Daily Bitcoin Time Series Analysis (2014–2025)

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1. Setup & Libraries

This section initializes all required R packages for time series analysis, data manipulation, and visualization.

- **tidyverse** is used for data wrangling and plotting.
- **tsibble** provides a tidy framework for handling temporal data with explicit time indices.
- **lubridate** simplifies date manipulation.
- **slider** enables rolling-window calculations such as moving averages and rolling volatility.
- **fable** supplies modern forecasting models (e.g., Naive, Random Walk, ARIMA).
- **here** ensures robust and reproducible relative file paths across environments.

Loading libraries at the beginning guarantees reproducibility and avoids namespace conflicts later in the analysis.

```
library(tidyverse)
```

```
## ── Attaching core tidyverse packages ──────────────────────── tidyverse 2.0.0 ──
## ✓ dplyr     1.1.4     ✓ readr     2.1.6
## ✓ forcats   1.0.1     ✓ stringr   1.6.0
## ✓ ggplot2   4.0.1     ✓ tibble    3.3.0
## ✓ lubridate 1.9.4     ✓ tidyr     1.3.2
## ✓ purrr     1.2.0
## ── Conflicts ────────────────────────────────────────── tidyverse_conflicts() ──
## ✕ dplyr::filter() masks stats::filter()
## ✕ dplyr::lag()    masks stats::lag()
## ℹ Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to be
come errors
```

```
library(tsibble)
```

```
## Registered S3 method overwritten by 'tsibble':
##   method               from
##   as_tibble.grouped_df dplyr
##
## Attaching package: 'tsibble'
##
## The following object is masked from 'package:lubridate':
##
##     interval
##
## The following objects are masked from 'package:base':
##
##     intersect, setdiff, union
```

```
library(lubridate)
library(slider)
library(fable)
```

```
## Loading required package: fabletools
```

```
library(here)
```

```
## here() starts at C:/Users/U1/Documents/bitcoin-ts-2
```

2. Load Daily Bitcoin Data

This section loads the daily Bitcoin price dataset from a relative file path using the `here` package.

Using a relative path improves project portability and ensures the analysis runs consistently across different machines and directory structures.

The dataset is expected to contain: - A `date` column representing daily timestamps - A `close` column representing daily closing prices

Immediately after loading, the total number of observations is printed to verify that the data was imported correctly.

```
btc_raw <- read_csv(
  here::here("data", "btc_2014_2025.csv"),
  show_col_types = FALSE
)

message("Rows loaded (daily): ", nrow(btc_raw))
```

```
## Rows loaded (daily): 4121
```

2.1. Validation

Before proceeding with analysis, basic schema validation is performed.

The code checks whether all required columns (`date` , `close`) exist in the dataset.
If any required column is missing, the script stops execution with a clear error message.

This defensive programming step prevents silent failures and ensures that downstream transformations and models operate on valid inputs.

```
required_cols <- c("date", "close")

missing_cols <- setdiff(required_cols, names(btc_raw))
if (length(missing_cols) > 0) {
stop(
"Missing required columns: ",
paste(missing_cols, collapse = ", ")
)
}
```

3. Data Cleaning & Tsibble Conversion

In this step, the raw dataset is transformed into a clean, structured time series object.

Key operations include: - Converting `date` to a proper `Date` class - Casting `close` prices to numeric values - Sorting observations chronologically - Converting the dataset into a `tsibble` using `date` as the time index

The resulting `tsibble` explicitly encodes temporal structure, enabling time-aware operations such as forecasting, gap detection, and rolling statistics.

```
btc_ts <- btc_raw %>%
mutate(
date = as.Date(date),
close = as.numeric(close)
) %>%
arrange(date) %>%
as_tsibble(index = date)

btc_ts
```

```
## # A tsibble: 4,121 x 6 [1D]
##    date        open  high   low close   volume
##    <date>     <dbl> <dbl> <dbl> <dbl>    <dbl>
##  1 2014-09-17  466.  468.  452.  457. 21056800
##  2 2014-09-18  457.  457.  413.  424. 34483200
##  3 2014-09-19  424.  428.  385.  395. 37919700
##  4 2014-09-20  395.  423.  390.  409. 36863600
##  5 2014-09-21  408.  412.  393.  399. 26580100
##  6 2014-09-22  399.  407.  397.  402. 24127600
##  7 2014-09-23  402.  442.  396.  436. 45099500
##  8 2014-09-24  436.  436.  421.  423. 30627700
##  9 2014-09-25  423.  424.  409.  412. 26814400
## 10 2014-09-26  411.  415.  400.  404. 21460800
## # ℹ 4,111 more rows
```

3.1. Sanity Checks

Sanity checks are performed to ensure time series integrity.

