

# Análisis del tipo de cambio USD/PEN alrededor de elecciones peruanas

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## 1. Introducción

La hipótesis de esta investigación (breve y exploratoria) es:

El tipo de cambio USD/PEN se aprecia en los  $N$  días previos a las elecciones y se deprecia en los  $N$  días posteriores a las elecciones.

siendo  $N = 5, 10, 15, 20, 30, 60, 90, 120$  días.

### 1.1. Contexto y Motivación

Las elecciones presidenciales peruanas se caracterizan por un sistema de dos vueltas, donde la primera ronda selecciona a los dos candidatos más votados y la segunda ronda define al ganador. Este proceso genera distintos períodos de incertidumbre política que pueden afectar diferencialmente el comportamiento del tipo de cambio:

1. **Primera vuelta:** Alta incertidumbre sobre el abanico de posibles ganadores
2. **Segunda vuelta:** Incertidumbre reducida a dos opciones, pero potencialmente mayor polarización

### 1.2. Metodología General

El análisis sigue un enfoque por etapas:

1. **Preprocesamiento de datos:** Limpieza, transformación y segmentación de datos (creando tres conjuntos: primera vuelta, segunda vuelta y total)
2. **Análisis descriptivo:** Visualización de patrones temporales alrededor de eventos electorales
3. **Modelado estadístico:** Pruebas de hipótesis adaptadas al tamaño muestral limitado
4. **Recomendaciones especulativas:** Estrategias de trading exploratorias basadas en hallazgos

## 2. Configuración

```
# Load libraries
library(tidyverse)
library(summariser)
library(dplyr)
library(lubridate)
library(quantmod)
library(ggplot2)
library(knitr)
library(scales)
library(ggrepel)
library(patchwork)

set.seed(42) # Set random seed for reproducibility
theme_set(theme_minimal(base_size = 12)) # Set plotting theme
```

### 3. Preprocesamiento de datos

Primero se preprocesan los cierres del tipo de cambio desde 2004 hasta 2026. Esta información es extraída del repositorio del BCRP.

```
df_ex_ra <- read.csv("./data/exchange_rate.csv")
df_ex_ra$value <- as.double(df_ex_ra$value)
df_ex_ra$date <- as.Date(df_ex_ra$date, "%d.%m.%y")
df_ex_ra <- df_ex_ra %>% arrange(date)
summary(df_ex_ra)
```

```
##      date      value
## Min.   :2004-01-19   Min.   :2.537
## 1st Qu.:2009-07-16   1st Qu.:2.906
## Median :2015-01-14   Median :3.265
## Mean   :2015-01-14   Mean   :3.252
## 3rd Qu.:2020-07-13   3rd Qu.:3.488
## Max.   :2026-01-09   Max.   :4.137
##                      NA's   :263
```

En el caso de la información respecto a las elecciones, se creó un archivo de forma manual extrayendo información de Wikipedia. La información divide entre rondas electorales (primera y segunda).

```
df_elect <- read.csv("./data/elections.csv", header = TRUE, sep = ",", dec = ".",)
df_elect$date <- as.Date(df_elect$date, "%d.%m.%y")
df_elect$round <- as.factor(df_elect$round)
df_elect$winner <- as.factor(df_elect$winner)
summary(df_elect)
```

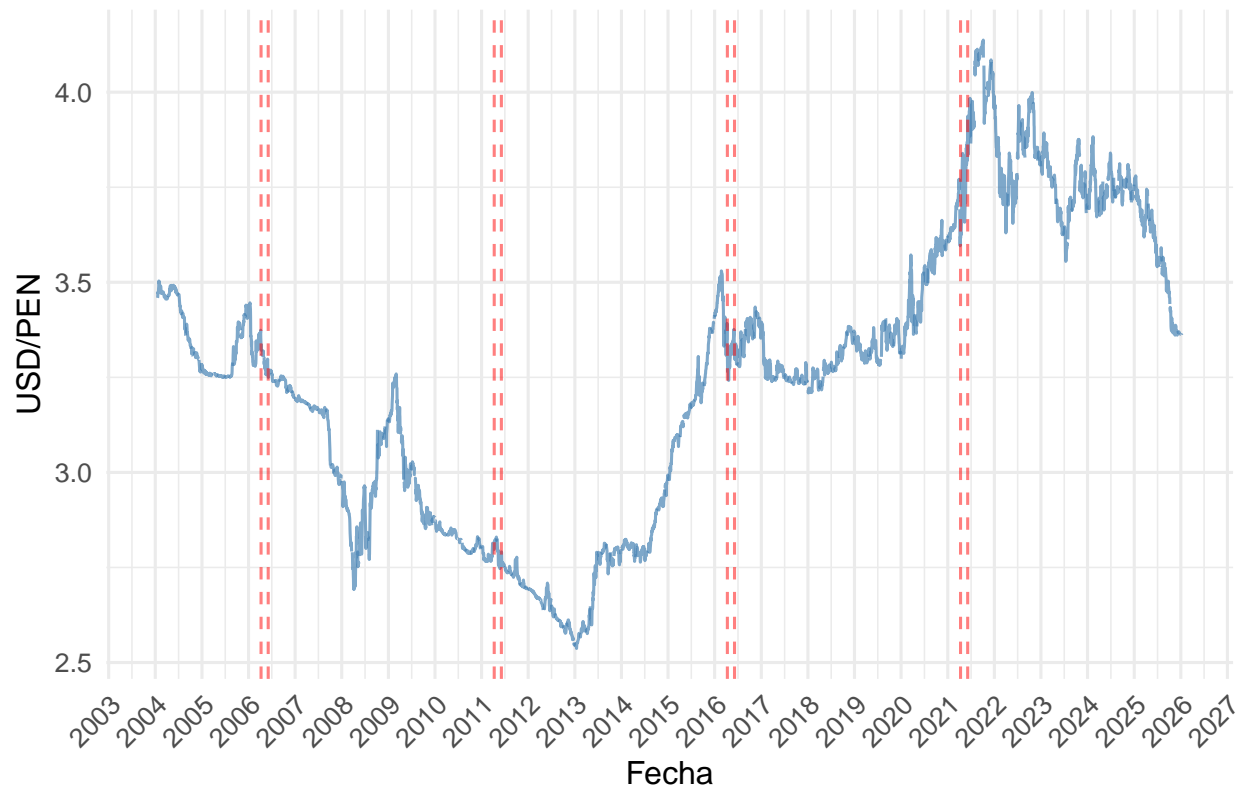
```
##      date      round  winner
## Min.   :2006-04-09 first :4   left  :2
## 1st Qu.:2010-01-22 second:4   none  :4
## Median :2013-11-06                right:2
## Mean   :2013-11-06
## 3rd Qu.:2017-08-21
## Max.   :2021-06-06
```

