Predicting the Future Corporate Profit with Vector Autoregression

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1 Introduction

In capitalism, profits motivate firms to employ labor and produce output for sale (Veblen 1904). Due to the fundamental uncertainty of the future, firms expect future profits and make investments accordingly, often disproportionately influenced by recent sales and profit conditions (Keynes 1936). Changes in current and expected future corporate profits significantly affect economic outlooks. Additionally, the equity valuation in firms is often based on the discounted value of future profits. Lenders extend loans to firms based on their earnings capacity, and the soundness of these loans depends on the profits firms realize in the future (Minsky 1982). Therefore, profit is seen as one of the most critical concepts in economics and finance. The Kalecki-Levy profit equation is an accounting identity that shows how aggregate corporate profit is determined by economic variables such as investment and government deficits (Levy, Farnham, and Rajan 2008). This project aims to use the variables in the Kalecki-Levy equation to build a predictive model for the next-quarter corporate profit.

2 Theoretical Background

2.1 Kalecki-Levy Profit Equation

Levy, Farnham, and Rajan (2008) presented a stylized Kalecki-Levy equation for open economies (signs of RHS variables are adjusted here according to the National Income and Product Accounts (NIPA) accounting convention):

$$\begin{aligned} \text{Profit after tax} = {} & \text{Net Investment} \\ & - \text{Personal Saving} \\ & + \text{Foreign Saving} \\ & - \text{Government Saving} \\ & + \text{Net Dividend} \end{aligned} \tag{1}$$

The Kalecki-Levy equation, as an accounting identity, is tautologically true. Here is the proof:

$$I = S = PS + CS + FS + GS$$

$$I = PS + (CP - ND) + FS + GS$$

$$CP = I - PS - FS - GS + ND$$

where I is net investment (gross investment - depreciation), S is net saving, PS is personal saving, CS is corporate saving, FS is foreign saving, GS is government saving, CP is net corporate profit, and ND is net dividend (total dividend excluding dividends paid to firms). Since in the NIPA account, *Foreign Saving* is recorded as a negative figure, after flipping the sign of it, we get Equation 1. For technical details, please refer to BEA (2024).

Since the above analysis is purely an accounting analysis, it does not imply any behavioral relations or causality. However, Minsky argued that it is the RHS that determines corporate profit, not vice versa. The straightforward explanation for investment causing profit is that firms cannot control future profit but can determine how much they invest in the next quarter based on their expectations of future economic conditions. For a detailed analysis, please refer to Minsky (1986, Chapter 2).

2.2 Research Motivation

Given the Kalecki-Levy framework for profit determination, a key motivation of this study is to explore how the relationships defined in these identities might serve as practical tools for prediction, rather than merely theoretical constructs. While the original equations hold by definition, leveraging them in a predictive model allows us to investigate whether observable trends in the determinants of profit—and profit itself—can reliably signal changes in future corporate profit.

For example, does a consistent increase in net investment over the past year suggest momentum that could continue into the next quarter, thereby boosting profits? Similarly, could a high personal saving rate over several quarters indicate an upcoming decline, indirectly increasing corporate profit? Shifting the focus to prediction invites us to examine not only if these relationships hold as identities but also if they possess empirical stability and value in forecasting applications.

Although prior research, such as Trofimov (2022), utilized panel VAR to assess the impact of profit determinants on margins—finding a positive effect from trade surpluses and a negative one from government deficits—such studies have not applied these equations in a forward-looking, predictive context. By employing a rolling-window Vector Auto-Regression (VAR) model, this project specifically aims to predict corporate profit for the next quarter. This method leverages both historical values of profit itself and its key determinants, building on the identity to test its predictive utility, as discussed in the next section.

3 Data

The quarterly and annual series of corporate profit, personal savings, foreign savings, government savings, and net dividends are collected from NIPA (https://www.bea.gov/itable/national-gdp-and-personal-income). The monthly series of the S&P 500 price and earnings are collected from Robert Shiller (http://www.econ.yale.edu/~shiller/data.htm). Currently, only the quarterly series of NIPA is explored.

