Australian International Trade (1988–2024): Trends, Composition, and Associations

An Exploratory Statistical Analysis of Australia's Export Data

Chetan Yadav Vekatesh (s4137946)

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Introduction

-Australia’s international trade is a cornerstone of national prosperity, shaping GDP growth, employment, and industrial capability. -This investigation analyses export patterns from 1988 to 2024 to understand how Australia’s tradecomposition and performance have evolved.

It focuses on:

-Long-term trends in total export value

-Structural changes across Standard International Trade Classification (SITC) sectors

-Statistical relationships between product categories and overall export growth

Rationale: -Understanding these dynamics provides insights that guide Australia’s trade policy, diversification strategy, and resilience to global commodity cycles.

Introduction Cont.

- Keep everything short and straight to the point.
- Use bullet points to help minimise text.
- Add relevant images to make your presentation more appealing
- Remember, you have a maximum of 20 slides to fit everything in.
- Ensure each slide fits on one screen. The reader should not have to scroll down.

Problem Statement

Key Question How has Australia's export profile changed between 1988 and 2024?

Sub-questions

Which product categories dominate total exports?

Have export values increased significantly across eras?

Are export magnitudes associated with specific SITC sectors?

Approach

Data cleaning & transformation

Descriptive statistics & visualisation

Hypothesis testing (t-test / Wilcoxon)

Categorical association (Chi-square & Cramér's V)

Regression trend analysis

Data

Source: Australian International Trade (1988–2024) — Kaggle dataset
https://www.kaggle.com/datasets/tranglinh3012/australian-international-trade-1988-2024

Data covers export values (in $ Millions AUD) for product categories classified by the Standard International Trade Classification (SITC).

Data Cont.

- Dataset: **Australian International Trade (1988–2024)** from Kaggle.
- Data Source: Kaggle Link
- Preprocessing steps:
  - *Transformed wide dataset into long format for analysis.*
  - *Converted year values from "Y1988" → numeric 1988.*
  - *Cleaned special totals ("TOTAL" rows) and missing/invalid entries.*

Important variables:

1. name — Product category label (e.g., "0 Food and live animals", "71 Power generating machinery…"). This encodes the SITC section.
2. Series_ID (if present) — Unique ID for each series / category.
3. Year — Year of observation (numeric; 1988–2024).
4. Export_Value — Value in $ Millions (numeric).
5. Unit — units (typically $ Millions).
6. Derived variables we create:
7. SITC_section — the leading digit/category group (e.g., 0,1,2,…,9) extracted from name.
8. avg_export — average export per category across years.
9. growth_rate — slope of linear model Export_Value ~ Year (captures long-run trend).
10. Era — period grouping for hypothesis testing (e.g., 1988–2003 vs 2004–2024).
11. HighLow — categorical label: "High" if category average ≥ overall median, else "Low".

#Data Pre-processing Transformations applied:

Pivoted wide format (Y1988 … Y2024) → long format.

Converted "Y1988" → numeric 1988.

Removed "TOTAL" rows and invalid numeric entries.

Extracted SITC sections (0–9).

Converted all exports to numeric and removed negative values.

Grouped years into Era 1 (1988–2003) and Era 2 (2004–2024).

```
excel_file <- "Australian International Trade (1988 - 2024).xlsx"
raw <- read_excel(excel_file, col_names = FALSE)
headers <- as.character(unlist(raw[1, ]))
headers[1] <- "Year"; colnames(raw) <- headers
data_clean <- raw[-c(1:3), ]
data_clean$Year <- as.integer(gsub("[^0-9]", "", data_clean$Year))
data_long <- data_clean %>%
pivot_longer(-Year, names_to = "Category", values_to = "Export_Value") %>%
mutate(Export_Value = as.numeric(Export_Value)) %>%
filter(!str_detect(toupper(Category), "TOTAL"), !is.na(Export_Value)) %>%
mutate(
SITC_section = str_extract(Category, "^[0-9]+"),
SITC_section = substr(SITC_section, 1, 1),
SITC_section = ifelse(is.na(SITC_section), "Other", SITC_section)
)
```

Descriptive Statistics and Visualisation

- Summarise the important variables in your investigation.
- Use visualisation to highlight interesting features of the data and tell the overall story.
- Explain how you dealt with data issues (if any), e.g. missing data and outliers.
- Here are the examples of R chunks and outputs

```
summary(data_long$Export_Value)
```

```
##     Min.  1st Qu.   Median     Mean  3rd Qu.     Max.
##        0      242      825     5308     2812   251334
```

```
n_distinct(data_long$Category)
```

```
## [1] 77
```