Siguiendo la metodología de la Subsección 1.2., se generan tres datasets separados para el análisis comparativo.

```
df_total <- df_elect # 1. TODAS las elecciones (primera + segunda vuelta)
df_first<- df_elect %>% filter(round == "first") # 2. Solo PRIMERA vuelta
df_second <- df_elect %>% filter(round == "second") # 3. Solo SEGUNDA vuelta
```

En general, se trata de 4 elecciones generales, cada una con una primera y segunda vuelta desde el 2004 hasta 2025

### Tipo de cambio USD/PEN con fechas electorales



## 4. Función principal

La función principal calcula los retornos previos y posteriores según el número de días elegido.

```
# Function to calculate pre and post returns for a given window
calculate_window_returns <- function(df_exchange, df_elections, window_days) {
  results <- list()

  election_dates <- df_elections$date

  for(i in seq_along(election_dates)) {
    election_date <- election_dates[i]

    # Find the closest trading day to the election date
```

```

date_diffs <- abs(df_exchange$date - election_date)
election_idx <- which.min(date_diffs)
closest_date <- df_exchange$date[election_idx]

# Check if the closest date is within a reasonable range
if(as.numeric(difftime(closest_date, election_date, units = "days")) > 2) {
  warning(paste("No exchange rate data found within 2 days of election date:",
    election_date))
  next
}

# Find pre-election window start (N trading days before)
pre_window_start_date <- election_date - window_days

# Find the closest trading day to pre_window_start_date
pre_diffs <- abs(df_exchange$date - pre_window_start_date)
pre_start_idx <- which.min(pre_diffs)
pre_start_date <- df_exchange$date[pre_start_idx]

# Find pre-election window end (1 trading day before election)
dates_before <- df_exchange$date[df_exchange$date < election_date]
if(length(dates_before) == 0) {
  warning(paste("No exchange rate data before election date:", election_date))
  next
}
pre_end_date <- max(dates_before)
pre_end_idx <- which(df_exchange$date == pre_end_date)

# Find post-election window start (1 trading day after election)
dates_after <- df_exchange$date[df_exchange$date > election_date]
if(length(dates_after) == 0) {
  warning(paste("No exchange rate data after election date:", election_date))
  next
}
post_start_date <- min(dates_after)
post_start_idx <- which(df_exchange$date == post_start_date)

post_window_end_date <- election_date + window_days

# Find the closest trading day to post_window_end_date
post_diffs <- abs(df_exchange$date - post_window_end_date)
post_end_idx <- which.min(post_diffs)
post_end_date <- df_exchange$date[post_end_idx]

# Ensure indices are within bounds
if(pre_start_idx >= 1 && pre_start_idx <= nrow(df_exchange) &&
  pre_end_idx >= 1 && pre_end_idx <= nrow(df_exchange) &&
  post_start_idx >= 1 && post_start_idx <= nrow(df_exchange) &&
  post_end_idx >= 1 && post_end_idx <= nrow(df_exchange)) {

  pre_start_price <- df_exchange$value[pre_start_idx]
  pre_end_price <- df_exchange$value[pre_end_idx]

```

```

post_start_price <- df_exchange$value[post_start_idx]
post_end_price <- df_exchange$value[post_end_idx]

# Calculate percentage returns
pre_return <- (pre_end_price - pre_start_price) / pre_start_price * 100
post_return <- (post_end_price - post_start_price) / post_start_price * 100

# Calculate actual number of calendar days in each window
pre_calendar_days <- as.numeric(difftime(pre_end_date, pre_start_date, units = "days"))
post_calendar_days <- as.numeric(difftime(post_end_date, post_start_date, units = "days"))

results[[i]] <- tibble(
  election_id = i,
  election_date = election_date,
  round = ifelse("round" %in% names(df_elections),
                 df_elections$round[i], "none"),
  winner = ifelse("winner" %in% names(df_elections),
                 df_elections$winner[i], "none"), #TODO: FIX
  window_days = window_days,
  pre_start_date = pre_start_date,
  pre_end_date = pre_end_date,
  post_start_date = post_start_date,
  post_end_date = post_end_date,
  pre_calendar_days = pre_calendar_days,
  post_calendar_days = post_calendar_days,
  pre_start_price = pre_start_price,
  pre_end_price = pre_end_price,
  post_start_price = post_start_price,
  post_end_price = post_end_price,
  pre_return_pct = pre_return,
  post_return_pct = post_return,
  net_effect = pre_return - post_return,
  # Annualized returns for comparison across different window lengths
  pre_annualized = ifelse(pre_calendar_days > 0,
                          (1 + pre_return/100)^(365/pre_calendar_days) - 1,
                          NA),
  post_annualized = ifelse(post_calendar_days > 0,
                          (1 + post_return/100)^(365/post_calendar_days) - 1,
                          NA)
)
}
}

# Combine all elections for this window
if(length(results) > 0) {
  bind_rows(results)
} else {
  tibble() # Return empty tibble if no results
}
}

