

FDI Impacts on Income Inequality

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Setup and summary information

General Set-up

```
setwd("/Users/arthurjohnson/Library/CloudStorage/OneDrive-UniversityofEdinburgh/Year  
↳ 4/Dissertation/Meta-Analysis/Dissertation_Data_Analysis")  
FDII <- read_excel("FDI_Inequality_R_input.xlsx")  
FDII$control_variables_1 <- as.factor(FDII$control_variables_1)  
FDII$control_variables_2 <- as.factor(FDII$control_variables_2)  
FDII$control_variables_3 <- as.factor(FDII$control_variables_3)  
FDII$control_variables_4 <- as.factor(FDII$control_variables_4)  
FDII$control_variables_5 <- as.factor(FDII$control_variables_5)  
FDII$estimation_methods <- as.factor(FDII$estimation_methods)  
FDII$coefficient <- as.numeric(FDII$coefficient)  
FDII$journal_rank <- as.numeric(FDII$journal_rank)  
FDII$log_journal_rank <- log(FDII$journal_rank)  
FDII$se <- as.numeric(FDII$se)  
FDII$t_value <- as.numeric(FDII$t_value)  
FDII$t_value_calculated <- as.numeric(FDII$t_value_calculated)  
FDII$p_value <- as.numeric(FDII$p_value)
```

```
# This data is from the Maddison Project (2020)  
Income_Data <- read.csv("Country_Income_Data.csv")  
Income_Data$avg_GDPPC_pc <-  
↳ log((Income_Data$Developed_Sum)/(Income_Data$Country_table_count*(Income_Data$sample_period_end-I  
FDII$mean_log_GDPPC <- Income_Data$avg_GDPPC_pc  
Income_Data$log10_GDPPC_pc <-  
↳ log10((Income_Data$Developed_Sum)/(Income_Data$Country_table_count*(Income_Data$sample_period_end-I  
FDII$mean_log10_GDPPC <- Income_Data$log10_GDPPC_pc
```

```
Income_Data[, 200:8648] <- apply(Income_Data[, 200:8648], 2, function(x) {  
  x <- as.numeric(x)  
  x[x == 0] <- NA  
  return(x)  
})
```

```
Income_Data$median_GDPPC <- apply(Income_Data[, 200:8648], 1, median, na.rm = TRUE)  
FDII$median_log_GDPPC <- log(Income_Data$median_GDPPC)
```

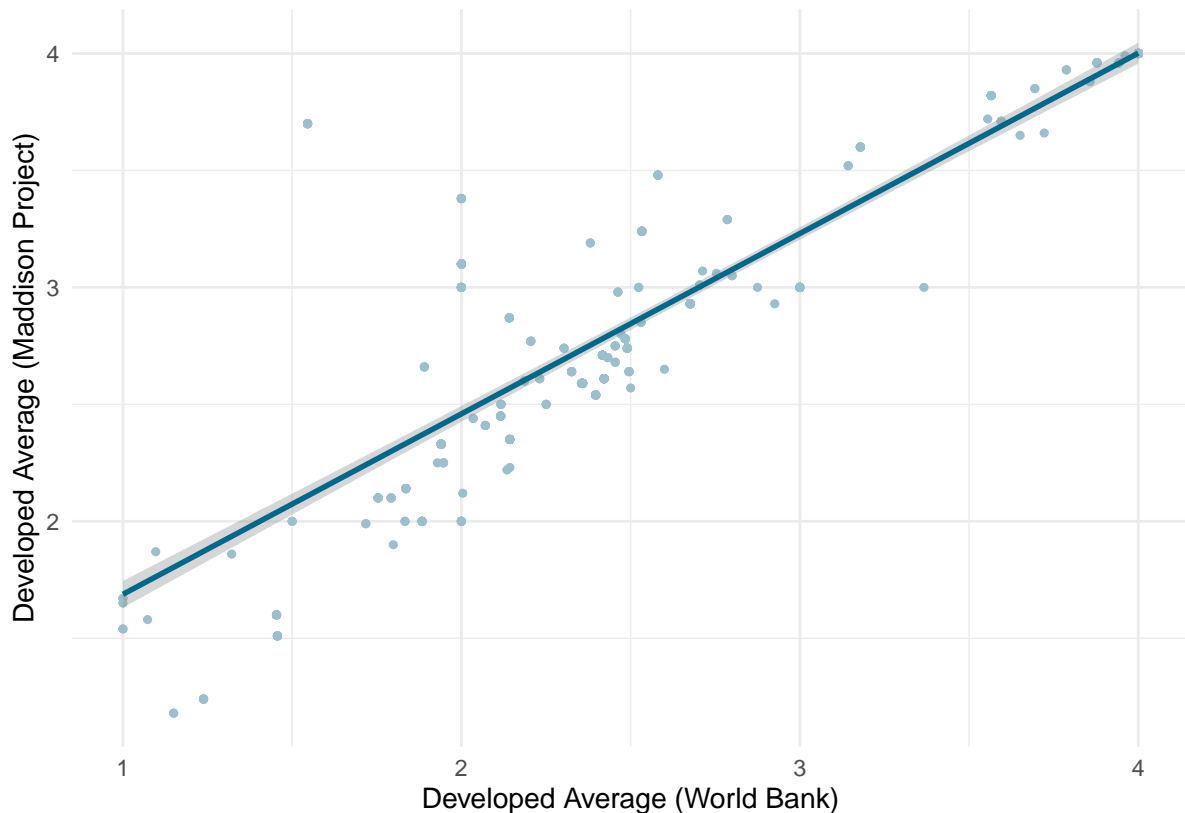
```
MP_df <- read.csv("MADDISON_PROJECT_DATA.csv")  
MP_df <- MP_df[!MP_df$unique_id %in% c("16005", "16006", "45013", "45014", "45015",  
↳ "45016", "45017", "45018", "45019", "45020", "45021", "45022", "45023",  
↳ "45024"), ]
```

```
MP_df <- MP_df[, -(4:195)]
MP_df <- MP_df[, -(11:11434)]
```

```
FDII$MP_LI_count <- MP_df$LI_count
FDII$MP_LMI_count <- MP_df$LMI_count
FDII$MP_MHI_count <- MP_df$MHI_count
FDII$MP_HI_count <- MP_df$HI_count
FDII$MP_dev_avg <- MP_df$Developed_Average
FDII$MP_dev_sum <- MP_df$Developed_Sum
FDII$MP_incl_count <- MP_df$Developed_Count
```

```
# Plot thw two different averages
ggplot(FDII, aes(x = developed_average, y = MP_dev_avg)) +
  geom_point(size = 1, color = "lightblue3") +
  geom_smooth(method = "lm", color = "deepskyblue4") +
  labs(x = "Developed Average (World Bank)",
       y = "Developed Average (Maddison Project)") +
  theme_minimal()
```

```
## `geom_smooth()` using formula = 'y ~ x'
```



Collective country count

```
collective_country_codes <- unlist(strsplit(as.character(FDII$country_code),
  ↳ ";\\s*"))
collective_country_code_frequencies <-
  ↳ as.data.frame(table(collective_country_codes))
names(collective_country_code_frequencies) <- c('ISO_code', 'frequency')
collective_country_code_frequencies$ISO_code <-
  ↳ as.character(collective_country_code_frequencies$ISO_code)
```

```

collective_country_code_frequencies$country_name <-
  ↳ countrycode(collective_country_code_frequencies$ISO_code, origin = 'iso3c',
  ↳ 'iso3c')
collective_country_code_frequencies$ISO_code <-
  ↳ as.numeric(collective_country_code_frequencies$ISO_code)
collective_country_code_frequencies$country_name <-
  ↳ countrycode(collective_country_code_frequencies$ISO_code, 'iso3n',
  ↳ 'country.name')
ordered_collective_frequencies <-
  ↳ collective_country_code_frequencies[order(collective_country_code_frequencies$frequency,
  ↳ decreasing = TRUE), ]
collective_count_output <- ordered_collective_frequencies[, c("country_name",
  ↳ "frequency")]
sum(collective_count_output$frequency)

```

```
## [1] 18238
```

Individual country count

```

single_country_studies <- FDII[FDII$level != 3, ]
single_country_codes <-
  ↳ unlist(strsplit(as.character(single_country_studies$country_code), ";\\s*"))
single_country_code_frequencies <- as.data.frame(table(single_country_codes))
names(single_country_code_frequencies) <- c('ISO_code', 'frequency')
single_country_code_frequencies$ISO_code <-
  ↳ as.character(single_country_code_frequencies$ISO_code)
single_country_code_frequencies$country_name <-
  ↳ countrycode(single_country_code_frequencies$ISO_code, origin = 'iso3c', 'iso3c')
single_country_code_frequencies$ISO_code <-
  ↳ as.numeric(single_country_code_frequencies$ISO_code)
single_country_code_frequencies$country_name <-
  ↳ countrycode(single_country_code_frequencies$ISO_code, 'iso3n', 'country.name')
ordered_single_frequencies <-
  ↳ single_country_code_frequencies[order(single_country_code_frequencies$frequency,
  ↳ decreasing = TRUE), ]
single_count_output <- ordered_single_frequencies[, c('country_name', 'frequency')]
sum(single_count_output$frequency)

```

```
## [1] 252
```

Multi-country count

```

multi_country_studies <- FDII[FDII$level == 3, ]
multi_country_codes <-
  ↳ unlist(strsplit(as.character(multi_country_studies$country_code), ";\\s*"))
multi_country_code_frequencies <- as.data.frame(table(multi_country_codes))
names(multi_country_code_frequencies) <- c('ISO_code', 'frequency')
multi_country_code_frequencies$ISO_code <-
  ↳ as.character(multi_country_code_frequencies$ISO_code)
multi_country_code_frequencies$country_name <-
  ↳ countrycode(multi_country_code_frequencies$ISO_code, origin = 'iso3c', 'iso3c')
multi_country_code_frequencies$ISO_code <-
  ↳ as.numeric(multi_country_code_frequencies$ISO_code)
multi_country_code_frequencies$country_name <-
  ↳ countrycode(multi_country_code_frequencies$ISO_code, 'iso3n', 'country.name')

```

```
ordered_multi_frequencies <-
  ↳ multi_country_code_frequencies[order(multi_country_code_frequencies$frequency,
  ↳ decreasing = TRUE), ]
multi_count_output <- ordered_multi_frequencies[, c('country_name', 'frequency')]
sum(multi_count_output$frequency)
```

```
## [1] 17986
```

Find counts and other relevant data to for the summary table creation

```
# Count of regression tests used:
table(FDII$estimation_methods)
```

```
##
##              2SLS              3SLS
##              21              1
##              ARDL      Between effects
##              3              2
##              CCE              DOLS
##              4              24
##              ECM              FM-OLS
##              2              6
##              GLS              GMM
##              7              104
##              IV Johansen's cointegration test
##              28              16
##              LIML              LSDV
##              5              1
##              OLS              Panel
##              139             215
##              Parks              Probit
##              2              4
##              Random effect      SUR
##              24              1
##              SURE
##              7
```

```
# Count of published papers:
table(FDII$if_published)
```

```
##
##    0    1
## 50 566
```

```
# Count of FDI measure used:
# Number 1 and 9 are the Gini coefficients
table(FDII$FDI)
```

```
##
##  1  2  3  4  5  6  7  8  9 11 12 13 15 18
## 263  6  2 26 44 44 14 16 180  4  4  4  2  7
```

```
# Count of Inequality measure used:
table(FDII$Inequality)
```

```
##
##  1  3  4  5  8  9 10 13 14 15 16 17
```

```
## 413 20 37 91 3 11 1 6 19 13 1 1
```

```
# Count of single and multi-country studies:  
table(FDII$level)
```

```
##  
## 1 2 3  
## 148 104 364
```

```
# Count of regression tests used given they were published:  
table(FDII$estimation_methods, FDII$if_published==1)
```

```
##  
## FALSE TRUE  
## 2SLS 2 19  
## 3SLS 0 1  
## ARDL 0 3  
## Between effects 0 2  
## CCE 0 4  
## DOLS 10 14  
## ECM 0 2  
## FM-OLS 0 6  
## GLS 0 7  
## GMM 8 96  
## IV 0 28  
## Johansen's cointegration test 10 6  
## LIML 0 5  
## LSDV 0 1  
## OLS 10 129  
## Panel 9 206  
## Parks 0 2  
## Probit 0 4  
## Random effect 1 23  
## SUR 0 1  
## SURE 0 7
```

```
# Count of Inequality measure used given they were published:  
table(FDII$Inequality, FDII$if_published==1)
```

```
##  
## FALSE TRUE  
## 1 42 371  
## 3 0 20  
## 4 8 29  
## 5 0 91  
## 8 0 3  
## 9 0 11  
## 10 0 1  
## 13 0 6  
## 14 0 19  
## 15 0 13  
## 16 0 1  
## 17 0 1
```

```
# Count of FDI measure used given they were published  
table(FDII$FDI, FDII$if_published==1)
```

```
##
```

```
##      FALSE TRUE
##  1      38  225
##  2       0   6
##  3       0   2
##  4       0  26
##  5       0  44
##  6       0  44
##  7       0  14
##  8       0  16
##  9       4 176
## 11       4   0
## 12       4   0
## 13       0   4
## 15       0   2
## 18       0   7
```

```
#Replace all NAs with 'BLANK' in the control variables
```

```
FDII$control_variables_1 <- as.character(FDII$control_variables_1)
FDII$control_variables_1[is.na(FDII$control_variables_1)] <- "NO CONTROL"
FDII$control_variables_2 <- as.character(FDII$control_variables_2)
FDII$control_variables_2[is.na(FDII$control_variables_2)] <- "NO CONTROL"
FDII$control_variables_3 <- as.character(FDII$control_variables_3)
FDII$control_variables_3[is.na(FDII$control_variables_3)] <- "NO CONTROL"
FDII$control_variables_4 <- as.character(FDII$control_variables_4)
FDII$control_variables_4[is.na(FDII$control_variables_4)] <- "NO CONTROL"
FDII$control_variables_5 <- as.character(FDII$control_variables_5)
FDII$control_variables_5[is.na(FDII$control_variables_5)] <- "NO CONTROL"
```

```
# Info on control variable counts
```

```
selected_columns <- FDII[, c("control_variables_1", "control_variables_2",
  ↪ "control_variables_3", "control_variables_4", "control_variables_5")]
unlist <- tolower(unlist(selected_columns, use.names = FALSE))
count_table <- table(unlist)
count_df <- as.data.frame(count_table)
names(count_df) <- c("Variable", "Included")
count_df$notincl <- 616 - count_df$Included
count_df[order(-count_df$Included), ]
```

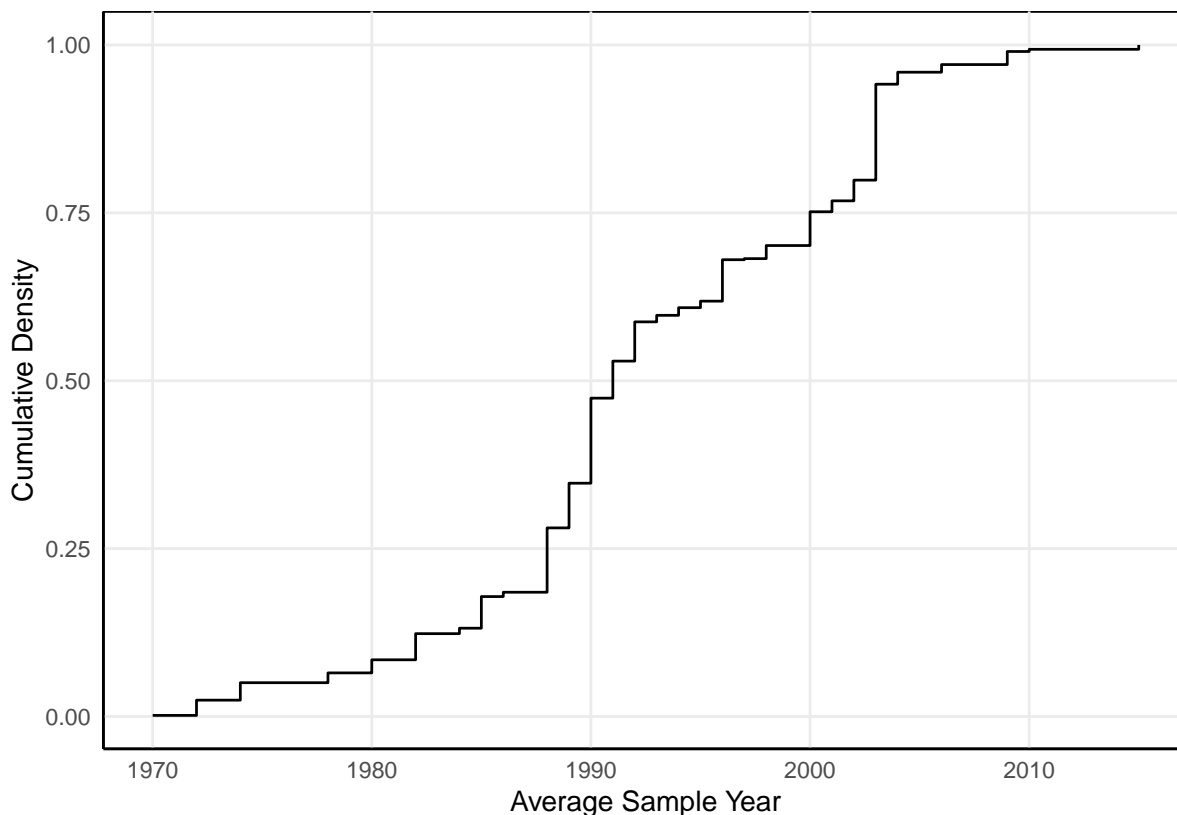
```
##      Variable Included notincl
## 47      no control      813    -197
## 16 education_secondary_school_enrollment      292     324
## 28              gdppc      263     353
## 71              trade      176     440
## 52              pop      167     449
## 39      inflation      162     454
## 25              gdp      118     498
## 72      unemployment      115     501
## 32              gov_exp      98     518
## 29              gdppc^2      88     528
## 48      openness      74     542
## 3      agriculture      70     546
## 27              gdpgr      65     551
## 57      private_credit      45     571
## 35      human_capital      40     576
## 7      capital      39     577
## 54              popgr      34     582
## 36      import      32     584
```

## 22	exports	28	588
## 75	value-added	26	590
## 66	tariff	23	593
## 19	exchange_rate	20	596
## 67	tech	20	596
## 38	industry_employment	16	600
## 58	r&d	16	600
## 73	union	15	601
## 37	industry	13	603
## 30	gini	12	604
## 11	cpi	11	605
## 15	education_middle_school_enrollment	11	605
## 61	sector_dualism	11	605
## 8	communist	10	606
## 13	democracy	10	606
## 53	pop_over_65	10	606
## 55	portfolio_inflow	9	607
## 9	company	8	608
## 26	gdp^2	8	608
## 33	gov_quality	8	608
## 34	herfindahl-hirschman_index	8	608
## 44	manufacturing_real_gross_output	8	608
## 45	market_share	8	608
## 24	financial_development	7	609
## 6	black_market	6	610
## 74	urbanisation	6	610
## 68	tech_import	4	612
## 5	asia	3	613
## 10	country_size	3	613
## 17	elect	3	613
## 18	exchange	3	613
## 23	fdi*exports	3	613
## 41	lac	3	613
## 63	shadow_economy	3	613
## 64	socialist_state	3	613
## 69	tourism	3	613
## 14	economic_freedom	2	614
## 21	export_incentives	2	614
## 40	labor_productivity	2	614
## 42	landpc	2	614
## 43	m2	2	614
## 46	migration	2	614
## 62	service	2	614
## 65	soe_share	2	614
## 70	tourism^2	2	614
## 1	-	1	615
## 2	agricultural_exports	1	615
## 4	aid	1	615
## 12	debt	1	615
## 20	export_growth	1	615
## 31	gni	1	615
## 49	pcm	1	615
## 50	phone	1	615
## 51	political_integration	1	615
## 56	poverty	1	615
## 59	relative_productivity	1	615

Average year visualisation

```
FDII$avg_sample_year <- round((FDII$sample_period_start + (FDII$sample_period_end -
  ↪ FDII$sample_period_start)/2),0)

ggplot(FDII, aes(x = avg_sample_year), width = 8, height = 6) +
  stat_ecdf(geom = "step", pad = FALSE) +
  labs(x = "Average Sample Year",
    y = "Cumulative Density") +
  theme_minimal() +
  theme(plot.background = element_rect(fill = "transparent", color = NA),
    panel.background = element_rect(fill = "white"),
    panel.grid.minor = element_blank(),
    panel.border = element_blank(),
    axis.line = element_line(color = "black"))
```



```
ggsave("average_sample_year_plot.png", bg = "transparent", width = 8, height = 6)
```

t-statistic density by strength

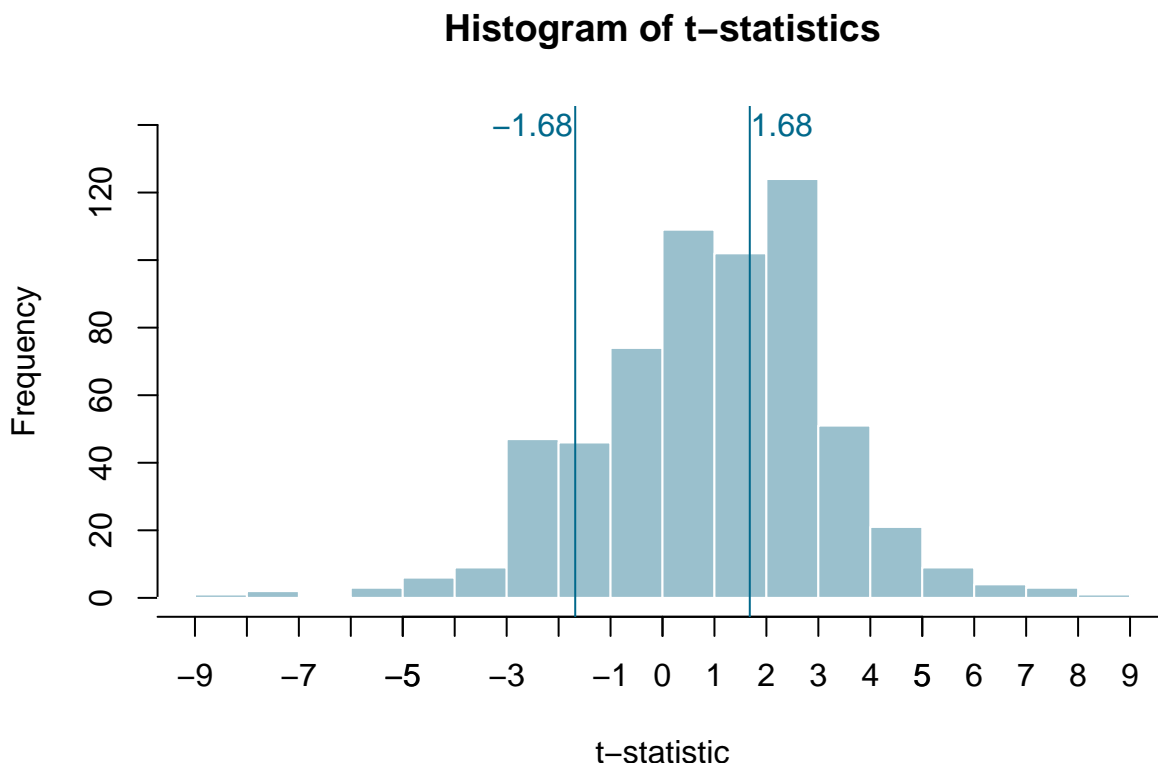
```
hist(FDII$t_value_calculated,
  breaks = 30,
  xlim = c(-9, 9),
  ylim = c(0, 140),
  xlab = "t-statistic",
  col = "lightblue3",
  border = "white",
```



```

main = "Histogram of t-statistics")
axis(1, at = -10:10)
abline(v = -1.68, col = "deepskyblue4", lwd = 1, lty = 1)
text(x = -2.5, y = 140, '-1.68', col = "deepskyblue4")
abline(v = 1.68, col = "deepskyblue4", lwd = 1, lty = 1)
text(x = 2.3, y = 140, '1.68', col = "deepskyblue4")

```



Further setup for MRA and initial tests

Set up Partial Correlation Coefficient

```

FDII$PCC <-
  ↪ (FDII$t_value_calculated)/sqrt((FDII$t_value_calculated)^2+FDII$degree_freedom)
FDII$PCC_se <- sqrt((1-(FDII$PCC)^2)/FDII$degree_freedom)
mean(FDII$PCC)

```

```
## [1] 0.08913153
```

```
mean(FDII$PCC_se)
```

```
## [1] 0.1014291
```

This is from Stanley and Doucouliagos (2012) - ENSURE citation!!