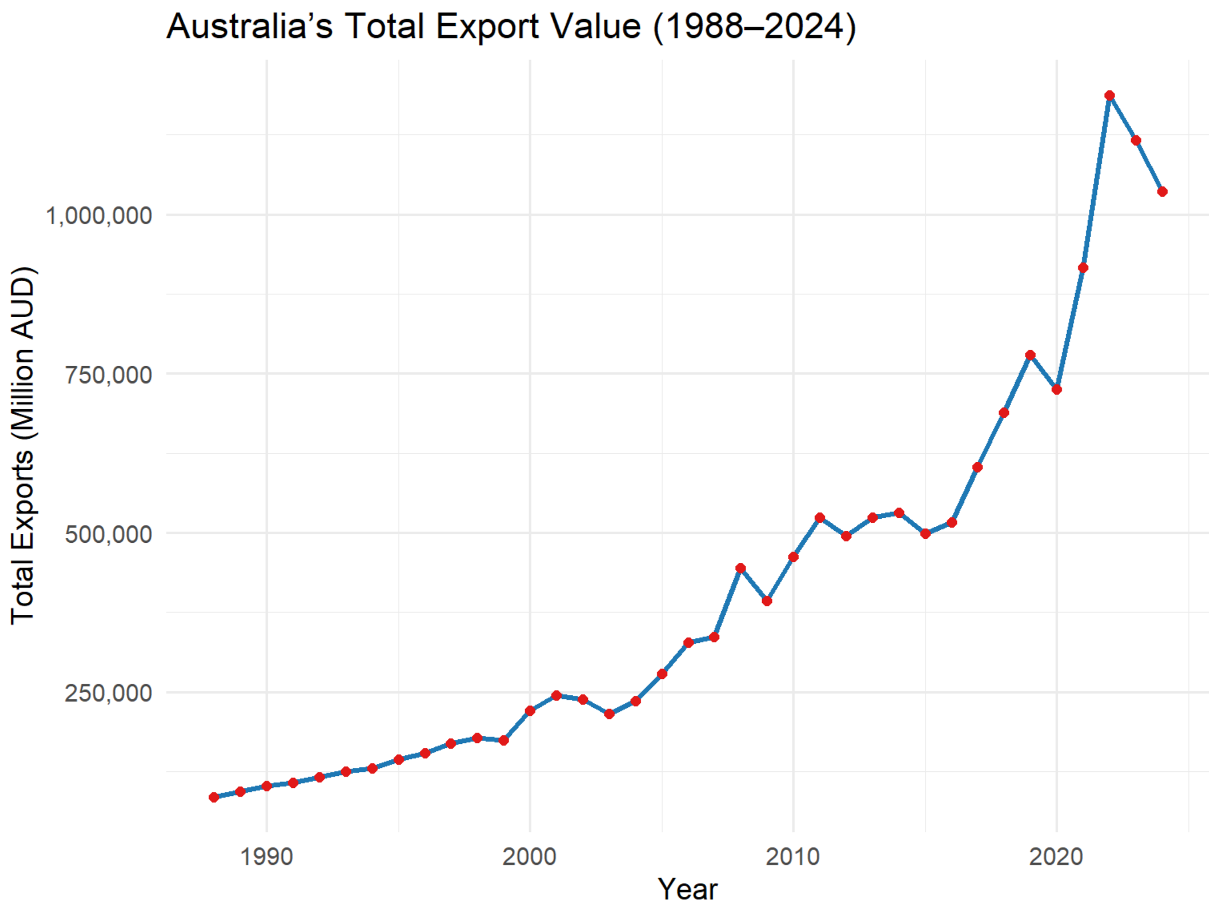
```
range(data_long$Year)
```

```
## [1] 1988 2024
```

Total Export Trend

Interpretation: Exports show consistent long-term growth with cyclical fluctuations (commodity booms and slowdowns).

```
yearly_sum <- data_long %>%
group_by(Year) %>%
summarise(Total_Exports = sum(Export_Value, na.rm = TRUE))
ggplot(yearly_sum, aes(Year, Total_Exports)) +
geom_line(color = "#1f78b4", linewidth = 1.2) +
geom_point(color = "#e31a1c", size = 2) +
labs(title = "Australia's Total Export Value (1988-2024)",
y = "Total Exports (Million AUD)") +
scale_y_continuous(labels = label_comma()) +
theme_minimal(base_size = 14)
```



