x = "Period",
       y = "Interest Rate",
       color = "Forecast Origin") +
  theme_minimal()

```

Forecast of f_tr3 vs Actual Rate



Plots of FE

```
df_all_3 <- df_all

# Compute forecast error
df_all_3$forecast_error <- df_all_3[[model]] - df_all_3$actuals

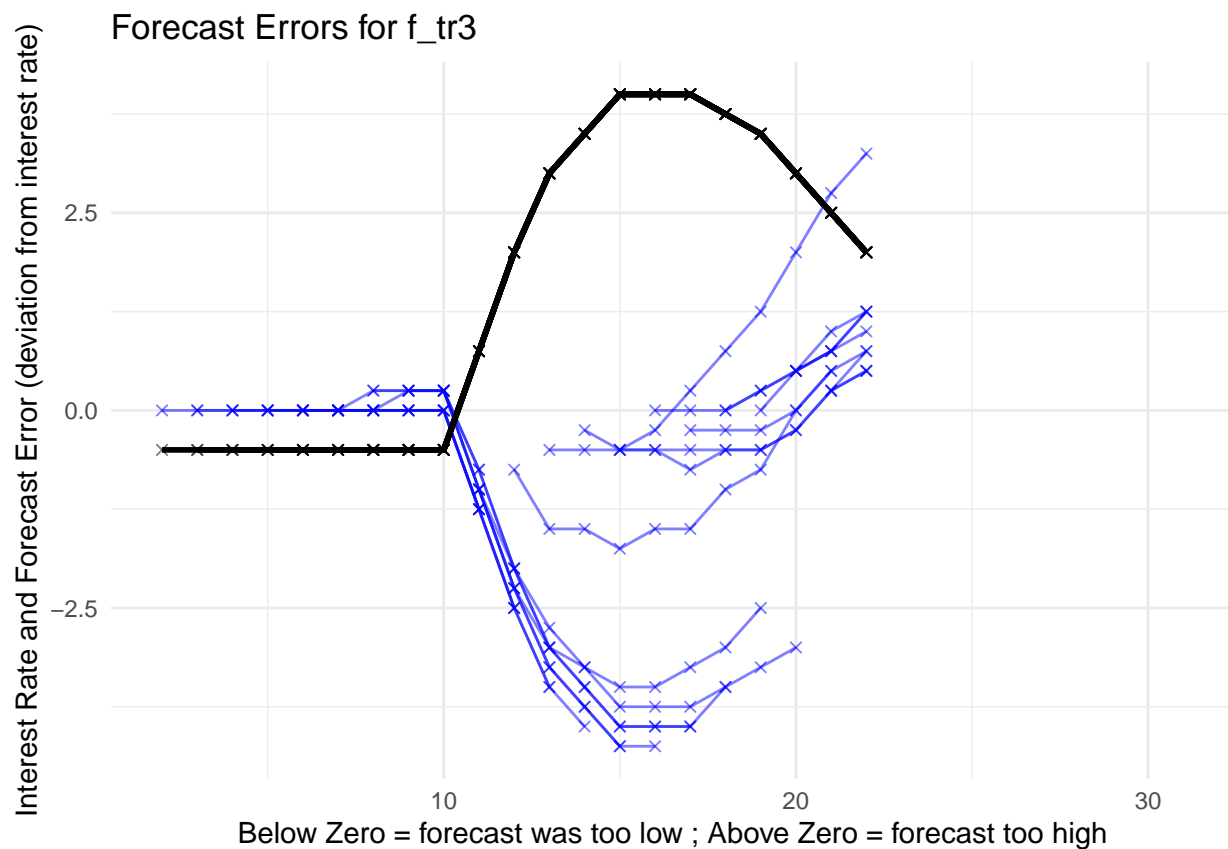
#compute date_of_forecast for x-axis
df_all_3$date_of_forecast <- df_all_3$period + df_all_3$horizon

ggplot(df_all_3, aes(x = date_of_forecast, group = period)) +
  # Forecast error lines
  geom_line(aes(y = forecast_error), color = "blue", alpha = 0.5) +
  geom_point(aes(y = forecast_error), color = "blue", alpha = 0.5, shape = 4) +

  # Actuals line
  geom_line(aes(y = actuals), color = "black", size = 1) +
  geom_point(aes(y = actuals), color = "black", shape = 4, alpha = 0.5) +

  labs(
    title = paste("Forecast Errors for", model),
    x = "Below Zero = forecast was too low ; Above Zero = forecast too high",
    y = "Interest Rate and Forecast Error (deviation from interest rate)"
  )
```