Calculate averages within and out of OECD countries

```

# Number and proportion of studies that were conducted in only OECD countries (both
  ↪ individual and multi-country studies)
print(paste("The number of studies that focused solely on OECD countries is",
  ↪ length(FDII$if_OECD[FDII$if_OECD==1]), "-- This includes individual-level
  ↪ studies"))

```

```
## [1] "The number of studies that focused solely on OECD countries is 188 -- This includes individual-level studies"
print(paste("The number of studies that focused solely on non-OECD countries is",
  ↳ length(FDII$if_OECD[FDII$if_OECD==0]), "-- This includes individual-level studies"))

## [1] "The number of studies that focused solely on non-OECD countries is 428 -- This includes individual-level studies"
print(paste("The proportion of studies that focused solely on OECD countries is",
  ↳ round(100*length(FDII$if_OECD[FDII$if_OECD==1])/(length(FDII$if_OECD[FDII$if_OECD==1])
  ↳ + length(FDII$if_OECD[FDII$if_OECD==0])), 2),"%"))

## [1] "The proportion of studies that focused solely on OECD countries is 30.52 %"
OECD_multi <- length(FDII$if_OECD[FDII$if_OECD == 1 & FDII$level == 3])
print(paste("The number of multi-country studies that focused solely on OECD
  ↳ countries is", OECD_multi))

## [1] "The number of multi-country studies that focused solely on OECD countries is 22"
nonOECD_multi <- length(FDII$if_OECD[FDII$if_OECD == 0 & FDII$level == 3])
print(paste("The number of multi-country studies that focused solely on non-OECD
  ↳ countries is", nonOECD_multi))

## [1] "The number of multi-country studies that focused solely on non-OECD countries is 342"
print(paste("The proportion of multi-country studies that focused solely on OECD
  ↳ countries is", round(100*OECD_multi/(OECD_multi + nonOECD_multi), 2),"%"))

## [1] "The proportion of multi-country studies that focused solely on OECD countries is 6.04 %"
OECD_single <- length(FDII$if_OECD[FDII$if_OECD == 1 & FDII$level != 3])
print(paste("The number of single-country studies that focused solely on OECD
  ↳ countries is", OECD_single))

## [1] "The number of single-country studies that focused solely on OECD countries is 166"
nonOECD_single <- length(FDII$if_OECD[FDII$if_OECD == 0 & FDII$level != 3])
print(paste("The number of single-country studies that focused solely on non-OECD
  ↳ countries is", nonOECD_single))

## [1] "The number of single-country studies that focused solely on non-OECD countries is 86"
print(paste("The proportion of single-country studies that focused solely on OECD
  ↳ countries is", round(100*OECD_single/(OECD_single + nonOECD_single), 2),"%"))

## [1] "The proportion of single-country studies that focused solely on OECD countries is 65.87 %"
print(paste("The mean of the PCC of non-OECD focussed studies (single- and
  ↳ multi-country studies)", round(mean(FDII$PCC[FDII$if_OECD==0]),3)))

## [1] "The mean of the PCC of non-OECD focussed studies (single- and multi-country studies) 0.138"
print(paste("The standard error of the PCC of non-OECD focussed studies (single- and
  ↳ multi-country studies)", round(mean(FDII$PCC_se[FDII$if_OECD==0]),3)))

## [1] "The standard error of the PCC of non-OECD focussed studies (single- and multi-country studies) 0.022"
print(paste("The mean of the PCC of OECD-focussed studies (single- and multi-country
  ↳ studies)", round(mean(FDII$PCC[FDII$if_OECD==1]),3)))

## [1] "The mean of the PCC of OECD-focussed studies (single- and multi-country studies) -0.022"
```

```
print(paste("The standard error of the PCC of OECD-focussed studies (single- and
→ multi-country studies)", round(mean(FDII$PCC_se[FDII$if_OECD==1]),3)))
```

```
## [1] "The standard error of the PCC of OECD-focussed studies (single- and multi-country studies) 0."
```

```
print(paste("The mean of the PCC of OECD-focussed studies (single-country studies)",
→ round(mean(FDII$PCC[FDII$if_OECD == 1 & FDII$level != 3]),3)))
```

```
## [1] "The mean of the PCC of OECD-focussed studies (single-country studies) -0.013"
```

```
print(paste("The standard error of the PCC of OECD-focussed studies (single-country
→ studies)", round(mean(FDII$PCC_se[FDII$if_OECD == 1 & FDII$level != 3]),3)))
```

```
## [1] "The standard error of the PCC of OECD-focussed studies (single-country studies) 0.068"
```

```
print(paste("The mean of the PCC of non-OECD focussed studies (single-country
→ studies)", round(mean(FDII$PCC[FDII$if_OECD == 0 & FDII$level != 3]),3)))
```

```
## [1] "The mean of the PCC of non-OECD focussed studies (single-country studies) 0.066"
```

```
print(paste("The standard error of the PCC of non-OECD focussed studies
→ (single-country studies)", round(mean(FDII$PCC_se[FDII$if_OECD == 0 & FDII$level
→ != 3]),3)))
```

```
## [1] "The standard error of the PCC of non-OECD focussed studies (single-country studies) 0.181"
```

```
print(paste("The mean of the PCC of OECD-focussed studies (multi-country studies)",
→ round(mean(FDII$PCC[FDII$if_OECD == 1 & FDII$level == 3]),3)))
```

```
## [1] "The mean of the PCC of OECD-focussed studies (multi-country studies) -0.089"
```

```
print(paste("The standard error of the PCC of OECD-focussed studies (multi-country
→ studies)", round(mean(FDII$PCC_se[FDII$if_OECD == 1 & FDII$level == 3]),3)))
```

```
## [1] "The standard error of the PCC of OECD-focussed studies (multi-country studies) 0.076"
```

```
print(paste("The mean of the PCC of non-OECD focussed studies (multi-country
→ studies)", round(mean(FDII$PCC[FDII$if_OECD == 0 & FDII$level == 3]),3)))
```

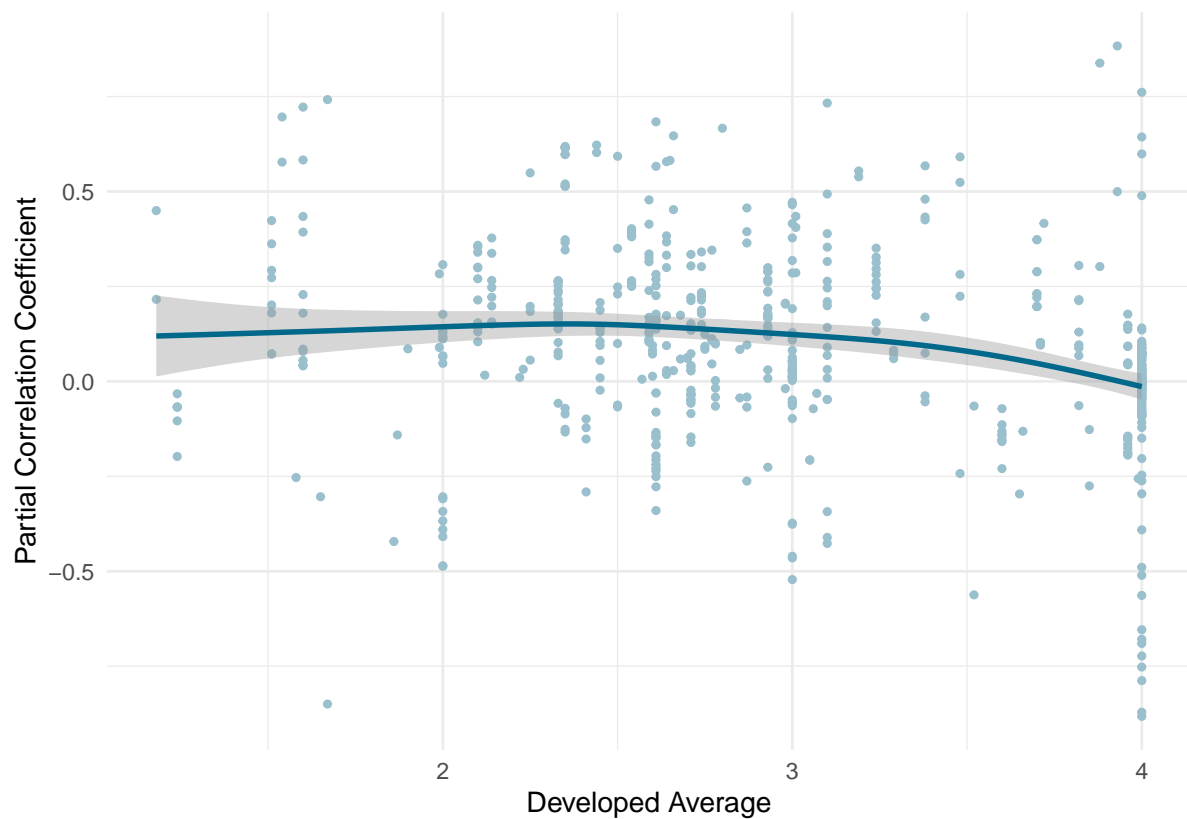
```
## [1] "The mean of the PCC of non-OECD focussed studies (multi-country studies) 0.156"
```

```
print(paste("The standard error of the PCC of non-OECD focussed studies
→ (multi-country studies)", round(mean(FDII$PCC_se[FDII$if_OECD == 0 & FDII$level
→ == 3]),3)))
```

```
## [1] "The standard error of the PCC of non-OECD focussed studies (multi-country studies) 0.1"
```

Initial plots

```
ggplot(data = FDII, aes(x = MP_dev_avg, y = PCC)) +
  geom_point(size = 1, color = "lightblue3") +
  geom_smooth(method = "gam", formula = y ~ s(x, bs = "cs"), color = "deepskyblue4")
→ +
  labs(x = "Developed Average",
  y = "Partial Correlation Coefficient") +
  theme_minimal()
```

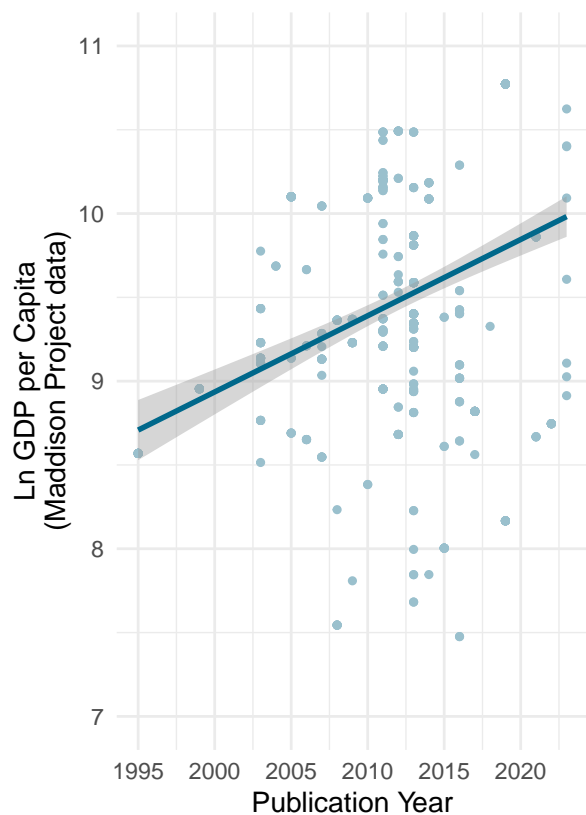
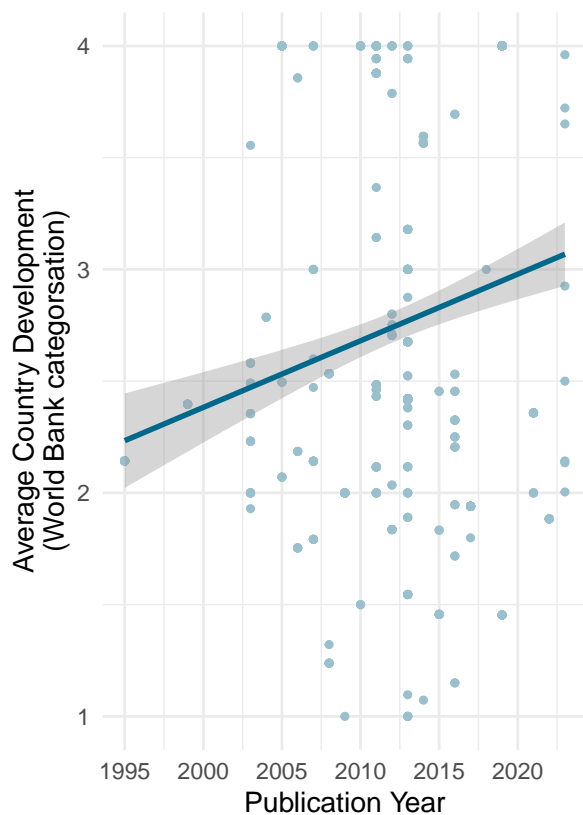


```
WB_pub <- ggplot(data = FDII, aes(x = publication_time, y = developed_average)) +
  geom_point(color = "lightblue3", size = 1) +
  geom_smooth(method = "lm", color = "deepskyblue4") +
  labs(x = "Publication Year",
       y = "Average Country Development\n(World Bank categorisation)") +
  theme_minimal()

MP_pub <- ggplot(data = FDII, aes(x = publication_time, y =
  ↪ Income_Data$avg_GDPPC_pc)) +
  geom_point(color = "lightblue3", size = 1) +
  geom_smooth(method = "lm", color = "deepskyblue4") +
  ylim(7, 11) +
  labs(x = "Publication Year",
       y = "Ln GDP per Capita\n(Maddison Project data)") +
  theme_minimal()

grid.arrange(WB_pub, MP_pub, ncol = 2)
```

```
## `geom_smooth()` using formula = 'y ~ x'
## `geom_smooth()` using formula = 'y ~ x'
```

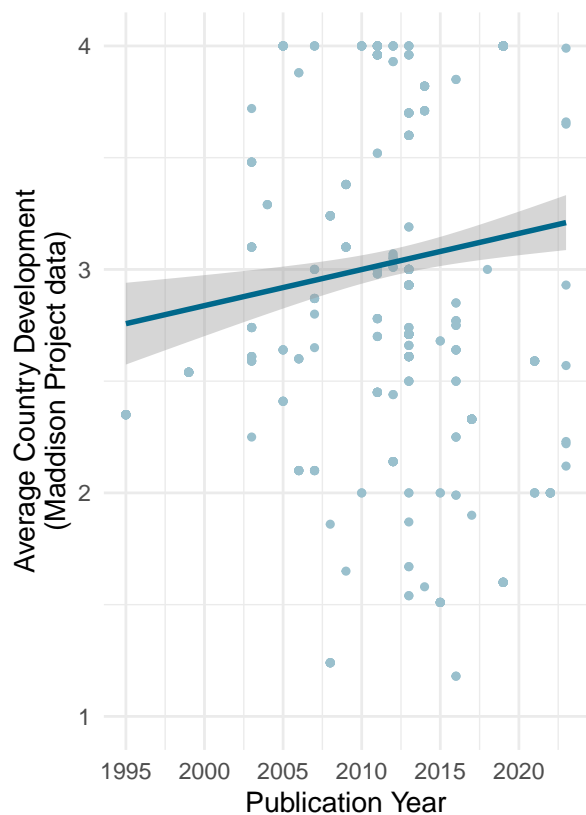
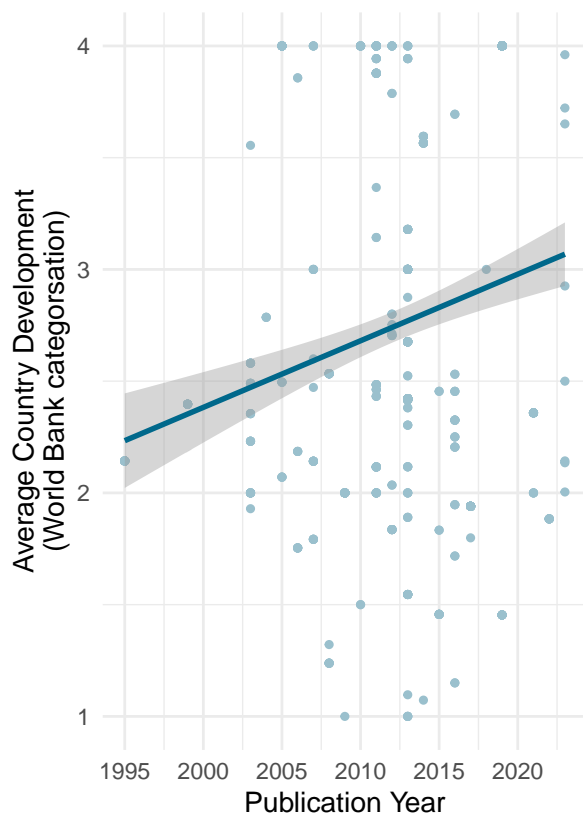


```
WB_pub <- ggplot(data = FDII, aes(x = publication_time, y = developed_average)) +
  geom_point(color = "lightblue3", size = 1) +
  geom_smooth(method = "lm", color = "deepskyblue4") +
  labs(x = "Publication Year",
       y = "Average Country Development\n(World Bank categorisation)") +
  theme_minimal()

MP_pub <- ggplot(data = FDII, aes(x = publication_time, y = MP_dev_avg)) +
  geom_point(color = "lightblue3", size = 1) +
  geom_smooth(method = "lm", color = "deepskyblue4") +
  ylim(1, 4) +
  labs(x = "Publication Year",
       y = "Average Country Development\n(Maddison Project data)") +
  theme_minimal()

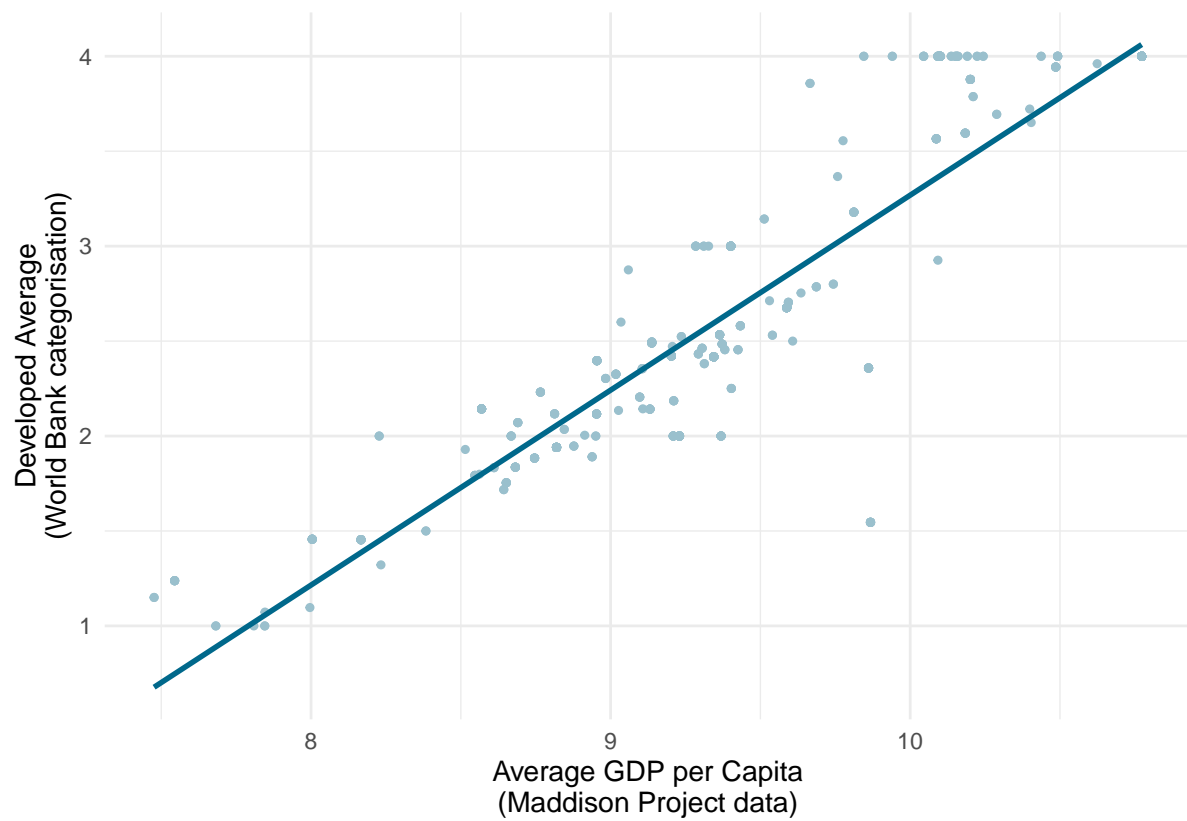
grid.arrange(WB_pub, MP_pub, ncol = 2)
```

```
## `geom_smooth()` using formula = 'y ~ x'
## `geom_smooth()` using formula = 'y ~ x'
```



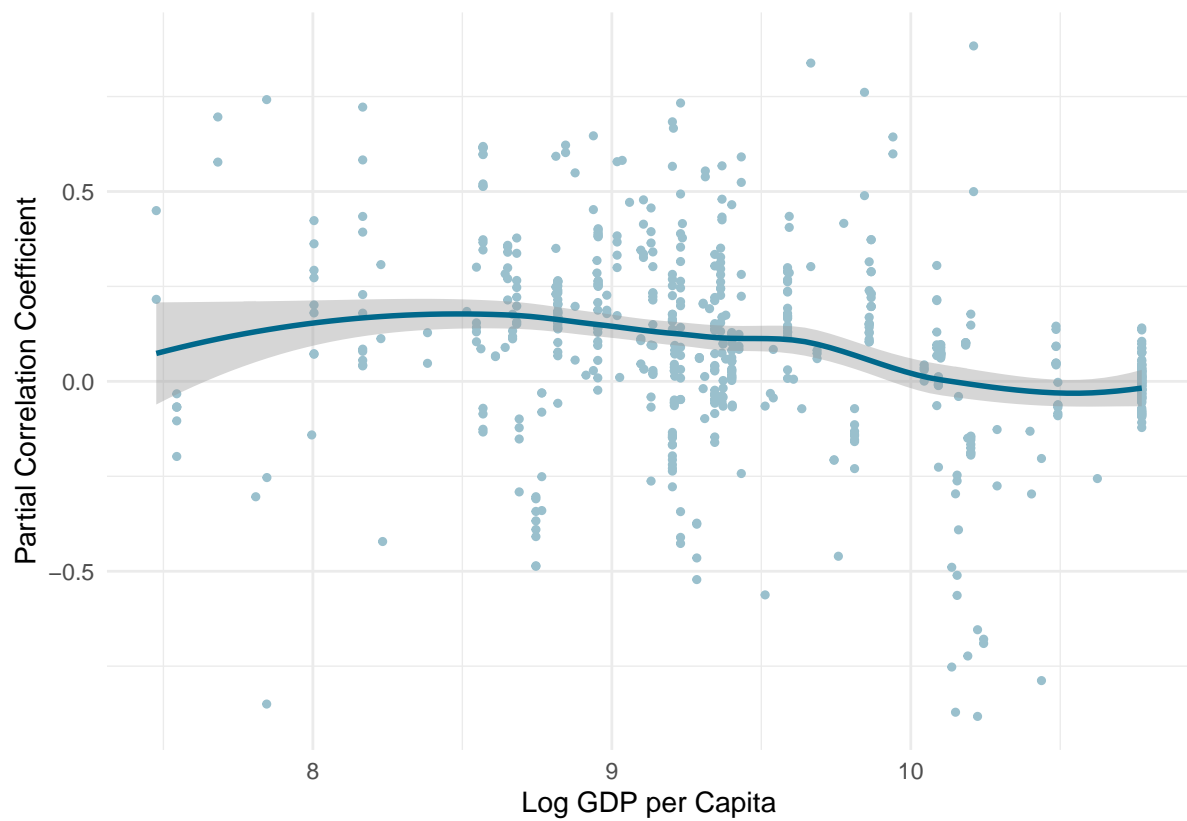
```
ggplot(data = data.frame(Income_Data$avg_GDPPC_pc, FDII$developed_average)) +
  geom_point(aes(x = Income_Data$avg_GDPPC_pc, y = FDII$developed_average), color =
    ↪ "lightblue3", size = 1) +
  geom_smooth(aes(x = Income_Data$avg_GDPPC_pc, y = FDII$developed_average), method
    ↪ = "lm", color = "deepskyblue4", se = FALSE) +
  labs(x = "Average GDP per Capita\n(Maddison Project data)",
    y = "Developed Average\n(World Bank categorisation)") +
  theme_minimal()
```

```
## `geom_smooth()` using formula = 'y ~ x'
```



