Economics of Financial Markets (ECON30024/ECON90024) - Assignment 1

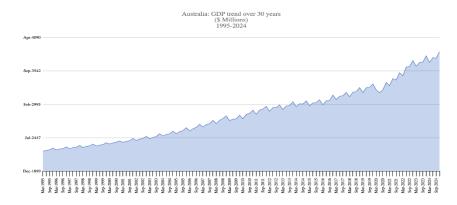
- The time and attendants for each group meeting you have had in the process of completing the assignment (you can, but not required to, include a brief description of the tasks for each meeting).
 - We compiled the answers to Question 1 and Question 2 into this document and completed Question 3 together on Sunday 30th arch 14:00 to 16:00.
- The role of each group member in completing this assignment, such as collecting data, writing report for Question 1, etc. (you can, but not required to, give a percentage of each member's contribution to the assignment)
 - o Question 1: Shashwat Bharadwaj and Arjuna Bhattacharya.
 - o Question 2: Josh Copeland and Oliver van Druten.
 - Question 3: Shashwat Bharadwaj, Arjuna Bhattacharya, Josh Copeland and Oliver van Druten.
- The signatures of all group members to indicate an agreement to what's being stated on the page (sign and scan or using electronic signatures).
 - Electronic signatures:
 - Olivier van Druten
 - Shashwat Bharadwaj
 - Arjuna Bhattacharya
 - Josh Copeland.

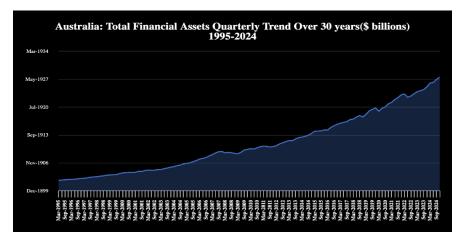
Question 1 (5-page limit)

A) Ratio of total financial assets to GDP, where 'total financial assets' refers to total financial assets owned by Australian households and private nonfinancial businesses or corporations.

As the graphs depict, the Total Financial Assets (TFA) and Gross Domestic Product (GDP) have both steadily increased over the last 30 years. However, the consistent rise in the TFA to GDP ratio over the last 3 decades implies that the TFA increased by a higher rate than the GDP, a trend supported by the following figures:

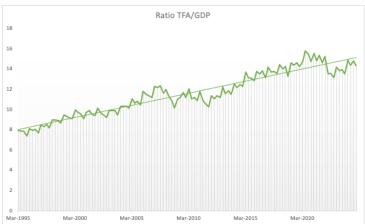
The average annual GDP growth rate over the last 3 decades is 5.61 percent (CAGR) and the average annual TFA growth rate over the same period is 7.95 percent. This difference in the respective growth rates partly explains the significant increase in the ratio over the last three decades.





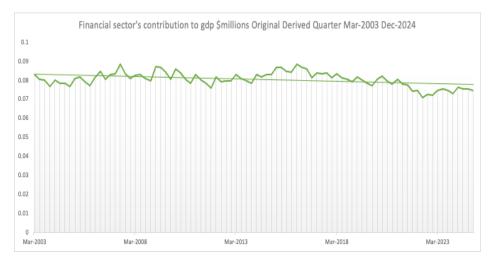
A higher TFA to GDP ratio, indicates a higher demand for financial assets by households and non-financial private companies at a given GDP. It also may indicate a higher level of interdependence between the financial markets and the real economy, additionally improved access to capital, and stronger financial infrastructure.

The data indicates that the ratio of household and private non – financial businesses' assets to GDP is 14.253 as of December 2024 and has almost doubled since March of 1995, when it was 7.904.



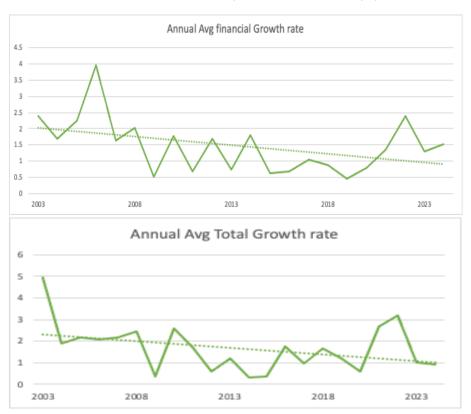
The ratio has seen a significant drop during the last quarter of 2007 due to the global financial crisis where the GDP remained roughly consistent but there was a sharp decline in the value of total financial assets (RBA 2009, a). The ratio also experienced a significant drop in the 2nd quarter of 2013 possibly because households increased their savings rate and reduced their investments in financial assets due to a decrease in interest rates (ABS 2013). The third sharp decline happened during the 3rd quarter of 2020, where both GDP and TFA reduced, which may have been caused by the effects of covid-19 (RBA 2020).