3.1 Exploratory Data Analysis: Identity

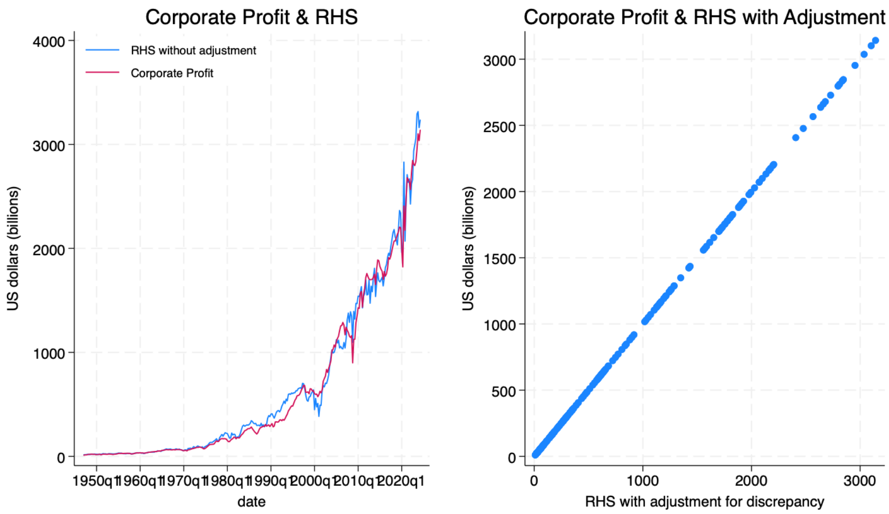

Figure 1: Identity between Corporate Profit and RHS

This graph shows that the Kalecki-Levy equation holds in the NIPA. The left graph shows the close relationship between corporate profit and the sum of the RHS. The right graph shows the exact identity between corporate profit and the RHS after adjusting for the statistical discrepancy term in the NIPA. Exploratory data analysis is presented below.

3.2 Exploratory Data Analysis: Stationarity

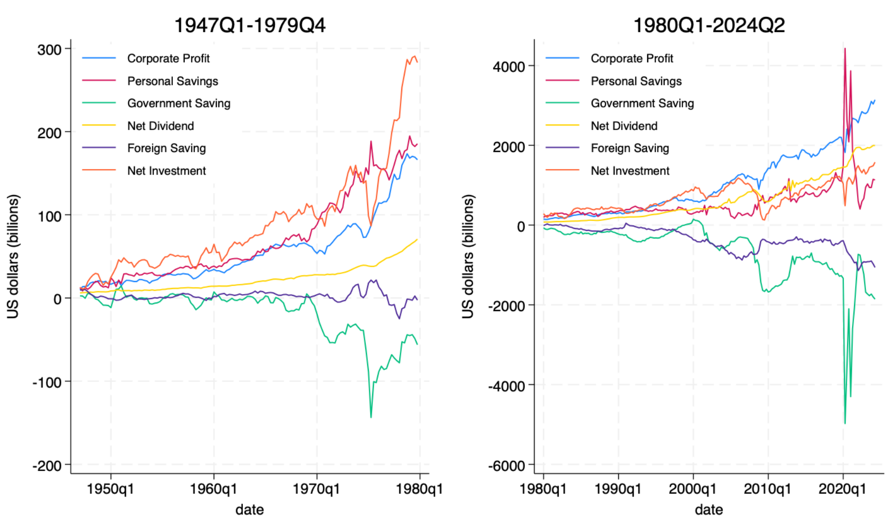

Figure 2: Time-Series of the Variables in Kalecki-Levy Equation

This graph shows that all six variables in the Kalecki-Levy equation trend with time and are therefore not stationary. For time series analysis, detrending the variables is necessary.