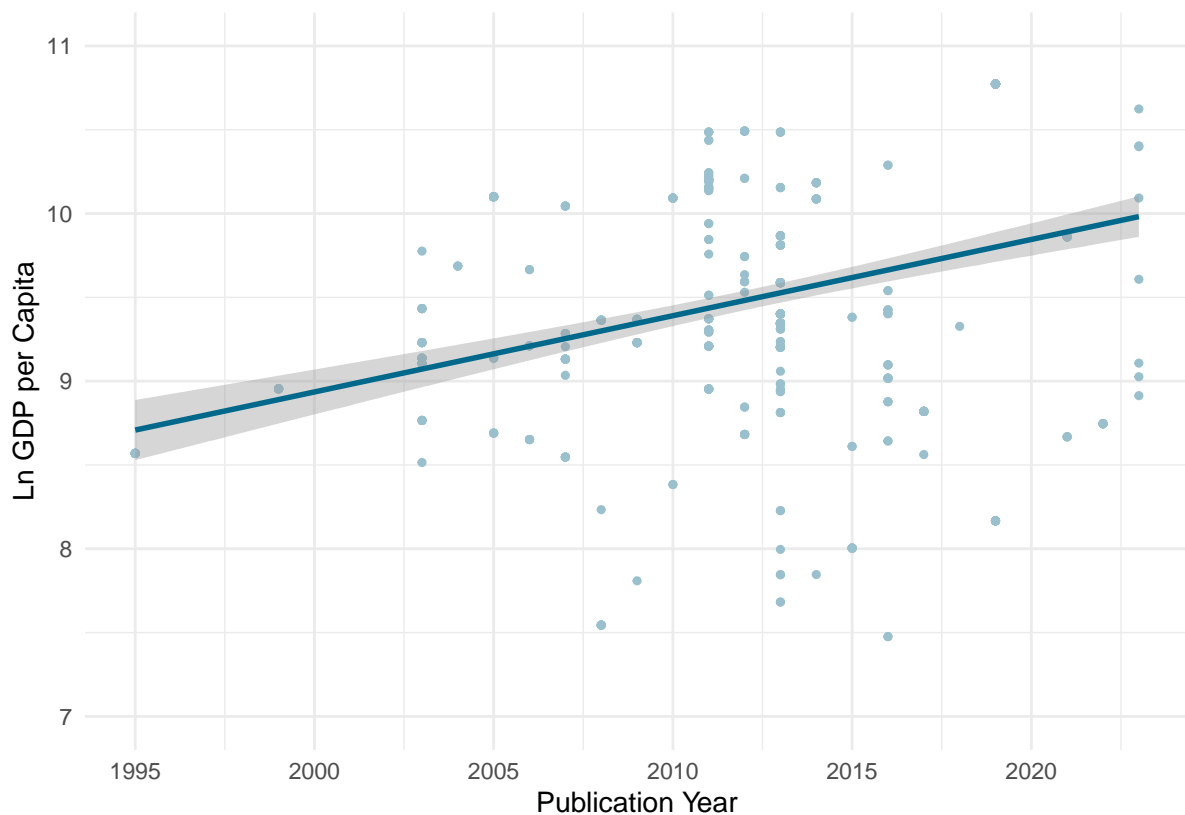
```
ggplot(data = Income_Data, aes(x = avg_GDPPC_pc, y = FDII$PCC)) +
  geom_point(size = 1, color = "lightblue3") +
  geom_smooth(method = "loess", color = "deepskyblue4") +
  labs(x = "Log GDP per Capita",
       y = "Partial Correlation Coefficient") +
  theme_minimal()
```

```
## `geom_smooth()` using formula = 'y ~ x'
```



```
ggplot(data = FDII, aes(x = publication_time, y = Income_Data$avg_GDPPC_pc)) +
  geom_point(color = "lightblue3", size = 1) +
  geom_smooth(method = "lm", color = "deepskyblue4") +
  ylim(7, 11) +
  labs(x = "Publication Year",
       y = "Ln GDP per Capita")+
  theme_minimal()
```

```
## `geom_smooth()` using formula = 'y ~ x'
```

```
maddison_df <- read.csv("Maddison_Data.csv")

maddison_df$LogGDPpc <- log(maddison_df$GDP.per.capita)
maddison_df_recent <- maddison_df[maddison_df$Year > 1950,]

unique_codes <- unique(maddison_df_recent$Code)
grey_blue_colors <- colorRampPalette(c("lightgrey",
  ↪ "lightblue3"))(length(unique_codes))
color_mapping <- setNames(grey_blue_colors, unique_codes)

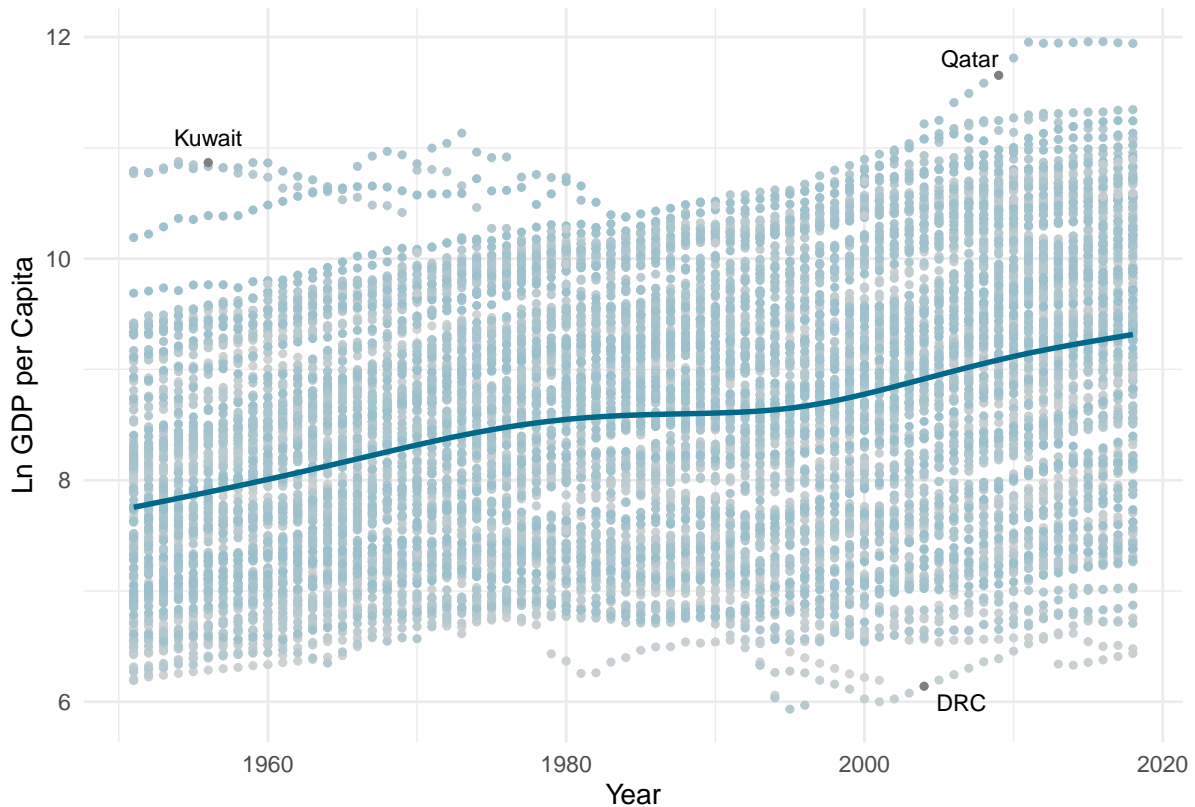
ggplot(data = maddison_df_recent, aes(x = Year, y = LogGDPpc, color = Code)) +
  geom_point(size = 1) +
  geom_smooth(method = "gam", se = FALSE, color = "deepskyblue4") +
  labs(x = "Year",
    y = "Ln GDP per Capita") +
  scale_color_manual(values = color_mapping, breaks = NULL) +
  theme_minimal() +
  geom_text(data = subset(maddison_df_recent, Code == "QAT" & Year == 2009),
    aes(label = "Qatar"),
    vjust = -0.5,
    hjust = 1,
    color = "black",
    size = 3) +
  geom_text(data = subset(maddison_df_recent, Code == "KWT" & Year == 1956),
    aes(label = "Kuwait"),
    vjust = -1,
    color = "black",
    size = 3) +
  geom_text(data = subset(maddison_df_recent, Code == "COD" & Year == 2004),
    aes(label = "DRC"),
```

```

    vjust = 1.5,
    hjust = -0.25,
    color = "black",
    size = 3) +
  geom_point(data = subset(maddison_df_recent, (Code == "QAT" & Year == 2009) |
    (Code == "KWT" & Year == 1956) |
    (Code == "COD" & Year == 2004)),
    aes(color = "black"),
    size = 1)

```

```
## `geom_smooth()` using formula = 'y ~ s(x, bs = "cs")'
```

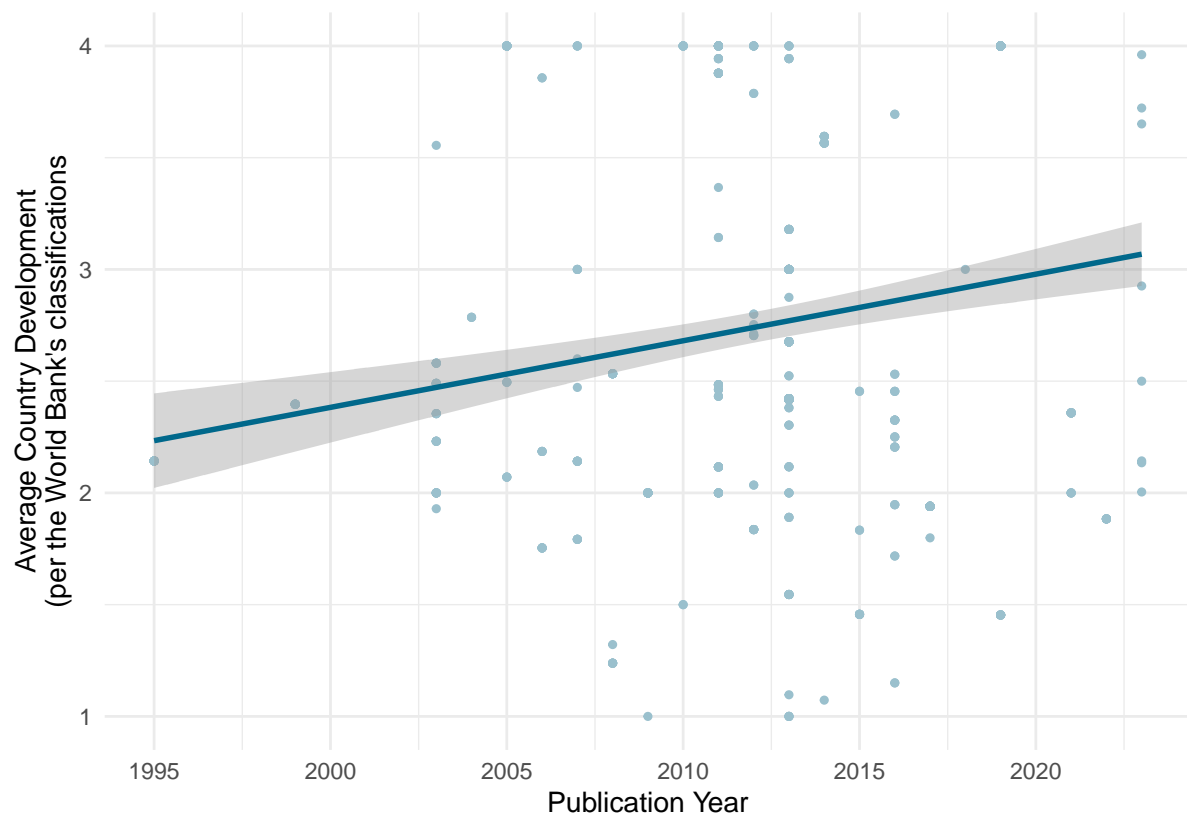


```

ggplot(data = FDII, aes(x = publication_time, y = developed_average)) +
  geom_point(size = 1, color = "lightblue3") +
  geom_smooth(method = "lm", color = "deepskyblue4") +
  labs(x = "Publication Year",
    y = "Average Country Development\n(per the World Bank's classifications)") +
  theme_minimal()

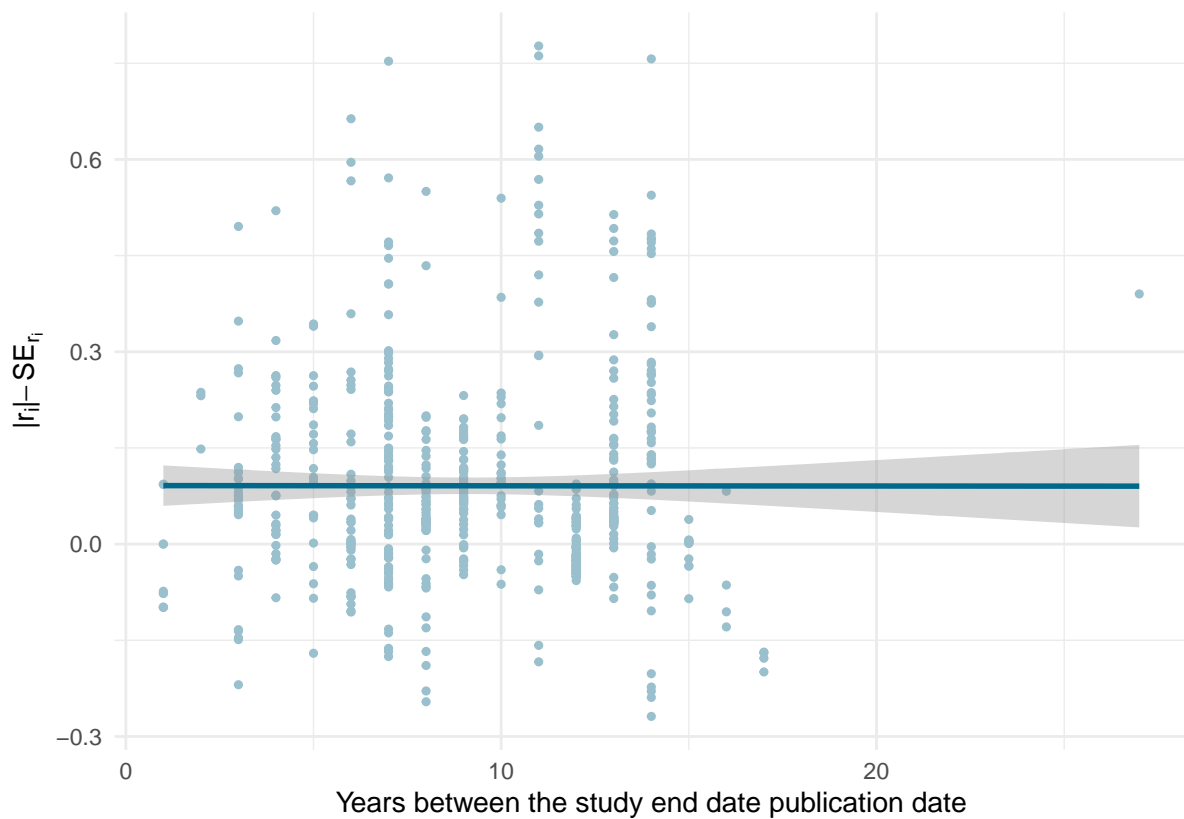
```

```
## `geom_smooth()` using formula = 'y ~ x'
```



```
ggplot(data = FDII, aes(x = publication_time-sample_period_end, y =
  ↪ abs(PCC)-PCC_se)) +
  geom_point(size = 1, color = "lightblue3") +
  geom_smooth(method = "lm", color = "deepskyblue4") +
  labs(x = "Years between the study end date publication date",
    y = expression(paste("|", r[i], "|", - SE[r[i]]))) +
  theme_minimal()
```

```
## `geom_smooth()` using formula = 'y ~ x'
```



Setup for meta regression analysis by drawing out control variables into binary data

```
# Step 1: Pivot longer
FDII_long <- FDII %>%
  pivot_longer(cols = starts_with("control_variables_"),
               names_to = "Control_Variable_Type",
               values_to = "Control_Variable_Name") %>%
  filter(!is.na(Control_Variable_Name) & Control_Variable_Name != "")

# Step 2: Pivot wider and create indicator variables
FDII_wide <- FDII_long %>%
  mutate(Presence = 1) %>%
  pivot_wider(names_from = Control_Variable_Name, values_from = Presence,
             values_fill = list(Presence = 0))

# Step 3: Group by and summarise only numeric columns
FDII_merged <- FDII_wide %>%
  group_by(citation, coefficient, t_value_calculated, study_country, journal_name,
           estimation_methods, journal_rank) %>%
  summarise(across(where(is.numeric), ~if(all(is.na(.))) 0 else max(., na.rm =
    TRUE)), .groups = 'drop')

# Left join to put the control variables back into FDII
FDII <- left_join(FDII, FDII_merged, by = c("citation", "coefficient",
  "t_value_calculated", "study_country", "journal_name", "estimation_methods",
  "journal_rank"))

# Remove duplicate columns
```

```

FDII <- FDII %>% dplyr::select(-matches("\\.y$"))
FDII <- FDII %>% dplyr::rename_with(~str_replace(., "\\..x$", ""), .cols =
  ↪ ends_with(".x"))

FDII$GDPpc_2 <- FDII$`GDPpc^2`

```

Filters for meta analyses

```

# Measures of FDI and Inequality
FDII$stock <- ifelse(FDII$FDI %in% c(1, 3, 9), 1, 0)
FDII$GINI_control <- ifelse(FDII$Inequality == 1, 1, 0)
FDII$W_I_Dis <- ifelse(FDII$Inequality %in% c(4, 7, 8, 11, 12, 13, 14, 16, 17, 18),
  ↪ 1, 0)
FDII$I_Share <- ifelse(FDII$Inequality %in% c(2, 5, 6), 1, 0)
FDII$Other_I_measure <- ifelse(FDII$Inequality %in% c(3, 9, 10, 15), 1, 0)

# Measures of controlling for endogeneity
FDII$est_method <- ifelse(FDII$estimation_methods %in% c('GMM', 'IV', '2SLS'), 1, 0)

# Single Country
FDII$single_country <- ifelse(FDII$level %in% c(1, 2), 1, 0)

# Control(s)
FDII$GDP_control <- ifelse(FDII$control_variables_1 %in% c('GDPpc', 'GDP',
  ↪ 'GDPpc^2', 'GDP^2') | FDII$control_variables_2 %in% c('GDPpc', 'GDP',
  ↪ 'GDPpc^2', 'GDP^2') | FDII$control_variables_3 %in% c('GDPpc', 'GDP',
  ↪ 'GDPpc^2', 'GDP^2') | FDII$control_variables_4 %in% c('GDPpc', 'GDP',
  ↪ 'GDPpc^2', 'GDP^2') | FDII$control_variables_5 %in% c('GDPpc', 'GDP',
  ↪ 'GDPpc^2', 'GDP^2'), 1, 0)
FDII$GDP_control <- ifelse(!is.na(FDII$GDP_control), FDII$GDP_control, 0)

FDII$education_control <- ifelse(FDII$control_variables_1 %in%
  ↪ c('education_secondary_school_enrollment', 'education_middle_school_enrollment')
  ↪ | FDII$control_variables_2 %in% c('education_secondary_school_enrollment',
  ↪ 'education_middle_school_enrollment') | FDII$control_variables_3 %in%
  ↪ c('education_secondary_school_enrollment', 'education_middle_school_enrollment')
  ↪ | FDII$control_variables_4 %in% c('education_secondary_school_enrollment',
  ↪ 'education_middle_school_enrollment') | FDII$control_variables_5 %in%
  ↪ c('education_secondary_school_enrollment',
  ↪ 'education_middle_school_enrollment'), 1, 0)
FDII$education_control <- ifelse(!is.na(FDII$education_control),
  ↪ FDII$education_control, 0)

FDII$trade_control <- ifelse(FDII$control_variables_1 == 'trade' |
  ↪ FDII$control_variables_2 == 'trade' | FDII$control_variables_3 == 'trade' |
  ↪ FDII$control_variables_4 == 'trade' | FDII$control_variables_5 == 'trade', 1, 0)
FDII$trade_control <- ifelse(!is.na(FDII$trade_control), FDII$trade_control, 0)

FDII$inflation_control <- ifelse(FDII$control_variables_1 == 'inflation' |
  ↪ FDII$control_variables_2 == 'inflation' | FDII$control_variables_3 ==
  ↪ 'inflation' | FDII$control_variables_4 == 'inflation' | FDII$control_variables_5
  ↪ == 'inflation', 1, 0)
FDII$inflation_control <- ifelse(!is.na(FDII$inflation_control),
  ↪ FDII$inflation_control, 0)

FDII$population_control <- ifelse(FDII$control_variables_1 %in% c('pop') |
  ↪ FDII$control_variables_2 %in% c('pop') | FDII$control_variables_3 %in% c('pop')
  ↪ | FDII$control_variables_4 %in% c('pop') | FDII$control_variables_5 %in%
  ↪ c('pop'), 1, 0)

```

```

FDII$population_control <- ifelse(!is.na(FDII$population_control),
  ↪ FDII$population_control, 0)

FDII$gov_inequality_effort_control <- ifelse(FDII$control_variables_1 %in%
  ↪ c('gov_exp', 'qov_quality') | FDII$control_variables_2 %in% c('gov_exp',
  ↪ 'qov_quality') | FDII$control_variables_3 %in% c('gov_exp', 'qov_quality') |
  ↪ FDII$control_variables_4 %in% c('gov_exp', 'qov_quality') |
  ↪ FDII$control_variables_5 %in% c('gov_exp', 'qov_quality'), 1, 0)
FDII$gov_inequality_effort_control <-
  ↪ ifelse(!is.na(FDII$gov_inequality_effort_control),
  ↪ FDII$gov_inequality_effort_control, 0)

FDII$unemployment_control <- ifelse(FDII$control_variables_1 == 'unemployment' |
  ↪ FDII$control_variables_2 == 'unemployment' | FDII$control_variables_3 ==
  ↪ 'unemployment' | FDII$control_variables_4 == 'unemployment' |
  ↪ FDII$control_variables_5 == 'unemployment', 1, 0)
FDII$unemployment_control <- ifelse(!is.na(FDII$unemployment_control),
  ↪ FDII$unemployment_control, 0)

save(FDII, file = "FDI_Inequality_R.rda")

```

Split data into income buckets

```

FDII_higher <- FDII[FDII$developed_average > 3,]
FDII_middle <- FDII[FDII$developed_average > 2 & FDII$developed_average <= 3,]
FDII_lower <- FDII[FDII$developed_average <= 2,]

```

Means for the different income levels

```

mean(FDII_higher$PCC)

## [1] -0.02479306
mean(FDII_higher$PCC_se)

## [1] 0.06929961
mean(FDII_middle$PCC)

## [1] 0.143201
mean(FDII_middle$PCC_se)

## [1] 0.1014354
mean(FDII_lower$PCC)

## [1] 0.143991
mean(FDII_lower$PCC_se)

## [1] 0.1421433

```

Meta generation setup

```
# Meta generation set-up
m.gen <- metagen(TE = FDII$PCC,
                 seTE = FDII$PCC_se,
                 studlab = FDII$citation,
                 data = FDII,
                 sm = "SMD",
                 comb.fixed = FALSE,
                 comb.random = TRUE,
                 method.tau = "ML",
                 weighted = TRUE,
                 hakn = TRUE,
                 test = "knha",
                 title = "FDI Impacts on Income Inequality")
m.gen

## Review:      FDI Impacts on Income Inequality
##
## Number of studies: k = 616
##
##              SMD          95%-CI    t  p-value
## Random effects model (HK) 0.0822 [0.0642; 0.1001] 8.99 < 0.0001
##
## Quantifying heterogeneity:
## tau^2 = 0.0356 [0.0360; 0.0492]; tau = 0.1886 [0.1899; 0.2217]
## I^2 = 84.9% [83.8%; 85.9%]; H = 2.57 [2.49; 2.66]
##
## Test of heterogeneity:
##      Q d.f. p-value
## 4070.12 615      0
##
## Details on meta-analytical method:
## - Inverse variance method
## - Maximum-likelihood estimator for tau^2
## - Q-Profile method for confidence interval of tau^2 and tau
## - Hartung-Knapp adjustment for random effects model (df = 615)
```

Meta generation for different income levels

```
m.higher <- metagen(TE = FDII_higher$PCC,
                    seTE = FDII_higher$PCC_se,
                    studlab = FDII_higher$citation,
                    data = FDII_higher,
                    sm = "SMD",
                    comb.fixed = FALSE,
                    comb.random = TRUE,
                    method.tau = "ML",
                    weighted = TRUE,
                    hakn = TRUE,
                    test = "knha",
                    title = "FDI Impacts on Income Inequality (Higher Income)")
m.higher

## Review:      FDI Impacts on Income Inequality (Higher Income)
##
## Number of studies: k = 199
##
```

```

##                               SMD                95%-CI      t  p-value
## Random effects model (HK) -0.0170 [-0.0458; 0.0117] -1.17  0.2434
##
## Quantifying heterogeneity:
## tau^2 = 0.0279 [0.0305; 0.0526]; tau = 0.1670 [0.1747; 0.2294]
## I^2 = 83.6% [81.5%; 85.5%]; H = 2.47 [2.33; 2.62]
##
## Test of heterogeneity:
##      Q d.f.  p-value
## 1208.42  198 < 0.0001
##
## Details on meta-analytical method:
## - Inverse variance method
## - Maximum-likelihood estimator for tau^2
## - Q-Profile method for confidence interval of tau^2 and tau
## - Hartung-Knapp adjustment for random effects model (df = 198)

m.middle <- metagen(TE = FDII_middle$PCC,
                    seTE = FDII_middle$PCC_se,
                    studlab = FDII_middle$citation,
                    data = FDII_middle,
                    sm = "SMD",
                    comb.fixed = FALSE,
                    comb.random = TRUE,
                    method.tau = "ML",
                    weighted = TRUE,
                    hakn = TRUE,
                    test = "knha",
                    title = "FDI Impacts on Income Inequality (Middle Income)")

m.middle

## Review:      FDI Impacts on Income Inequality (Middle Income)
##
## Number of studies: k = 260
##
##                               SMD                95%-CI      t  p-value
## Random effects model (HK) 0.1360 [0.1113; 0.1607] 10.83 < 0.0001
##
## Quantifying heterogeneity:
## tau^2 = 0.0269 [0.0247; 0.0408]; tau = 0.1642 [0.1571; 0.2019]
## I^2 = 79.0% [76.5%; 81.2%]; H = 2.18 [2.06; 2.31]
##
## Test of heterogeneity:
##      Q d.f.  p-value
## 1233.00  259 < 0.0001
##
## Details on meta-analytical method:
## - Inverse variance method
## - Maximum-likelihood estimator for tau^2
## - Q-Profile method for confidence interval of tau^2 and tau
## - Hartung-Knapp adjustment for random effects model (df = 259)

m.lower <- metagen(TE = FDII_lower$PCC,
                    seTE = FDII_lower$PCC_se,
                    studlab = FDII_lower$citation,
                    data = FDII_lower,
                    sm = "SMD",

```



```

        comb.fixed = FALSE,
        comb.random = TRUE,
        method.tau = "ML",
        weighted = TRUE,
        hakn = TRUE,
        test = "knha",
        title = "FDI Impacts on Income Inequality (Lower Income)")
m.lower

```

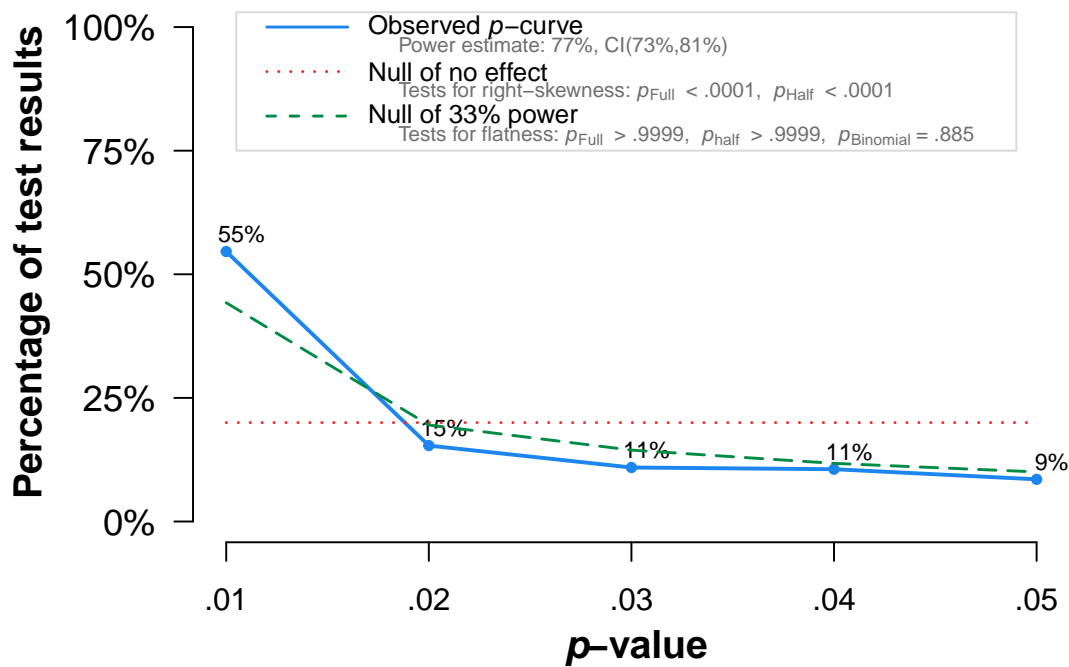
```

## Review:      FDI Impacts on Income Inequality (Lower Income)
##
## Number of studies: k = 157
##
##              SMD          95%-CI    t  p-value
## Random effects model (HK) 0.1413 [0.1042; 0.1783] 7.53 < 0.0001
##
## Quantifying heterogeneity:
##  tau^2 = 0.0341 [0.0266; 0.0534]; tau = 0.1846 [0.1631; 0.2312]
##  I^2 = 85.4% [83.4%; 87.2%]; H = 2.62 [2.45; 2.80]
##
## Test of heterogeneity:
##      Q d.f.  p-value
## 1069.09 156 < 0.0001
##
## Details on meta-analytical method:
## - Inverse variance method
## - Maximum-likelihood estimator for tau^2
## - Q-Profile method for confidence interval of tau^2 and tau
## - Hartung-Knapp adjustment for random effects model (df = 156)

```

p-value test

```
pcurve(m.gen)
```



Note: The observed p -curve includes 293 statistically significant ($p < .05$) results, of which 218 are $p < .025$. There were 323 additional results entered but excluded from p -curve because they were $p > .05$.