- **Gap detection** verifies whether any calendar days are missing in the daily series.
- **Missing value checks** ensure that no `NA` values exist in the closing price column.

These checks are critical for financial time series, as missing days or values can bias rolling statistics and forecasting models.

```
gaps <- has_gaps(btc_ts)

if (nrow(gaps) > 0) {
warning("⚠️ Time series has missing DAYS (gaps detected)")
print(gaps)
}
```

```
## Warning: ⚠️ Time series has missing DAYS (gaps detected)
## # A tibble: 1 × 1
##   .gaps
##   <lgl>
## 1 TRUE
```

```
if (any(is.na(btc_ts$close))) {
warning("⚠️ Missing values detected in 'close'")
}
```

4. Exploratory Data Analysis (EDA)

Exploratory Data Analysis (EDA) provides an initial understanding of Bitcoin's price dynamics over time.

Visual inspection helps identify: - Long-term growth trends - Structural breaks - Periods of extreme volatility - Regime shifts commonly observed in cryptocurrency markets

EDA is a crucial step before applying any statistical or forecasting models.

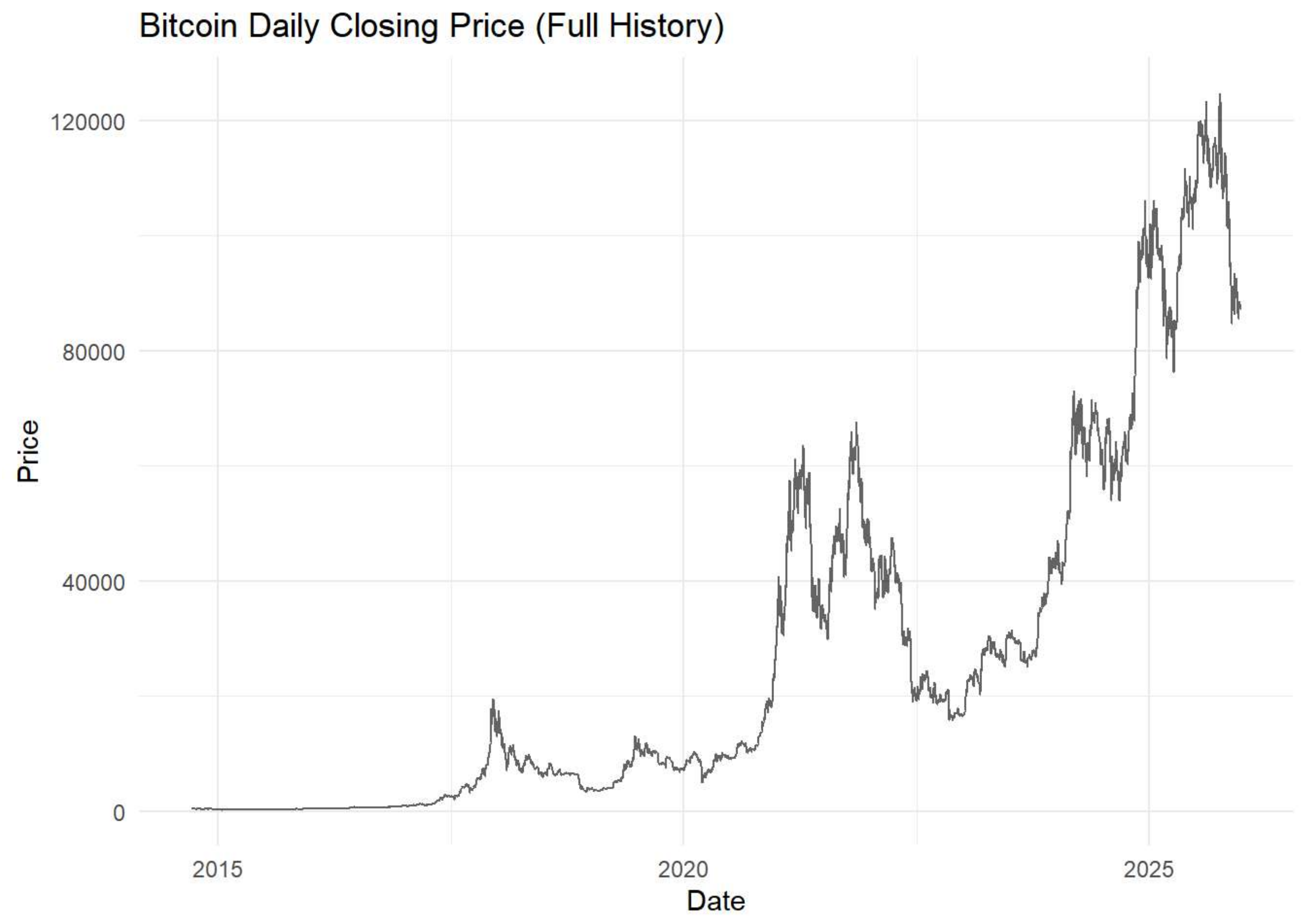
4.1. Full History Price

This plot visualizes the entire daily Bitcoin price history from 2014 to 2025.

It highlights: - The long-term upward trend - High volatility relative to traditional assets - Distinct bull and bear market cycles

This global view provides context for subsequent focused analyses on shorter time horizons.

```
ggplot(btc_ts, aes(date, close)) +
geom_line(alpha = 0.6) +
theme_minimal() +
labs(
title = "Bitcoin Daily Closing Price (Full History)",
x = "Date",
y = "Price"
)
```



4.2. Last 2 Years

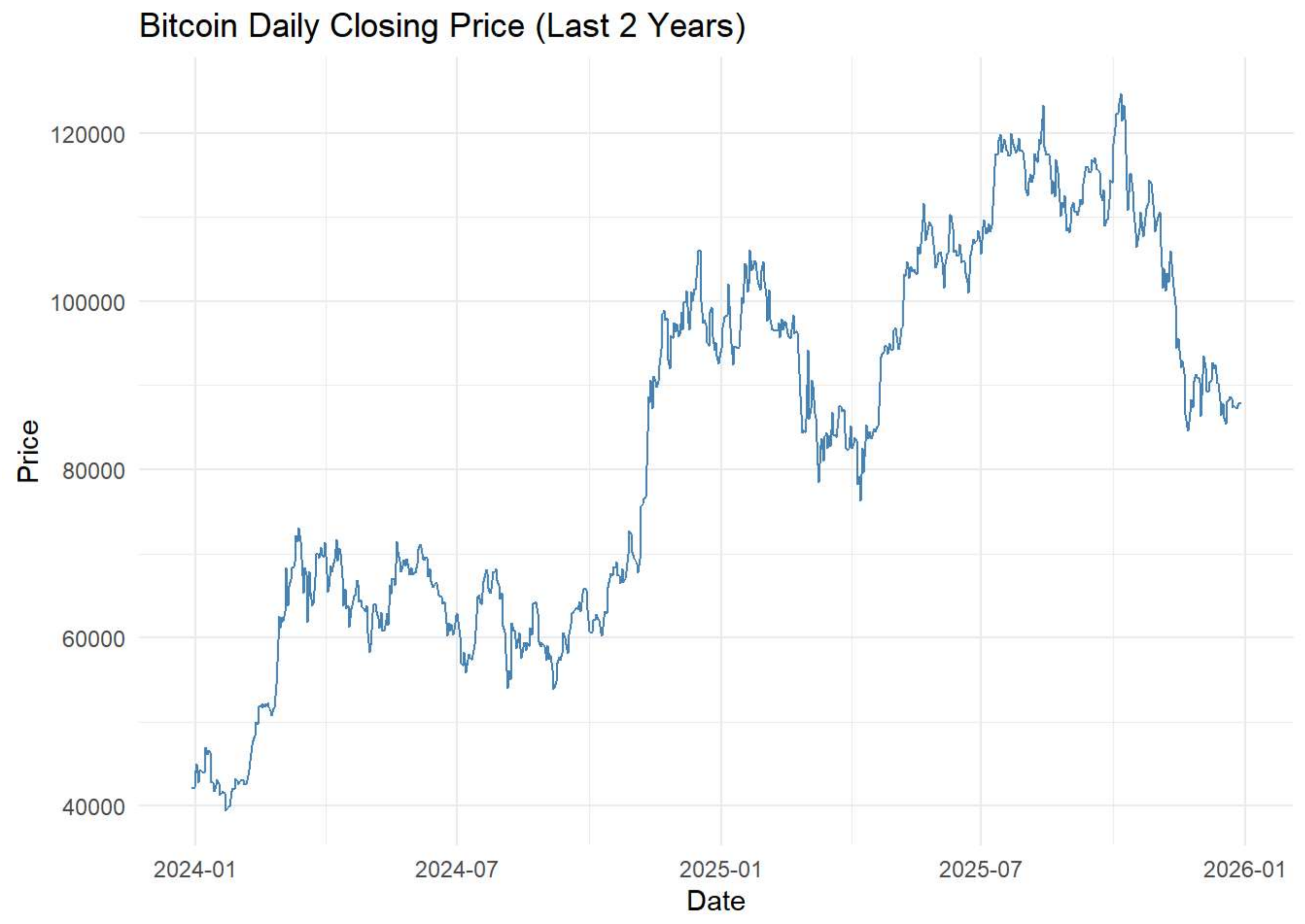
This section zooms into the most recent two years of Bitcoin price data.