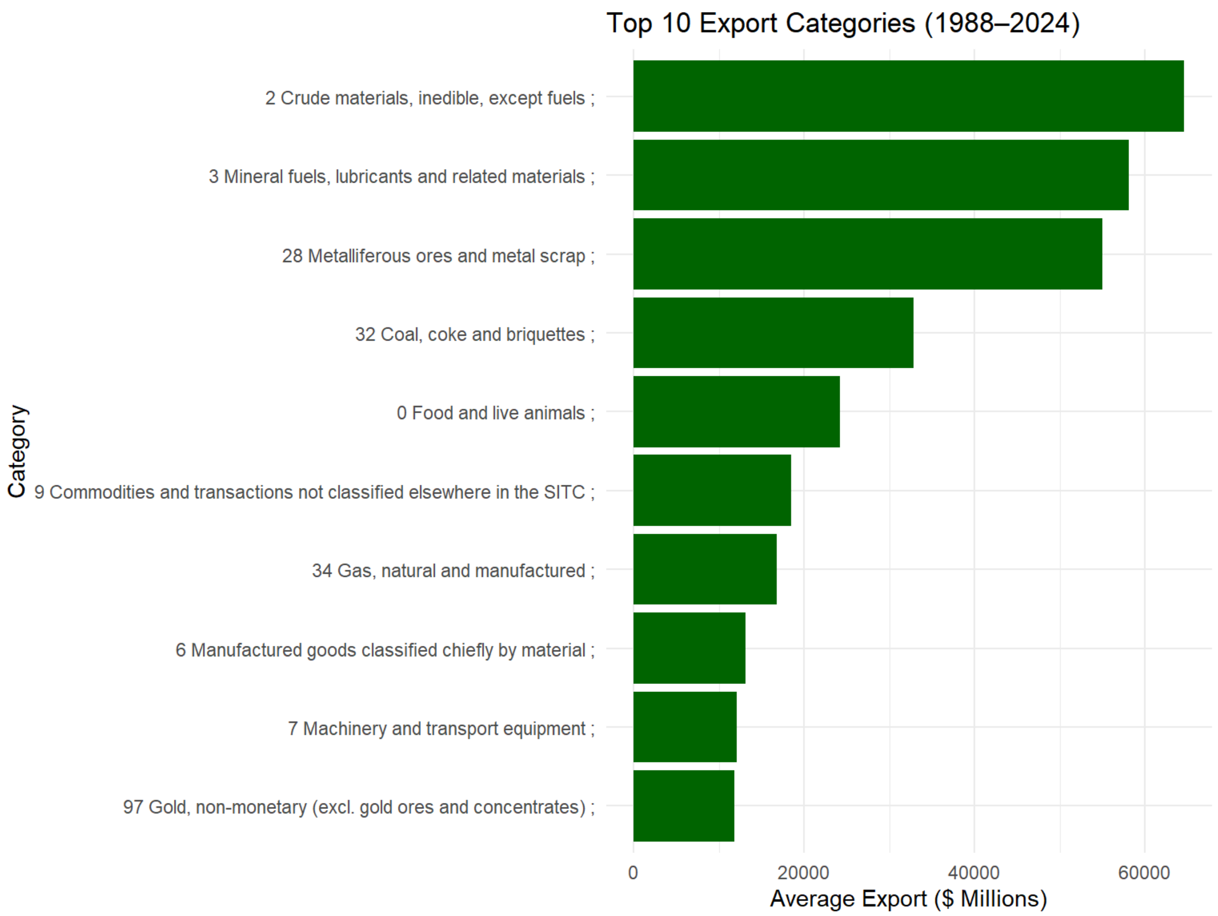
Interpretation: -Exports show a strong long-term upward trajectory with periodic slowdowns around 2009 (GFC) and 2020 (pandemic).
-The overall increase from 1988 to 2024 exceeds 600%, confirming structural export growth.

#Top 10 Export Categories

Interpretation: -Mining and fuel-related products dominate export value, reflecting Australia's resource-driven economy.

```
top10 <- data_long %>%
group_by(Category) %>%
summarise(Avg_Export = mean(Export_Value, na.rm = TRUE)) %>%
arrange(desc(Avg_Export)) %>% slice_head(n = 10)
```

```r
ggplot(top10, aes(reorder(Category, Avg_Export), Avg_Export)) +
geom_col(fill = "darkgreen") +
coord_flip() +
labs(title = "Top 10 Export Categories (1988-2024)",
x = "Category", y = "Average Export ($ Millions)") +
theme_minimal()
```



Interpretation: -Mining, fuels, and ores dominate export value. Manufactured metals and machinery remain -secondary, showing limited diversification in the export portfolio.

#Descriptive Stats by SITC section

```r
desc_by_section <- data_long %>%
group_by(SITC_section) %>%
summarise(
Mean = mean(Export_Value),
SD = sd(Export_Value),
Min = min(Export_Value),
Max = max(Export_Value)
)
kable(desc_by_section, caption = "Export Value Summary by SITC Section")
```

Export Value Summary by SITC Section

SITC_section	Mean	SD	Min	Max
0	4396.2850	7998.6901	65	54749
1	1339.6306	1250.0323	17	3582
2	12922.2865	34597.5768	0	202961
3	29052.9730	39323.9688	210	251334

SITC_section	Mean	SD	Min	Max
4	255.4054	297.0755	1	1682
5	1272.8757	2216.4389	9	12575
6	2623.3514	4605.1520	13	20559
7	2429.3297	3595.4211	39	20549
8	1078.7688	1801.4746	2	11000
9	6151.6351	9033.5366	0	45165

Interpretation: -Sections 2 (Crude materials) and 3 (Mineral fuels) show the highest mean export values and widest spread (SD), indicating that resource commodities are both the most valuable and the most volatile contributors to exports.