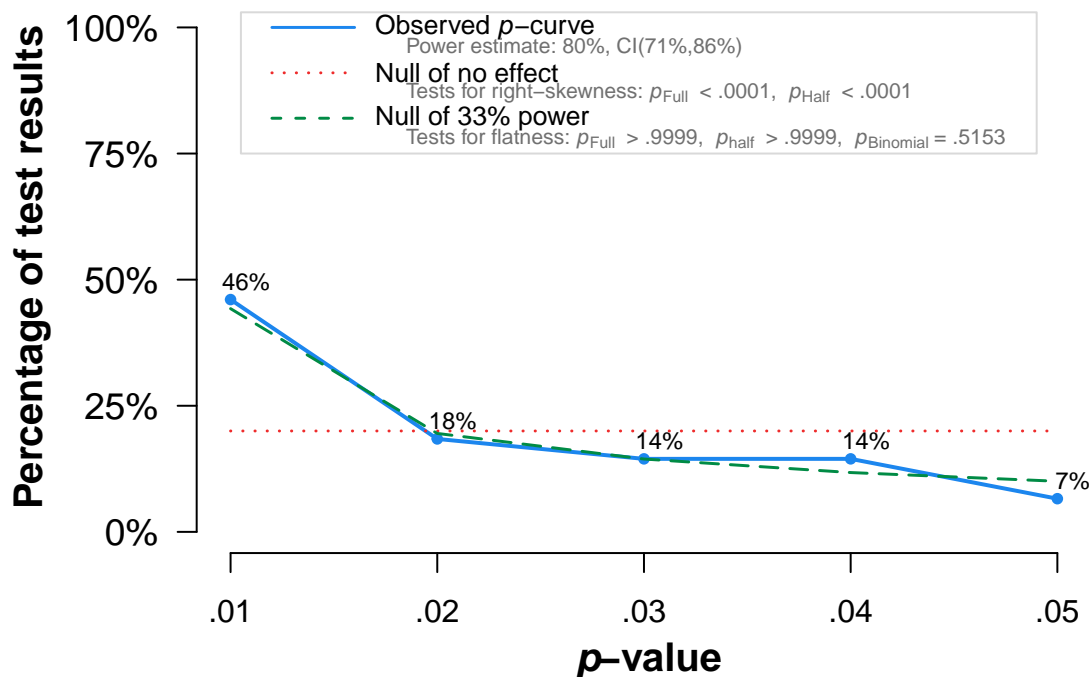
```
## P-curve analysis
## -----
## - Total number of provided studies: k = 616
## - Total number of  $p < 0.05$  studies included into the analysis: k = 293 (47.56%)
## - Total number of studies with  $p < 0.025$ : k = 218 (35.39%)
##
## Results
## -----
##               pBinomial    zFull pFull    zHalf pHalf
## Right-skewness test      0.000 -24.912    0 -25.329    0
## Flatness test            0.885  12.531    1  27.610    1
## Note: p-values of 0 or 1 correspond to  $p < 0.001$  and  $p > 0.999$ , respectively.
## Power Estimate: 77% (72.9%-81.2%)
##
## Evidential value
## -----
## - Evidential value present: yes
## - Evidential value absent/inadequate: no
```

Talk about how this protects against not just publication bias, but also against p-hacking.

This p-curve test plots statistically-significant ($p < 0.05$) values and assesses whether there is 'evidential' value in the underlying impact of FDI on income inequality. C.47% of results being statistically significant. The flatness test (the graph) and the right-skewness test suggest that our data is not flat, but is skewed to the right – this is what we expect to witness if there is a true underlying effect. There is a 77% chance of detecting that true underlying effect should it exist.

Other studies need to be considered (heterogeneity, study quality, etc.), but this indicates that there is an effect.

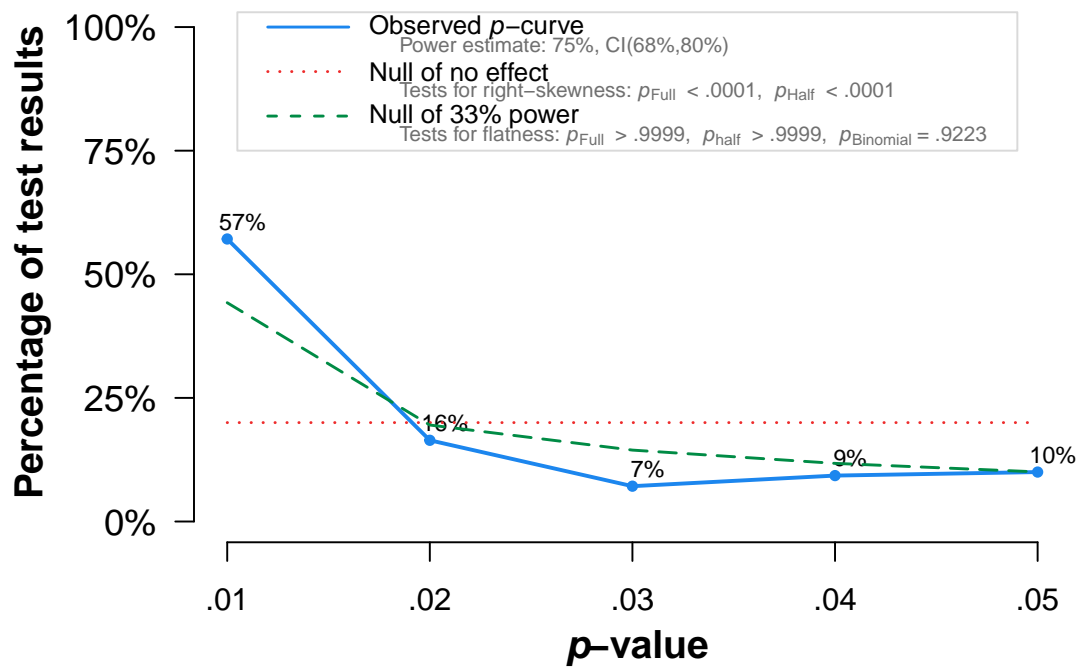
```
pcurve(m.higher)
```



Note: The observed p -curve includes 76 statistically significant ($p < .05$) results, of which 54 are $p < .025$. There were 123 additional results entered but excluded from p -curve because they were $p > .05$.

```
## P-curve analysis
## -----
## - Total number of provided studies: k = 199
## - Total number of p<0.05 studies included into the analysis: k = 76 (38.19%)
## - Total number of studies with p<0.025: k = 54 (27.14%)
##
## Results
## -----
##               pBinomial    zFull pFull    zHalf pHalf
## Right-skewness test      0.000 -12.792      0 -12.992      0
## Flatness test            0.515   6.771      1  14.872      1
## Note: p-values of 0 or 1 correspond to p<0.001 and p>0.999, respectively.
## Power Estimate: 80% (71%-86.2%)
##
## Evidential value
## -----
## - Evidential value present: yes
## - Evidential value absent/inadequate: no
```

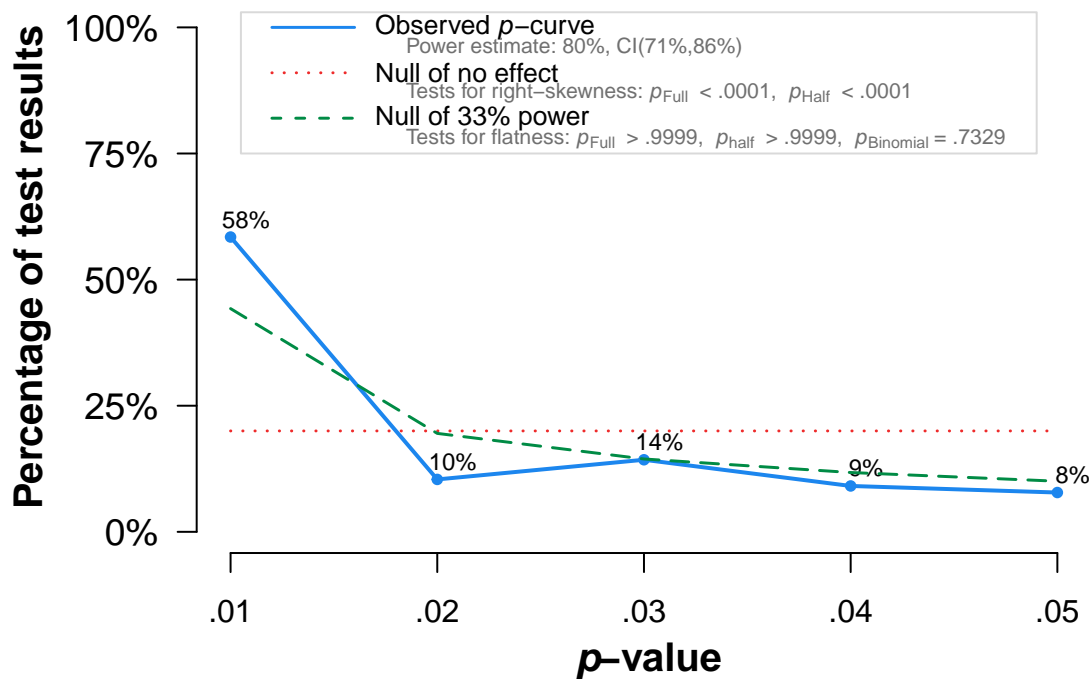
```
pcurve(m.middle)
```



Note: The observed p -curve includes 140 statistically significant ($p < .05$) results, of which 107 are $p < .025$. There were 120 additional results entered but excluded from p -curve because they were $p > .05$.

```
## P-curve analysis
## -----
## - Total number of provided studies: k = 260
## - Total number of  $p < 0.05$  studies included into the analysis: k = 140 (53.85%)
## - Total number of studies with  $p < 0.025$ : k = 107 (41.15%)
##
## Results
## -----
##               pBinomial    zFull pFull    zHalf pHalf
## Right-skewness test      0.000 -16.917    0 -16.878    0
## Flatness test            0.922   8.057    1  18.081    1
## Note: p-values of 0 or 1 correspond to  $p < 0.001$  and  $p > 0.999$ , respectively.
## Power Estimate: 75% (67.6%-80.5%)
##
## Evidential value
## -----
## - Evidential value present: yes
## - Evidential value absent/inadequate: no

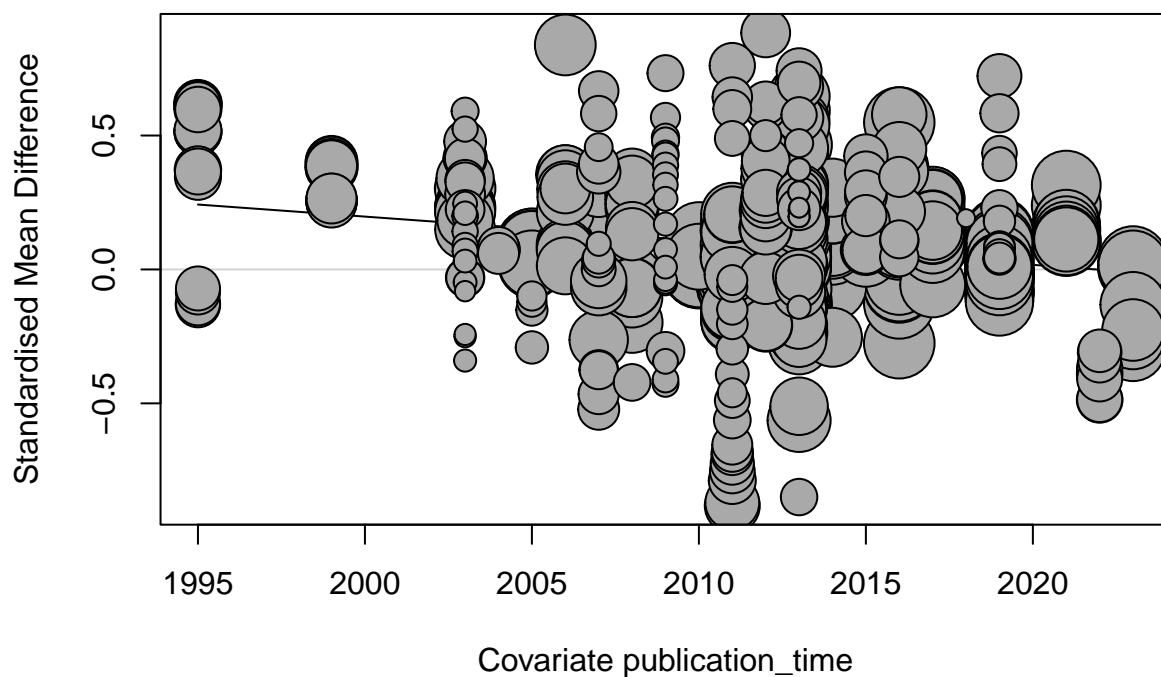
pcurve(m.lower)
```



Note: The observed p -curve includes 77 statistically significant ($p < .05$) results, of which 57 are $p < .025$. There were 80 additional results entered but excluded from p -curve because they were $p > .05$.

```
## P-curve analysis
## -----
## - Total number of provided studies: k = 157
## - Total number of p<0.05 studies included into the analysis: k = 77 (49.04%)
## - Total number of studies with p<0.025: k = 57 (36.31%)
##
## Results
## -----
##               pBinomial   zFull pFull   zHalf pHalf
## Right-skewness test    0.000 -13.077    0 -13.764    0
## Flatness test          0.733   6.853    1  14.747    1
## Note: p-values of 0 or 1 correspond to p<0.001 and p>0.999, respectively.
## Power Estimate: 80% (71.2%-86.3%)
##
## Evidential value
## -----
## - Evidential value present: yes
## - Evidential value absent/inadequate: no

mgen.test <- metareg(m.gen, ~publication_time)
bubble(mgen.test, studlab = FALSE)
```



```
FDII[c("if_published", "publication_time", "PCC", "developed_average")] %>% cor()
```

```
##               if_published publication_time      PCC developed_average
## if_published      1.0000000      0.1998576  0.1814428      -0.2568392
## publication_time  0.1998576      1.0000000 -0.2115030      0.1997580
## PCC               0.1814428     -0.2115030  1.0000000     -0.3075202
## developed_average -0.2568392      0.1997580 -0.3075202      1.0000000
```

```
FDII_higher[c("if_published", "publication_time", "PCC", "developed_average")] %>%
  cor()
```

```
##               if_published publication_time      PCC developed_average
## if_published      1.0000000      0.3913788  0.24122324     -0.09181083
## publication_time  0.3913788      1.0000000 -0.05010500      0.13128095
## PCC               0.24122324    -0.0501050  1.00000000      0.03194525
## developed_average -0.09181083      0.1312810  0.03194525      1.00000000
```

```
FDII_middle[c("if_published", "publication_time", "PCC", "developed_average")] %>%
  cor()
```

```
##               if_published publication_time      PCC developed_average
## if_published      1.0000000      0.2634164 -0.01485552      0.06354018
## publication_time  0.2634164      1.0000000 -0.23807062      0.23534066
## PCC               -0.01485552    -0.2380706  1.00000000     -0.20033693
## developed_average  0.06354018      0.2353407 -0.20033693      1.00000000
```

```
FDII_lower[c("if_published", "publication_time", "PCC", "developed_average")] %>%
  cor()
```

```
## Warning in cor(.): the standard deviation is zero
```

```
##               if_published publication_time      PCC developed_average
## if_published      1              NA          NA              NA
## publication_time  NA      1.00000000 -0.098600583     -0.057941622
## PCC               NA     -0.09860058  1.000000000      0.002377134
## developed_average NA     -0.05794162  0.002377134      1.000000000
```

PET-PEESE tests

```
data.petpeese <- data.frame(TE = m.gen$TE, seTE = m.gen$seTE, varTE = m.gen$seTE^2)
data.petpeese$w_k <- 1/(data.petpeese$varTE)

pet <- lm(TE ~ seTE, weights = w_k, data = data.petpeese)
pet_summary <- summary(pet)$coefficients
print(round(pet_summary, 3))

##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    0.003      0.004   0.767   0.443
## seTE           0.924      0.124   7.434   0.000

peese <- lm(TE ~ varTE, weights = w_k, data = data.petpeese)
peese_summary <- summary(peese)$coefficients
print(round(peese_summary, 3))

##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    0.017      0.004   4.529     0
## varTE          4.813      0.864   5.571     0

### m.gen.inf <- InfluenceAnalysis(m.gen, random = TRUE) # This takes a long time to
  ↳ run!
### plot(m.gen.inf, "baujat")
```

Only run the noted aspects when necessary as the influence analysis takes forever to run!

Inputs to run meta regression

```
# Set it such that the control variables are put into one column
FDII_long <- FDII %>%
  pivot_longer(cols = starts_with("control_variables_"),
    names_to = "Control_Variable_Type",
    values_to = "Control_Variable_Name",
    names_repair = "unique") %>%
  filter(!is.na(Control_Variable_Name) & Control_Variable_Name != "")

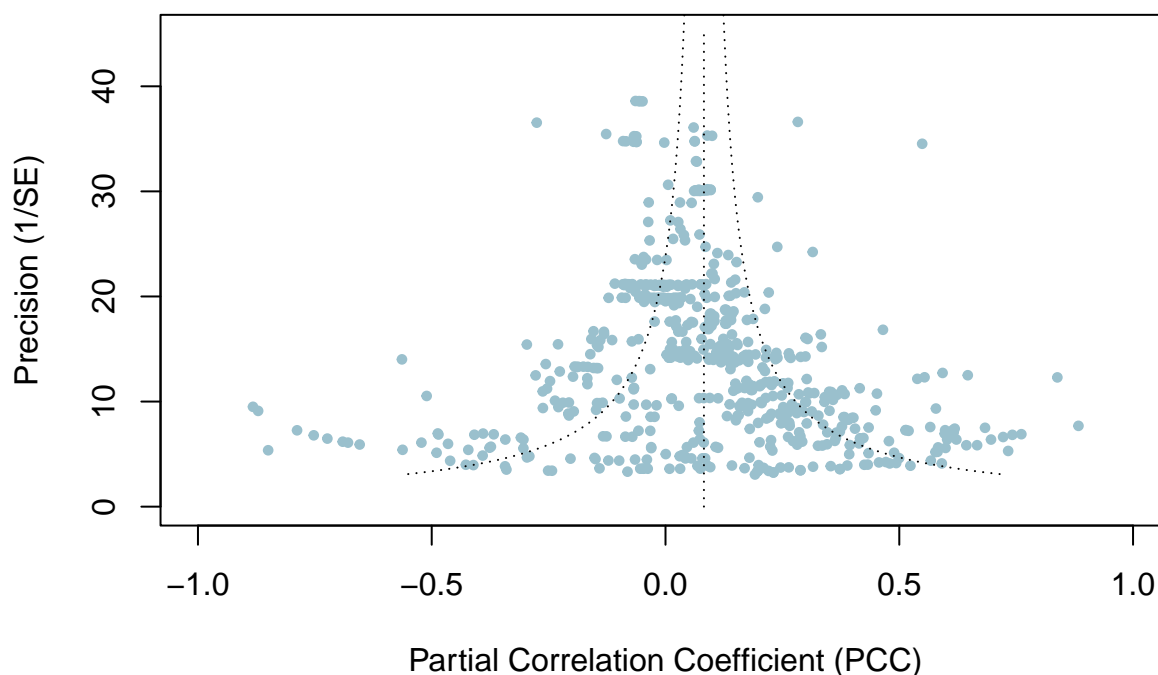
# Turn that one column into a grid of binary variables
FDII_wide <- FDII_long %>%
  mutate(Presence = 1) %>%
  pivot_wider(names_from = Control_Variable_Name, values_from = Presence,
    ↳ values_fill = list(Presence = 0), names_repair = "unique")

# Flatten to remove duplicate rows and merge the binary variables
FDII_merged <- FDII_wide %>%
  group_by(citation, coefficient, t_value_calculated, study_country, journal_name,
    ↳ estimation_methods) %>%
  summarise(across(where(is.numeric), ~if(all(is.na(.))) 0 else max(., na.rm =
    ↳ TRUE)), .groups = 'drop')

# Perform a left join to integrate the new columns from FDII_merged back into FDII
FDII <- left_join(FDII, FDII_merged, by = c("citation", "coefficient",
  ↳ "t_value_calculated", "study_country", "journal_name", "estimation_methods",
  ↳ "journal_rank"))
FDII <- FDII %>% dplyr::select(-matches("\\.y$"))
FDII <- FDII %>% dplyr::rename_with(~str_replace(., "\\..x$", ""), .cols =
  ↳ ends_with(".x"))
```

Funnel plot for meta analysis (FAT)

```
funnel_data <- metafor::funnel(m.gen,  
  title = "FDI Impacts on Income Inequality",  
  xlim = c(-1, 1),  
  ylim = rev(c(45, 0)),  
  studlab = FALSE,  
  xlab = "Partial Correlation Coefficient (PCC)",  
  ylab = "Precision (1/SE)",  
  yaxis = "invse",  
  col = "lightblue3",  
  bg = "lightblue3",  
  cex = 0.6)
```



```
egggers.test(m.gen)
```

```
## Eggers' test of the intercept  
## =====  
##  
##   intercept      95% CI      t          p  
##      0.924 0.68 - 1.17 7.434 0.0000000000003562739  
##  
## Eggers' test indicates the presence of funnel plot asymmetry.
```

The presence of funnel plot asymmetry could suggest that we have a publication bias. It could also be indicative of (Page et al., 2020):

- Between-study heterogeneity - the plot assumes effect sizes are the result of the studies' sampling error, but it could be different true sizes
- Different study methods, leading to greater effects
- Lower-quality studies could show greater effect sizes as a result of greater bias risk
- Could occur by chance (unlikely)

```
ggplot(data = FDII, aes(x = PCC, y = 1/PCC_se)) +  
  geom_point(color = "lightblue3", size = 1) +  
  geom_vline(aes(xintercept = mean(FDII$PCC_se)), linetype = "dashed", color =  
    ↪ "deepskyblue4") +
```



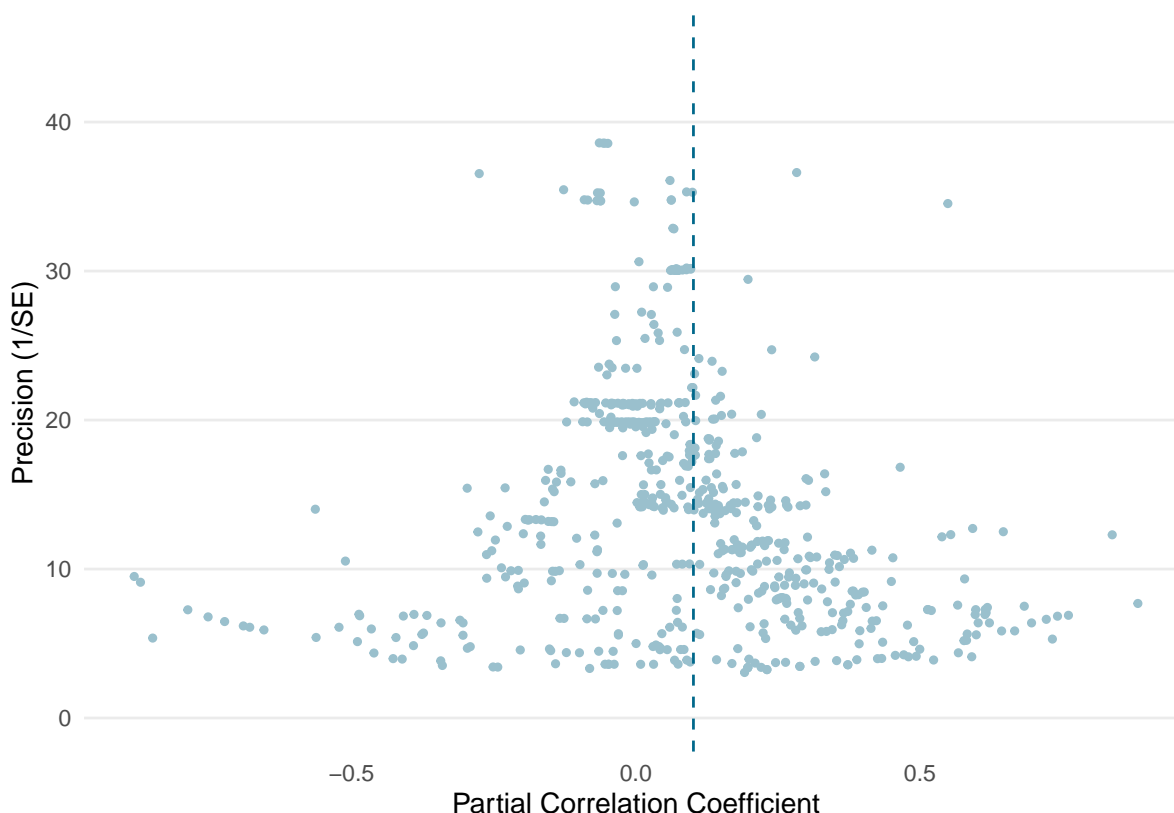
```
ylim(0, 45) +
labs(x = "Partial Correlation Coefficient",
     y = "Precision (1/SE)") +
theme_minimal() +
theme(panel.grid.minor.y = element_blank(),
      panel.grid.minor.x = element_blank(),
      panel.grid.major.x = element_blank())
```

```
## Warning: Use of `FDII$PCC_se` is discouraged.
```

```
## i Use `PCC_se` instead.
```

```
## Warning: Removed 12 rows containing missing values or values outside the scale range
```

```
## (`geom_point()`).
```