Focusing on recent history allows:

- - Better inspection of current market behavior
- - Identification of short-term trends and volatility patterns
- - Alignment with practical forecasting horizons used in trading and risk analysis

```
btc_recent <- btc_ts %>%
filter(date >= max(date) - years(2))

ggplot(btc_recent, aes(date, close)) +
geom_line(color = "steelblue") +
theme_minimal() +
labs(
title = "Bitcoin Daily Closing Price (Last 2 Years)",
x = "Date",
y = "Price"
)
```



4.3. 30-Day Rolling Mean

The 30-day rolling mean smooths short-term fluctuations and highlights medium-term price trends.

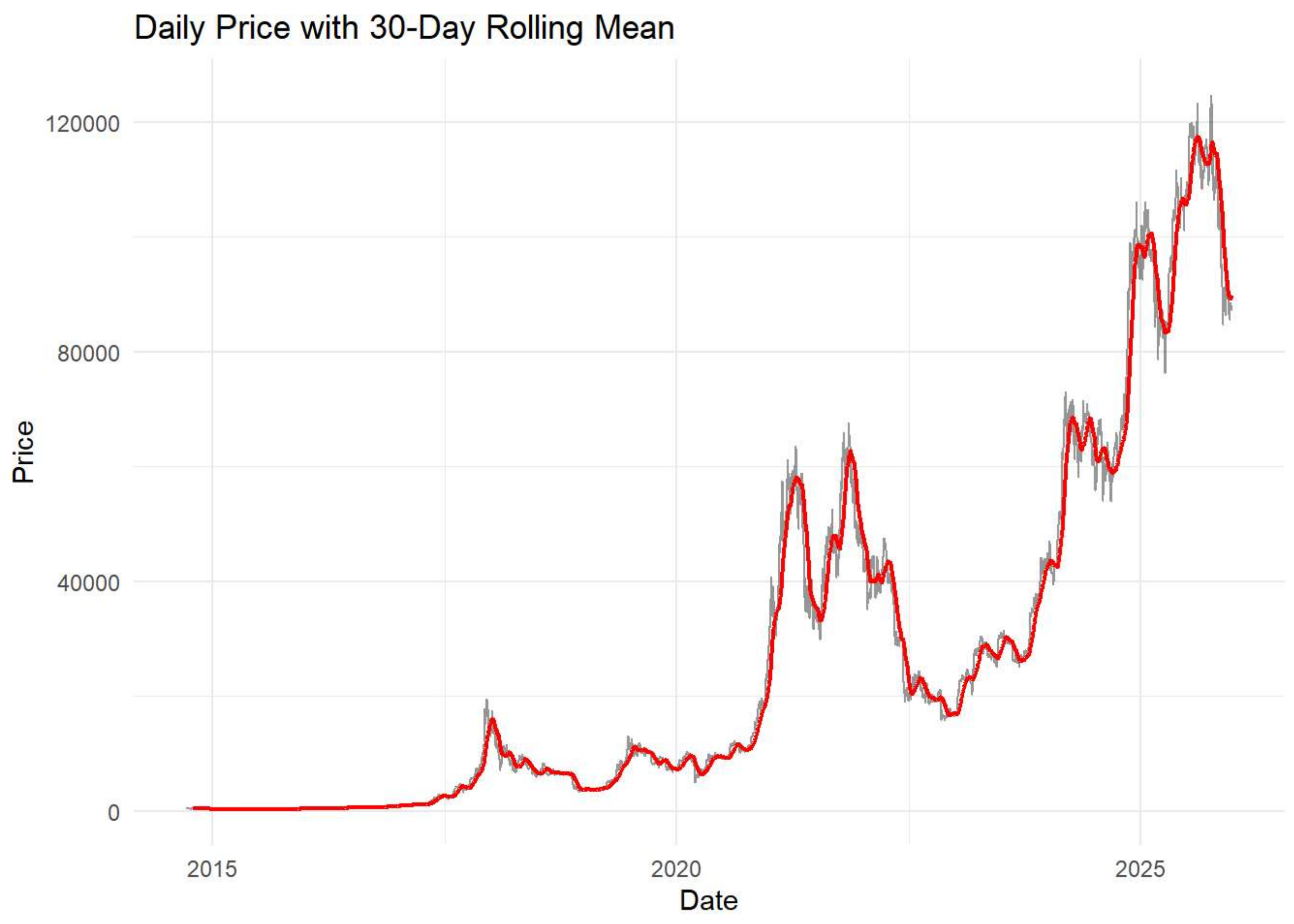
A rolling window of 30 days is commonly used in financial analysis to approximate monthly market behavior.

Overlaying the rolling mean on the raw price series helps distinguish: - Trend movements - Noise-driven daily fluctuations

```
btc_roll <- btc_ts %>%
mutate(
close_ma_30 = slide_dbl(
close,
mean,
.before = 29,
.complete = TRUE
)
)

ggplot(btc_roll, aes(date)) +
geom_line(aes(y = close), alpha = 0.4) +
geom_line(aes(y = close_ma_30), color = "red", linewidth = 0.8) +
theme_minimal() +
labs(
title = "Daily Price with 30-Day Rolling Mean",
x = "Date",
y = "Price"
)
```

```
## Warning: Removed 29 rows containing missing values or values outside the scale range
## (`geom_line()`).
```



4.4. 30-Day Rolling Volatility

This section computes a 30-day rolling standard deviation of Bitcoin prices as a proxy for market volatility.