B) The financial sector's contribution to GDP (i.e., its value-added share of GDP), where the financial sector refers to the financial and insurance services industry in Australia.



Financial value added refers to the net contribution of the finance and insurance sector to the total GDP of the country. The financial sector contributed 7.46 percent to the total GDP of Australia in the last quarter of 2024, and roughly 7.5 percent over the last year.

The financial sector's highest contribution has been 8.84 percent in the 3rd quarter of 2007. Which may have been driven by relatively lenient regulations (RBA 2009 a), and easy access to credit due to low interest rates for households and businesses at the time (RBA 2009). The lowest contribution in the 3rd quarter of 2022 may have been because of the temporary boost other industries received in Australia once the economy opened after the pandemic (Fifth Quadrant 2024); (Seek.com.au 2024).



The financial and insurance sector in Australia has grown significantly over the last 22 years from 14735 million dollars contributed to the first quarter of 2003 to 49841 million dollars contributed to the final quarter of last year. The average annual growth rate of total gross value added is 4.00 percent (CAGR) of the last 22 years with 15808 million dollars in the final quarter of 2003 and 667634 million dollars in the last quarter of 2024. The average annual financial growth rate over the same time is 3.902 percent (CAGR).

Thus, the growth rate of all industries has been marginally higher than that of the financial and insurance sector and lead to a decline of financial value added by the finance and insurance industry. This difference in the respective rates of growth can be due to factors such as regulatory changes post the 2008 financial crisis, and strong growth in sectors such as mining, health care and construction. (RBA 2009),

As indicated by the graph, there's a marked decline in the value-added contribution of the finance and insurance sector since the end of 2021. This recent decline can be attributed to a high interest rate set by the Reserve Bank of Australia to counter inflation over this period, leading to credit contraction and households allocating a greater portion of their income into passive savings accounts rather than actively managed

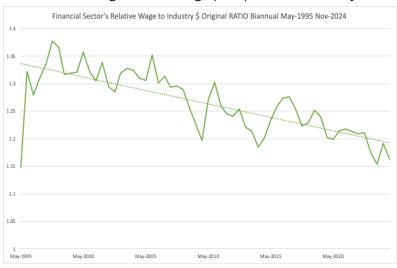
investment funds and other financial assets. The high interest rates thus had a negative impact on the profitability and growth of the financial sector.

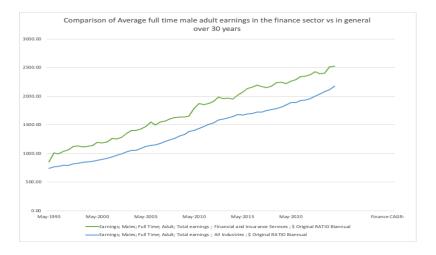
C) The financial sector's average wage relative to the average wage in all industries, where 'average wage' is usually measured by a full-time male adult's average weekly earnings.

As of the final quarter of 2024, the average weekly wage for a full-time adult male working in finance and insurance is 2526.3 dollars, and 2172.3 over all industries.

The relative wage in finance and insurance is 1.16 indicating that finance professionals earn 16 percent more than the average as of end 2024.

This relative wage has remained stable over the last three decades with a standard deviation of 0.057, which indicates that the majority of the observations are clustered around the average relative wage (1.27) over the last 30 years.





The relative wage hit its 3-decade high of 1.38 in November 1997, and its 3-decade low 1.149 as of in May 1995, indicating a relatively higher variance in wages over time during mid to late 90s compared to 2020s.

The relative wage has been steadily declining over time, with the average relative wage of 1.31 from May 1995 to May 1996 to an average relative wage of 1.19 from November 2021 to November 2024, indicating a drop of 8.7 percent over the last 3 decades.

The average growth rate of wages in the finance and insurance sector over the last 3 decades is 3.102 percent, while the average total rate of growth for all industries is 3.546 percent. This has led to the decline in relative wages.

There are multiple plausible explanations for the difference in growth rates of wages in finance and insurance and all other jobs. This difference may be explained by disproportionately high automation of certain low paying finance jobs such as that of bank tellers, data entry clerks, and insurance underwriters leading to a relative wage stagnation. This includes a high number of jobs that were replaced by robotic process automation, and artificial intelligence as well fin-tech solutions that cut out intermediaries (Mckinsey 2020).