FAT-PET test

```
res <- rma(FDII$PCC, sei = FDII$PCC_se)
#FATPET test
regtest(res, model = "rma", ret.fit = TRUE)
```

```
##
```

```
## Regression Test for Funnel Plot Asymmetry
```

```
##
```

```
## Model:      mixed-effects meta-regression model
```

```
## Predictor: standard error
```

```
##
```

```
## Mixed-Effects Model (k = 616; tau^2 estimator: REML)
```

```
##
```

```
## tau^2 (estimated amount of residual heterogeneity):      0.0341 (SE = 0.0024)
```

```
## tau (square root of estimated tau^2 value):          0.1847
## I^2 (residual heterogeneity / unaccounted variability): 96.26%
## H^2 (unaccounted variability / sampling variability):  26.72
## R^2 (amount of heterogeneity accounted for):          4.36%
##
## Test for Residual Heterogeneity:
## QE(df = 614) = 3734.0544, p-val < .0001
##
## Test of Moderators (coefficient 2):
## QM(df = 1) = 14.1993, p-val = 0.0002
##
## Model Results:
##
##           estimate      se    zval    pval    ci.lb    ci.ub
## intrcpt    0.0330  0.0155  2.1293  0.0332  0.0026  0.0634    *
## sei        0.5828  0.1547  3.7682  0.0002  0.2797  0.8859   ***
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Test for Funnel Plot Asymmetry: z = 3.7682, p = 0.0002
## Limit Estimate (as sei -> 0):   b = 0.0330 (CI: 0.0026, 0.0634)
```

FAT-PET test – Higher income

```
res_higher <- rma(FDII_higher$PCC, sei = FDII_higher$PCC_se)
#FATPET test
regtest(res_higher, model = "rma", ret.fit = TRUE)

##
## Regression Test for Funnel Plot Asymmetry
##
## Model:      mixed-effects meta-regression model
## Predictor: standard error
##
## Mixed-Effects Model (k = 199; tau^2 estimator: REML)
##
## tau^2 (estimated amount of residual heterogeneity):      0.0268 (SE = 0.0031)
## tau (square root of estimated tau^2 value):              0.1638
## I^2 (residual heterogeneity / unaccounted variability):  97.50%
## H^2 (unaccounted variability / sampling variability):     39.94
## R^2 (amount of heterogeneity accounted for):              4.67%
##
## Test for Residual Heterogeneity:
## QE(df = 197) = 1200.1232, p-val < .0001
##
## Test of Moderators (coefficient 2):
## QM(df = 1) = 7.0943, p-val = 0.0077
##
## Model Results:
##
##           estimate      se    zval    pval    ci.lb    ci.ub
## intrcpt    0.0353  0.0233  1.5142  0.1300  -0.0104  0.0810
## sei       -0.8783  0.3298 -2.6635  0.0077  -1.5247 -0.2320   **
##
```

```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Test for Funnel Plot Asymmetry: z = -2.6635, p = 0.0077
## Limit Estimate (as sei -> 0):  b =  0.0353 (CI: -0.0104, 0.0810)
```

FAT-PET test – Middle income

```
res_middle <- rma(FDII_middle$PCC, sei = FDII_middle$PCC_se)
#FATPET test
regtest(res_middle, model = "rma", ret.fit = TRUE)

##
## Regression Test for Funnel Plot Asymmetry
##
## Model:      mixed-effects meta-regression model
## Predictor: standard error
##
## Mixed-Effects Model (k = 260; tau^2 estimator: REML)
##
## tau^2 (estimated amount of residual heterogeneity):      0.0246 (SE = 0.0029)
## tau (square root of estimated tau^2 value):             0.1569
## I^2 (residual heterogeneity / unaccounted variability): 83.94%
## H^2 (unaccounted variability / sampling variability):    6.22
## R^2 (amount of heterogeneity accounted for):             9.19%
##
## Test for Residual Heterogeneity:
## QE(df = 258) = 1104.7160, p-val < .0001
##
## Test of Moderators (coefficient 2):
## QM(df = 1) = 11.6317, p-val = 0.0006
##
## Model Results:
##
##           estimate      se    zval    pval   ci.lb   ci.ub
## intrcpt    0.0583  0.0253  2.3011  0.0214  0.0086  0.1080   *
## sei        0.8792  0.2578  3.4105  0.0006  0.3739  1.3844  ***
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Test for Funnel Plot Asymmetry: z = 3.4105, p = 0.0006
## Limit Estimate (as sei -> 0):  b = 0.0583 (CI: 0.0086, 0.1080)
```

FAT-PET test – Lower income

```
res_lower <- rma(FDII_lower$PCC, sei = FDII_lower$PCC_se)
#FATPET test
regtest(res_lower, model = "rma", ret.fit = TRUE)

##
## Regression Test for Funnel Plot Asymmetry
##
## Model:      mixed-effects meta-regression model
```

```
## Predictor: standard error
##
## Mixed-Effects Model (k = 157; tau^2 estimator: REML)
##
## tau^2 (estimated amount of residual heterogeneity):      0.0345 (SE = 0.0056)
## tau (square root of estimated tau^2 value):             0.1858
## I^2 (residual heterogeneity / unaccounted variability): 95.59%
## H^2 (unaccounted variability / sampling variability):    22.67
## R^2 (amount of heterogeneity accounted for):             0.00%
##
## Test for Residual Heterogeneity:
## QE(df = 155) = 941.0447, p-val < .0001
##
## Test of Moderators (coefficient 2):
## QM(df = 1) = 0.3828, p-val = 0.5361
##
## Model Results:
##
##           estimate      se    zval    pval    ci.lb    ci.ub
## intrcpt    0.1240  0.0335  3.7053  0.0002   0.0584  0.1895 ***
## sei        0.1548  0.2502  0.6187  0.5361  -0.3356  0.6452
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Test for Funnel Plot Asymmetry: z = 0.6187, p = 0.5361
## Limit Estimate (as sei -> 0):  b = 0.1240 (CI: 0.0584, 0.1895)
```

Meta Regression Analyses (MRAs)

Basic meta analysis test with no moderators

```
meta.anal <- rma(yi = PCC,
                 sei = PCC_se,
                 data = FDII,
                 method = "REML",
                 mods = ~ PCC_se,
                 test = "knha")

meta.anal

##
## Mixed-Effects Model (k = 616; tau^2 estimator: REML)
##
## tau^2 (estimated amount of residual heterogeneity):      0.0341 (SE = 0.0024)
## tau (square root of estimated tau^2 value):             0.1847
## I^2 (residual heterogeneity / unaccounted variability): 96.26%
## H^2 (unaccounted variability / sampling variability):    26.72
## R^2 (amount of heterogeneity accounted for):             4.36%
##
## Test for Residual Heterogeneity:
## QE(df = 614) = 3734.0544, p-val < .0001
##
## Test of Moderators (coefficient 2):
## F(df1 = 1, df2 = 614) = 12.4933, p-val = 0.0004
##
## Model Results:
```

```
##
##          estimate      se    tval   df    pval   ci.lb   ci.ub
## intrcpt      0.0330  0.0165  1.9973  614  0.0462  0.0006  0.0655   *
## PCC_se       0.5828  0.1649  3.5346  614  0.0004  0.2590  0.9066  ***
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

selmodel(meta.anal, type = "stepfun", steps = 0.025, alternative = "two.sided")

##
## Mixed-Effects Model (k = 616; tau^2 estimator: ML)
##
## tau^2 (estimated amount of residual heterogeneity): 0.0462 (SE = 0.0050)
## tau (square root of estimated tau^2 value):          0.2148
##
## Test for Residual Heterogeneity:
## LRT(df = 1) = 1396.7982, p-val < .0001
##
## Test of Moderators (coefficient 2):
## QM(df = 1) = 12.5437, p-val = 0.0004
##
## Model Results:
##
##          estimate      se    zval   pval   ci.lb   ci.ub
## intrcpt      0.0476  0.0195  2.4424  0.0146  0.0094  0.0857   *
## PCC_se       0.6530  0.1844  3.5417  0.0004  0.2916  1.0143  ***
##
## Test for Selection Model Parameters:
## LRT(df = 1) = 20.5873, p-val < .0001
##
## Selection Model Results:
##
##          k estimate      se    zval   pval   ci.lb   ci.ub
## 0      < p <= 0.025  218    1.0000    ---    ---    ---    ---
## 0.025 < p <= 1      398    1.7544  0.2174  3.4699  0.0005  1.3283  2.1805  ***
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
meta.anal.full.model <- rma(yi = PCC,
  sei = PCC_se,
  data = FDII,
  method = "REML",
  mods = ~ stock + GINI_control + I_Share + W_I_Dis + Other_I_measure + mean_log_GDPPC + est_method +
  ↪ GDP_control + education_control + single_country + trade_control + population_control +
  ↪ inflation_control + unemployment_control + gov_inequality_effort_control + if_published + PCC_se,
  test = "knha",
  digits = 3)
```

Warning: Redundant predictors dropped from the model.

```
meta.anal.full.model
```

```
##
## Mixed-Effects Model (k = 616; tau^2 estimator: REML)
##
## tau^2 (estimated amount of residual heterogeneity):      0.027 (SE = 0.002)
## tau (square root of estimated tau^2 value):             0.164
## I^2 (residual heterogeneity / unaccounted variability): 94.92%
## H^2 (unaccounted variability / sampling variability):    19.67
## R^2 (amount of heterogeneity accounted for):             24.96%
##
## Test for Residual Heterogeneity:
## QE(df = 599) = 3073.598, p-val < .001
##
## Test of Moderators (coefficients 2:17):
## F(df1 = 16, df2 = 599) = 8.055, p-val < .001
##
## Model Results:
##
##               estimate      se    tval   df   pval   ci.lb
## intrcpt          0.348  0.200   1.743  599  0.082  -0.044
## stock            0.019  0.027   0.719  599  0.472  -0.034
## GINI_control     0.144  0.033   4.368  599 <.001   0.079
## I_Share          0.250  0.067   3.755  599 <.001   0.119
## W_I_Dis          0.197  0.041   4.792  599 <.001   0.116
```

```

## mean_log_GDPPC          -0.056  0.018  -3.022  599  0.003  -0.092
## est_method              0.018  0.021   0.824  599  0.410  -0.024
## GDP_control             0.019  0.022   0.900  599  0.369  -0.023
## education_control       -0.008  0.024  -0.342  599  0.732  -0.054
## single_country          -0.106  0.026  -4.094  599  <.001  -0.156
## trade_control           -0.007  0.023  -0.321  599  0.749  -0.053
## population_control       0.000  0.033   0.013  599  0.990  -0.065
## inflation_control       -0.029  0.034  -0.837  599  0.403  -0.096
## unemployment_control    -0.036  0.043  -0.833  599  0.405  -0.120
## gov_inequality_effort_control -0.015  0.030  -0.494  599  0.622  -0.074
## if_published            0.128  0.040   3.169  599  0.002   0.049
## PCC_se                  0.323  0.198   1.630  599  0.104  -0.066
##                          ci.ub
## intrcpt                 0.740   .
## stock                   0.072
## GINI_control            0.208  ***
## I_Share                 0.381  ***
## W_I_Dis                 0.278  ***
## mean_log_GDPPC         -0.020  **
## est_method              0.060
## GDP_control             0.062
## education_control       0.038
## single_country          -0.055  ***
## trade_control           0.038
## population_control       0.066
## inflation_control       0.039
## unemployment_control    0.049
## gov_inequality_effort_control 0.044
## if_published            0.208  **
## PCC_se                  0.712
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

```

meta.anal.select.model <- rma(yi = PCC,
                             sei = PCC_se,
                             data = FDII,

```

```

method = "REML",
mods = ~ GINI_control + I_Share + W_I_Dispatch + mean_log_GDPPC + single_country + if_published + PCC_se,
test = "knha",
digits = 3)

```

```
meta.anal.select.model
```

```

##
## Mixed-Effects Model (k = 616; tau^2 estimator: REML)
##
## tau^2 (estimated amount of residual heterogeneity):      0.026 (SE = 0.002)
## tau (square root of estimated tau^2 value):             0.162
## I^2 (residual heterogeneity / unaccounted variability): 94.98%
## H^2 (unaccounted variability / sampling variability):    19.90
## R^2 (amount of heterogeneity accounted for):             26.09%
##
## Test for Residual Heterogeneity:
## QE(df = 608) = 3207.924, p-val < .001
##
## Test of Moderators (coefficients 2:8):
## F(df1 = 7, df2 = 608) = 17.978, p-val < .001
##
## Model Results:
##
##              estimate      se    tval   df    pval   ci.lb   ci.ub
## intrcpt          0.392  0.180   2.174  608   0.030   0.038   0.746   *
## GINI_control      0.140  0.031   4.508  608  <.001   0.079   0.202  ***
## I_Share           0.194  0.043   4.538  608  <.001   0.110   0.278  ***
## W_I_Dispatch      0.192  0.039   4.949  608  <.001   0.116   0.268  ***
## mean_log_GDPPC    -0.059  0.017  -3.546  608  <.001  -0.091  -0.026  ***
## single_country    -0.102  0.023  -4.489  608  <.001  -0.147  -0.057  ***
## if_published       0.124  0.038   3.265  608   0.001   0.050   0.199   **
## PCC_se            0.366  0.182   2.018  608   0.044   0.010   0.723   *
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```



```
meta.anal.select.model.median <- rma(yi = PCC,
  sei = PCC_se,
  data = FDII,
  method = "REML",
  mods = ~ GINI_control + I_Share + W_I_Dispatch + median_log_GDPPC + single_country + if_published +
    ↪ PCC_se,
  test = "knha",
  digits = 3)
```

```
meta.anal.select.model.median
```

```
##
## Mixed-Effects Model (k = 616; tau^2 estimator: REML)
##
## tau^2 (estimated amount of residual heterogeneity):      0.027 (SE = 0.002)
## tau (square root of estimated tau^2 value):            0.164
## I^2 (residual heterogeneity / unaccounted variability): 95.05%
## H^2 (unaccounted variability / sampling variability):   20.21
## R^2 (amount of heterogeneity accounted for):            24.89%
##
## Test for Residual Heterogeneity:
## QE(df = 608) = 3218.079, p-val < .001
##
## Test of Moderators (coefficients 2:8):
## F(df1 = 7, df2 = 608) = 17.169, p-val < .001
##
## Model Results:
##
##              estimate      se    tval   df   pval   ci.lb   ci.ub
## intrcpt          0.224  0.168   1.333  608  0.183  -0.106  0.553
## GINI_control      0.144  0.031   4.578  608 <.001   0.082  0.205 ***
## I_Share           0.177  0.042   4.189  608 <.001   0.094  0.260 ***
## W_I_Dispatch      0.192  0.039   4.894  608 <.001   0.115  0.268 ***
## median_log_GDPPC -0.043  0.015  -2.789  608  0.005  -0.073 -0.013 **
## single_country    -0.094  0.024  -3.981  608 <.001  -0.141 -0.048 ***
## if_published       0.132  0.038   3.440  608 <.001   0.057  0.208 ***
```

```
## PCC_se          0.410  0.182   2.259  608  0.024   0.054   0.767   *
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Meta tests – Higher income

```
meta.anal.higher <- rma(yi = PCC,
  sei = PCC_se,
  data = FDII_higher,
  method = "REML",
  mods = ~ PCC_se,
  test = "knha",
  digits = 3)
meta.anal.higher
```

```
##
## Mixed-Effects Model (k = 199; tau^2 estimator: REML)
##
## tau^2 (estimated amount of residual heterogeneity):      0.027 (SE = 0.003)
## tau (square root of estimated tau^2 value):             0.164
## I^2 (residual heterogeneity / unaccounted variability): 97.50%
## H^2 (unaccounted variability / sampling variability):    39.94
## R^2 (amount of heterogeneity accounted for):             4.67%
##
## Test for Residual Heterogeneity:
## QE(df = 197) = 1200.123, p-val < .001
##
## Test of Moderators (coefficient 2):
## F(df1 = 1, df2 = 197) = 5.520, p-val = 0.020
##
## Model Results:
##
##           estimate      se    tval   df   pval   ci.lb   ci.ub
## intrcpt      0.035  0.026   1.336  197  0.183  -0.017  0.087
## PCC_se     -0.878  0.374  -2.349  197  0.020  -1.616 -0.141  *
```

```
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

meta.anal.full.model.higher <- rma(yi = PCC,
  sei = PCC_se,
  data = FDII_higher,
  method = "REML",
  mods = ~ stock + GINI_control + I_Share + W_I_Dis + est_method + GDP_control + education_control +
  ↪ single_country + trade_control + population_control + inflation_control + unemployment_control +
  ↪ gov_inequality_effort_control + if_published + PCC_se,
  test = "knha",
  digits = 3)

meta.anal.full.model.higher

##
## Mixed-Effects Model (k = 199; tau^2 estimator: REML)
##
## tau^2 (estimated amount of residual heterogeneity):      0.006 (SE = 0.001)
## tau (square root of estimated tau^2 value):             0.074
## I^2 (residual heterogeneity / unaccounted variability): 89.34%
## H^2 (unaccounted variability / sampling variability):    9.38
## R^2 (amount of heterogeneity accounted for):             80.35%
##
## Test for Residual Heterogeneity:
## QE(df = 183) = 589.272, p-val < .001
##
## Test of Moderators (coefficients 2:16):
## F(df1 = 15, df2 = 183) = 9.827, p-val < .001
##
## Model Results:
##
##               estimate      se    tval   df    pval   ci.lb
## intrcpt          -0.339  0.074  -4.599  183  <.001  -0.484
## stock              0.089  0.049   1.826  183  0.069  -0.007
## GINI_control       0.009  0.043   0.204  183  0.838  -0.075
```



```

method = "REML",
mods = ~ stock + W_I_Dis + GDP_control + education_control + trade_control + population_control +
↪ inflation_control + unemployment_control + gov_inequality_effort_control + if_published + PCC_se,
test = "knha",
digits = 3)

```

```
meta.anal.select.model.higher
```

```

##
## Mixed-Effects Model (k = 199; tau^2 estimator: REML)
##
## tau^2 (estimated amount of residual heterogeneity):      0.005 (SE = 0.001)
## tau (square root of estimated tau^2 value):             0.070
## I^2 (residual heterogeneity / unaccounted variability): 88.08%
## H^2 (unaccounted variability / sampling variability):    8.39
## R^2 (amount of heterogeneity accounted for):             82.47%
##
## Test for Residual Heterogeneity:
## QE(df = 187) = 593.338, p-val < .001
##
## Test of Moderators (coefficients 2:12):
## F(df1 = 11, df2 = 187) = 13.568, p-val < .001
##
## Model Results:
##
##               estimate      se    tval   df    pval   ci.lb
## intrcpt          -0.325  0.061  -5.352  187  <.001  -0.445
## stock              0.089  0.046   1.942  187  0.054  -0.001
## W_I_Dis            0.303  0.053   5.712  187  <.001   0.198
## GDP_control       -0.206  0.054  -3.827  187  <.001  -0.312
## education_control -0.306  0.071  -4.304  187  <.001  -0.446
## trade_control      0.555  0.093   5.948  187  <.001   0.371
## population_control 0.688  0.107   6.450  187  <.001   0.478
## inflation_control  0.504  0.075   6.765  187  <.001   0.357
## unemployment_control -0.465  0.073  -6.346  187  <.001  -0.609
## gov_inequality_effort_control 0.656  0.080   8.243  187  <.001   0.499

```

```
## if_published          0.121  0.033   3.675  187  <.001   0.056
## PCC_se                -0.298  0.399  -0.747  187  0.456  -1.085
##                      ci.ub
## intrcpt              -0.205  ***
## stock                0.179    .
## W_I_Dis              0.407  ***
## GDP_control          -0.100  ***
## education_control    -0.166  ***
## trade_control        0.739  ***
## population_control   0.899  ***
## inflation_control    0.651  ***
## unemployment_control -0.320  ***
## gov_inequality_effort_control 0.813  ***
## if_published         0.187  ***
## PCC_se               0.489
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Meta tests – Middle income

```
meta.anal.full.model.middle <- rma(yi = PCC,
  sei = PCC_se,
  data = FDII_middle,
  method = "REML",
  mods = ~ stock + GINI_control + I_Share + W_I_Dis + est_method + GDP_control + education_control +
    ↪ single_country + trade_control + population_control + inflation_control + unemployment_control +
    ↪ gov_inequality_effort_control + if_published + PCC_se,
  test = "knha",
  digits = 3)
```

```
## Warning: Redundant predictors dropped from the model.
```

```
meta.anal.full.model.middle
```

```
##
## Mixed-Effects Model (k = 260; tau^2 estimator: REML)
```

```

##
## tau^2 (estimated amount of residual heterogeneity):      0.023 (SE = 0.003)
## tau (square root of estimated tau^2 value):             0.152
## I^2 (residual heterogeneity / unaccounted variability): 82.53%
## H^2 (unaccounted variability / sampling variability):    5.72
## R^2 (amount of heterogeneity accounted for):             14.74%
##
## Test for Residual Heterogeneity:
## QE(df = 245) = 978.155, p-val < .001
##
## Test of Moderators (coefficients 2:15):
## F(df1 = 14, df2 = 245) = 2.622, p-val = 0.001
##
## Model Results:
##
##               estimate      se    tval   df    pval   ci.lb
## intrcpt          -0.026  0.123  -0.212  245   0.832  -0.268
## stock             0.075  0.041   1.847  245   0.066  -0.005
## GINI_control      0.057  0.050   1.135  245   0.257  -0.042
## W_I_Dispatch      0.067  0.061   1.091  245   0.276  -0.054
## est_method        -0.084  0.039  -2.130  245   0.034  -0.162
## GDP_control       -0.047  0.030  -1.563  245   0.119  -0.105
## education_control -0.051  0.035  -1.435  245   0.153  -0.120
## single_country    -0.053  0.058  -0.913  245   0.362  -0.167
## trade_control      0.001  0.030   0.033  245   0.973  -0.058
## population_control -0.022  0.072  -0.311  245   0.756  -0.163
## inflation_control -0.016  0.056  -0.285  245   0.776  -0.127
## unemployment_control -0.057  0.060  -0.948  245   0.344  -0.176
## gov_inequality_effort_control 0.054  0.047   1.164  245   0.246  -0.038
## if_published       0.080  0.089   0.899  245   0.369  -0.095
## PCC_se            0.486  0.371   1.310  245   0.191  -0.244
##
##               ci.ub
## intrcpt          0.216
## stock            0.155
## GINI_control      0.156
## W_I_Dispatch      0.187
## est_method       -0.006

```

```
## GDP_control          0.012
## education_control    0.019
## single_country       0.061
## trade_control        0.060
## population_control   0.119
## inflation_control    0.095
## unemployment_control 0.062
## gov_inequality_effort_control 0.146
## if_published         0.255
## PCC_se               1.216
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
meta.anal.select.model.middle <- rma(yi = PCC,
                                     sei = PCC_se,
                                     data = FDII_middle,
                                     method = "REML",
                                     mods = ~ stock + est_method + if_published + PCC_se,
                                     test = "knha",
                                     digits = 3)
```

```
meta.anal.select.model.middle
```

```
##
## Mixed-Effects Model (k = 260; tau^2 estimator: REML)
##
## tau^2 (estimated amount of residual heterogeneity):    0.024 (SE = 0.003)
## tau (square root of estimated tau^2 value):          0.156
## I^2 (residual heterogeneity / unaccounted variability): 83.67%
## H^2 (unaccounted variability / sampling variability):  6.12
## R^2 (amount of heterogeneity accounted for):          10.09%
##
## Test for Residual Heterogeneity:
## QE(df = 255) = 1093.975, p-val < .001
##
## Test of Moderators (coefficients 2:5):
```



```
## F(df1 = 4, df2 = 255) = 4.166, p-val = 0.003
##
## Model Results:
##
##           estimate      se    tval   df   pval   ci.lb   ci.ub
## intrcpt      -0.027  0.100  -0.266  255  0.790  -0.223   0.170
## stock         0.058  0.039   1.493  255  0.137  -0.019   0.135
## est_method    -0.060  0.030  -1.983  255  0.048  -0.120  -0.000   *
## if_published   0.049  0.083   0.593  255  0.554  -0.114   0.212
## PCC_se        0.856  0.307   2.790  255  0.006   0.252   1.461  **
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Meta tests – Lower income

```
meta.anal.full.model.lower <- rma(yi = PCC,
                                   sei = PCC_se,
                                   data = FDII_lower,
                                   method = "REML",
                                   mods = ~ stock + GINI_control + I_Share + W_I_Dis + est_method + GDP_control + education_control +
↳ single_country + trade_control + population_control + inflation_control + unemployment_control +
↳ gov_inequality_effort_control + if_published + PCC_se,
                                   test = "knha",
                                   digits = 3)
```

```
## Warning: Redundant predictors dropped from the model.
```

```
meta.anal.full.model.lower
```

```
##
## Mixed-Effects Model (k = 157; tau^2 estimator: REML)
##
## tau^2 (estimated amount of residual heterogeneity):      0.022 (SE = 0.004)
## tau (square root of estimated tau^2 value):             0.149
## I^2 (residual heterogeneity / unaccounted variability): 91.77%
## H^2 (unaccounted variability / sampling variability):    12.15
```

```

## R^2 (amount of heterogeneity accounted for):          35.20%
##
## Test for Residual Heterogeneity:
## QE(df = 143) = 518.648, p-val < .001
##
## Test of Moderators (coefficients 2:14):
## F(df1 = 13, df2 = 143) = 4.260, p-val < .001
##
## Model Results:
##
##               estimate      se      tval   df    pval   ci.lb
## intrcpt           0.112 0.103   1.092  143  0.277  -0.091
## stock             0.074 0.074   1.008  143  0.315  -0.071
## GINI_control      -0.024 0.113  -0.212  143  0.832  -0.246
## W_I_Disp          -0.048 0.104  -0.464  143  0.643  -0.255
## est_method         0.088 0.058   1.514  143  0.132  -0.027
## GDP_control        0.126 0.045   2.785  143  0.006   0.036
## education_control  0.004 0.062   0.058  143  0.954  -0.119
## single_country     -0.075 0.059  -1.264  143  0.208  -0.191
## trade_control       0.035 0.043   0.811  143  0.419  -0.050
## population_control -0.073 0.063  -1.159  143  0.248  -0.198
## inflation_control  -0.339 0.072  -4.692  143  <.001  -0.482
## unemployment_control 0.146 0.115   1.272  143  0.205  -0.081
## gov_inequality_effort_control -0.054 0.062  -0.866  143  0.388  -0.176
## PCC_se            -0.164 0.406  -0.404  143  0.687  -0.966
##
##               ci.ub
## intrcpt         0.315
## stock           0.220
## GINI_control     0.199
## W_I_Disp         0.158
## est_method       0.203
## GDP_control      0.215  **
## education_control 0.126
## single_country   0.042
## trade_control    0.121
## population_control 0.052
## inflation_control -0.196  ***

```

```
## unemployment_control      0.373
## gov_inequality_effort_control 0.069
## PCC_se                     0.638
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
meta.anal.select.model.lower <- rma(yi = PCC,
                                     sei = PCC_se,
                                     data = FDII_lower,
                                     method = "REML",
                                     mods = ~ GDP_control + inflation_control + if_published + PCC_se,
                                     test = "knha",
                                     digits = 3)
```