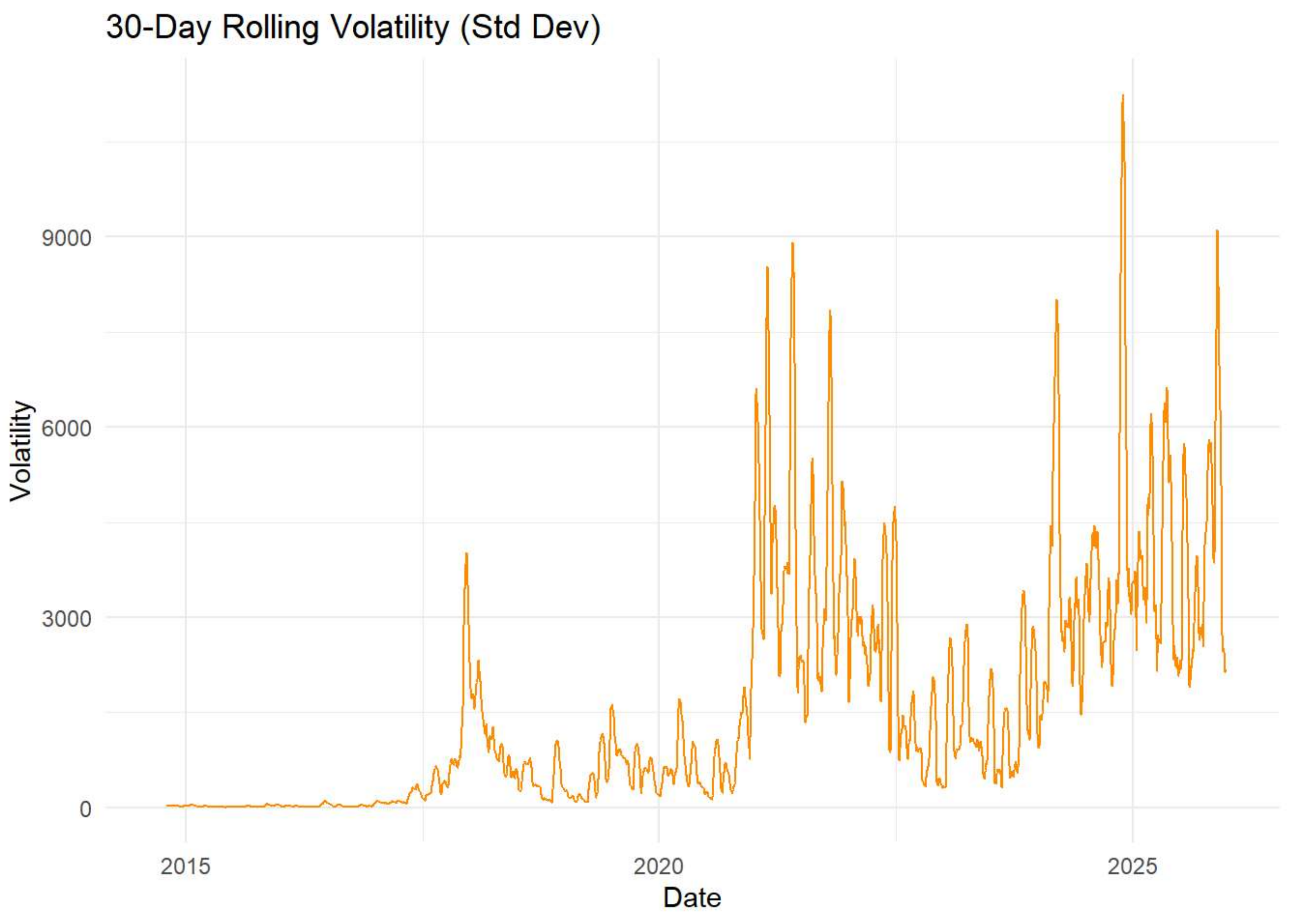
Rolling volatility reveals: - Volatility clustering - Periods of market stress - Calm versus turbulent regimes

Such patterns are characteristic of financial assets and motivate more advanced volatility models in later stages (e.g., GARCH).

```
btc_vol <- btc_ts %>%
mutate(
vol_30 = slide_dbl(
close,
sd,
.before = 29,
.complete = TRUE
)
)

ggplot(btc_vol, aes(date, vol_30)) +
geom_line(color = "darkorange") +
theme_minimal() +
labs(
title = "30-Day Rolling Volatility (Std Dev)",
x = "Date",
y = "Volatility"
)
```

```
## Warning: Removed 29 rows containing missing values or values outside the scale range
## (`geom_line()`).
```



5. Baseline Forecasting Models

Baseline models provide reference points against which more complex models can be evaluated.

In financial time series, simple models often perform surprisingly well, especially over short forecasting horizons.

Establishing baselines ensures that additional model complexity is justified by real performance gains.

5.1. Train–Test Split

The dataset is split into training and testing sets using a rolling-origin approach.