```
) +  
theme_minimal()
```



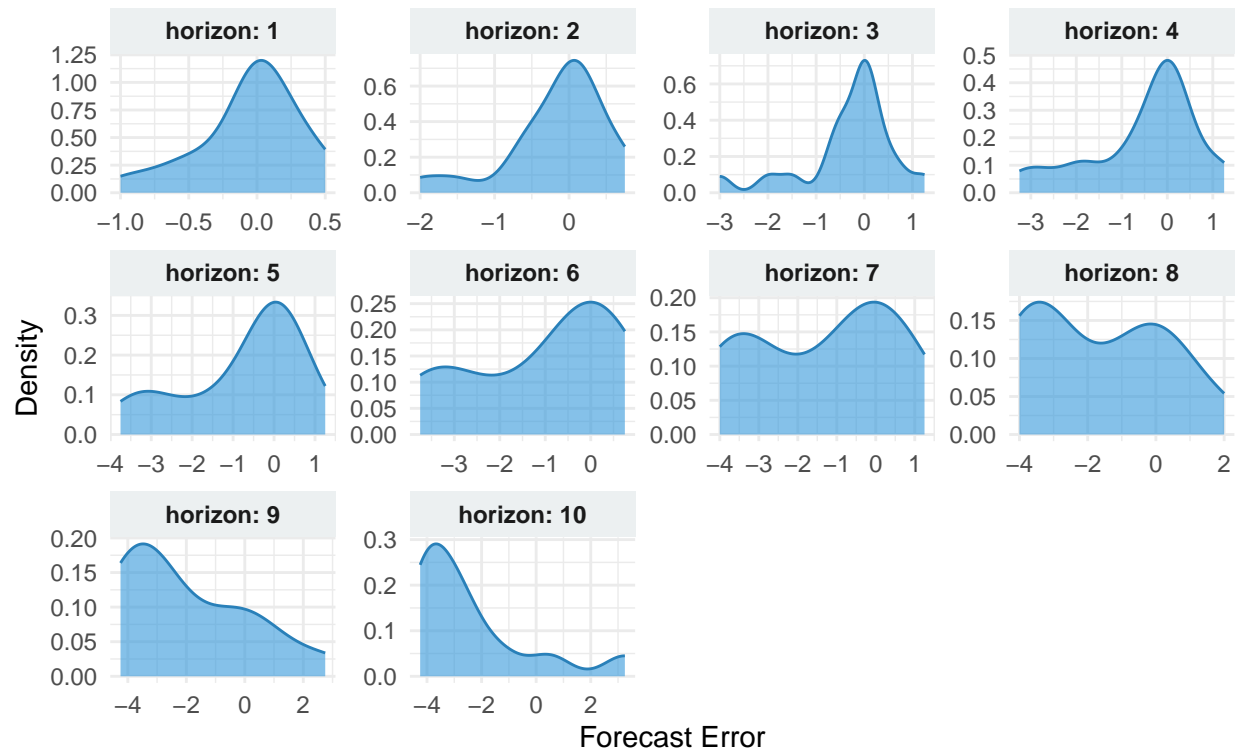
Density of FE

```
# Version 1: Non-Adjusted Scales  
plot_facet <- ggplot(df_all_3 %>% filter(horizon <= H), aes(x = forecast_error)) +  
  geom_density(fill = "#3498db", color = "#2980b9", alpha = 0.6) +  
  facet_wrap(~horizon, ncol = 4, labeller = label_both, scales = "free") +  
  labs(  
    title = "Density of Forecast Errors by Horizon (Non-Adjusted Scale)",  
    subtitle = "Comparing distribution shapes across 12 horizons",  
    x = "Forecast Error",  
    y = "Density") +  
  theme_minimal() +  
  theme(  
    strip.background = element_rect(fill = "#ecf0f1", color = NA), # Nice gray boxes for labels  
    strip.text = element_text(face = "bold"))  
print(plot_facet)
```

```
## Warning: Removed 45 rows containing non-finite outside the scale range  
## (`stat_density()`).
```


Density of Forecast Errors by Horizon (Non-Adjusted Scale)

Comparing distribution shapes across 12 horizons

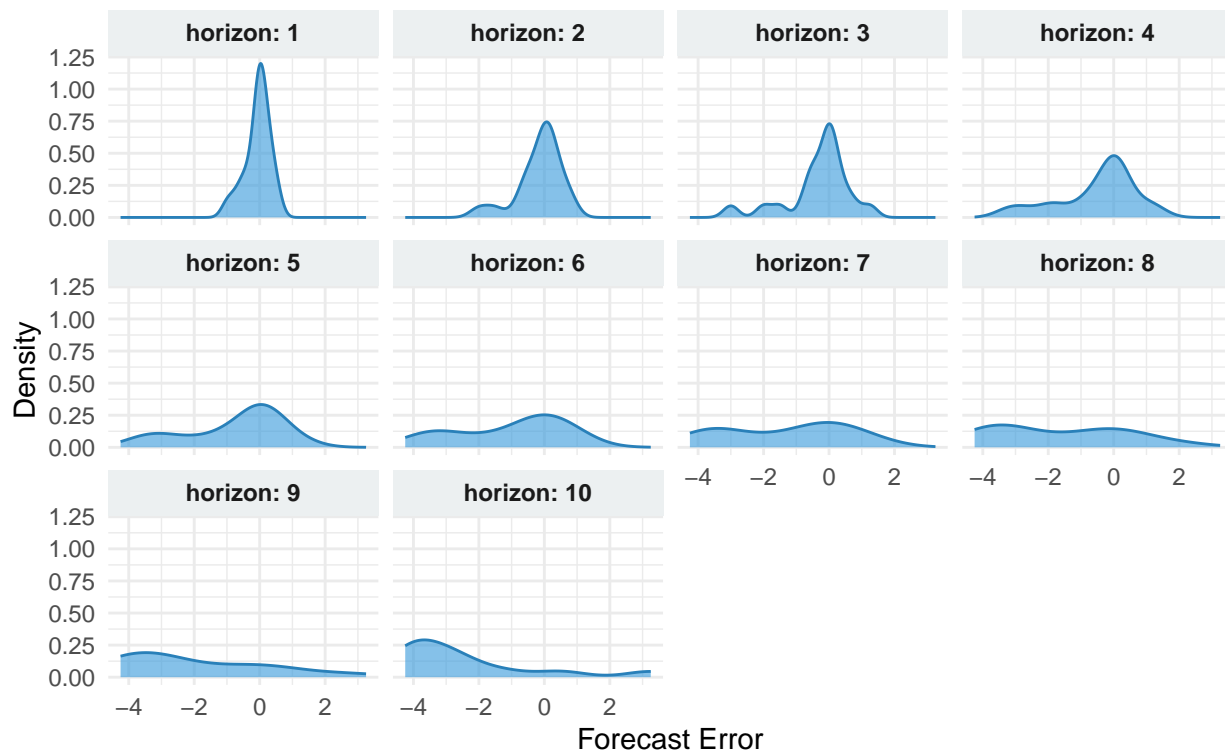