```
## Warning: Redundant predictors dropped from the model.
```

```
meta.anal.select.model.lower
```

```
##
## Mixed-Effects Model (k = 157; tau^2 estimator: REML)
##
## tau^2 (estimated amount of residual heterogeneity):      0.025 (SE = 0.004)
## tau (square root of estimated tau^2 value):             0.159
## I^2 (residual heterogeneity / unaccounted variability): 94.08%
## H^2 (unaccounted variability / sampling variability):    16.89
## R^2 (amount of heterogeneity accounted for):             26.36%
##
## Test for Residual Heterogeneity:
## QE(df = 153) = 649.298, p-val < .001
##
## Test of Moderators (coefficients 2:4):
## F(df1 = 3, df2 = 153) = 11.163, p-val < .001
##
## Model Results:
##
##              estimate      se    tval   df   pval   ci.lb   ci.ub
## intrcpt          0.083  0.034   2.404  153  0.017   0.015   0.151   *
```

```
## GDP_control      0.149  0.036   4.098  153 <.001   0.077   0.220  ***
## inflation_control -0.229  0.058  -3.974  153 <.001  -0.343  -0.115  ***
## PCC_se           -0.124  0.248  -0.500  153 0.618  -0.615   0.366
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Meta analysis test based on journal rank

```
meta.anal.journ <- rma(yi = PCC,
  sei = PCC_se,
  data = FDII,
  method = "REML",
  mods = ~ journal_rank,
  test = "knha")
```

```
## Warning: 71 studies with NAs omitted from model fitting.
```

```
meta.anal.journ
```

```
##
## Mixed-Effects Model (k = 545; tau^2 estimator: REML)
##
## tau^2 (estimated amount of residual heterogeneity):      0.0263 (SE = 0.0020)
## tau (square root of estimated tau^2 value):             0.1620
## I^2 (residual heterogeneity / unaccounted variability): 91.75%
## H^2 (unaccounted variability / sampling variability):    12.12
## R^2 (amount of heterogeneity accounted for):             0.85%
##
## Test for Residual Heterogeneity:
## QE(df = 543) = 3150.5280, p-val < .0001
##
## Test of Moderators (coefficient 2):
## F(df1 = 1, df2 = 543) = 3.5667, p-val = 0.0595
##
## Model Results:
##
```

```
##           estimate      se      tval   df    pval    ci.lb    ci.ub
## intrcpt         0.1146  0.0162   7.0765  543 <.0001    0.0828  0.1464 ***
## journal_rank   -0.0000  0.0000  -1.8886  543  0.0595   -0.0000  0.0000 .
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Meta analysis test based on log journal rank

```
meta.anal.lnjourn <- rma(yi = PCC,
                        sei = PCC_se,
                        data = FDII,
                        method = "ML",
                        mods = ~ log_journal_rank,
                        test = "knha")
```

```
## Warning: 71 studies with NAs omitted from model fitting.
```

```
meta.anal.lnjourn
```

```
##
## Mixed-Effects Model (k = 545; tau^2 estimator: ML)
##
## tau^2 (estimated amount of residual heterogeneity):      0.0251 (SE = 0.0019)
## tau (square root of estimated tau^2 value):             0.1585
## I^2 (residual heterogeneity / unaccounted variability): 91.39%
## H^2 (unaccounted variability / sampling variability):    11.62
## R^2 (amount of heterogeneity accounted for):             4.89%
##
## Test for Residual Heterogeneity:
## QE(df = 543) = 3043.2150, p-val < .0001
##
## Test of Moderators (coefficient 2):
## F(df1 = 1, df2 = 543) = 14.8951, p-val = 0.0001
##
## Model Results:
##
```

```
##              estimate      se      tval   df      pval      ci.lb      ci.ub
## intrcpt          0.3231  0.0615   5.2575  543 <.0001   0.2024   0.4438   ***
## log_journal_rank -0.0270  0.0070  -3.8594  543  0.0001  -0.0407  -0.0132   ***
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Meta analysis test without control variables

```
options(width = 200)

meta.anal.woCV <- rma(yi = PCC,
  sei = PCC_se,
  data = FDII,
  method = "ML",
  mods = ~ `study_country` + `estimation_methods` + `level` + `publication_time` + `avg_sample_year` +
    ↪ `data_type`,
  test = "t")
```

```
## Warning: Redundant predictors dropped from the model.
```

```
meta.anal.woCV
```

```
##
## Mixed-Effects Model (k = 616; tau^2 estimator: ML)
##
## tau^2 (estimated amount of residual heterogeneity):      0.0112 (SE = 0.0010)
## tau (square root of estimated tau^2 value):             0.1060
## I^2 (residual heterogeneity / unaccounted variability): 89.60%
## H^2 (unaccounted variability / sampling variability):    9.61
## R^2 (amount of heterogeneity accounted for):             68.39%
##
## Test for Residual Heterogeneity:
## QE(df = 549) = 2051.5311, p-val < .0001
##
## Test of Moderators (coefficients 2:67):
## F(df1 = 66, df2 = 549) = 10.1044, p-val < .0001
```

```

##
## Model Results:
##
##               estimate      se      tval   df      pval      ci.lb      ci.ub
## intrcpt          16.1703  3.0548   5.2934  549  <.0001  10.1698  22.1709 ***
## study_countryArabian      0.0535  0.1183   0.4519  549  0.6515  -0.1789   0.2858
## study_countryAsia      -0.1362  0.0673  -2.0232  549  0.0435  -0.2683  -0.0040  *
## study_countryBolivia     -0.4111  0.1977  -2.0790  549  0.0381  -0.7995  -0.0227  *
## study_countryBrazil      -0.1313  0.3107  -0.4226  549  0.6727  -0.7416   0.4790
## study_countryCentral and Eastern Europe  -0.0427  0.0787  -0.5422  549  0.5879  -0.1972   0.1119
## study_countryCentral and Eastern European countries -0.1775  0.1054  -1.6835  549  0.0929  -0.3845   0.0296  .
## study_countryChile       -0.0775  0.1949  -0.3978  549  0.6909  -0.4603   0.3053
## study_countryChina       -0.5252  0.1432  -3.6685  549  0.0003  -0.8065  -0.2440 ***
## study_countryColombia    -0.3227  0.1975  -1.6341  549  0.1028  -0.7105   0.0652
## study_countryEastern Europe and Central Asia -0.2528  0.0946  -2.6716  549  0.0078  -0.4387  -0.0669  **
## study_countryEgypt       -0.9179  0.1844  -4.9781  549  <.0001  -1.2801  -0.5557 ***
## study_countryEU          -0.3471  0.0646  -5.3751  549  <.0001  -0.4740  -0.2203 ***
## study_countryEU;APEC;LAIA -0.4166  0.1016  -4.1013  549  <.0001  -0.6161  -0.2171 ***
## study_countryFinland     -1.2220  0.2167  -5.6401  549  <.0001  -1.6477  -0.7964 ***
## study_countryGermany     -1.0868  0.2222  -4.8910  549  <.0001  -1.5233  -0.6503 ***
## study_countryHungary     -1.0902  0.3061  -3.5618  549  0.0004  -1.6914  -0.4890 ***
## study_countryIndia        0.0429  0.2242   0.1913  549  0.8484  -0.3976   0.4834
## study_countryIreland      0.0468  0.2195   0.2132  549  0.8313  -0.3843   0.4779
## study_countryItaly       -0.8021  0.2362  -3.3964  549  0.0007  -1.2660  -0.3382 ***
## study_countryLAC         -0.0525  0.0984  -0.5341  549  0.5935  -0.2458   0.1407
## study_countryLatin America  0.0463  0.0702   0.6597  549  0.5097  -0.0916   0.1842
## study_countryLDC         -0.0800  0.0611  -1.3081  549  0.1914  -0.2001   0.0401
## study_countryMalta       -0.9254  0.2309  -4.0076  549  <.0001  -1.3790  -0.4718 ***
## study_countryMENA         0.3411  0.1611   2.1175  549  0.0347   0.0247   0.6576  *
## study_countryMexico      -0.6058  0.1590  -3.8091  549  0.0002  -0.9181  -0.2934 ***
## study_countryNetherlands -0.8825  0.1907  -4.6286  549  <.0001  -1.2570  -0.5080 ***
## study_countrynon-OECD    -0.1565  0.0694  -2.2557  549  0.0245  -0.2928  -0.0202  *
## study_countryNorway      -1.1653  0.2173  -5.3624  549  <.0001  -1.5922  -0.7385 ***
## study_countryOECD        -0.2900  0.0671  -4.3226  549  <.0001  -0.4218  -0.1582 ***
## study_countryPakistan    -0.5319  0.1848  -2.8786  549  0.0041  -0.8949  -0.1689  **
## study_countrySouth Africa -0.3454  0.3821  -0.9038  549  0.3665  -1.0960   0.4052
## study_countrySouth asia   0.0070  0.0952   0.0737  549  0.9412  -0.1800   0.1940

```


Meta analysis test with control variables only

```
FDII$FDI_exports <- FDII$`FDI*exports`

meta.anal.cont <- rma(yi = PCC,
  sei = PCC_se,
  data = FDII,
  method = "ML",
  mods = ~ `GDP` + `GDPpc` + `trade` + `exports` + `openness` + `GNI` + `export_incentives` + `GDPgr` +
    ↪ `education_secondary_school_enrollment` + `gov_quality` + `inflation` + `unemployment` + `GDPpc^2` +
    ↪ `export_growth` + `gov_exp` + `education_middle_school_enrollment` + `popgr` + `financial_development`
    ↪ + `labor_productivity` + `Country_size` + `import` + `GDP^2` + `FDI_exports` + `relative_productivity`,
  test = "t")
```

```
## Warning: Redundant predictors dropped from the model.
```

```
meta.anal.cont
```

```
##
## Mixed-Effects Model (k = 616; tau^2 estimator: ML)
##
## tau^2 (estimated amount of residual heterogeneity):      0.0270 (SE = 0.0020)
## tau (square root of estimated tau^2 value):             0.1642
## I^2 (residual heterogeneity / unaccounted variability): 95.22%
## H^2 (unaccounted variability / sampling variability):    20.93
## R^2 (amount of heterogeneity accounted for):             24.18%
##
## Test for Residual Heterogeneity:
## QE(df = 592) = 3225.2929, p-val < .0001
##
## Test of Moderators (coefficients 2:24):
## F(df1 = 23, df2 = 592) = 5.3464, p-val < .0001
##
## Model Results:
##
##
```

	estimate	se	tval	df	pval	ci.lb	ci.ub
## intrcpt	0.0217	0.0191	1.1377	592	0.2557	-0.0157	0.0591

```

## GDP                0.0600  0.0331  1.8110  592  0.0706 -0.0051  0.1251  .
## GDPpc              0.0163  0.0224  0.7286  592  0.4665 -0.0277  0.0603
## trade              0.0473  0.0216  2.1880  592  0.0291  0.0048  0.0898  *
## exports            0.0474  0.0416  1.1390  592  0.2552 -0.0343  0.1291
## openness           0.0754  0.0317  2.3773  592  0.0178  0.0131  0.1377  *
## GNI                -0.0938  0.1843 -0.5088  592  0.6111 -0.4557  0.2682
## export_incentives -0.1571  0.1444 -1.0882  592  0.2770 -0.4407  0.1265
## GDPgr              0.0317  0.0351  0.9010  592  0.3679 -0.0374  0.1007
## education_secondary_school_enrollment 0.0020  0.0226  0.0904  592  0.9280 -0.0424  0.0465
## gov_quality         0.1486  0.0634  2.3439  592  0.0194  0.0241  0.2731  *
## inflation          -0.0502  0.0337 -1.4895  592  0.1369 -0.1165  0.0160
## unemployment       -0.0207  0.0431 -0.4803  592  0.6312 -0.1054  0.0640
## `GDPpc^2`          0.1696  0.0321  5.2902  592  <.0001  0.1066  0.2325  ***
## gov_exp            0.0174  0.0286  0.6100  592  0.5421 -0.0387  0.0735
## education_middle_school_enrollment 0.0838  0.0941  0.8907  592  0.3735 -0.1010  0.2686
## popgr              0.1921  0.0421  4.5642  592  <.0001  0.1094  0.2748  ***
## financial_development -0.3388  0.0975 -3.4727  592  0.0006 -0.5303 -0.1472  ***
## labor_productivity 0.0191  0.1245  0.1538  592  0.8778 -0.2253  0.2636
## Country_size        0.0454  0.1197  0.3790  592  0.7048 -0.1897  0.2805
## import             -0.1818  0.0724 -2.5101  592  0.0123 -0.3240 -0.0395  *
## `GDP^2`            0.0337  0.1138  0.2965  592  0.7670 -0.1897  0.2572
## FDI_exports         -0.1400  0.1621 -0.8641  592  0.3879 -0.4583  0.1782
## relative_productivity 0.0756  0.1801  0.4200  592  0.6746 -0.2781  0.4294
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

Meta analysis all

```

meta.anal.adv <- rma(yi = PCC,
  sei = PCC_se,
  data = FDII,
  method = "ML",
  mods = ~ `GDP` + `GDPpc` + `trade` + `exports` + `openness` + `GNI` + `export_incentives` + `GDPgr` +
    ↪ `education_secondary_school_enrollment` + `gov_quality` + `inflation` + `unemployment` + `GDPpc^2` +
    ↪ `export_growth` + `gov_exp` + `education_middle_school_enrollment` + `popgr` + `financial_development` +
    ↪ `labor_productivity` + `Country_size` + `import` + `GDP^2` + `FDI_exports` + `relative_productivity` +
    ↪ study_country + estimation_methods + study_country + estimation_methods + level + publication_time +
    ↪ avg_sample_year + data_type,

```

```
test = "t")
```

```
## Warning: Redundant predictors dropped from the model.
```

```
meta.anal.adv
```

```
##
## Mixed-Effects Model (k = 616; tau^2 estimator: ML)
##
## tau^2 (estimated amount of residual heterogeneity):      0.0071 (SE = 0.0007)
## tau (square root of estimated tau^2 value):             0.0842
## I^2 (residual heterogeneity / unaccounted variability): 84.16%
## H^2 (unaccounted variability / sampling variability):    6.31
## R^2 (amount of heterogeneity accounted for):             80.05%
##
## Test for Residual Heterogeneity:
## QE(df = 527) = 1653.6094, p-val < .0001
##
## Test of Moderators (coefficients 2:89):
## F(df1 = 88, df2 = 527) = 11.1984, p-val < .0001
##
## Model Results:
##
##               estimate      se      tval    df      pval      ci.lb      ci.ub
## intrcpt          10.6245  4.1476   2.5616  527   0.0107    2.4766  18.7724   *
## GDP               0.1225  0.0389   3.1494  527   0.0017    0.0461  0.1990  **
## GDPpc            -0.0359  0.0210  -1.7038  527   0.0890   -0.0772  0.0055   .
## trade            -0.0129  0.0245  -0.5274  527   0.5981   -0.0611  0.0353
## exports           0.0739  0.0341   2.1680  527   0.0306    0.0069  0.1409   *
## openness          -0.0058  0.0371  -0.1552  527   0.8767   -0.0787  0.0672
## GNI               0.1672  0.1835   0.9109  527   0.3628   -0.1933  0.5276
## export_incentives 0.1590  0.1750   0.9086  527   0.3640   -0.1847  0.5027
## GDPgr            -0.0869  0.0346  -2.5122  527   0.0123   -0.1549 -0.0190   *
## education_secondary_school_enrollment -0.0001  0.0286  -0.0019  527   0.9985   -0.0563  0.0562
## gov_quality        0.1608  0.0705   2.2800  527   0.0230    0.0223  0.2993   *
## inflation         0.0388  0.0299   1.2955  527   0.1957   -0.0200  0.0976
## unemployment      0.0530  0.0714   0.7423  527   0.4583   -0.0873  0.1934
```

## `GDPpc^2`	0.1495	0.0373	4.0061	527	<.0001	0.0762	0.2229	***
## gov_exp	0.0062	0.0310	0.2007	527	0.8410	-0.0548	0.0672	
## education_middle_school_enrollment	-0.3080	0.0962	-3.2030	527	0.0014	-0.4970	-0.1191	**
## popgr	0.1148	0.0483	2.3742	527	0.0179	0.0198	0.2098	*
## financial_development	-0.2685	0.1200	-2.2381	527	0.0256	-0.5042	-0.0328	*
## labor_productivity	-0.0691	0.0784	-0.8813	527	0.3786	-0.2231	0.0849	
## Country_size	-0.3127	0.1171	-2.6712	527	0.0078	-0.5426	-0.0827	**
## import	-0.3609	0.0620	-5.8217	527	<.0001	-0.4827	-0.2391	***
## `GDP^2`	-0.2353	0.1248	-1.8862	527	0.0598	-0.4805	0.0098	.
## FDI_exports	0.4831	0.1782	2.7106	527	0.0069	0.1330	0.8332	**
## relative_productivity	0.0634	0.1118	0.5675	527	0.5706	-0.1562	0.2831	
## study_countryArabian	0.0496	0.1236	0.4016	527	0.6882	-0.1931	0.2923	
## study_countryAsia	-0.3346	0.0833	-4.0183	527	<.0001	-0.4982	-0.1710	***
## study_countryBolivia	-0.3080	0.1920	-1.6044	527	0.1092	-0.6851	0.0691	
## study_countryBrazil	0.1027	0.3047	0.3369	527	0.7363	-0.4960	0.7013	
## study_countryCentral and Eastern Europe	-0.2246	0.1161	-1.9348	527	0.0535	-0.4527	0.0034	.
## study_countryChile	0.0249	0.1890	0.1319	527	0.8951	-0.3464	0.3962	
## study_countryChina	-0.5327	0.1496	-3.5609	527	0.0004	-0.8266	-0.2388	***
## study_countryColombia	-0.2203	0.1917	-1.1495	527	0.2509	-0.5968	0.1562	
## study_countryEastern Europe and Central Asia	-0.6014	0.1370	-4.3888	527	<.0001	-0.8706	-0.3322	***
## study_countryEgypt	-0.7331	0.1856	-3.9489	527	<.0001	-1.0978	-0.3684	***
## study_countryEU	-0.3831	0.0740	-5.1771	527	<.0001	-0.5285	-0.2377	***
## study_countryEU;APEC;LAIA	-0.5797	0.1661	-3.4907	527	0.0005	-0.9060	-0.2535	***
## study_countryFinland	-1.1500	0.2119	-5.4279	527	<.0001	-1.5662	-0.7338	***
## study_countryGermany	-1.0199	0.2174	-4.6919	527	<.0001	-1.4469	-0.5929	***
## study_countryHungary	-0.9174	0.3018	-3.0401	527	0.0025	-1.5102	-0.3246	**
## study_countryIndia	0.2778	0.2205	1.2599	527	0.2083	-0.1554	0.7110	
## study_countryIreland	0.1254	0.2149	0.5834	527	0.5598	-0.2968	0.5476	
## study_countryItaly	-0.7259	0.2319	-3.1302	527	0.0018	-1.1815	-0.2704	**
## study_countryLAC	-0.1163	0.1154	-1.0081	527	0.3139	-0.3429	0.1103	
## study_countryLatin America	-0.0240	0.0826	-0.2904	527	0.7716	-0.1861	0.1382	
## study_countryLDC	-0.1338	0.0757	-1.7664	527	0.0779	-0.2826	0.0150	.
## study_countryMalta	-0.8483	0.2265	-3.7455	527	0.0002	-1.2932	-0.4034	***
## study_countryMENA	0.4001	0.1589	2.5177	527	0.0121	0.0879	0.7123	*
## study_countryMexico	-0.4890	0.1653	-2.9573	527	0.0032	-0.8138	-0.1642	**
## study_countryNetherlands	-1.0222	0.1984	-5.1535	527	<.0001	-1.4119	-0.6326	***
## study_countrynon-OECD	-0.1422	0.0775	-1.8350	527	0.0671	-0.2944	0.0100	.

## study_countryNorway	-1.1019	0.2122	-5.1927	527	<.0001	-1.5188	-0.6850	***
## study_countryOECD	-0.3200	0.0750	-4.2661	527	<.0001	-0.4673	-0.1726	***
## study_countryPakistan	-0.5030	0.1836	-2.7405	527	0.0063	-0.8636	-0.1424	**
## study_countrySouth Africa	-0.3872	0.3797	-1.0198	527	0.3083	-1.1331	0.3587	
## study_countrySouth asia	-0.0175	0.1094	-0.1600	527	0.8730	-0.2325	0.1975	
## study_countrySouth Korea	-0.0782	0.1842	-0.4247	527	0.6712	-0.4401	0.2836	
## study_countrySpain	0.1565	0.2113	0.7407	527	0.4592	-0.2586	0.5716	
## study_countrysub-Saharan African	-0.2965	0.1031	-2.8761	527	0.0042	-0.4991	-0.0940	**
## study_countrySweden	-1.3067	0.1984	-6.5845	527	<.0001	-1.6965	-0.9168	***
## study_countryThailand	-0.6454	0.1687	-3.8261	527	0.0001	-0.9768	-0.3140	***
## study_countryTurkey	-0.5596	0.2760	-2.0278	527	0.0431	-1.1017	-0.0175	*
## study_countryUK	-0.5825	0.1647	-3.5361	527	0.0004	-0.9060	-0.2589	***
## study_countryUruguay	-0.5645	0.1927	-2.9295	527	0.0035	-0.9430	-0.1859	**
## study_countryUS	-0.6285	0.1097	-5.7313	527	<.0001	-0.8440	-0.4131	***
## study_countryVietnam	-0.4066	0.1295	-3.1405	527	0.0018	-0.6609	-0.1523	**
## study_countryworldwide	-0.1775	0.0715	-2.4839	527	0.0133	-0.3179	-0.0371	*
## estimation_methods3SLS	-0.2447	0.2412	-1.0145	527	0.3108	-0.7185	0.2291	
## estimation_methodsARDL	0.3819	0.2416	1.5807	527	0.1146	-0.0927	0.8566	
## estimation_methodsBetween effects	0.0483	0.0848	0.5696	527	0.5692	-0.1183	0.2149	
## estimation_methodsCCE	0.1606	0.0846	1.8983	527	0.0582	-0.0056	0.3268	.
## estimation_methodsDOLS	0.1095	0.0543	2.0145	527	0.0445	0.0027	0.2162	*
## estimation_methodsECM	0.0683	0.1058	0.6457	527	0.5188	-0.1396	0.2762	
## estimation_methodsFM-OLS	0.2352	0.0873	2.6936	527	0.0073	0.0637	0.4068	**
## estimation_methodsGLS	0.5458	0.0932	5.8574	527	<.0001	0.3627	0.7288	***
## estimation_methodsGMM	0.0025	0.0302	0.0835	527	0.9335	-0.0568	0.0618	
## estimation_methodsIV	0.0481	0.0609	0.7893	527	0.4303	-0.0716	0.1678	
## estimation_methodsJohansen's cointegration test	0.1354	0.0633	2.1376	527	0.0330	0.0110	0.2597	*
## estimation_methodsLIML	-0.0008	0.0632	-0.0123	527	0.9902	-0.1248	0.1233	
## estimation_methodsLSDV	-0.1326	0.1421	-0.9331	527	0.3512	-0.4117	0.1465	
## estimation_methodsOLS	0.0452	0.0315	1.4351	527	0.1518	-0.0167	0.1071	
## estimation_methodsPanel	-0.0149	0.0276	-0.5387	527	0.5903	-0.0692	0.0394	
## estimation_methodsParks	0.3959	0.0974	4.0637	527	<.0001	0.2045	0.5873	***
## estimation_methodsRandom effect	0.0527	0.0423	1.2452	527	0.2136	-0.0304	0.1357	
## estimation_methodsSUR	-0.0756	0.2578	-0.2934	527	0.7693	-0.5820	0.4307	
## estimation_methodsSURE	0.1370	0.0560	2.4470	527	0.0147	0.0270	0.2470	*
## level	-0.1210	0.0716	-1.6886	527	0.0919	-0.2617	0.0198	.
## publication_time	-0.0126	0.0027	-4.7062	527	<.0001	-0.0179	-0.0074	***

```
## avg_sample_year      0.0079  0.0024   3.2385  527  0.0013   0.0031   0.0126   **
## data_type            -0.1654  0.0325  -5.0866  527  <.0001  -0.2292  -0.1015   ***
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

ANOVA test for best model (to test against overfitting)

```
# meta.permutation <- permutest(meta.anal.adv)      # This takes c.40 minutes to run. It does not need to be run each time
```

```
anova(meta.anal.cont, meta.anal.adv)
```

```
##
##      df      AIC      BIC      AICc  logLik      LRT  pval      QE  tau^2      R^2
## Full   90 -500.2877 -102.1955 -469.0877 340.1438          1653.6094 0.0071
## Reduced 25 -112.0900  -1.5089 -109.8866  81.0450 518.1977 <.0001 3225.2929 0.0270 73.6848%
```

Further funnel plot asymmetry tests

Run the Eggers test for those with endogeneity controls

The tests used that allow for endogeneity controls are: - 2SLS \ - 3SLS \ - IV \ - ARDL \ - LIML \ - LSDV \ - FM-OLS \ - CCE \ - DOLS \ - ECM \ - GMM \

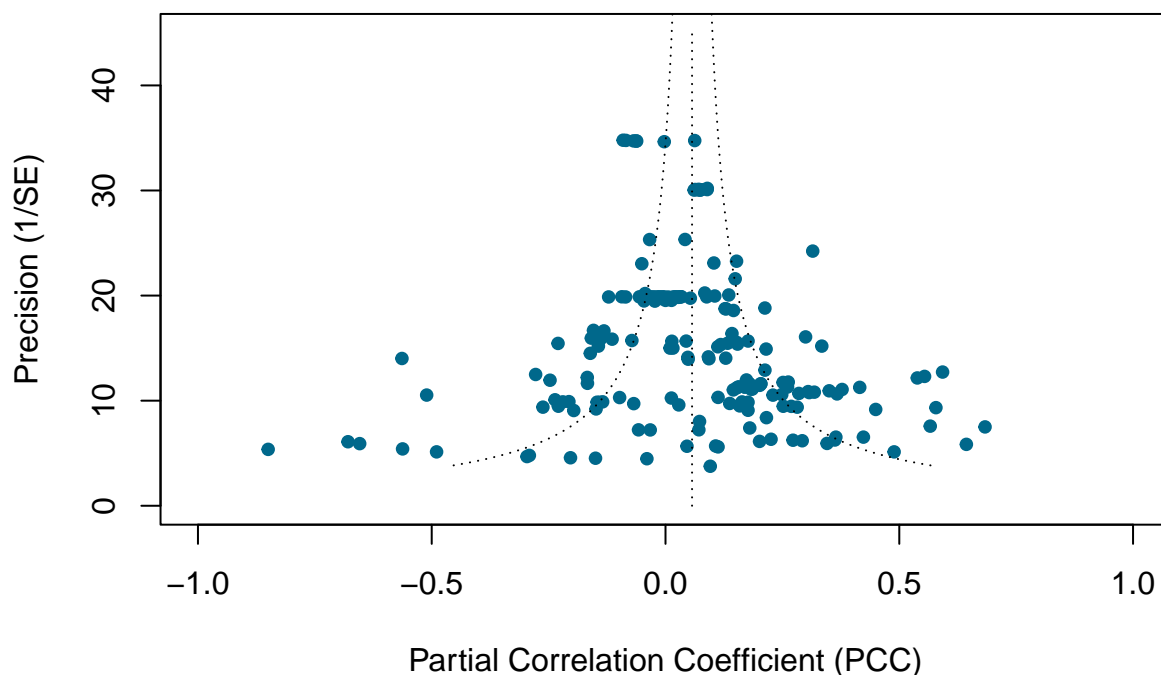
```
options(width = 70)

FDII_endo <- FDII %>%
  filter(estimation_methods %in% c("2SLS", "3SLS", "IV", "Johansen's cointegration
    ↪ test", "ARDL", "LIML", "LSDV", "FM-OLS", "CCE", "DOLS", "ECM", "GMM"))
m.gen.endo <- metagen(TE = FDII_endo$PCC,
  seTE = FDII_endo$PCC_se,
  studlab = FDII_endo$citation,
  data = FDII_endo,
  sm = "SMD",
  comb.fixed = FALSE,
  comb.random = TRUE,
  method.tau = "REML",
  hakn = TRUE,
  title = "FDI Impacts on Income Inequality (with endogeneity
    ↪ adjustments)")

eggers.test(m.gen.endo)

## Eggers' test of the intercept
## =====
##
## intercept      95% CI    t          p
##      0.829 0.44 - 1.22 4.13 0.00005361478
##
## Eggers' test indicates the presence of funnel plot asymmetry.

PCC_Funnel_Graph_endo <- metafor::funnel(m.gen.endo,
  xlim = c(-1, 1),
  ylim = rev(c(45, 0)),
  studlab = FALSE,
  xlab = "Partial Correlation Coefficient (PCC)",
  ylab = "Precision (1/SE)",
  yaxis = "invse",
  col = "deepskyblue4",
  bg = "deepskyblue4",
  cex = 0.8)
```



We see that when we run a funnel plot asymmetry test on only those which have accounted for endogeneity issues, we still witness funnel plot asymmetry.