- The last 14 days are reserved as the test set
- All earlier observations form the training set

This approach respects the temporal ordering of the data and avoids information leakage from the future.

```
horizon <- 14

btc_train <- btc_ts %>%
filter(date <= max(date) - days(horizon))

btc_test <- btc_ts %>%
filter(date > max(date) - days(horizon))

message("Train rows: ", nrow(btc_train))
```

```
## Train rows: 4108
```

```
message("Test rows : ", nrow(btc_test))
```

```
## Test rows : 13
```

5.2. Model Fitting

Three baseline forecasting models are fitted on the training data:

- **Naive model** — assumes future prices equal the last observed price
- **Random Walk with Drift** — allows for a constant average price change over time
- **ARIMA** — captures autocorrelation and differencing structure automatically

These models represent increasing levels of statistical sophistication while remaining interpretable.

```
models <- btc_train %>%
model(
naive = NAIVE(close),
drift = RW(close ~ drift()),
arima = ARIMA(close)
)

report(models)
```

```
## Warning in report.mdl_df(models): Model reporting is only supported for
## individual models, so a glance will be shown. To see the report for a specific
## model, use `select()` and `filter()` to identify a single model.
## # A tibble: 3 × 8
##   .model   sigma2 log_lik    AIC   AICc    BIC ar_roots   ma_roots
##   <chr>     <dbl>   <dbl>  <dbl>  <dbl>  <dbl> <list>     <list>
## 1 naive  1214937.      NA     NA     NA     NA <NULL>     <NULL>
## 2 drift  1214937.      NA     NA     NA     NA <NULL>     <NULL>
## 3 arima  1213359. -34594. 69193. 69193. 69205. <cpl [0]> <cpl [1]>
```

5.3. Forecasting

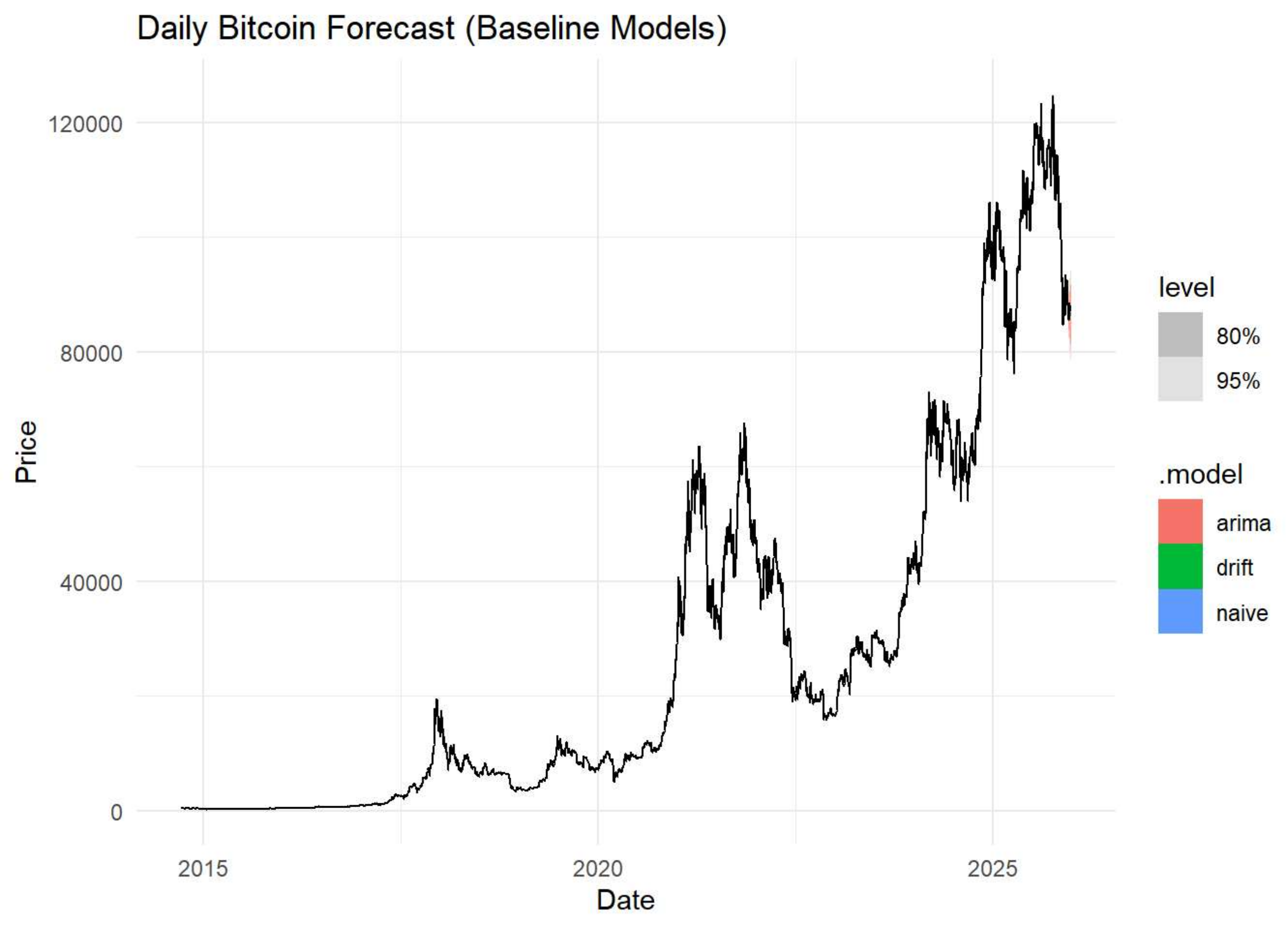
Each fitted model generates forecasts for the 14-day horizon.