```

## 4.1. Funciones secundarias

Las funciones secundarias automatizan el cálculo de la función principal.

```
# Wrapper function to calculate for multiple windows
calculate_all_windows <- function(df_exchange, df_elections, windows = c(5, 10)) {
  all_results <- map_df(windows, ~calculate_window_returns(df_exchange, df_elections, .x))

  all_results <- all_results %>%
    group_by(window_days) %>%
    mutate(
      pre_rank = rank(-pre_return_pct), # Rank by pre-return (highest = 1)
      post_rank = rank(post_return_pct) # Rank by post-return (lowest = 1)
    ) %>%
    ungroup()

  return(all_results)
}

# Wrapper function to create summary statistics
create_summary_table <- function(all_results) {
  summary_table <- all_results %>%
    group_by(window_days) %>%
    summarise(
      n_elections = n(),
      avg_pre_return = mean(pre_return_pct, na.rm = TRUE),
      median_pre_return = median(pre_return_pct, na.rm = TRUE),
      sd_pre_return = sd(pre_return_pct, na.rm = TRUE),
      avg_post_return = mean(post_return_pct, na.rm = TRUE),
      median_post_return = median(post_return_pct, na.rm = TRUE),
      sd_post_return = sd(post_return_pct, na.rm = TRUE),
      pre_positive_pct = mean(pre_return_pct > 0, na.rm = TRUE) * 100,
      post_negative_pct = mean(post_return_pct < 0, na.rm = TRUE) * 100,
      avg_net_effect = mean(net_effect, na.rm = TRUE)
    ) %>%
    mutate(across(where(is.numeric), ~round(., 3)))
  return(summary_table)
}
```

Considerando los datasets de la Sección 3 y la metodología de la Sección 1, se obtienen los siguientes resultados:

```
windows <- c(5, 10, 15, 20, 30, 45, 60, 75, 90, 105, 120)

total_results <- calculate_all_windows(df_ex_ra, df_elect, windows)
total_table <- create_summary_table(total_results)

first_results <- calculate_all_windows(df_ex_ra, df_first, windows)
first_table <- create_summary_table(first_results)

second_results <- calculate_all_windows(df_ex_ra, df_second, windows)
second_table <- create_summary_table(second_results)
```

## 5. Resultados

### 5.1. Resultados generales

```
kable(total_table[c(1,3,5,6,8)])
```

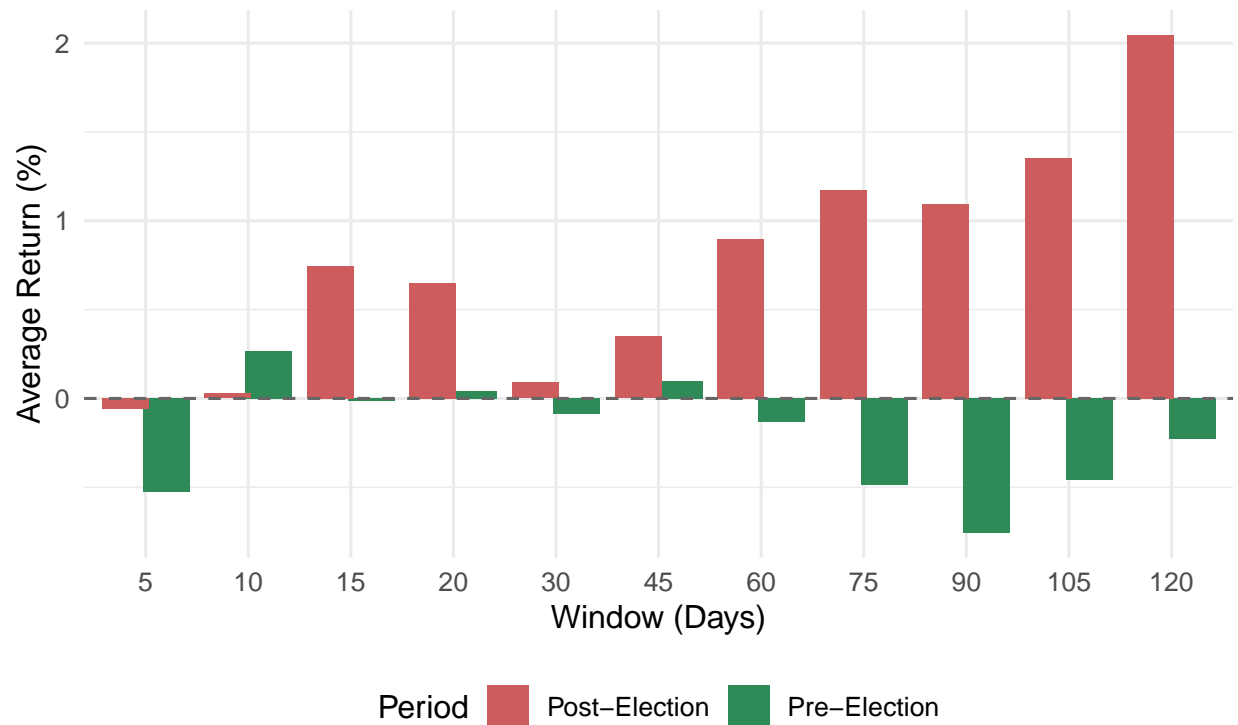
window_days	avg_pre_return	sd_pre_return	avg_post_return	sd_post_return
5	-0.525	0.377	-0.059	0.783
10	0.267	0.758	0.028	1.207
15	-0.015	1.570	0.747	2.262
20	0.041	1.669	0.649	1.748
30	-0.088	1.273	0.090	1.380
45	0.096	2.496	0.349	2.813
60	-0.134	3.327	0.895	3.239
75	-0.486	2.015	1.174	4.026
90	-0.757	2.181	1.096	4.151
105	-0.457	2.834	1.352	3.772
120	-0.229	2.759	2.047	5.246

```
kable(total_table[c(9:11)])
```