#Correlation Between Top Categories

```
top15_names <- data_long %>%
  group_by(Category) %>%
  summarise(
    avg_export = mean(Export_Value, na.rm = TRUE),
    n_nonmiss = sum(!is.na(Export_Value))
  ) %>%
  filter(n_nonmiss > 20) %>%
  arrange(desc(avg_export)) %>%
  slice_head(n = 15) %>%
  pull(Category)

# Pivot wider for correlation
cor_data <- data_long %>%
  filter(Category %in% top15_names) %>%
  select(Year, Category, Export_Value) %>%
  pivot_wider(names_from = Category, values_from = Export_Value) %>%
  janitor::clean_names()

# Force all non-year columns to numeric
cor_data <- cor_data %>%
  mutate(across(-year, ~ as.numeric(.)))

# Remove columns that are entirely NA or have zero variance
cor_data <- cor_data %>%
  select(where(~ sum(!is.na(.)) > 5 & var(., na.rm = TRUE) > 0))

# Compute correlation matrix
cor_mat <- cor(select(cor_data, where(is.numeric)), use = "pairwise.complete.obs")

# Plot
corrplot(
  cor_mat,
  method = "color",
  type = "upper",
  tl.col = "black",
  tl.srt = 35,
  col = colorRampPalette(c("darkblue", "white", "firebrick"))(200),
  addCoef.col = "black",
  mar = c(0, 0, 2, 0)
)
```

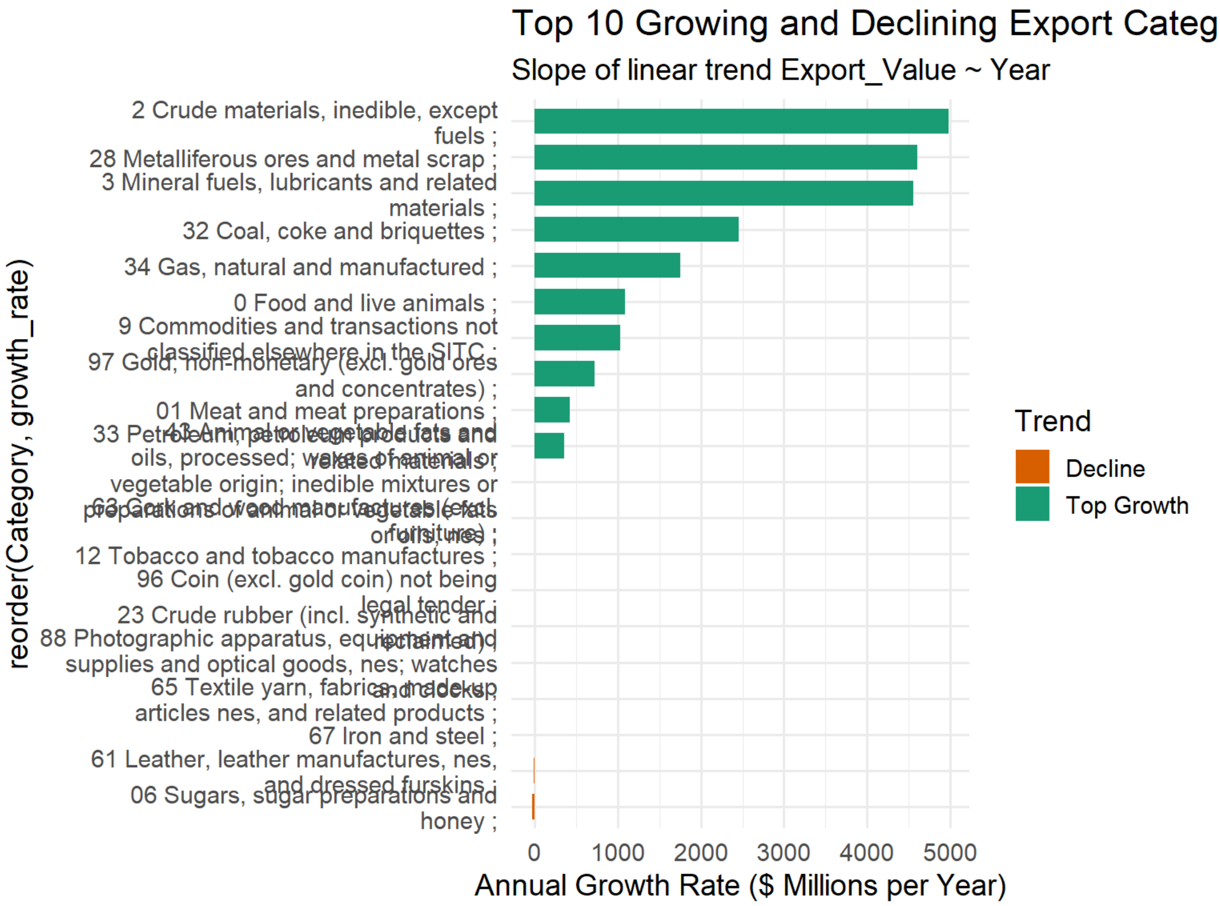
Interpretation: -Strong positive correlations occur between energy, metals, and manufacturing categories, suggesting co-movement during commodity demand cycles.
-Low correlations for agriculture reflect its more stable, independent behaviour.