```
# Version 2: Adjusted scales
plot_facet <- ggplot(df_all_3 %>% filter(horizon <= H), aes(x = forecast_error)) +
  geom_density(fill = "#3498db", color = "#2980b9", alpha = 0.6) +
  facet_wrap(~horizon, ncol = 4, labeller = label_both) +
  labs(title = "Density of Forecast Errors by Horizon (Adjusted Scale)",
       subtitle = "Comparing distribution shapes across 12 horizons",
       x = "Forecast Error",
       y = "Density") +
  theme_minimal() +
  theme(strip.background = element_rect(fill = "#ecf0f1", color = NA),
        strip.text = element_text(face = "bold"))
print(plot_facet)
```

```
## Warning: Removed 45 rows containing non-finite outside the scale range
## (`stat_density()`).
```

Density of Forecast Errors by Horizon (Adjusted Scale)

Comparing distribution shapes across 12 horizons



```
# Version 3: "Ridges"
plot_ridge <- ggplot(df_all_3 %>% filter(horizon <= H),
  aes(x = forecast_error, y = as.factor(horizon), fill = stat(x))) +
  geom_density_ridges_gradient(scale = 3, rel_min_height = 0.01) +
  scale_fill_viridis_c(name = "Error", option = "C") +
  labs(title = "Evolution of Forecast Error Densities",
    subtitle = "Ridge plot showing widening variance over longer horizons",
    x = "Forecast Error",
    y = "Forecast Horizon") +
  theme_minimal()