Run the Eggers test for those without endogeneity controls

```
FDII_no_test <- FDII %>%
  filter(estimation_methods %in% c("Between effects", "GLS", "SUR", "SURE", "Random
    ↪ effect", "Probit", "Parks", "Panel", "OLS"))
m.gen.no.test <- metagen(TE = FDII_no_test$PCC,
  seTE = FDII_no_test$PCC_se,
  studlab = FDII_no_test$citation,
  data = FDII_no_test,
  sm = "SMD",
  comb.fixed = FALSE,
  comb.random = TRUE,
  method.tau = "REML",
  hakn = TRUE,
  title = "FDI Impacts on Income Inequality (without
    ↪ endogeneity adjustments)")

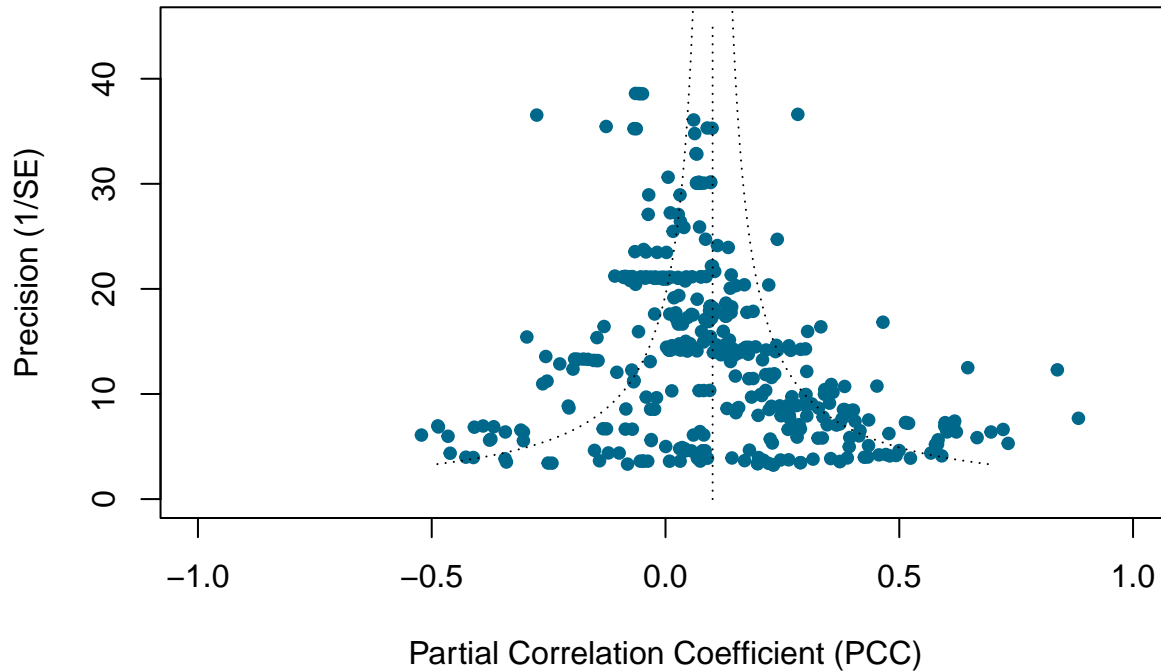
eggers.test(m.gen.no.test)

## Eggers' test of the intercept
## =====
##
## intercept      95% CI      t      p
##      0.903 0.61 - 1.19 6.081 0.000000002796337
##
## Eggers' test indicates the presence of funnel plot asymmetry.

PCC_Funnel_Graph_no_test <- metafor::funnel(m.gen.no.test,
  xlim = c(-1, 1),
  ylim = rev(c(45, 0)),
  studlab = FALSE,
  xlab = "Partial Correlation Coefficient (PCC)",
```



```
ylab = "Precision (1/SE)",
yaxis = "invse",
col = "deepskyblue4",
bg = "deepskyblue4",
cex = 0.8,
title = "FDI Impacts on Income Inequality
↪ (without endogeneity adjustments)"
```



As expected, we again witness funnel plot asymmetry on those who have not accounted for endogeneity

FAT - single-country

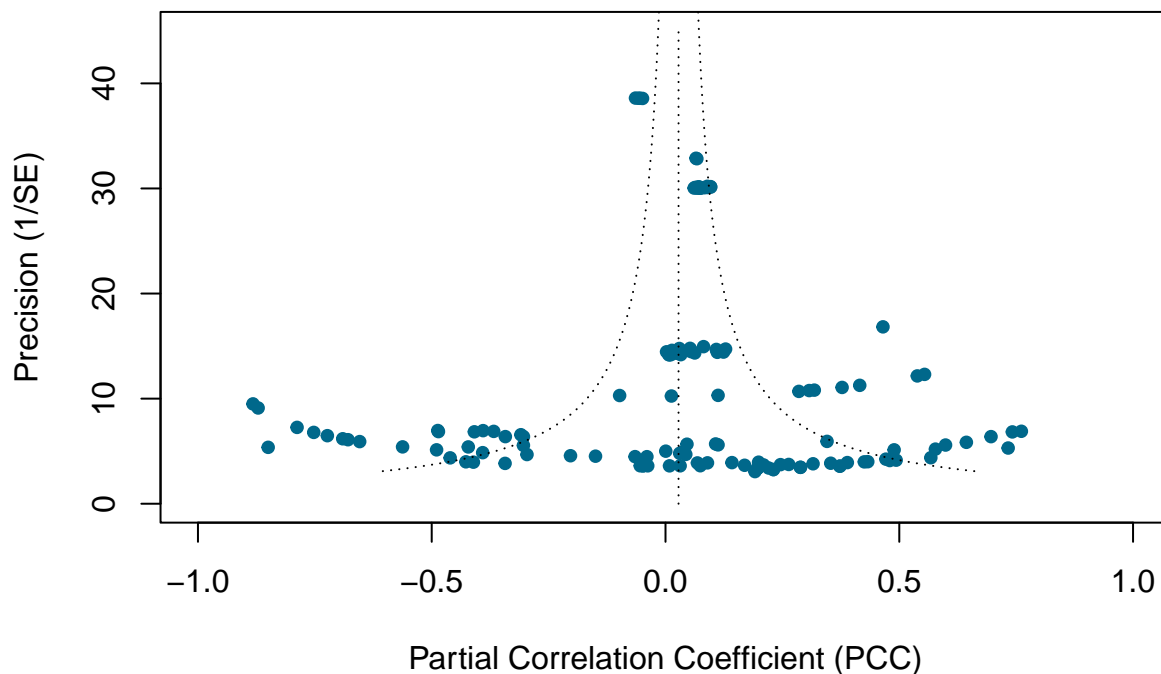
```
FDII_single <- subset(FDII, level == 1)

m.gen.single <- metagen(TE = FDII_single$PCC,
  seTE = FDII_single$PCC_se,
  studlab = FDII_single$citation,
  data = FDII_single,
  sm = "SMD",
  comb.fixed = FALSE,
  comb.random = TRUE,
  method.tau = "REML",
  hakn = TRUE,
  title = "FDI Impacts on Income Inequality (single country)")

eggers.test(m.gen.single)

## Eggers' test of the intercept
## =====
##
##   intercept      95% CI      t      p
##      0.36 -0.12 - 0.84 1.477 0.1418879
##
## Eggers' test does not indicate the presence of funnel plot asymmetry.
```

```
PCC_Funnel_Graph_single <- metafor::funnel(m.gen.single,
  xlim = c(-1, 1),
  ylim = rev(c(45, 0)),
  studlab = FALSE,
  xlab = "Partial Correlation Coefficient (PCC)",
  ylab = "Precision (1/SE)",
  yaxis = "invse",
  col = "deepskyblue4",
  bg = "deepskyblue4",
  cex = 0.8)
```



FAT - multiple-country

```
FDII_multi <- subset(FDII, level != 1)

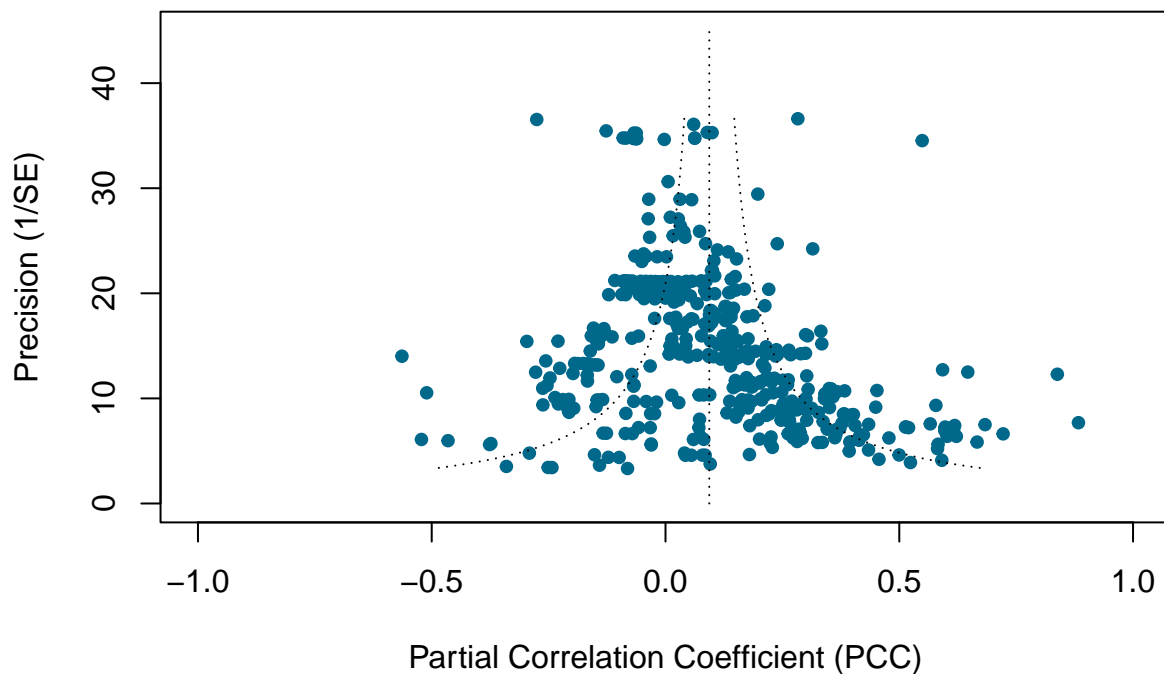
m.gen.multi <- metagen(TE = FDII_multi$PCC,
  seTE = FDII_multi$PCC_se,
  studlab = FDII_multi$citation,
  data = FDII_multi,
  sm = "SMD",
  comb.fixed = FALSE,
  comb.random = TRUE,
  method.tau = "REML",
  hakn = TRUE,
  title = "FDI Impacts on Income Inequality (multi country)")
```

```
eggers.test(m.gen.multi)
```

```
## Eggers' test of the intercept
## =====
##
## intercept      95% CI      t      p
##      1.741 1.24 - 2.24 6.864 0.00000000002149276
##
```

```
## Eggers' test indicates the presence of funnel plot asymmetry.
```

```
PCC_Funnel_Graph_multi <- metafor::funnel(m.gen.multi,
                                           xlim = c(-1, 1),
                                           ylim = rev(c(45, 0)),
                                           studlab = FALSE,
                                           xlab = "Partial Correlation Coefficient
                                           ↪ (PCC)",
                                           ylab = "Precision (1/SE)",
                                           yaxp = "invse",
                                           col = "deepskyblue4",
                                           bg = "deepskyblue4",
                                           cex = 0.8)
```



FAT - published papers

```
FDII_published <- subset(FDII, if_published == 1)

m.gen.published <- metagen(TE = FDII_published$PCC,
                          seTE = FDII_published$PCC_se,
                          studlab = FDII_published$citation,
                          data = FDII_published,
                          sm = "SMD",
                          comb.fixed = FALSE,
                          comb.random = TRUE,
                          method.tau = "REML",
                          haki = TRUE,
                          title = "FDI Impacts on Income Inequality (single country)")

eggers.test(m.gen.published)
```

```
## Eggers' test of the intercept
```

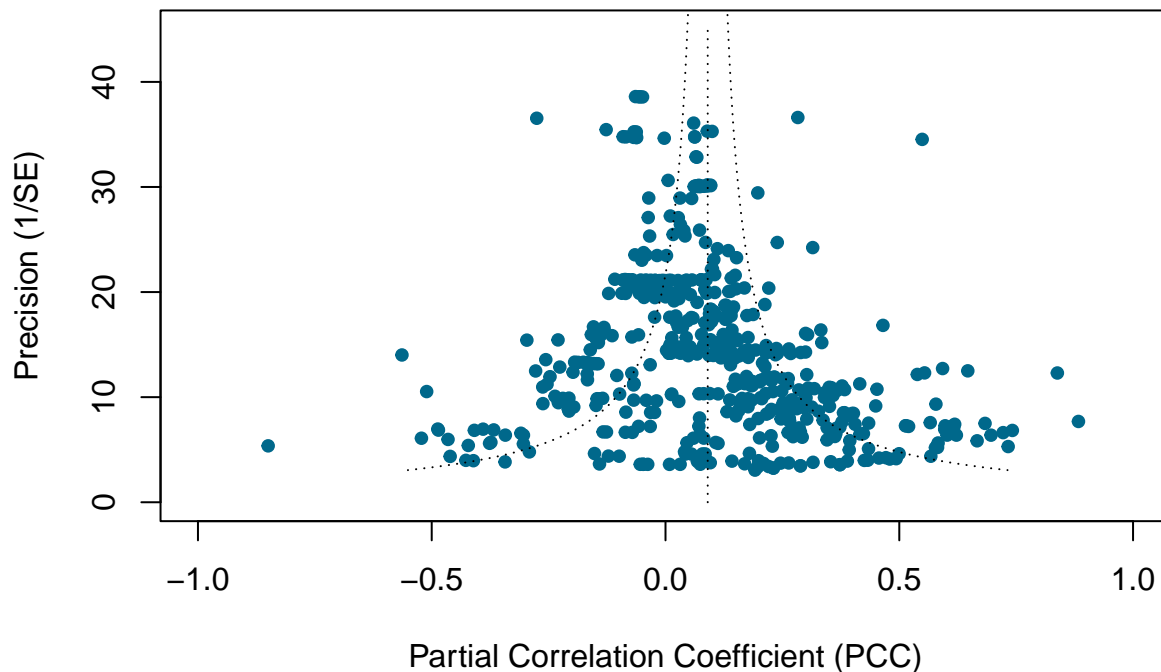
```
## =====
```

```
##
```

```
## intercept      95% CI      t      p
```

```
##      0.872 0.58 - 1.17 5.817 0.00000001003444
##
## Eggers' test indicates the presence of funnel plot asymmetry.
```

```
PCC_Funnel_Graph_published <- metafor::funnel(m.gen.published,
                                              xlim = c(-1, 1),
                                              ylim = rev(c(45, 0)),
                                              studlab = FALSE,
                                              xlab = "Partial Correlation Coefficient
                                              ↪ (PCC)",
                                              ylab = "Precision (1/SE)",
                                              yaxis = "invse",
                                              col = "deepskyblue4",
                                              bg = "deepskyblue4",
                                              cex = 0.8)
```



FAT - unpublished papers

```
FDII_not_published <- subset(FDII, if_published == 0)

m.gen.not.published <- metagen(TE = FDII_not_published$PCC,
                              seTE = FDII_not_published$PCC_se,
                              studlab = FDII_not_published$citation,
                              data = FDII_not_published,
                              sm = "SMD",
                              comb.fixed = FALSE,
                              comb.random = TRUE,
                              method.tau = "REML",
                              hakn = TRUE,
                              title = "FDI Impacts on Income Inequality (single
                              ↪ country)")

eggers.test(m.gen.not.published)
```

```
## Eggers' test of the intercept
```

```
## =====
```

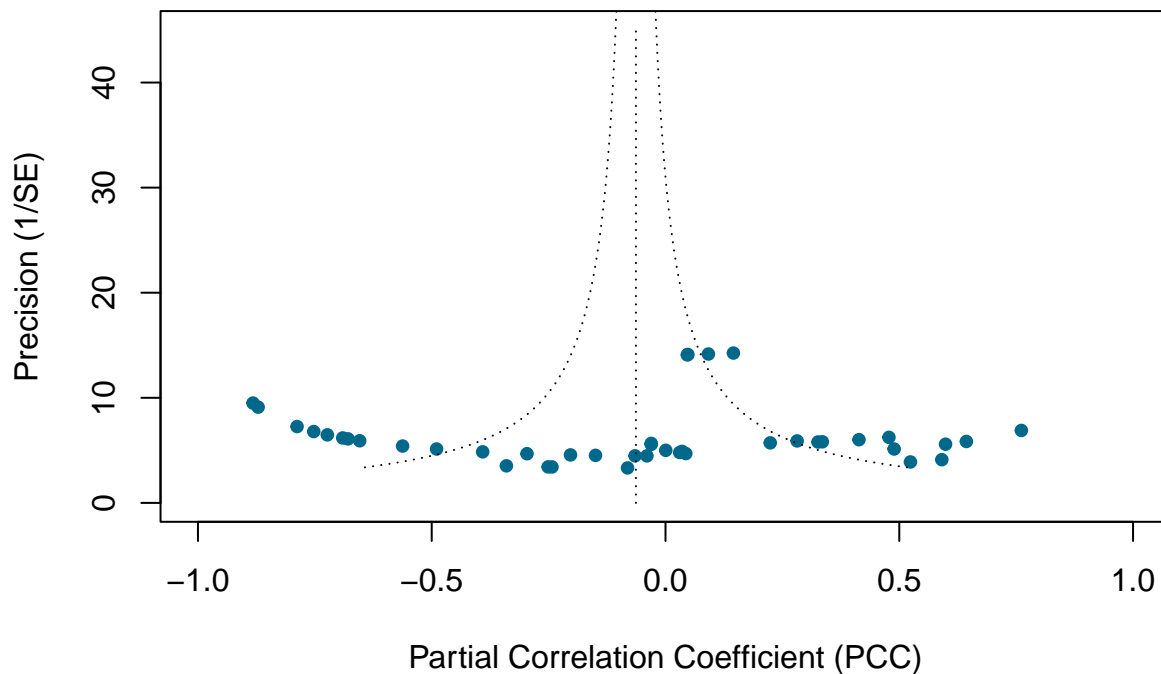
```
##
```

```
## intercept      95% CI      t      p
##    -0.536 -1.45 - 0.38 -1.152 0.2551092
```

```
##
```

```
## Eggers' test does not indicate the presence of funnel plot asymmetry.
```

```
PCC_Funnel_Graph_not_published <- metafor::funnel(m.gen.not.published,
  xlim = c(-1, 1),
  ylim = rev(c(45, 0)),
  studlab = FALSE,
  xlab = "Partial Correlation Coefficient
  ↪ (PCC)",
  ylab = "Precision (1/SE)",
  yaxis = "invse",
  col = "deepskyblue4",
  bg = "deepskyblue4",
  cex = 0.8)
```



FAT - core tests (from those in the permutest with $p < 0.05$)

```
FDII_core_tests <- subset(FDII, GDP == 1 |
  GDPpc == 1 |
  GNI == 1 |
  export_incentives == 1 |
  GDPgr == 1 |
  gov_quality == 1 |
  unemployment == 1 |
  `GDPpc^2` == 1 |
  gov_exp == 1 |
  education_middle_school_enrollment == 1 |
  popgr == 1 |
  financial_development == 1 |
  labor_productivity == 1 |
```

```

Country_size == 1 |
import == 1 |
`GDP^2` == 1)

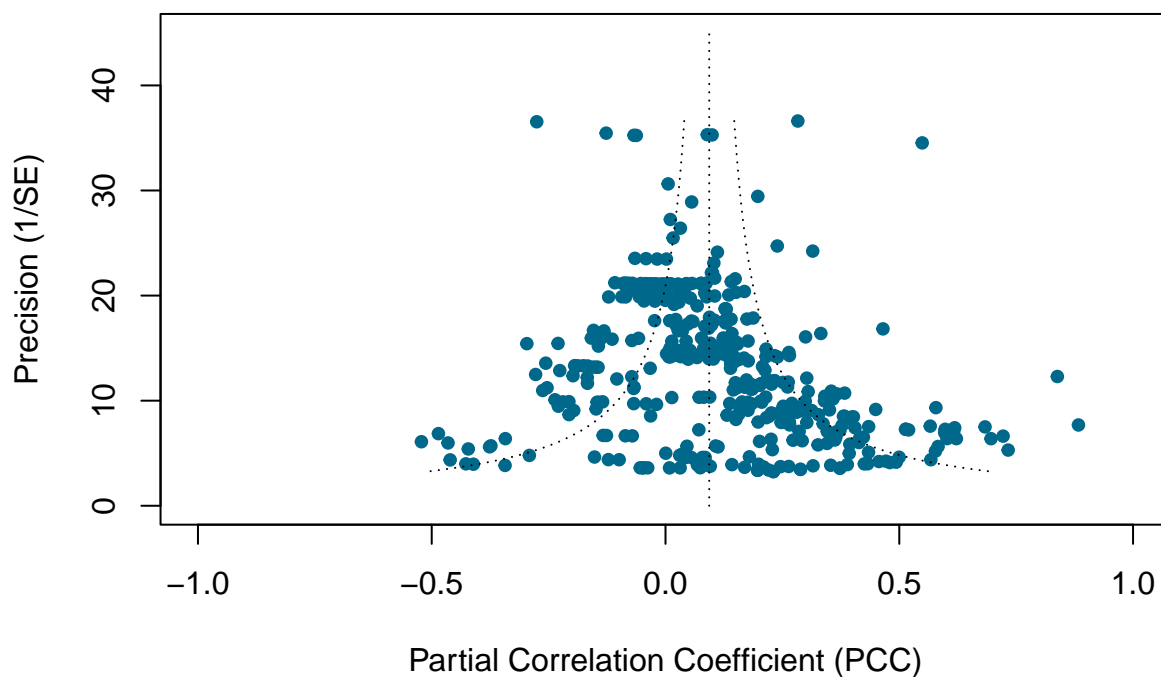
m.gen.core.tests <- metagen(TE = FDII_core_tests$PCC,
  seTE = FDII_core_tests$PCC_se,
  studlab = FDII_core_tests$citation,
  data = FDII_core_tests,
  sm = "SMD",
  comb.fixed = FALSE,
  comb.random = TRUE,
  method.tau = "REML",
  hakn = TRUE,
  title = "FDI Impacts on Income Inequality (core tests)")

eggers.test(m.gen.core.tests)

## Eggers' test of the intercept
## =====
##
##   intercept      95% CI      t      p
##      1.371 0.91 - 1.83 5.806 0.00000001224257
##
## Eggers' test indicates the presence of funnel plot asymmetry.

PCC_Funnel_Graph_core_tests <- metafor::funnel(m.gen.core.tests,
  xlim = c(-1, 1),
  ylim = rev(c(45, 0)),
  studlab = FALSE,
  xlab = "Partial Correlation Coefficient
↪ (PCC)",
  ylab = "Precision (1/SE)",
  yaxis = "invse",
  col = "deepskyblue4",
  bg = "deepskyblue4",
  cex = 0.8)