pre_positive_pct	post_negative_pct	avg_net_effect
0.000	42.857	-0.495
57.143	62.500	0.599
71.429	37.500	-0.830
50.000	37.500	-0.608
62.500	50.000	-0.178
57.143	50.000	-0.574
37.500	50.000	-1.029
37.500	50.000	-1.660
25.000	50.000	-1.853
25.000	50.000	-1.809
25.000	50.000	-2.276

## Average USD/PEN Returns Around Elections

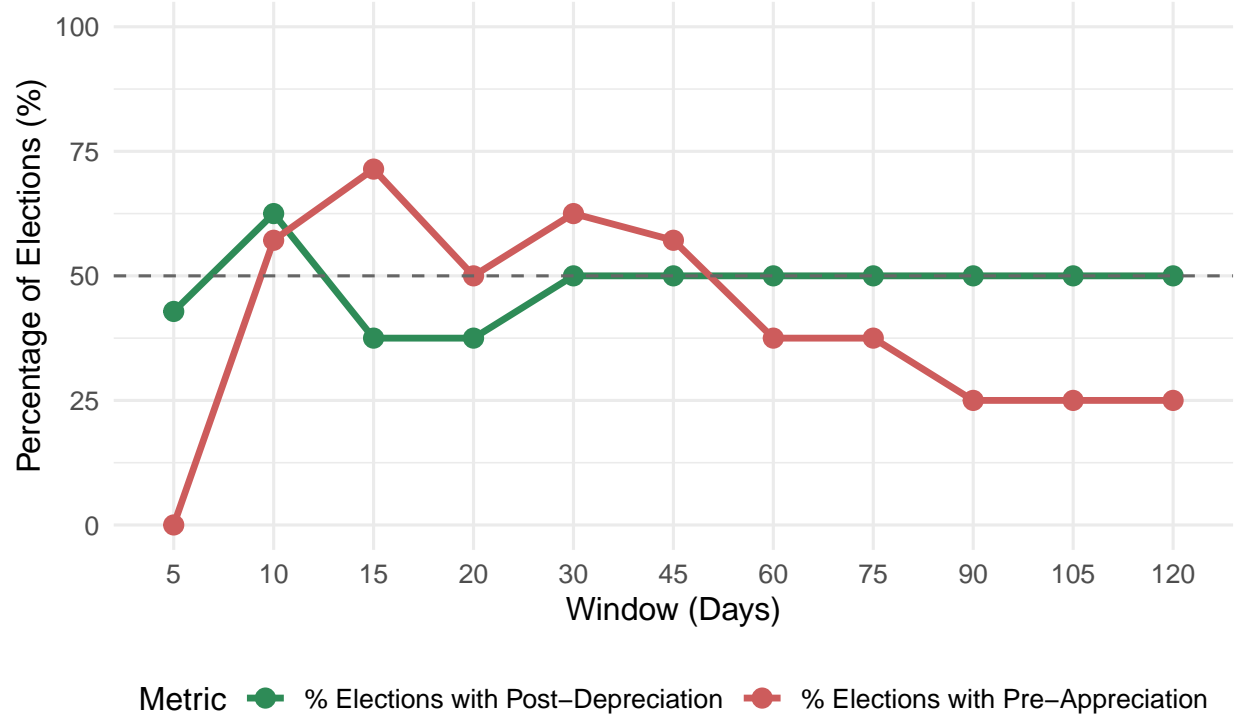
By Analysis Window





## Consistency of Election Effect

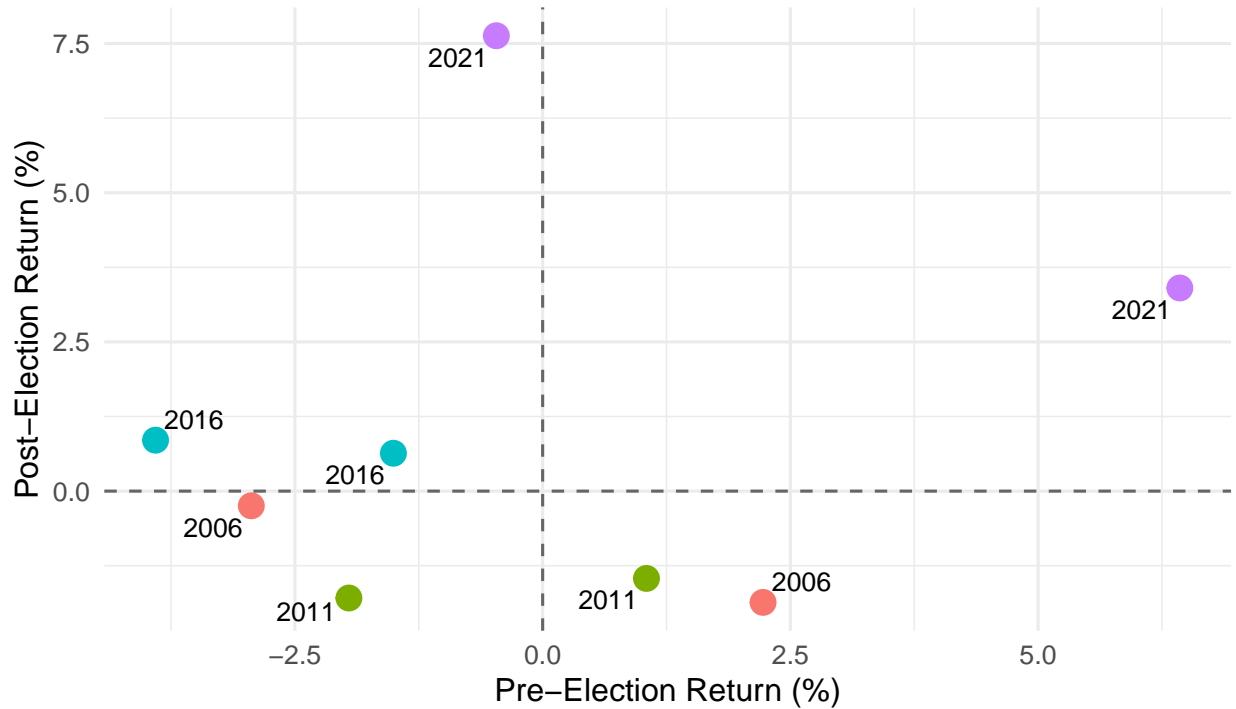
Percentage of elections following the hypothesized pattern



## Individual Election Outcomes (60-Day Window)

Each point represents one election