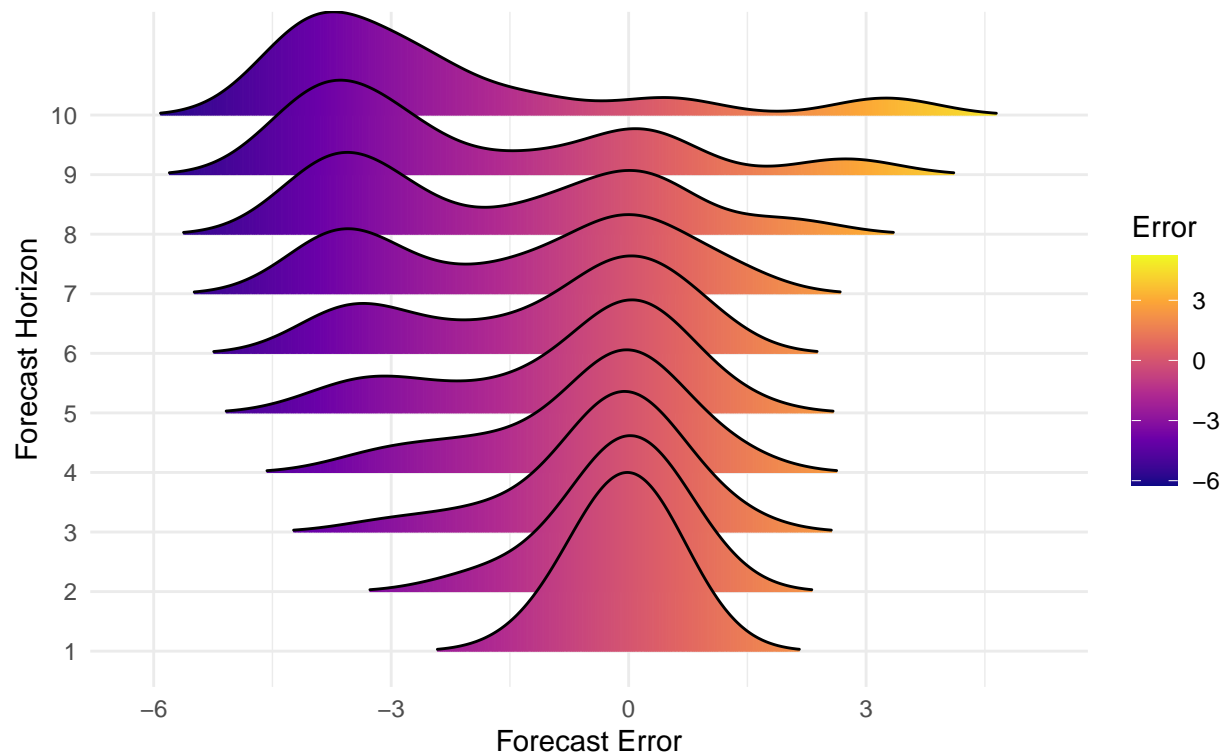
print(plot_ridge)
```

```
## Warning: `stat(x)` was deprecated in ggplot2 3.4.0.
## i Please use `after_stat(x)` instead.
## This warning is displayed once every 8 hours.
## Call `lifecycle::last_lifecycle_warnings()` to see where this warning was
## generated.
```

```
## Picking joint bandwidth of 0.66
```

Evolution of Forecast Error Densities

Ridge plot showing widening variance over longer horizons

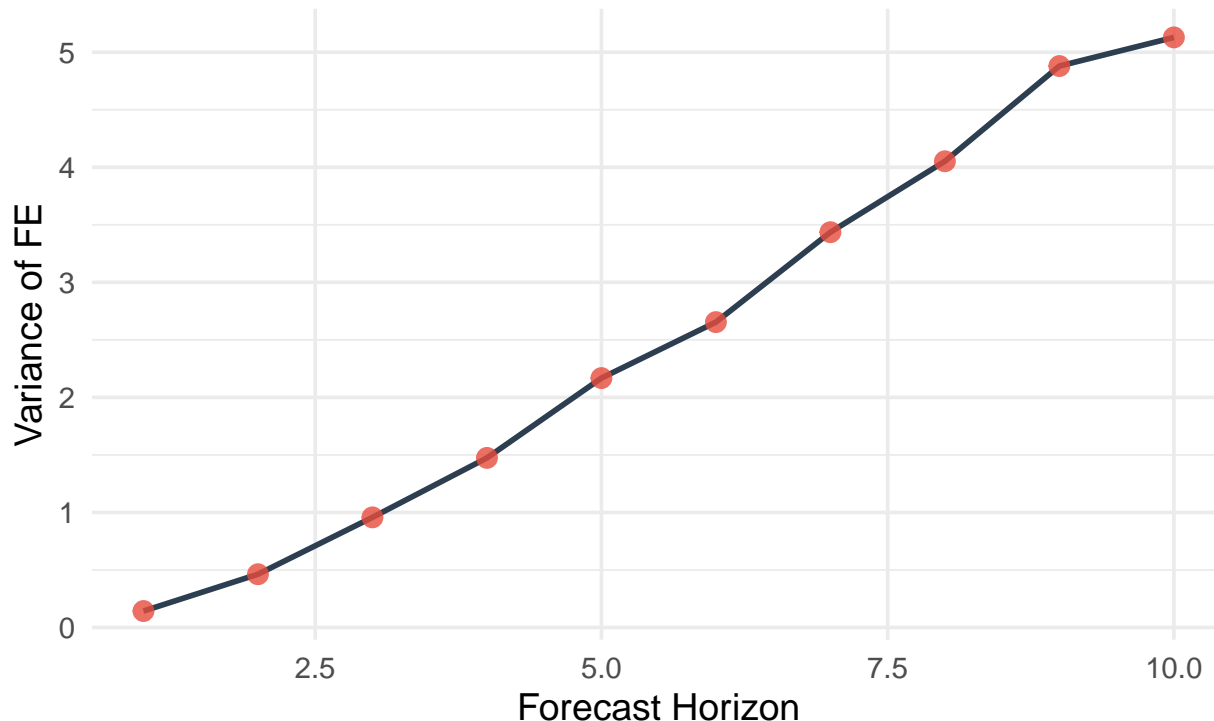


Variance of FE

```
# This gives us the mean forecast error for the h step ahead forecast
var_by_horizon <- df_all_3 %>%
  group_by(horizon) %>%
  summarize(
    mean_fe = mean(forecast_error, na.rm=T),
    var_fe = sd(forecast_error, na.rm=T)^2, n = n() )

ggplot(var_by_horizon, aes(x = horizon, y = var_fe)) +
  geom_line(color = "#2c3e50", size = 1) +
  geom_point(color = "#e74c3c", size = 3, alpha = 0.8) +
  theme_minimal(base_size = 14) +
  scale_y_continuous(labels = scales::comma) +
  labs(title = "Variance of FE by Horizon",
       x = "Forecast Horizon",
       y = "Variance of FE",
       caption = "Data source: df_all_3") +
  theme(plot.title = element_text(face = "bold"),
        plot.subtitle = element_text(color = "gray50"),
        panel.grid.minor.x = element_blank() )
```

Variance of FE by Horizon



Data source: df_all_3

Absolute Performance: Efficiency & Bias

```
# Call MZ-test helper function 4 times.