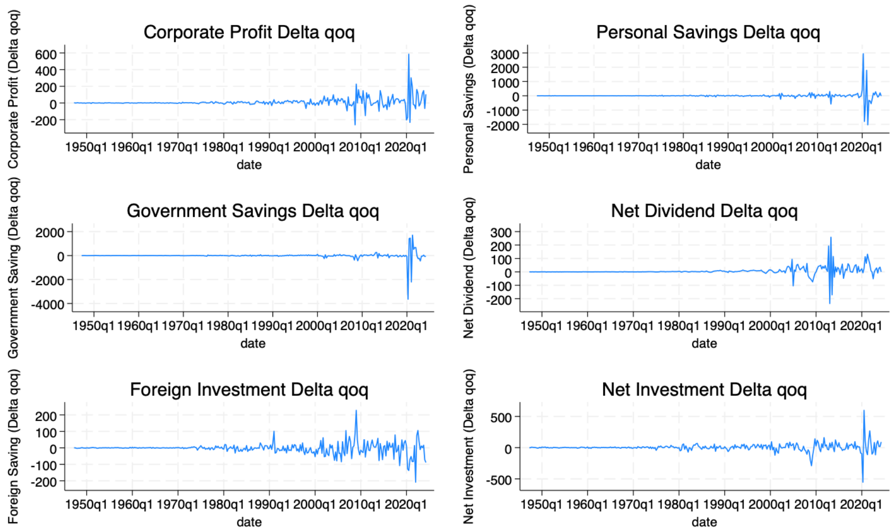

Figure 3: Detrending the variables - Level change QoQ

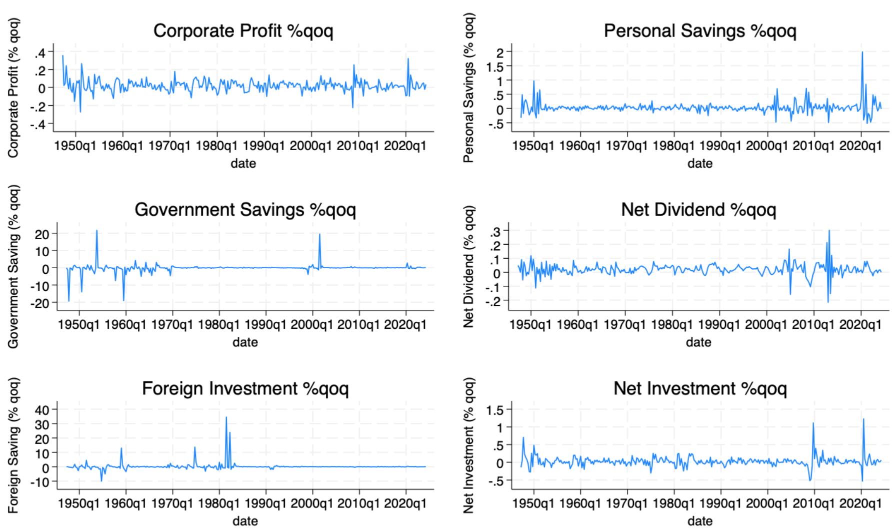

Figure 4: Detrending the variables - % change QoQ

The results of Phillips-Perron unit root tests reject the null hypothesis with p-values under 0.001 for all six variables in both approaches, indicating that they do not follow a random walk. No obvious trend could be observed in both graphs. However, two approaches to detrending come with their advantages and disadvantages.

Figure 3 shows the quarter-on-quarter difference of the six variables. For some variables, such as corporate profit, net dividend, foreign savings, and net investment, there appears to be an increasing standard deviation. Figure 4 shows the quarter-on-quarter percentage change of the six variables. There appears to be no increasing standard deviation. However, this approach produces highly volatile outcomes, with some changes over 1000%. When these variables change signs, the percentage change will always be negative, not necessarily indicating a decline of magnitude. Besides, if the relative magnitude of the RHS variables changes over time, using percentage change may not capture structural shifts.

The difficulty of capturing structural change could be mitigated by using a smaller training sample in the later rolling-window VAR tests. However, for the level changes, increasing standard deviation remains a big issue; even if the sample is smaller, the magnitude of the variable still could change a lot in years. For the percentage changes, high volatility and sign changes in the percentage change approach remain problems. In the next section, it is found that percentage changes do much better for either explanation or prediction purposes.