Format: Year | Pre-Return% / Post-Return%



### 5.1. Resultados primera vuelta

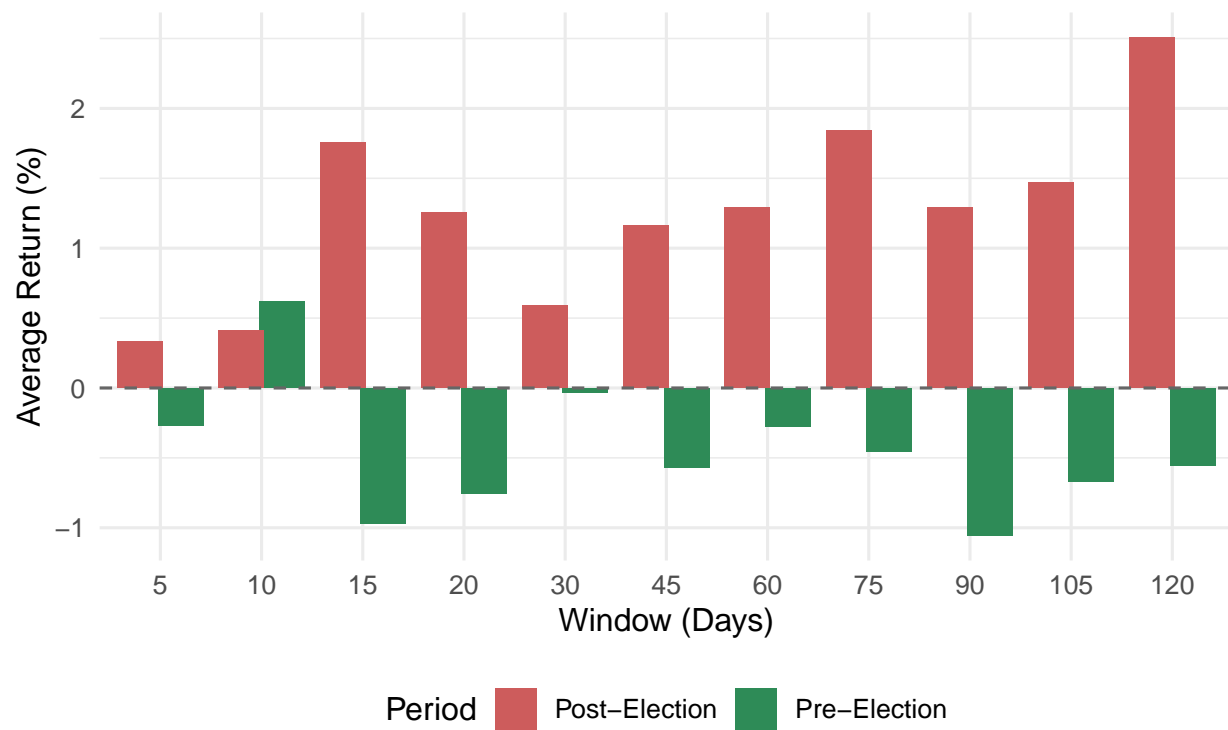
```
kable(first_table[c(1,3,5,6,8)])
```

window_days	avg_pre_return	sd_pre_return	avg_post_return	sd_post_return
5	-0.269	0.181	0.335	0.443
10	0.619	1.122	0.415	1.592
15	-0.972	1.779	1.755	2.929
20	-0.756	1.349	1.256	2.325
30	-0.031	1.606	0.591	1.725
45	-0.571	2.872	1.162	3.967
60	-0.275	2.660	1.289	4.394
75	-0.453	1.637	1.843	5.356
90	-1.056	1.255	1.289	5.721
105	-0.668	0.784	1.469	5.023
120	-0.555	1.059	2.508	7.570

```
kable(first_table[c(9:11)])
```