# MZ Report 1: Actual Rate, No Lag
mz_report_1 <- generate_mincer_zarnowitz_report(
  F_model = F_TR_1,
  Actual_values = Actuals,
  H = H,
  model_caption = "Mincer-Zarnowitz Test: Actual Rate, No Lag",
  format = format)

# MZ Report 2: Shadow Rate, No Lag (
# Note: This report is wrapped in trycatch as it sometimes fails
#       If it does fail, simply decrease R in order to have more
#       observations, thus no problem in multicollinearity.
mz_report_2 <- tryCatch({
  generate_mincer_zarnowitz_report(
    F_model = F_TR_2,
    Actual_values = Actuals,
    H = H,
    model_caption = "Mincer-Zarnowitz Test: Shadow Rate, No Lag",
    format = format)}, error = function(e) {
  message(" Error generating MZ Report (Shadow Rate, No Lag): ", e$message)
```

```

message(">> Skipping this report and continuing...")
return(NULL)}

# MZ Report 3: Actual Rate, with Lag
mz_report_3 <- generate_mincer_zarnowitz_report(
  F_model = F_TR_3,
  Actual_values = Actuals,
  H = H,
  model_caption = "Mincer-Zarnowitz Test: Actual Rate, with Lag",
  format = format)

# MZ Report 4: Shadow Rate, with Lag
mz_report_4 <- generate_mincer_zarnowitz_report(
  F_model = F_TR_4,
  Actual_values = Actuals,
  H = H,
  model_caption = "Mincer-Zarnowitz Test: Shadow Rate, with Lag",
  format = format)

# MZ Report 5: Benchmark
mz_report_BM <- generate_mincer_zarnowitz_report(
  F_model = F_BM,
  Actual_values = Actuals,
  H = H,
  model_caption = "Mincer-Zarnowitz Test: Benchmark ARIMA",
  format = format)

list(
  mz_report_1,
  mz_report_2,
  mz_report_3,
  mz_report_4,
  mz_report_BM)

```

```
[[1]]
```

```
[[2]]
```

```
[[3]]
```

```
[[4]]
```

```
[[5]]
```

Relative Performance (against benchmark)

```

# Call DM-test helper function 4 times.

# Report 1: Actual Rate, No Lag
report_1 <- generate_report_table(
  FE_TR_model = FE_TR_1,
  FE_BM_model = FE_BM,
  H = H,

```

Table 5: Mincer-Zarnowitz Test: Actual Rate, No Lag

h	Alpha	Beta	pv(Joint)	
1	1.1720	0.3204	0.2184	
2	1.2313	0.3734	0.7658	
3	0.9667	0.8076	0.8783	
4	0.7954	1.2455	0.2386	
5	0.8566	1.4292	0.0103	**
6	1.0184	1.4755	0.0000	***
7	1.2284	1.3395	0.0000	***
8	1.6124	1.0576	0.0000	***
9	2.2021	0.6248	0.0001	***
10	2.9629	0.0414	0.0030	***

Note:

pv(Joint) is the p-value for the joint hypothesis H_0 : $(\text{Alpha}, \text{Beta}) = (0, 1)$. A high p-value means we fail to reject the null hypothesis of an unbiased, efficient forecast.

* Signif. codes: '***' 0.01, '**' 0.05, '*' 0.1

Table 6: Mincer-Zarnowitz Test: Shadow Rate, No Lag

h	Alpha	Beta	pv(Joint)	
1	1.8291	-0.3686	0.000	***
2	1.8683	-0.2358	0.000	***
3	1.7703	-0.0464	0.000	***
4	1.8226	0.0077	0.000	***
5	1.9919	-0.0130	0.000	***
6	2.2042	-0.0405	0.000	***
7	2.4555	-0.0686	0.000	***
8	2.7444	-0.0937	0.000	***
9	2.9316	-0.0653	0.000	***
10	3.1597	-0.0446	0.000	***

Note:

pv(Joint) is the p-value for the joint hypothesis H_0 : $(\text{Alpha}, \text{Beta}) = (0, 1)$. A high p-value means we fail to reject the null hypothesis of an unbiased, efficient forecast.

* Signif. codes: '***' 0.01, '**' 0.05, '*' 0.1

Table 7: Mincer-Zarnowitz Test: Actual Rate, with Lag

h	Alpha	Beta	pv(Joint)
1	0.0568	1.0019	0.7940
2	0.2189	0.9525	0.7692
3	0.4799	0.8824	0.6682
4	0.7583	0.8148	0.6830
5	1.1378	0.6906	0.5505
6	1.4947	0.5933	0.4541
7	1.9075	0.4131	0.1574
8	2.3049	0.2375	0.0148 **
9	2.7110	0.0277	0.0010 ***
10	3.0873	-0.1496	0.0003 ***

Note:

pv(Joint) is the p-value for the joint hypothesis H_0 : $(\text{Alpha}, \text{Beta}) = (0, 1)$. A high p-value means we fail to reject the null hypothesis of an unbiased, efficient forecast.

* Signif. codes: '***' 0.01, '**' 0.05, '*' 0.1

Table 8: Mincer-Zarnowitz Test: Shadow Rate, with Lag

h	Alpha	Beta	pv(Joint)
1	0.0533	0.9137	0.0771 *
2	0.1926	0.7985	0.1967
3	0.4409	0.6390	0.0084 ***
4	0.7725	0.4865	0.0000 ***
5	1.1435	0.3537	0.0000 ***
6	1.4715	0.2535	0.0000 ***
7	1.8170	0.1656	0.0000 ***
8	2.2158	0.0884	0.0000 ***
9	2.6636	0.0189	0.0000 ***
10	3.1629	-0.0418	0.0000 ***

Note:

pv(Joint) is the p-value for the joint hypothesis H_0 : $(\text{Alpha}, \text{Beta}) = (0, 1)$. A high p-value means we fail to reject the null hypothesis of an unbiased, efficient forecast.

* Signif. codes: '***' 0.01, '**' 0.05, '*' 0.1

Table 9: Mincer-Zarnowitz Test: Benchmark ARIMA

h	Alpha	Beta	pv(Joint)
1	0.1403	0.9439	0.4025
2	0.3980	0.8509	0.1991
3	0.7262	0.7193	0.2696
4	1.0868	0.5906	0.3892
5	1.4665	0.4339	0.2697
6	1.8291	0.3006	0.1350
7	2.1804	0.1495	0.3461
8	2.4846	0.0308	0.0078 ***
9	2.7628	-0.1282	0.0000 ***
10	2.9597	-0.3873	0.0000 ***

Note:

pv(Joint) is the p-value for the joint hypothesis $H_0: (\text{Alpha}, \text{Beta}) = (0, 1)$. A high p-value means we fail to reject the null hypothesis of an unbiased, efficient forecast.

* Signif. codes: '***' 0.01, '**' 0.05, '*' 0.1