```



FAT - no core tests

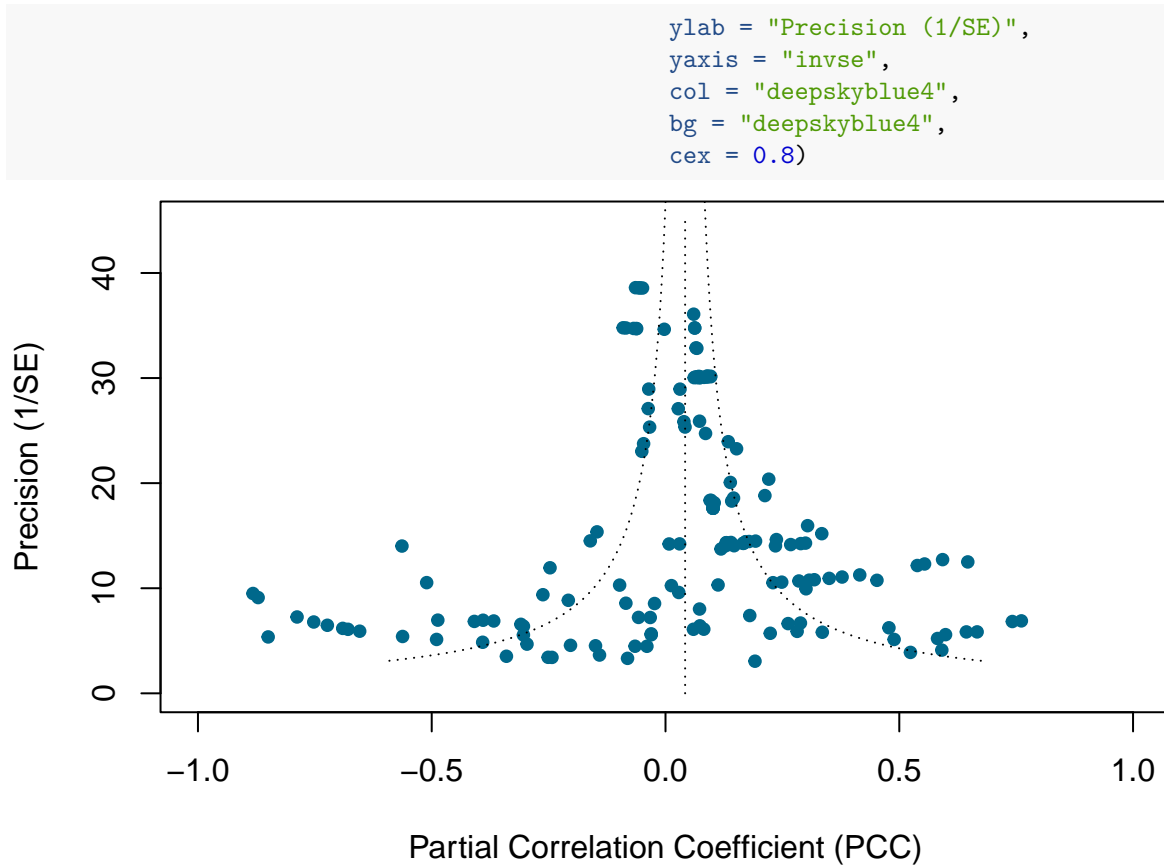
```
FDII_no_core_tests <- subset(FDII, !(GDP == 1 | GDPpc == 1 | GNI == 1 |
  ↳ export_incentives == 1 | GDPgr == 1 | gov_quality == 1 | unemployment == 1 |
  ↳ `GDPpc^2` == 1 | gov_exp == 1 | education_middle_school_enrollment == 1 | popgr
  ↳ == 1 | financial_development == 1 | labor_productivity == 1 | Country_size == 1
  ↳ | import == 1 | `GDP^2` == 1))

m.gen.no.core.tests <- metagen(TE = FDII_no_core_tests$PCC,
  seTE = FDII_no_core_tests$PCC_se,
  studlab = FDII_no_core_tests$citation,
  data = FDII_no_core_tests,
  sm = "SMD",
  comb.fixed = FALSE,
  comb.random = TRUE,
  method.tau = "REML",
  hakn = TRUE,
  title = "FDI Impacts on Income Inequality (core tests)")

eggers.test(m.gen.no.core.tests)

## Eggers' test of the intercept
## =====
##
## intercept      95% CI      t      p
##      0.694 0.17 - 1.22 2.612 0.009815691
##
## Eggers' test indicates the presence of funnel plot asymmetry.

PCC_Funnel_Graph_no_core_tests <- metafor::funnel(m.gen.no.core.tests,
  xlim = c(-1, 1),
  ylim = rev(c(45, 0)),
  studlab = FALSE,
  xlab = "Partial Correlation
  ↳ Coefficient (PCC)",
```



Tests over time

PCC over time (to publication)

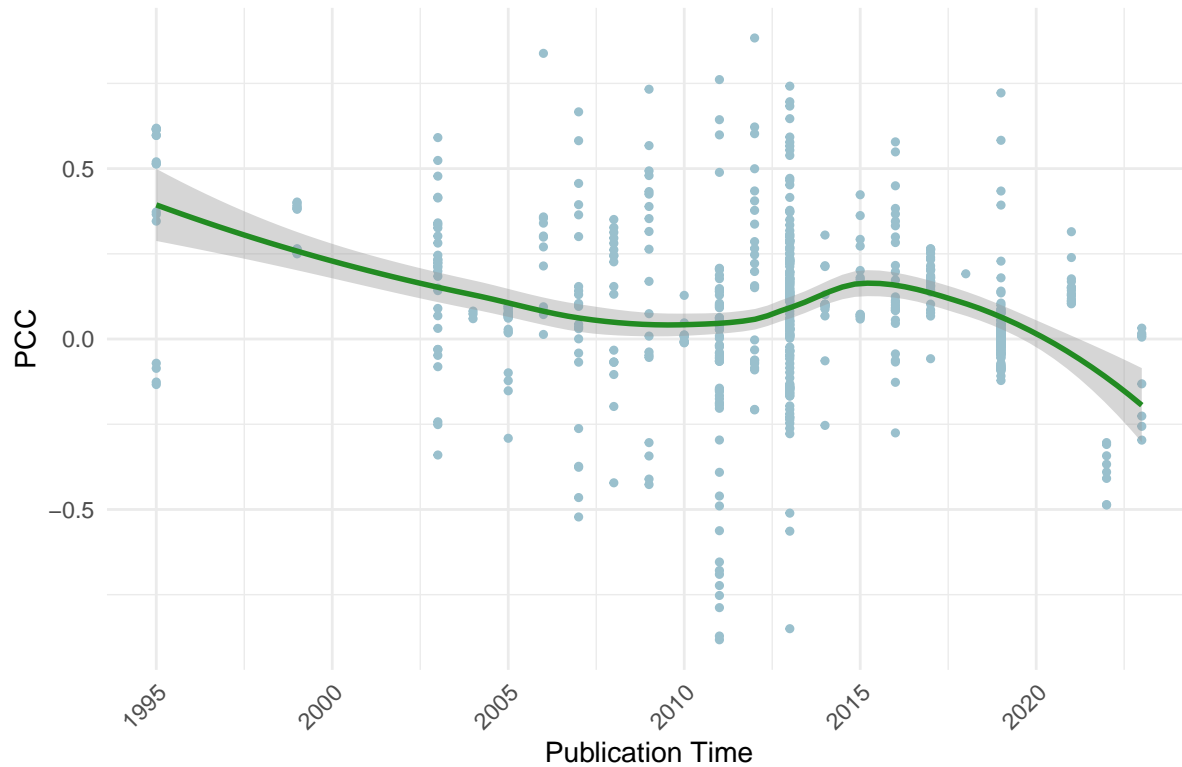
```

ggplot(FDII, aes(x = publication_time, y = PCC)) +
  geom_point(size = 1, color = "lightblue3") +
  geom_smooth(method = "loess", col = "forestgreen") +
  labs(title = "PCC over Time with Trend Line", x = "Publication Time", y = "PCC") +
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))

```

```
## `geom_smooth()` using formula = 'y ~ x'
```


PCC over Time with Trend Line



This is super interesting, because it could be showing changes in the underlying economic phenomenon

```
summary(lm(FDII$PCC ~ FDII$publication_time))
```

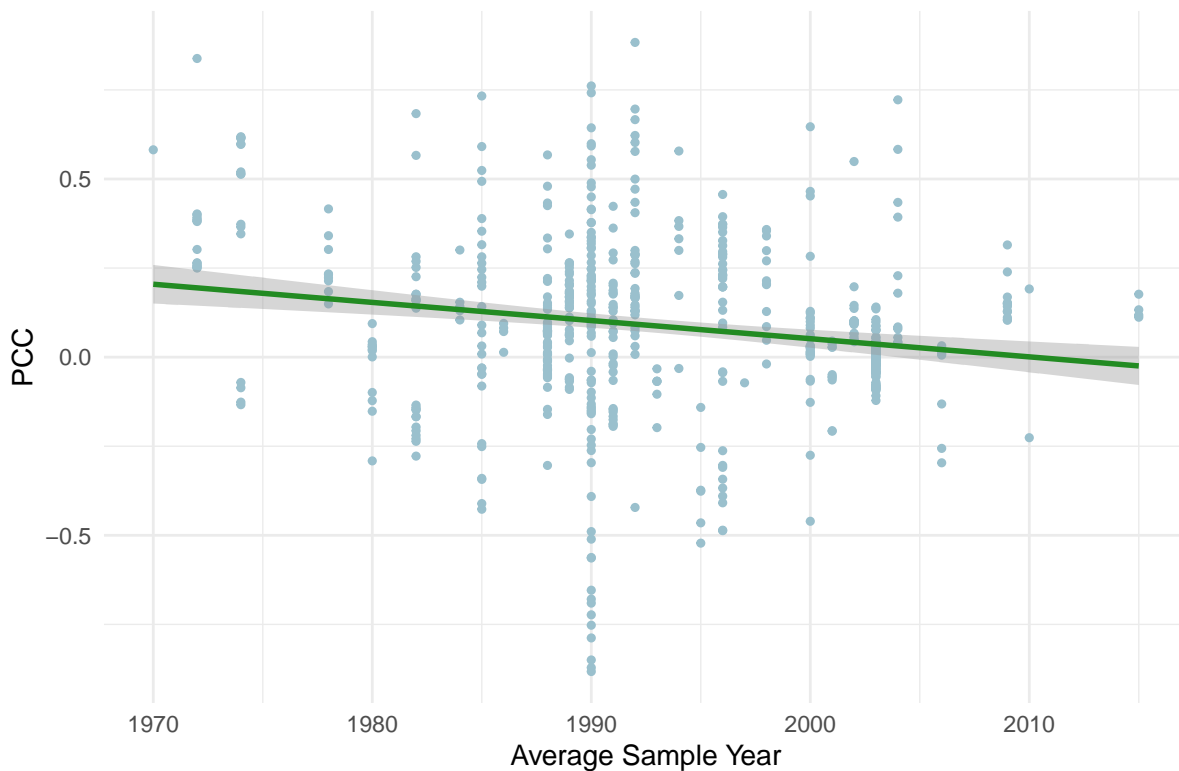
```
##
## Call:
## lm(formula = FDII$PCC ~ FDII$publication_time)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.98255 -0.10791  0.00262  0.13298  0.79183
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    17.905310   3.322600   5.389 0.000000101 ***
## FDII$publication_time -0.008854   0.001651  -5.362 0.000000117 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.2424 on 614 degrees of freedom
## Multiple R-squared:  0.04473,    Adjusted R-squared:  0.04318
## F-statistic: 28.75 on 1 and 614 DF,  p-value: 0.0000001166
```

PCC trend over time (average year of the sample)

```
ggplot(FDII, aes(x = avg_sample_year, y = PCC)) +
  geom_point(size = 1, color = "lightblue3") +
  geom_smooth(method = "lm", col = "forestgreen") +
  labs(title = "PCC over Time with Trend Line", x = "Average Sample Year", y =
    ↪ "PCC") +
  theme_minimal()
```

```
## `geom_smooth()` using formula = 'y ~ x'
```

PCC over Time with Trend Line



We do, as expected

```
summary(lm(FDII$PCC ~ FDII$avg_sample_year))
```

```
##
## Call:
## lm(formula = FDII$PCC ~ FDII$avg_sample_year)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.98498 -0.11107  0.00022  0.12535  0.79073
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    10.241536   2.265050   4.522 0.00000737 ***
## FDII$avg_sample_year -0.005095   0.001137  -4.482 0.00000881 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.2441 on 614 degrees of freedom
## Multiple R-squared:  0.03168,    Adjusted R-squared:  0.03011
## F-statistic: 20.09 on 1 and 614 DF,  p-value: 0.000008813
```

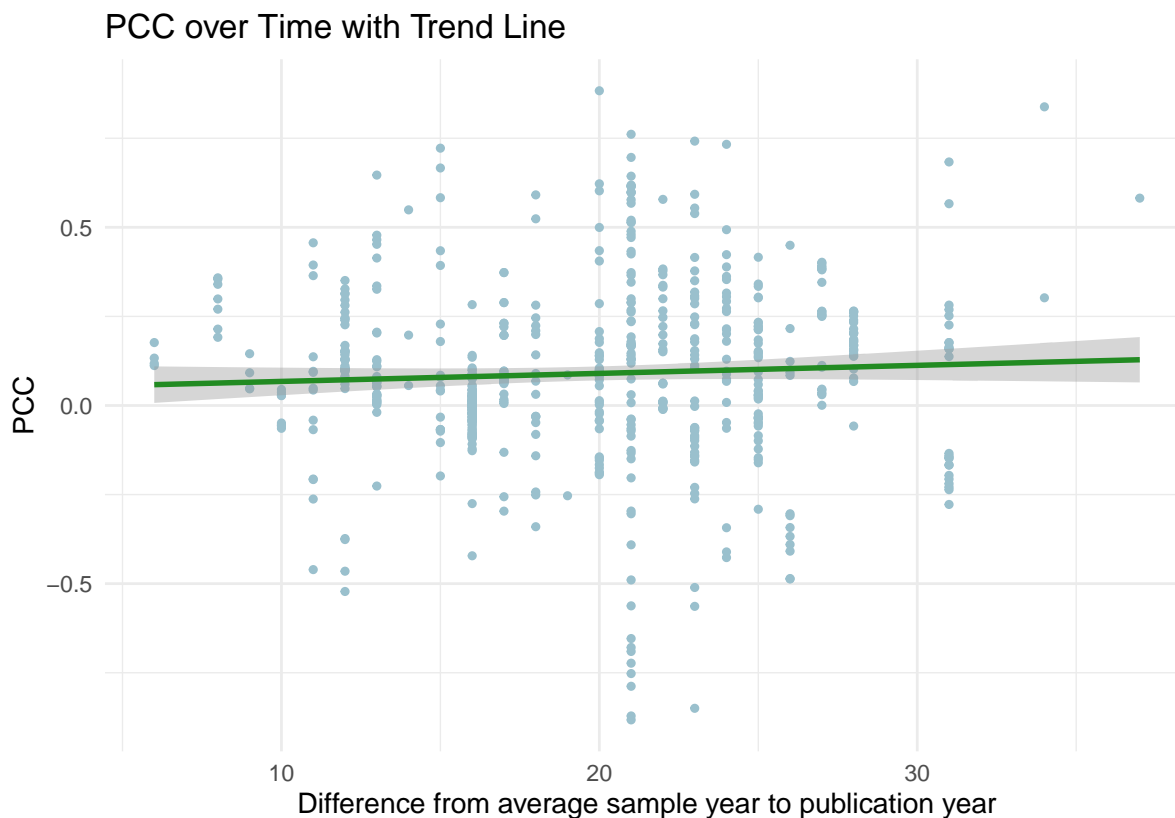
Difference between publication and sample year trend

```
FDII$difference <- FDII$publication_time - FDII$avg_sample_year
```

```
ggplot(FDII, aes(x = difference, y = PCC)) +
  geom_point(size = 1, color = "lightblue3") +
```

```
geom_smooth(method = "lm", col = "forestgreen") +
labs(title = "PCC over Time with Trend Line", x = "Difference from average sample
↪ year to publication year", y = "PCC") +
theme_minimal()
```

```
## `geom_smooth()` using formula = 'y ~ x'
```



```
summary(lm(FDII$PCC ~ FDII$difference))
```

```
##
## Call:
## lm(formula = FDII$PCC ~ FDII$difference)
##
## Residuals:
```

	Min	1Q	Median	3Q	Max
	-0.97458	-0.11401	-0.00833	0.12937	0.79320

```
##
## Coefficients:
```

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	0.044973	0.036121	1.245	0.214
FDII\$difference	0.002254	0.001772	1.272	0.204

```
##
## Residual standard error: 0.2477 on 614 degrees of freedom
## Multiple R-squared: 0.002629, Adjusted R-squared: 0.001004
## F-statistic: 1.618 on 1 and 614 DF, p-value: 0.2038
```

I wanted to see whether articles that are published closer to their average sample year have greater impacts or not. I could test later whether these are heterogeneous or not. They are not statistically significant, suggesting that the recency of the article bears little-to-no weight in the likelihood of prediction. Stanley talks in the book about how papers are often quicker to publish if there are statistically-significant results.

Average sample year trend (statistical significance)

```
FDII$mod_t_value <- ifelse(sqrt(FDII$t_value_calculated^2) < 8,
                           sqrt(FDII$t_value_calculated^2),
                           NA)

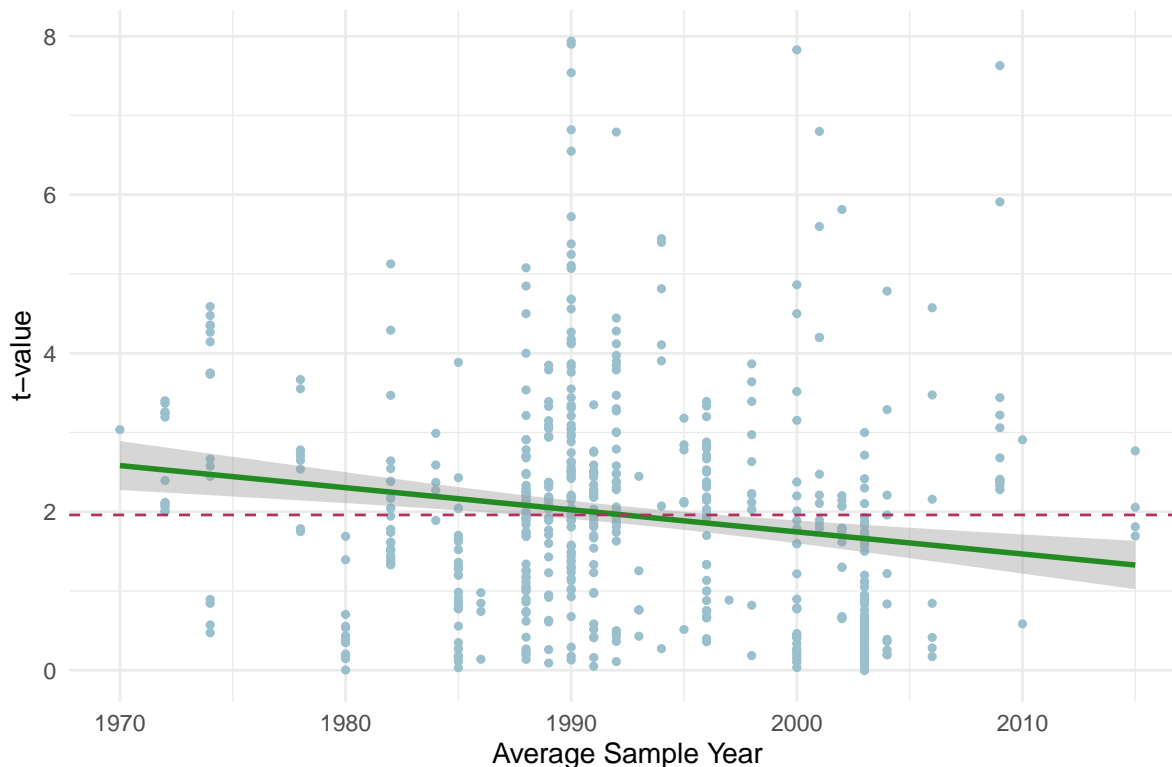
ggplot(FDII, aes(x = avg_sample_year, y = mod_t_value)) +
  geom_point(size = 1, color = "lightblue3") +
  geom_smooth(method = "lm", col = "forestgreen") +
  geom_hline(yintercept = 1.96, color = "maroon", linetype = "dashed") +
  labs(title = "Statistical Significance over Time with Trend Line",
       x = "Average Sample Year",
       y = "t-value") +
  theme_minimal()
```

```
## `geom_smooth()` using formula = 'y ~ x'
```

```
## Warning: Removed 6 rows containing non-finite outside the scale range
## (`stat_smooth()`).
```

```
## Warning: Removed 6 rows containing missing values or values outside the scale
## range (`geom_point()`).
```

Statistical Significance over Time with Trend Line



```
summary(lm(FDII$mod_t_value ~ FDII$avg_sample_year))
```

```
##
```

```
## Call:
```

```
## lm(formula = FDII$mod_t_value ~ FDII$avg_sample_year)
```

```
##
```

```
## Residuals:
```

```
##      Min       1Q   Median       3Q      Max
```

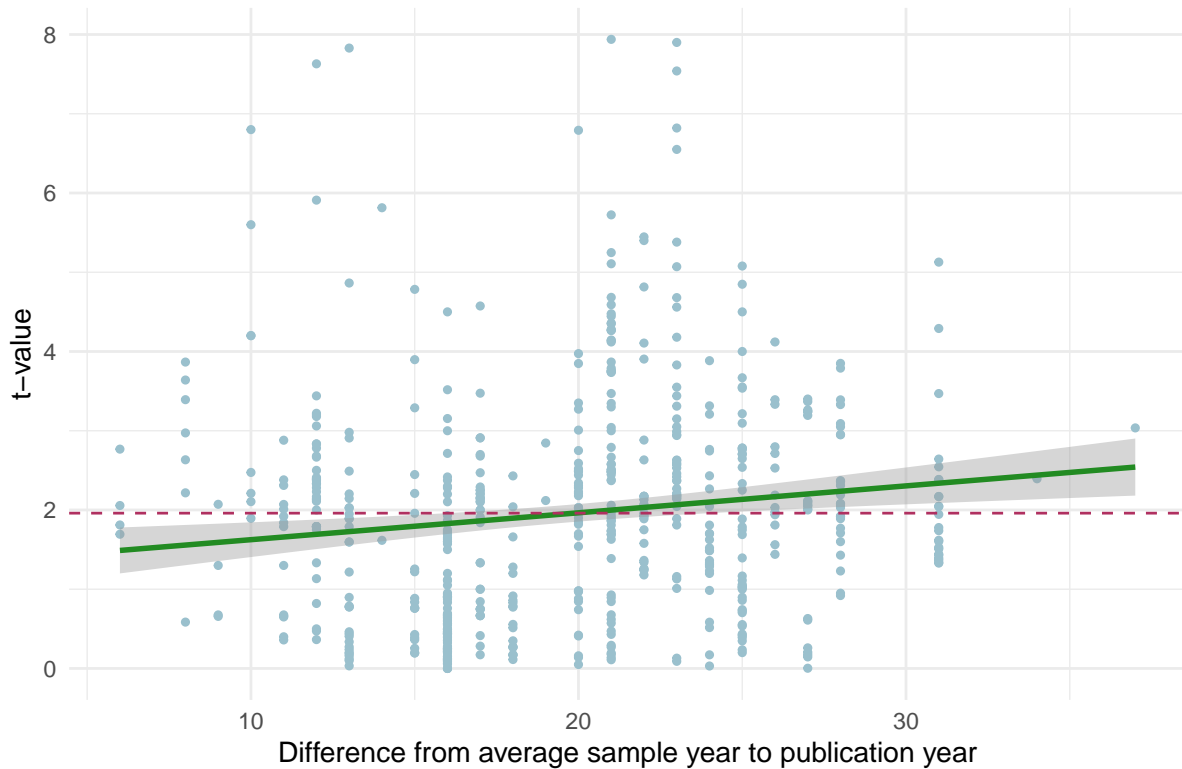
```
## -2.3008 -1.0349 -0.0765  0.6100  6.1353
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    57.54155    12.93309   4.449 0.0000103 ***
## FDII$avg_sample_year -0.02790     0.00649  -4.298 0.0000200 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.383 on 608 degrees of freedom
## (6 observations deleted due to missingness)
## Multiple R-squared:  0.02949,    Adjusted R-squared:  0.0279
## F-statistic: 18.48 on 1 and 608 DF,  p-value: 0.00002004
```

Difference between publication and sample year trend (statistical significance)

```
ggplot(FDII, aes(x = difference, y = mod_t_value)) +
  geom_point(size = 1, color = "lightblue3") +
  geom_smooth(method = "lm", col = "forestgreen") +
  geom_hline(yintercept = 1.96, color = "maroon", linetype = "dashed") +
  labs(title = "Statistical Significance over Time with Trend Line",
       x = "Difference from average sample year to publication year",
       y = "t-value") +
  theme_minimal()
```

```
## `geom_smooth()` using formula = 'y ~ x'
## Warning: Removed 6 rows containing non-finite outside the scale range
## (`stat_smooth()`).
## Warning: Removed 6 rows containing missing values or values outside the scale
## range (`geom_point()`).
```

Statistical Significance over Time with Trend Line



```
summary(lm(FDII$mod_t_value ~ FDII$difference))
```

```
##
## Call:
## lm(formula = FDII$mod_t_value ~ FDII$difference)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -2.1990 -1.0700 -0.1144  0.6286  6.1021
##
## Coefficients:
##              Estimate Std. Error t value    Pr(>|t|)
## (Intercept)    1.28561    0.20449   6.287 0.000000000618 ***
## FDII$difference  0.03394    0.01003   3.384   0.00076 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.391 on 608 degrees of freedom
## (6 observations deleted due to missingness)
## Multiple R-squared:  0.01849,    Adjusted R-squared:  0.01687
## F-statistic: 11.45 on 1 and 608 DF,  p-value: 0.0007601
```

Machine Learning Setup

```
# Use World Bank API
library(WDI)

# Import CPI data
```

```
## Corruption Perceptions Index data
CPI_Corruption <- read_excel("CPI_2012-2022.xlsx")

## WGI Corruption Indicators data
WGI_Corruption <- read_excel("WGI_Corruption_Indicators.xlsx")
## Adjust WGI data from a scale of -2.5-2.5 to 0-100
WGI_adjustment <- WGI_Corruption[, 5:ncol(WGI_Corruption)]
WGI_adjustment <- (WGI_adjustment + 2.5) * 20
WGI_adjustment <- round(WGI_adjustment, 3)
WGI_Corruption[, 5:ncol(WGI_Corruption)] <- WGI_adjustment

dat = WDI(indicator='CC.EST', country =
  ↪ c('CHN', 'FRA', 'GUY', 'USA', 'CAN', 'SWE', 'NPL'), start=2012, end=2022)

dat$CC.EST <- (dat$CC.EST + 2.5)*20

ggplot(dat, aes(year, CC.EST, color=country)) + geom_line() +
  xlab('Year') + ylab('Corruption Prediction') + ylim(0,100)
```