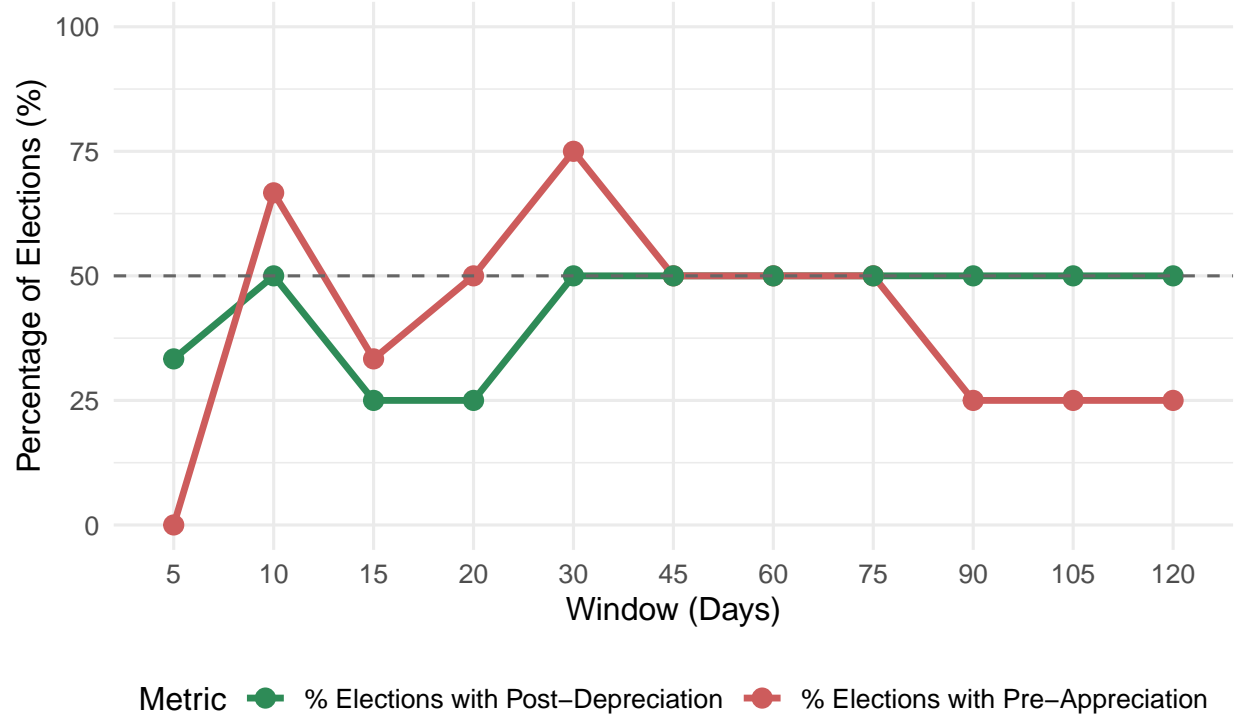
pre_positive_pct	post_negative_pct	avg_net_effect
0.000	33.333	-0.584
66.667	50.000	0.914
33.333	25.000	-3.220
50.000	25.000	-2.012
75.000	50.000	-0.622
50.000	50.000	-1.733
50.000	50.000	-1.565
50.000	50.000	-2.296
25.000	50.000	-2.346
25.000	50.000	-2.137
25.000	50.000	-3.063

Average USD/PEN Returns Around Elections  
By Analysis Window



## Consistency of Election Effect

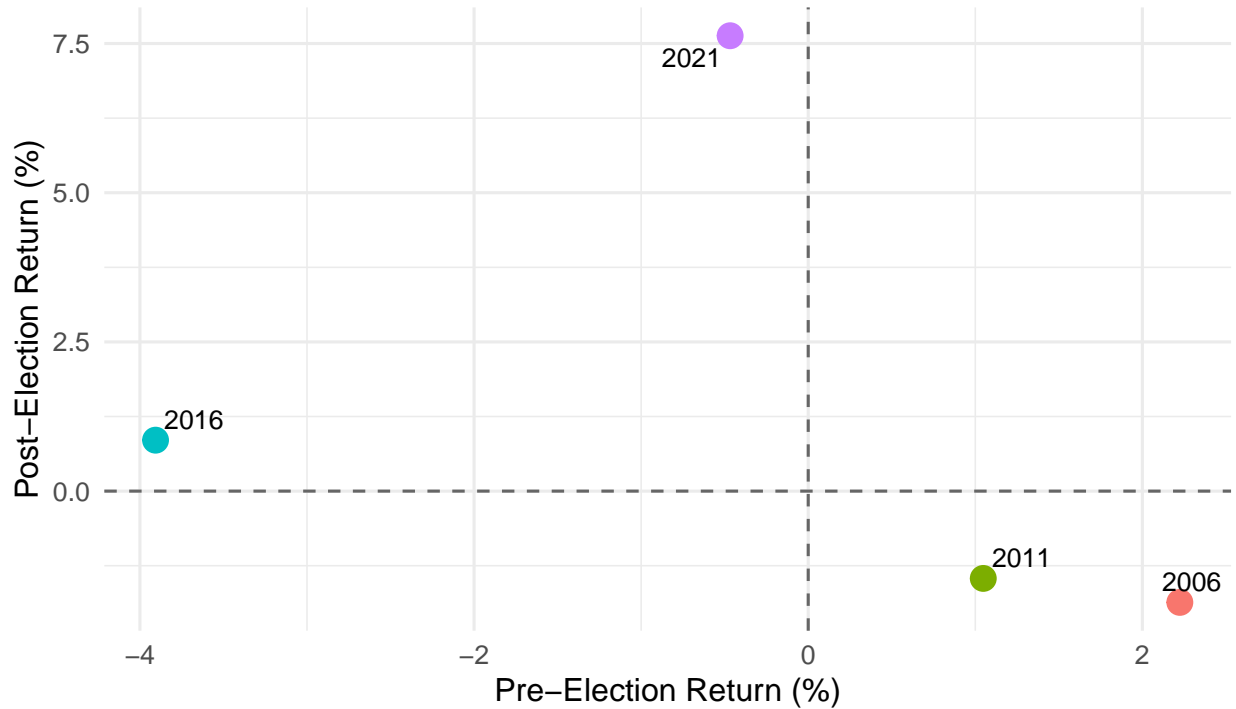
Percentage of elections following the hypothesized pattern