```

model_caption = "MSFE Comparison, Trained on Actual Rate, No Lag",
format = format)

# Report 2: Shadow Rate, No Lag
report_2 <- generate_report_table(
  FE_TR_model = FE_TR_2,
  FE_BM_model = FE_BM,
  H = H,
  model_caption = "MSFE Comparison, Trained on Shadow Rate, No Lag",
  format = format)

# Report 3: Actual Rate, with Lag
report_3 <- generate_report_table(
  FE_TR_model = FE_TR_3,
  FE_BM_model = FE_BM,
  H = H,
  model_caption = "MSFE Comparison, Trained on Actual Rate, with Lag",
  format = format)

# Report 4: Shadow Rate, with Lag
report_4 <- generate_report_table(
  FE_TR_model = FE_TR_4,
  FE_BM_model = FE_BM,
  H = H,
  model_caption = "MSFE Comparison, Trained on Shadow Rate, with Lag",
  format = format)

list(report_1, report_2, report_3, report_4)

```

[[1]]

Table 10: MSFE Comparison, Trained on Actual Rate, No Lag

h	MSFE TR	MSFE BM	Ratio	DM Two-Sided	DM Greater	DM Lesser
1	4.0655	0.1637	24.8364	0.0001 ***	0.9999	0.0001 ***
2	4.1094	0.6781	6.0599	0.0339 **	0.9831	0.0169 **
3	3.5461	1.6776	2.1137	0.4047	0.7977	0.2023
4	3.1944	2.8924	1.1044	0.9159	0.5421	0.4579
5	3.1434	4.4596	0.7049	0.5990	0.2995	0.7005
6	3.3438	5.9961	0.5577	0.1229	0.0614 *	0.9386
7	3.6083	7.7500	0.4656	0.0120 **	0.0060 ***	0.9940
8	4.1384	9.0357	0.4580	0.0021 ***	0.0010 ***	0.9990
9	5.0865	10.7260	0.4742	0.0002 ***	0.0001 ***	0.9999
10	6.1823	12.0156	0.5145	0.0000 ***	0.0000 ***	1.0000

Note: TR refers to the forecast made with an estimated Taylor Rule. BM refers to a benchmark of the interest rate using an ARIMA model. Ratio < 1 indicates that the TR model has lower MSFE. *DM Test Alternative Hypotheses (H_A):*

* 'DM Greater' tests if the TR model is significantly more accurate than the BM model.

† 'DM Lesser' tests if the TR model is significantly less accurate than the BM model.

[[2]]

[[3]]

[[4]]

Table 11: MSFE Comparison, Trained on Shadow Rate, No Lag

h	MSFE TR	MSFE BM	Ratio	DM Two-Sided	DM Greater	DM Lesser
1	8.9315	0.1637	54.5636	0.0001 ***	1.0000	0.0000 ***
2	9.6781	0.6781	14.2719	0.0022 ***	0.9989	0.0011 ***
3	9.8684	1.6776	5.8824	0.0376 **	0.9812	0.0188 **
4	12.6875	2.8924	4.3866	0.2253	0.8873	0.1127
5	17.4890	4.4596	3.9217	0.3242	0.8379	0.1621
6	24.5508	5.9961	4.0945	0.3671	0.8165	0.1835
7	32.6333	7.7500	4.2108	0.3816	0.8092	0.1908
8	43.9464	9.0357	4.8636	0.3157	0.8421	0.1579
9	53.8942	10.7260	5.0247	0.2236	0.8882	0.1118
10	64.6667	12.0156	5.3819	0.0520 *	0.9740	0.0260 **

Note: TR refers to the forecast made with an estimated Taylor Rule. BM refers to a benchmark of the interest rate using an ARIMA model. Ratio < 1 indicates that the TR model has lower MSFE. *DM Test Alternative Hypotheses (H_A):*

* 'DM Greater' tests if the TR model is significantly more accurate than the BM model.

† 'DM Lesser' tests if the TR model is significantly less accurate than the BM model.

Table 12: MSFE Comparison, Trained on Actual Rate, with Lag

h	MSFE TR	MSFE BM	Ratio	DM Two-Sided	DM Greater	DM Lesser
1	0.1399	0.1637	0.8545	0.5402	0.2701	0.7299
2	0.4625	0.6781	0.6820	0.1832	0.0916 *	0.9084
3	1.0066	1.6776	0.6000	0.1295	0.0647 *	0.9353
4	1.6562	2.8924	0.5726	0.1212	0.0606 *	0.9394
5	2.6250	4.4596	0.5886	0.0449 **	0.0224 **	0.9776
6	3.6172	5.9961	0.6033	0.0143 **	0.0072 ***	0.9928
7	5.0292	7.7500	0.6489	0.0143 **	0.0072 ***	0.9928
8	6.5804	9.0357	0.7283	0.0000 ***	0.0000 ***	1.0000
9	8.5817	10.7260	0.8001	0.0220 **	0.0110 **	0.9890