Forecasts are visualized together with historical data to: - Compare model behavior - Inspect forecast uncertainty - Assess plausibility of predicted trajectories

Visualization is especially important in financial contexts where numerical accuracy alone may be misleading.

```
fc <- models %>%
forecast(h = horizon)

autoplot(fc, btc_ts) +
theme_minimal() +
labs(
title = "Daily Bitcoin Forecast (Baseline Models)",
x = "Date",
y = "Price"
)
```



6. Model Evaluation

Forecast accuracy is evaluated using out-of-sample test data.

Common error metrics include:

- **MAE (Mean Absolute Error)**
- **RMSE (Root Mean Squared Error)**
- **MAPE (Mean Absolute Percentage Error)**

Evaluating models on unseen data provides an unbiased estimate of real-world forecasting performance.

```
acc <- accuracy(fc, btc_test)
```

```
## Warning: The future dataset is incomplete, incomplete out-of-sample data will be treated a
s missing.
## 1 observation is missing at 2025-12-28
```

```
acc
```

```
## # A tibble: 3 × 10
##   .model .type    ME  RMSE   MAE   MPE  MAPE  MASE RMSSE  ACF1
##   <chr>  <chr> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>
## 1 arima  Test  1063. 1371. 1276.  1.20  1.45   NaN   NaN 0.393
## 2 drift  Test   990. 1304. 1196.  1.12  1.36   NaN   NaN 0.371
## 3 naive  Test  1138. 1430. 1328.  1.29  1.51   NaN   NaN 0.393
```

6.1. Summary Comparison

Model performance metrics are summarized and ranked by RMSE.

This comparison identifies:

- The strongest baseline model
- Whether increased model complexity improves accuracy
- A benchmark for future, more advanced models

Such summaries are essential for transparent and reproducible model selection.

```
acc_summary <- acc %>%
select(.model, MAE, RMSE, MAPE) %>%
arrange(RMSE)

acc_summary
```

```
## # A tibble: 3 × 4
##   .model   MAE  RMSE  MAPE
##   <chr>  <dbl> <dbl> <dbl>
## 1 drift  1196. 1304.  1.36
## 2 arima  1276. 1371.  1.45
## 3 naive  1328. 1430.  1.51
```

7. Conclusion

This analysis successfully models Bitcoin daily prices as a structured time series.

Key outcomes:

- Data validated and converted into a daily tsibble
- Core price dynamics explored through EDA
- Baseline forecasting models established and evaluated
- A robust foundation created for advanced financial time series modeling

The analysis is now ready for extensions such as:

- Log-return modeling
- Volatility models (GARCH)
- Weekly aggregation
- Regime and structural break analysis