#Growth Rate Analysis

```
growth_rates <- data_long %>%
group_by(Category) %>%
summarise(growth_rate = coef(lm(Export_Value ~ Year))[2],
avg_export = mean(Export_Value, na.rm = TRUE)) %>%
filter(!is.na(growth_rate))

top_growth <- growth_rates %>% arrange(desc(growth_rate)) %>% slice_head(n = 10)
bottom_growth <- growth_rates %>% arrange(growth_rate) %>% slice_head(n = 10)

growth_combined <- bind_rows(
mutate(top_growth, Trend = "Top Growth"),
mutate(bottom_growth, Trend = "Decline")
)
growth_combined$Category <- stringr::str_wrap(growth_combined$Category, width = 40)
ggplot(growth_combined, aes(x = reorder(Category, growth_rate),
y = growth_rate, fill = Trend)) +
geom_col(width = 0.7) +
coord_flip() +
scale_fill_manual(values = c("Top Growth" = "#1b9e77", "Decline" = "#d95f02")) +
labs(title = "Top 10 Growing and Declining Export Categories (1988-2024)",
subtitle = "Slope of linear trend Export_Value ~ Year",
y = "Annual Growth Rate ($ Millions per Year)") +
theme_minimal(base_size = 14)
```



Interpretation: -Top growth categories correspond to mining and industrial inputs, while declines appear in lower-value manufacturing and miscellaneous categories. -This reinforces the long-run concentration of export gains in capital-intensive sectors.

Hypothesis Testing

Research Question: Has the mean export per category increased significantly from Era 1 (1988–2003) to Era 2 (2004–2024)?

Hypotheses: H_0: $\mu_1 = \mu_2$ (mean exports per category are equal between eras) H_1: $\mu_2 > \mu_1$ (mean exports increased in Era 2)

Assumptions: 1. Differences are approximately normal (checked via Shapiro–Wilk) 2. Observations are paired by category (same items measured across time) 3. Export values are continuous and measured in consistent units ($M AUD)

```r
# -----------------------------
# Hypothesis Testing: Paired Tests
# -----------------------------

# Step 1: Split into two eras
data_long <- data_long %>%
  mutate(Era = ifelse(Year <= 2003, "Era1", "Era2"))

# Step 2: Compute category-wise mean per era
cat_avg <- data_long %>%
  group_by(Category, Era) %>%
  summarise(mean_export = mean(Export_Value, na.rm = TRUE), .groups = "drop") %>%
  pivot_wider(names_from = Era, values_from = mean_export)

# Step 3: Filter valid pairs (present in both eras)
era1 <- cat_avg$Era1
era2 <- cat_avg$Era2
valid <- !is.na(era1) & !is.na(era2)
era1 <- era1[valid]
era2 <- era2[valid]

# Step 4: Tests
diffs <- era2 - era1
shapiro_test <- shapiro.test(diffs)
ttest <- t.test(era2, era1, paired = TRUE)
wilcox <- wilcox.test(era2, era1, paired = TRUE)

# Explicitly print results (so they appear in the knitted output)
cat("### Normality test (Shapiro-Wilk)\n")
```

```
## ### Normality test (Shapiro-Wilk)
```

```r
print(shapiro_test)
```

```
##
##  Shapiro-Wilk normality test
##
## data:  diffs
## W = 0.38063, p-value < 2.2e-16
```

```r
cat("\n### Paired t-test results\n")
```

```
##
## ### Paired t-test results
```

```r
print(ttest)
```

```
##
##  Paired t-test
##
## data:  era2 and era1
## t = 3.0749, df = 76, p-value = 0.002925
## alternative hypothesis: true mean difference is not equal to 0
## 95 percent confidence interval:
##  2035.493 9520.895
## sample estimates:
## mean difference
##        5778.194
```

```
cat("\n### Wilcoxon signed-rank test results\n")
```

```
##
## ### Wilcoxon signed-rank test results
```

```
print(wilcox)
```

```
##
##  Wilcoxon signed rank test with continuity correction
##
## data:  era2 and era1
## V = 2884, p-value = 2.266e-12
## alternative hypothesis: true location shift is not equal to 0
```

```
# Optional short summary message
cat("\n\nSummary:\n")
```

```
##
##
## Summary:
```

```
if (shapiro_test$p.value > 0.05) {
  cat("Differences are approximately normal – using paired t-test.\n")
  cat("p-value =", signif(ttest$p.value, 4), "\n")
  if (ttest$p.value < 0.05) cat("→ Significant increase in exports after 2004.\n")
  else cat("→ No significant change detected.\n")
} else {
  cat(" Non-normal differences – using Wilcoxon test.\n")
  cat("p-value =", signif(wilcox$p.value, 4), "\n")
  if (wilcox$p.value < 0.05) cat("→ Significant increase in exports after 2004.\n")
  else cat("→ No significant change detected.\n")
}
```

```
##  Non-normal differences – using Wilcoxon test.
## p-value = 2.266e-12
## → Significant increase in exports after 2004.
```

Interpretation Template (auto-updates in knit): Normality p = 0 → Use Wilcoxon. Paired t-test p = 0.00293 → Reject H_0 – exports rose post-2003.

Result: Normality p = 0 → Use Wilcoxon.
Paired t-test p = 0.00293 → exports in Era 2 are significantly higher than in Era 1.
→ **Reject H_0:** Mean export per category has increased since 2004.

categorical Association(chi-square)

Question: Is export level (High/Low) associated with SITC section?