Another possible explanation is a significant rise in high paying software and tech jobs that had positively skewed the average wage rate of all industries, and in turn had a negative effect on the relative wage of the finance and insurance industry.

Other plausible reasons include higher regulatory and compliance requirements leading to less flexible wages, outsourcing mid-level roles, and a relatively stronger growth in low-income jobs due to the government raising the minimum wage, and labour shortages. (RBA 2009).

Question 2 (5-page limit)

(a) Find monthly data series for All Ordinaries and S&P/ASX 200 indices. Clearly state your data source and sample period in your report, but please do not include the observations of the data series in your report.

We have used the *tidyquant* package to directly retrieve timeseries for the All Ordinaries and ASX200 series from January 2000 to February 2025. By default, the function we have used to retrieve this data (*getSymbols()*) retrieves its data from Yahoo Finance, as noted on page 50 of the *quantmod* documentation.

The tickers used were: ASX 200: Data sourced via Yahoo Fiancé S&P/ASX 200 ETF and All Ordinaries: Data sourced via Yahoo finance S&P/ASX Small Ordinaries ETF

See Appendix for R Code.

(b) For each price index, calculate the corresponding return series. Do this using the exact formula for calculating rates of return on a price index or use the logdifference approximation. Then use the Box-Ljung test (also called Ljung-Box test) to test the joint significance of the first 12 autocorrelations of each return series.

Returns were calculated using the log-difference of prices:

We create returns using the exact formula on both price indices and conduct the Box-Ljung test on both returns separately. The null hypothesis of the Box-Ljung test is there there are no significant autocorrelations up to lag 12 (you can use any number of lags, but that's what we're using in this assignment). More formally:

$$H_0: \rho_1=\rho_2=\cdots=\rho_{12}=0$$

$$H_1: \exists \ k\in\{1,2,\ldots,12\} \ such \ that \ \rho_k\neq 0$$

$$\alpha=0.05$$

Our result for this test is summarised on both indices is summarised in Table 1. As both these p-values are greater than 0.1, we are unable to reject the null hypothesis of these tests, even at the 10% significance level. This means neither time series has no significant autocorrelation up to lag 12 at any reasonable significance level.

This is consistent with the weak form of the Efficient Market Hypothesis (EMH): the past prices (and therefore returns) are assumed to contain no useful information on future prices. If there was, there would be significant autocorrelation in this return series.

However, we need to consider these results in context of the joint hypothesis problem. Our failure to reject the null hypothesis, and therefore confirm the EMH, is actually conditional on us

being confident about our test having sufficient power to detect significant autocorrelations. In our test, we are only testing for autocorrelations up to order 12. Therefore, our conclusion about finding support for the weak form EMH is conditional on both us having confidence about the Box-Ljung test to do this consistently and effectively, and that testing up to the 12th order autocorrelation is sufficient for our support.

Table 1: Ljung-Box test results

Index	Ljung-Box test statistic	Degrees of freedom	P-value
S&P/ASX 200	16.063	12	0.1884
All Ordinaries	18.311	12	0.1066

Note: refer to R code appendix for further information.

3) Use a unit root test or a regression to test whether the logarithm of each price index follows a random walk. For the regression analysis, you can estimate a simple regression as discussed on slide 11 of Topic 2 (if you don't have much experience in Econometrics), or try to estimate the regression of Groenewold and Kang (1993) as given in Eq. (3) of the paper, or estimate an alternative regression that you think suitable.

Rather than using the regression of the form given in Groenewold and Kang (1993) we instead use the Augmented Dicky-Fuller (ADF) test to for the presence of a unit root in the logarithm of our stock market indices. We think this is reasonable for two reasons:

- It is a very popular unit root test in empirical economic papers.
- It allows us to test for the two different hypotheses tested by Groenewold and Kang (1993): the process is random walk with a trend and drift; the process is a random walk with a drift.

Consistent with Groenewold and Kang (1993) our results test for the presence of a unit root with a drift, as well as a drift and a trend. When testing for the case of there being just a drift the regression we are estimating is:

$$\Delta y_t = \alpha + \rho y_{t-1} + \Sigma \alpha_i \Delta y_{t-i} + \epsilon_t$$

To evaluate the presence of a unit root, the hypothesis test we would impose is if $\rho=0$. Rejecting this hypothesis would allow us to conclude the time series is stationary.

In the instance of testing for the presence of a unit root with a drift and trend, we are estimating the following regression

$$\Delta y_t = \alpha + \beta t + \rho y_{t-1} + \Sigma \alpha_i \Delta y_{t-i} + \epsilon_t$$

To evaluate the presence of a unit root, the hypothesis test we would impose is if $\rho = \beta = 0$. Rejecting this hypothesis would allow us to conclude the time series is stationary.