10	10.5417	12.0156	0.8773	0.1656	0.0828 *	0.9172

Note: TR refers to the forecast made with an estimated Taylor Rule. BM refers to a benchmark of the interest rate using an ARIMA model. Ratio < 1 indicates that the TR model has lower MSFE.

DM Test Alternative Hypotheses (H_A): * 'DM Greater' tests if the TR model is significantly more accurate than the BM model.

† 'DM Lesser' tests if the TR model is significantly less accurate than the BM model.

Table 13: MSFE Comparison, Trained on Shadow Rate, with Lag

h	MSFE TR	MSFE BM	Ratio	DM Two-Sided	DM Greater	DM Lesser
1	0.1637	0.1637	1.0000	1.0000	0.5000	0.5000
2	0.5781	0.6781	0.8525	0.7065	0.3533	0.6467
3	1.6678	1.6776	0.9941	0.9464	0.4732	0.5268
4	3.7257	2.8924	1.2881	0.3371	0.8315	0.1685
5	7.0993	4.4596	1.5919	0.1935	0.9033	0.0967 *
6	11.6367	5.9961	1.9407	0.0913 *	0.9544	0.0456 **
7	18.5458	7.7500	2.3930	0.1470	0.9265	0.0735 *
8	27.9643	9.0357	3.0949	0.1615	0.9193	0.0807 *
9	40.1971	10.7260	3.7476	0.1525	0.9238	0.0762 *
10	55.4635	12.0156	4.6160	0.1044	0.9478	0.0522 *

Note: TR refers to the forecast made with an estimated Taylor Rule. BM refers to a benchmark of the interest rate using an ARIMA model. Ratio < 1 indicates that the TR model has lower MSFE.

DM Test Alternative Hypotheses (H_A): * 'DM Greater' tests if the TR model is significantly more accurate than the BM model.

† 'DM Lesser' tests if the TR model is significantly less accurate than the BM model.

Actual Forecast Model

Helpers

```
#-----  
# Helper function for displaying our final forecast results (table)  
#-----  
  
display_forecasts <- function(forecast_list,  
                              caption = "Interest Rate Forecasts",  
                              format = "html") {  
  
  # Determine the number of horizons and corresponding quarters  
  H <- length(forecast_list$TR_Forecast)  
  
  forecast_quarters <- seq(from = last(data$quarter) + 0.25,  
                           by = 0.25,  
                           length.out = H)  
  
  horizon_quarter_label <- paste0(1:H, ": ", as.character(forecast_quarters))  
  
  # Create a data frame for display  
  forecast_df <- data.frame(  
    Horizon_Quarter = horizon_quarter_label,  
    Taylor_Rule_Forecast = round(forecast_list$TR_Forecast,2),  
    Benchmark_ARIMA_Forecast = round(forecast_list$BM_Forecast,2),  
    Inflation_Gap_Forecast = round(forecast_list$Inflation_Forecast,2),  
    Output_Gap_Forecast = round(forecast_list$OutputGap_Forecast,2))  
  
  # Create the table  
  table_output <- kable(  
    forecast_df,  
    format = format,  
    digits = 4,  
    col.names = c("Horizon: Quarter", "Taylor Rule Forecast", "Benchmark Forecast",  
                  "Inflation Forecast", "Output Gap Forecast"),  
    caption = caption,  
    booktabs = TRUE) %>%  
  kable_styling(  
    latex_options = "striped",  
    position = "center") %>%  
  column_spec(1, bold = TRUE, border_right = TRUE)  
  return(table_output) }  
  
#-----  
# Helper function for plotting our final forecast results  
#-----  
  
plot_forecasts <- function(forecast_list,  
                           title = "Interest Rate and Component Forecasts") {
```

```

# Create the data frame for plotting w/ numerical quarters
H <- length(forecast_list$TR_Forecast)
forecast_quarters_yearqtr <- seq(from = last(data$quarter) + 0.25,
                                by = 0.25,
                                length.out = H)