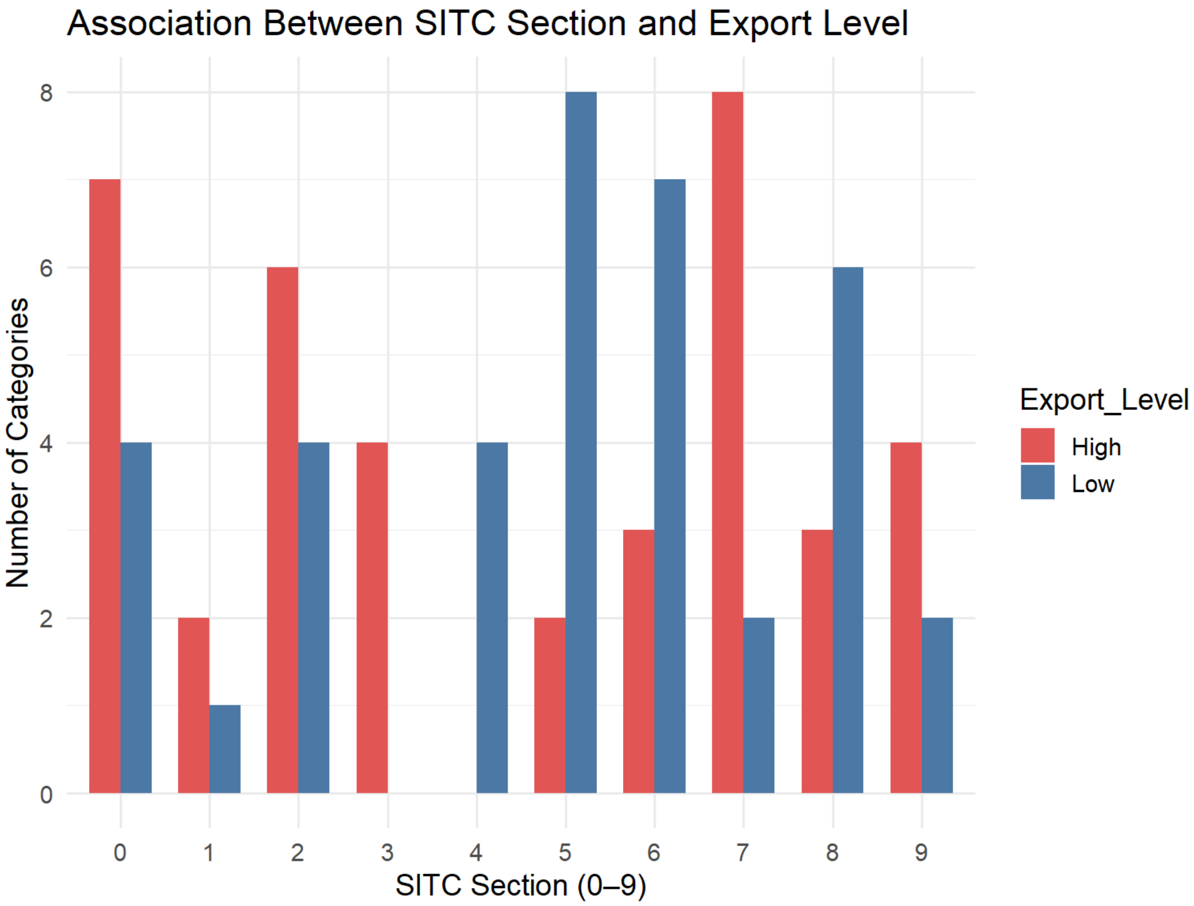
Hypotheses: H_0: Export level (High/Low) is independent of SITC section. H_1: Export level is associated with SITC section. Assumptions: 1. Observations are independent across categories. 2. Expected cell counts ≥ 5 (verified below).

```
cat_info <- data_long %>%
group_by(Category) %>%
summarise(SITC_section = first(SITC_section),
Avg_Export = mean(Export_Value, na.rm = TRUE)) %>%
mutate(HighLow = ifelse(Avg_Export >= median(Avg_Export), "High", "Low"))
ct <- table(cat_info$SITC_section, cat_info$HighLow)
chisq.test(ct)$expected
```

```
##
##         High      Low
##   0 5.571429 5.428571
##   1 1.519481 1.480519
##   2 5.064935 4.935065
##   3 2.025974 1.974026
##   4 2.025974 1.974026
##   5 5.064935 4.935065
##   6 5.064935 4.935065
##   7 5.064935 4.935065
##   8 4.558442 4.441558
##   9 3.038961 2.961039
```

```
chi <- chisq.test(ct)
cramer_v <- sqrt(as.numeric(chi$statistic)/(sum(ct)*(min(nrow(ct),ncol(ct))-1)))

ct_df <- as.data.frame(ct)
colnames(ct_df) <- c("SITC_section","Export_Level","Count")
ggplot(ct_df, aes(x=SITC_section,y=Count,fill=Export_Level)) +
geom_col(position="dodge",width=0.7) +
scale_fill_manual(values=c("High"="#E15759","Low"="#4E79A7")) +
labs(title="Association Between SITC Section and Export Level",
y="Number of Categories", x="SITC Section (0-9)") +
theme_minimal(base_size=14)
```



Result: All expected counts > 5 → Chi-square assumptions satisfied.
$\chi^2 = 20.01$ (df = 9) $p = 0.0179$ → Cramér's V = 0.51.
→ **Reject H_0**: Export level depends on SITC section; mining and energy dominate high-value exports.