## Individual Election Outcomes (60-Day Window)

Each point represents one election

Format: Year | Pre-Return% / Post-Return%



## 5.2. Resultados segunda vuelta

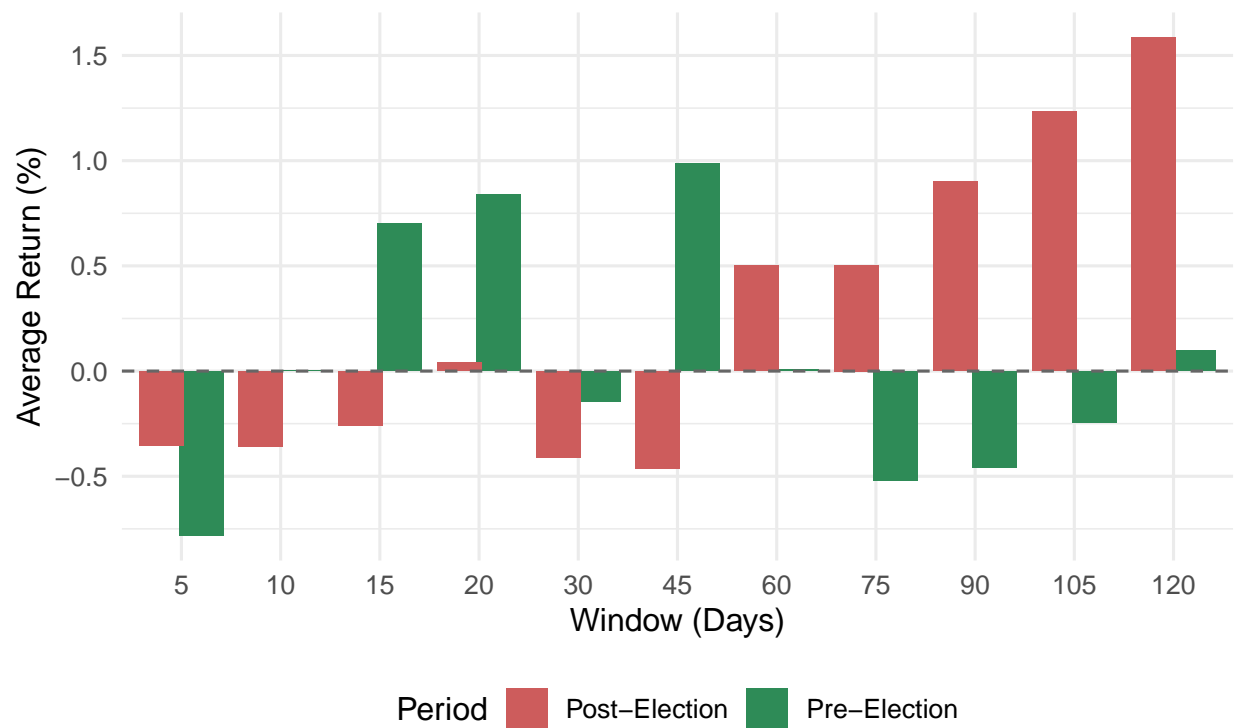
```
kable(second_table[c(1,3,5,6,8)])
```

window_days	avg_pre_return	sd_pre_return	avg_post_return	sd_post_return
5	-0.782	0.351	-0.354	0.907
10	0.004	0.307	-0.359	0.685
15	0.702	1.103	-0.260	0.808
20	0.838	1.727	0.042	0.862
30	-0.145	1.093	-0.411	0.893
45	0.986	2.058	-0.464	0.984
60	0.007	4.324	0.500	2.180
75	-0.519	2.606	0.504	2.815
90	-0.458	3.047	0.902	2.716
105	-0.246	4.243	1.235	2.817
120	0.096	4.044	1.586	2.519

```
kable(second_table[c(9:11)])
```