Our results for these ADF tests are presented in Table 2. As these are left-tailed tests, we need the test statistics to be lower than the relevant critical value at a given significance level. The lower the test statistic, the stronger the evidence against the null hypothesis. As neither of the

test statistics are below the 10% critical value, we cannot reject the null hypothesis of there being a unit root in either stock market index even at the 10% significance level.

These results support the weak form of the EMH, which says share prices reflect all past information, meaning future price movements are unpredictable base on past price data. Our failure to reject the null hypothesis of a random walk confirms this weak form of the EMH.

However, it's important to be aware of the fact the testing EMH with a unit root test is not independent of the underlying model of asset prices. Failing to reject the null hypothesis doesn't necessarily confirm EMH by itself as this test implicitly assumes it follows a random walk. If this is incorrect it could affect our conclusion. Therefore, our initial conclusion of confirming EMH is conditional on us assuming the data follows a random walk.

Table 2: ADF test results

Index	Drift test	Drift critical value	Drift + trend test	Drift + trend
	statistic		statistic	critical value
All	-0.66	-2.57	-2.73	-3.13
ordinaries				
ASX 200	-0.72	-2.57	-2.71	-3.13

Note: All critical values are given at the 10% significance level. Refer to the R code appendix for further information.

Question 3

(a) Are you going to play the game in scenario 1)? Are you going to play the game in scenario 2)? Based on your decisions, comment on your degree of risk aversion in terms of absolute risk aversion (ARA) and relative risk aversion (RRA). That is, do you think you have increasing, decreasing or constant ARA, and increasing or decreasing RRA?

My decisions are to play the game in scenario 1 and play the game in scenario 2.

Absolute risk aversion (ARA),

$$ARA(w) = -\frac{u''(w)}{u'(w)}$$

Relative risk Aversion (RRA),

$$RRA(w) = -w * \frac{u''(w)}{u'(w)}$$

The implications of my decisions, are that:

- I have a constant or decreasing ARA, as I do not have a decreasing willingness to take risk as the size of the risk increases in absolute terms. This is because I am willing to accept both gambles, regardless of the size of the bet.
- I have a constant RRA, as I do not have a decreasing willingness to take risk regardless of what share of my wealth is at stake. This is because I am willing to accept both gambles, regardless of what proportion of my wealth the bet accounts for.
 - (b) Choose a utility function that may describe your attitude toward risk (refer to Topic3 slides for some examples of utility function, but you are not restricted to choose from this list), and calculate your expected utilities from playing the game or staying away from it in both scenarios. Are your decisions in (a) justifiable by this utility function? If not, try different value(s) for parameter(s) in your utility function or try a different utility function until the utility function you choose to work with implies the decisions you have chosen in part (a). By doing this exercise, you somehow uncover your own utility function from your decisions.

I will use a Constant Relative Risk Aversion utility function to represent both gambles.

$$u(w) = \begin{cases} \frac{w^{1-\gamma}}{1-\gamma}, & \text{if } y \neq 1\\ \ln(w), & \text{if } \gamma = 1 \end{cases}$$

As you can see this function has decreasing Absolute Risk Aversion as,

$$ARA = \frac{\gamma}{w}$$

Therefore, as $\gamma=0.1$, as my wealth increases, my ARA must decrease, which matches with my choice to play both gambles and shows that my decisions to take risks doesn't change much although my wealth increases.

This function has a constant Relative Risk Aversion as,

$$RRA(w) = \gamma$$

Therefore, as $\gamma=0.1$, means my RRA is positive and remains constant. This also means my tolerance to risk relative to my wealth remains unchanged. This means that it aligns with my choice to play both gambles.

Expected utility calculations

$$EU = p * u(w + gain) + (1 - p) * u(w - cost)$$

- Game 1,

$$EU = 0.15 * u(100 - 50 + 500) + (1 - 0.15) * u(100 - 50)$$
$$EU = 0.15 * \frac{550^{0.9}}{0.9} + 0.8 * \frac{50^{0.9}}{0.9} = 80.71$$

- Game 2

$$EU = 0.15 * u(1000 - 500 + 5000) + (1 - 0.15) * u(1000 - 500)$$
$$EU = 0.15 * \frac{5500^{0.9}}{0.9} + 0.8 * \frac{500^{0.9}}{0.9} = 641.07$$

As the, CRRA function has decreasing ARA and constant RRA, it represents my risk preference correctly, as seen by the positive EU values for both gambles. Since both EU's are large numbers and positive, it indicates that the potential gains from playing the games outweigh the losses, making it a rational choice in relation to my risk preference. The choice of the CRRA utility function with $\gamma=0.1$ is rightly assumed appropriate because it correctly accurately reflects my mild risk aversion. A low positive value of γ indicates that I am not very cautious and very willing to take risks, especially when the potential reward significantly outweighs the loss. potential loss.