# b) numeric version (for plotting)
forecast_quarters_numeric <- as.numeric(forecast_quarters_yearqtr)

# c) character version (for labels)
forecast_quarters_labels <- as.character(forecast_quarters_yearqtr)

forecast_df <- data.frame(
  Quarter = forecast_quarters_numeric,
  "Taylor Rule" = forecast_list$TR_Forecast,
  "Benchmark ARIMA" = forecast_list$BM_Forecast,
  "Inflation" = forecast_list$Inflation_Forecast,
  "Output Gap" = forecast_list$OutputGap_Forecast,
  check.names = FALSE )

# Long format for ggplot
forecast_long <- forecast_df %>%
  pivot_longer(cols = -Quarter,
               names_to = "Forecast_Type",
               values_to = "Value") %>%
  mutate(Plot_Group = case_when(
    Forecast_Type %in% c("Taylor Rule", "Benchmark ARIMA") ~ "Interest Rate Forecasts",
    Forecast_Type %in% c("Inflation", "Output Gap") ~ "Model Input Forecasts"),
    Plot_Group = factor(Plot_Group, levels = c("Interest Rate Forecasts", "Model Input Forecasts")),
    Forecast_Type = factor(Forecast_Type, levels = c("Taylor Rule", "Benchmark ARIMA", "Inflation", "Output Gap")))

# Actual plot
plot <- ggplot(forecast_long, aes(x = Quarter, y = Value, color = Forecast_Type)) +
  geom_line(linewidth = 1.1) +
  geom_point(size = 2.5) +
  facet_wrap(~ Plot_Group, ncol = 1, scales = "free_y") +
  # Prettyness
  labs(title = title,
        x = "Quarter",
        y = "Value (%)",
        color = "Forecast Series") +
  scale_x_continuous(breaks = forecast_quarters_numeric,
                     labels = forecast_quarters_labels) +
  theme_minimal(base_size = 14) +
  theme(legend.position = "bottom",
        plot.title = element_text(face = "bold", size = 14),
        plot.subtitle = element_text(size = 12),
        strip.text = element_text(face = "bold", size = 12),
        axis.text.x = element_text(angle = 45, hjust = 1) ) +
  scale_color_brewer(palette = "Set1")
return(plot) }

```

Forecasting

```
# Formula 4 seems to work best
our_predict <- function(data, formula, H){

  # --- 1. Fit inputs and benchmark models ---
  inflation_arma <- my.auto.arima(data$inflation_gap, max.p=4, max.q=4, d=1)
  outputgap_arma <- my.auto.arima(data$output_gap, max.p=4, max.q=4, d=0)
  interest_arma <- my.auto.arima(data$rate, max.p=4, max.q=4, d=1) # Benchmark

  # --- 2. Get forecasts of inputs (all H horizons) ---
  inflation_forecasts <- my.forecast(inflation_arma, h = H)
  outputgap_forecasts <- my.forecast(outputgap_arma, h = H)
  BMpredicted_rates <- my.forecast(interest_arma, h = H)

  # --- 3. Fit TR model
  TR_model <- lm(formula, data = data)

  # --- 4. Build forecast input data frame (iteratively for lags) ---

  # Allocate storage for full horizon
  TR_preds <- numeric(H)

  # Get last known lags (starting point for lagged models)
  current_shadowrate_lag <- last(data$shadowrate)
  current_rate_lag <- last(data$rate)

  for (h in 1:H) {
    new_data_h <- data.frame(
      inflation_gap = inflation_forecasts[h],
      #exp_inflation_gap = exp_inflation_forecasts[h],
      output_gap = outputgap_forecasts[h],
      shadowrate_lag = current_shadowrate_lag,
      rate_lag = current_rate_lag)

    # Get forecasted values
    pred_h <- predict(TR_model, new_data_h)
    TR_preds[h] <- round(pmax(pred_h, min(data$rate)) / 0.25) * 0.25

    # Update the lag for h+1
    current_rate_lag <- pred_h }

  # --- 5. Compute forecast for BM ---
  BM_preds <- round(pmax(BMpredicted_rates, min(data$rate)) / 0.25) * 0.25

  return(list(TR_Forecast = TR_preds,
             BM_Forecast = BM_preds,
             Inflation_Forecast = inflation_forecasts + 2, #to add back target
             OutputGap_Forecast = outputgap_forecasts ))}

final_forecasts <- our_predict(data = data, formula = formula_3, H = H)
```

Table 14

Horizon: Quarter	Taylor Rule Forecast	Benchmark Forecast	Inflation Forecast	Output Gap Forecast
1: 2025 Q3	2.00	1.75	1.98	0.76
2: 2025 Q4	1.75	1.25	2.04	0.94
3: 2026 Q1	1.75	1.25	1.85	1.03
4: 2026 Q2	1.75	1.00	1.91	0.99
5: 2026 Q3	1.50	1.00	1.95	0.86
6: 2026 Q4	1.50	1.00	1.98	0.65
7: 2027 Q1	1.50	1.25	2.00	0.43
8: 2027 Q2	1.50	1.25	2.01	0.21
9: 2027 Q3	1.25	1.25	2.02	0.02
10: 2027 Q4	1.25	1.25	2.03	-0.11

```
display_forecasts(final_forecasts,
                  caption = "",
                  format = format)
```

```
plot_forecasts(final_forecasts)
```