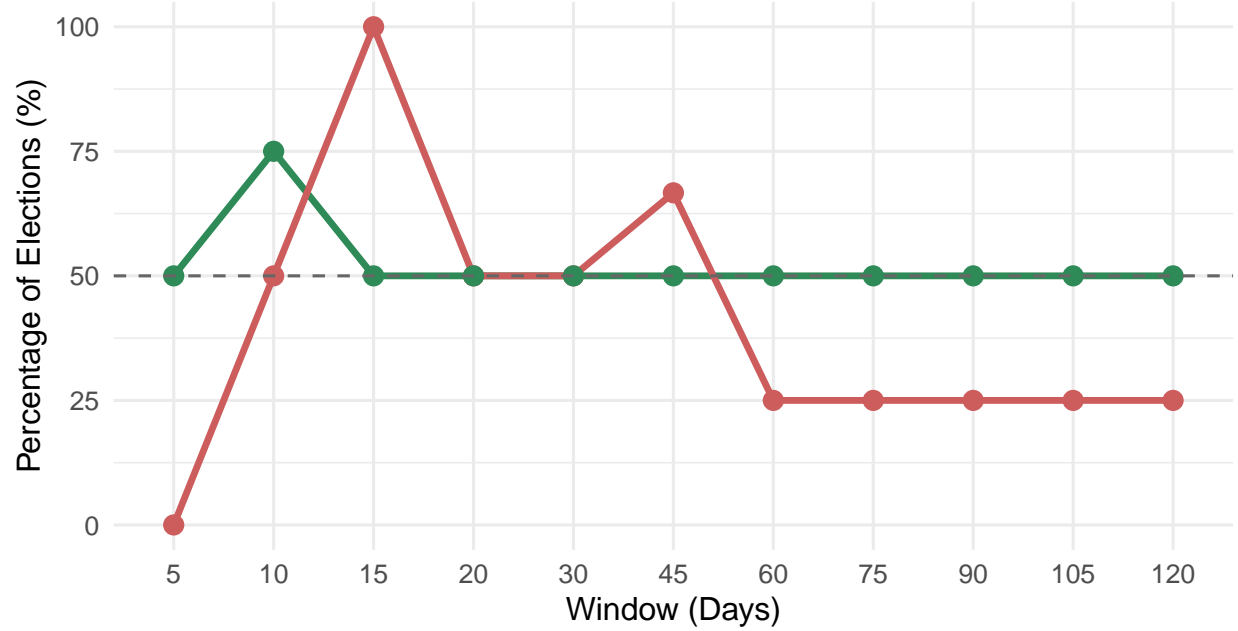
pre_positive_pct	post_negative_pct	avg_net_effect
0.000	50	-0.427
50.000	75	0.363
100.000	50	0.962
50.000	50	0.795
50.000	50	0.265
66.667	50	0.972
25.000	50	-0.493
25.000	50	-1.024
25.000	50	-1.360
25.000	50	-1.481
25.000	50	-1.490

Average USD/PEN Returns Around Elections  
By Analysis Window



## Consistency of Election Effect

Percentage of elections following the hypothesized pattern

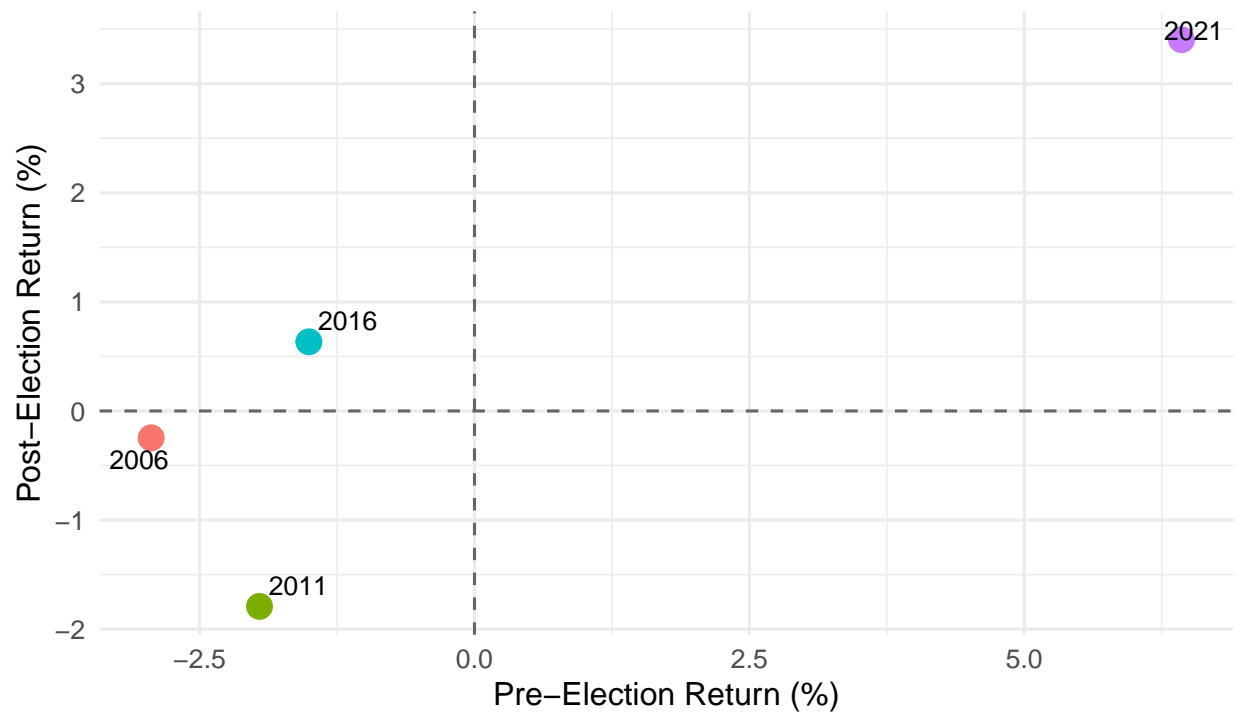


Metric ● % Elections with Post-Depreciation ● % Elections with Pre-Appreciation

## Individual Election Outcomes (60-Day Window)

Each point represents one election

Format: Year | Pre-Return% / Post-Return%



# 6. Análisis de resultados

## 7. Discusión

## 8. Cálculo de retorno

## 9. Recomendaciones