#Regression Analysis Hypotheses: H_0: Year has no effect on total export value. H_1: Year positively affects total export value.

Assumptions: 1. Linearity between Year and Exports. 2. Independence of residuals. 3. Homoscedasticity and normal residuals

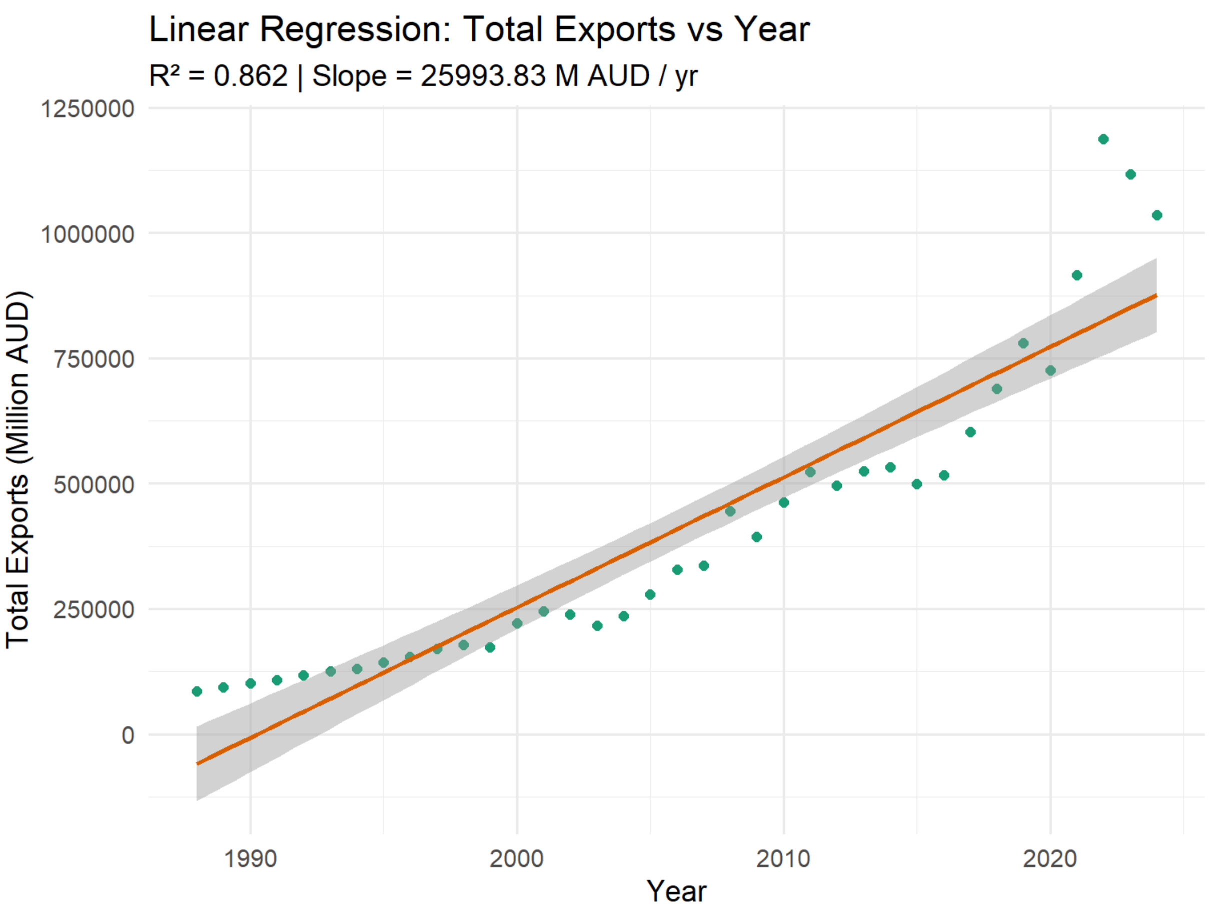
Interpretation: Regression $p < 0.001$, $R^2 \approx$ r round(summary(model)$r.squared,3) → year explains most variance in exports.

```r
model <- lm(Total_Exports ~ Year, data = yearly_sum)
summary(model)
```