The decreasing ARA implies that as my wealth increases, my willingness to take risks does not decline much, which matches my decision to take part in both gambles. Alongside, the constant RRA indicates that my risk-taking behaviour remains constant even when the proportion of wealth in the gamble rises. Therefore, the CRRA utility function with $\gamma=0.1$ captures my decisions well to engage in both games.

References

RBA (2009a). The Global Financial Crisis. Reserve Bank of Australia. Retrieved from https://www.rba.gov.au/education/resources/explainers/the-global-financial-crisis.html

RBA (2009b). Address to the Economic Society of Australia. Reserve Bank of Australia. Retrieved from https://www.rba.gov.au/speeches/2009/sp-ag-310309.html

ABS (2013). Australian National Accounts: National Income, Expenditure and Product, June 2013. Australian Bureau of Statistics.

RBA (2020). The COVID-19 Pandemic: 2020 to 2021. Reserve Bank of Australia. Retrieved from https://www.rba.gov.au/education/resources/explainers/the-covid-19-pandemic-2020-to-2021.html

ABS (2020). Australian System of National Accounts, 2019–20. Australian Bureau of Statistics. Retrieved from https://www.abs.gov.au/statistics/economy/national-accounts/australian-system-national-accounts/2019-20

Mckinsey (2019) Mckinsey.com/industries/financial-services/our-insights/rewriting-the-rules-digital-and-ai-powered-underwriting-in-life-insurance?ref=limit.com

Appendix - R Code

 Note: This code only applies to Question 2. for Question 1, please refer to Excel spreadsheet which has also been submitted.

```
library(quantmod)
library(tidyverse)
library(RColorBrewer)
library(urca)
getSymbols(c("^AXJO", "^AORD"), from = "2000-01-01", to = Sys.Date())
# Reformatting data into tidy format
data <- tibble(
date = as.Date(index(AXJO)),
ASX200_Close = as.numeric(AXJO$AXJO.Close),
AllOrds_Close = as.numeric(AORD$AORD.Close)
) %>%
select(date, asx200 = ASX200_Close, allords = AllOrds_Close) %>%
pivot_longer(-date)
# Creating monthly observations from daily data
data <- data %>%
mutate(year_month = floor_date(date, "month")) %>%
group_by(name, year_month) %>%
summarise(value = mean(value, na.rm = TRUE)) %>%
select(date = year_month, value) %>%
ungroup() %>%
filter(date < "2025-03-01")
# Calculating monthly returns
data <- data %>%
group_by(name) %>%
mutate(returns = ((value - lag(value)) / value) * 100) %>%
na.omit()
```

```
ggplot(data, aes(date, returns, colour = name)) +
geom_line() +
labs(title = "Australian stock market indice returns",
  y = "Returns",
  x = "Date") +
theme_minimal() +
scale_color_brewer(palette = "Set1")
# Conducting Box-Ljung test on allords
data %>%
filter(name == "allords") %>%
pull(returns) %>%
Box.test(lag = 12, type = "Ljung-Box")
# Conducting Box-Ljung test on asx200
data %>%
filter(name == "asx200") %>%
pull(returns) %>%
Box.test(lag = 12, type = "Ljung-Box")
# Turning price indexes into logarithms
data <- data %>%
mutate(value_log = log(value))
ggplot(data, aes(date, value_log, colour = name)) +
geom_line() +
labs(title = "Logarithms of Australian stock market indices",
  y = "Value",
  x = "Date") +
theme_minimal() +
scale_color_brewer(palette = "Set1")
# Producing ADF tests for the allords series
data %>%
filter(name == "allords") %>%
```

```
pull(value) %>%
ur.df(type = "drift", selectlags = "AIC") %>%
summary()
data %>%
filter(name == "allords") %>%
pull(value) %>%
ur.df(type = "trend", selectlags = "AIC") %>%
summary()
# Producing ADF tests for the asx200 series
data %>%
filter(name == "asx200") %>%
pull(value) %>%
ur.df(type = "drift", selectlags = "AIC") %>%
summary()
data %>%
filter(name == "asx200") %>%
pull(value) %>%
ur.df(type = "trend", selectlags = "AIC") %>%
summary()
```