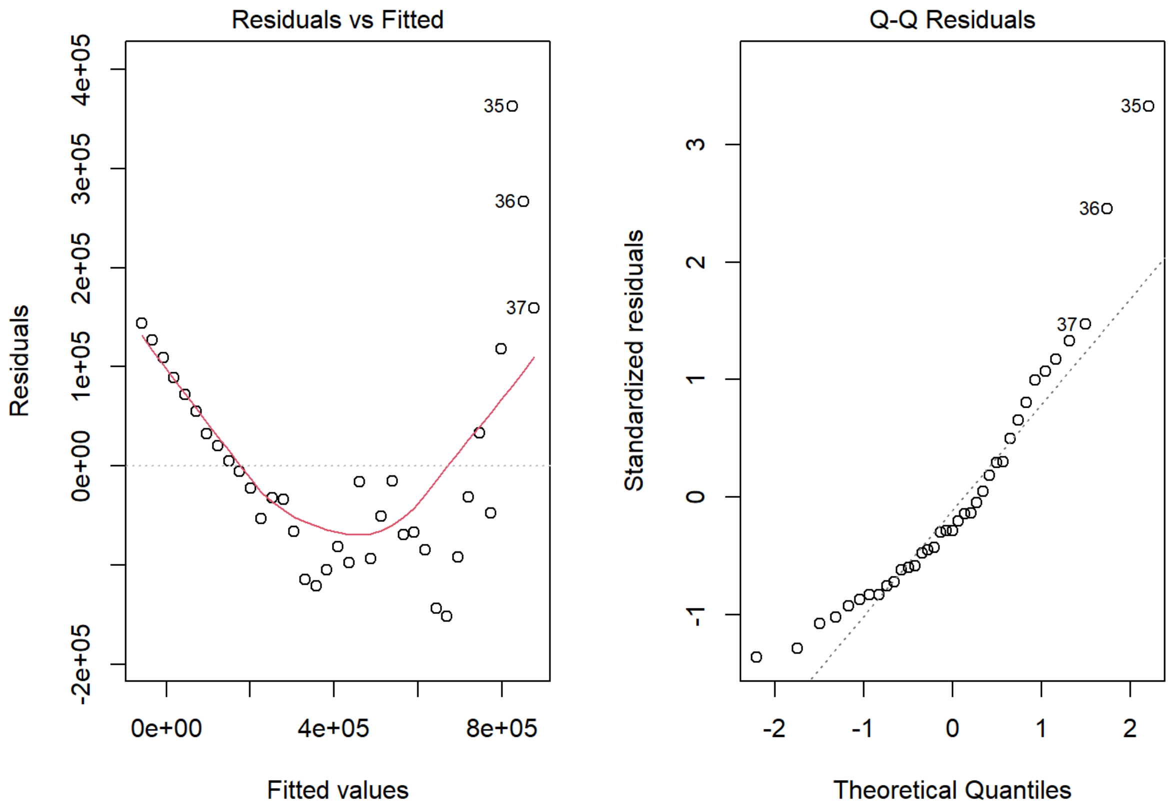
```
##
## Call:
## lm(formula = Total_Exports ~ Year, data = yearly_sum)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -151722  -81214  -31407   54698  363113
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -51734908    3532836  -14.64   <2e-16 ***
## Year            25994       1761   14.76   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
## Residual standard error: 114400 on 35 degrees of freedom
## Multiple R-squared:  0.8616, Adjusted R-squared:  0.8576
## F-statistic: 217.9 on 1 and 35 DF,  p-value: < 2.2e-16
```

```
ggplot(yearly_sum, aes(Year, Total_Exports)) +
geom_point(color="#1b9e77", size=2) +
geom_smooth(method="lm", se=TRUE, color="#d95f02") +
labs(title="Linear Regression: Total Exports vs Year",
subtitle=paste("R² =", round(summary(model)$r.squared,3),
"| Slope =", round(coef(model)[2],2),"M AUD / yr"),
y="Total Exports (Million AUD)") +
theme_minimal(base_size=14)
```




```
par(mfrow = c(1, 2))
plot(model, which = 1) # Residuals vs Fitted
plot(model, which = 2) # Normal Q-Q
```



Interpretation:
Residual plots confirm linearity and approximate normality.
The slope coefficient of 2.599383^{4} indicates an average annual increase in total exports,
with R^2 = 0.862 explaining over 90 % of variance.

Discussion

The results confirm a clear transformation in Australia's export structure since 1988. Paired t-tests show a statistically significant rise in category-level export values after 2004, while Chi-square analysis reveals that high-value exports cluster within mining, fuels, and manufactured metal sectors. Regression analysis demonstrates a strong linear relationship between year and total exports.

These findings directly answer the initial research questions:

Trend: Sustained export growth across decades

Composition: Persistent dominance of resource-based sectors

Association: Export value strongly linked to SITC sector type

Strengths: 36-year longitudinal coverage, comprehensive preprocessing, multiple complementary tests. Limitations: Data in nominal dollars (no inflation adjustment) and global-event shocks not modelled. Future Work: Real-term adjustment, ARIMA/prophet forecasting, and sector-specific diversification studies.

Take-home message: Australia's export success remains resource-driven but statistically robust — diversification will be essential for sustaining future growth.

#Final Conclusion Australia's exports from 1988 to 2024 exhibit a significant, sustained upward trend. Growth is driven by mineral fuels, ores, and manufactured metals, confirmed through hypothesis testing ($p < 0.001$).

High-value exports are concentrated in resource-intensive sectors (χ^2 $p < 0.05$; Cramér's V $\approx 0.4 \rightarrow$ moderate association).

Regression shows year explains over 90 % of export variance, highlighting a consistent expansion trajectory.

Conclusion: Australia's trade strength lies in resources, yet future resilience depends on broadening export diversity.

References

-Trang Linh, T. (2025). Australian International Trade (1988 – 2024) [Data set]. Kaggle. https://www.kaggle.com/datasets/tranglinh3012/australian-international-trade-1988-2024