4 Methodology and Analysis

4.1 VAR and Granger Causality Tests

Vector autoregressions(Békés and Kézdi 2021, 505) are conducted on the entire dataset, using both level and percentage difference variables, followed by Granger causality tests(“Granger Causality” 2024). The results for percentage changes with eight lags of endogenous variables and time as an exogenous variable are presented below. The mathematical model is expressed as:

$$\begin{aligned} p_{cp,t} = \alpha_{cp} + \sum_{i=1}^{8} \big(& \beta_{cp,cp,i} p_{cp,t-i} + \beta_{cp,ps,i} p_{ps,t-i} + \beta_{cp,gs,i} p_{gs,t-i} \\ & + \beta_{cp,ni,i} p_{ni,t-i} + \beta_{cp,fi,i} p_{fi,t-i} + \beta_{cp,nd,i} p_{nd,t-i} + \gamma_{cp} \cdot \text{date}_t + \epsilon_{cp,t} \big) \end{aligned} \tag{2}$$

where α_{cp} is the intercept, $\beta_{cp,*,i}$ are coefficients for lagged endogenous variables, γ_{cp} is the time coefficient, and $\epsilon_{cp,t}$ is the error term. Only the corporate profit equation is shown, as our primary interest is in profit prediction.

Table 1: VAR Results for Equation 2

Predictor	Coefficient	Predictor	Coefficient
L.c__ps	0.084** (0.033)	**L4.c__ps**	-0.043** (0.021)
L3.c__ps	0.051** (0.023)	**L2.c__gs**	0.007** (0.003)
L4.c__gs	0.002* (0.001)	**L5.c__gs**	0.002* (0.001)
L7.c__ni	0.044** (0.020)	**L2.c__fi**	-0.002*** (0.001)
L3.c__fi	0.002** (0.001)	**L5.c__fi**	0.002** (0.001)
L6.c__fi	0.001* (0.001)	**L7.c__fi**	0.001* (0.001)
L.c__nd	-0.206* (0.112)	**L2.c__nd**	-0.153* (0.087)
L4.c__nd	0.185* (0.109)	**date**	-0.000 (0.000)
_cons	0.028*** (0.009)	R2	0.2673

Robust std. err. in parenthses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Only significant coefficients are reported. Lags are denoted by L#, indicating the number of quarters past (e.g., L3.c__ps is the percentage change in personal savings from three quarters ago).

The results in Table 1 are complex to interpret. Lagged changes in corporate profit do not correlate with next-quarter profit changes. Personal saving shows a short-term positive correlation with profit changes, shifting to negative over time. Government savings (typically negative, implying a deficit) and net investment display a positive correlation with profit changes after a delay of at least one year. Foreign saving (often negative, reflecting a current account deficit) is negatively correlated with profit change in the short run but has a consistent positive correlation over the longer term. Finally, net dividends exhibit a short-term negative correlation with profit changes, turning positive over a longer horizon. Given that this model includes six variables with eight lags each (a total of 48 lagged variables), caution is advised when interpreting p-values, even with robust standard errors. The model explains approximately 26% of next-quarter profit variation, but without out-of-sample testing, overfitting remains a risk.

The Granger causality test for Equation 2 (not reported) suggests that, except for net investment, we can reject the null hypothesis that the independent variables do not Granger-cause percentage changes in corporate profit. Notably, none of the variables Granger-cause government saving, indicating it may behave autonomously in our sample.

For the model using level changes, the mathematical formula is:

$$\begin{aligned} d_{cp,t} = \alpha_{cp} + \sum_{i=1}^{8} \big(& \beta_{cp,cp,i} d_{cp,t-i} + \beta_{cp,ps,i} d_{ps,t-i} + \beta_{cp,gs,i} d_{gs,t-i} \\ & + \beta_{cp,ni,i} d_{ni,t-i} + \beta_{cp,fi,i} d_{fi,t-i} + \gamma_{cp} \cdot \text{date}_t + \epsilon_{cp,t} \big) \end{aligned} \tag{3}$$

The model using level changes requires dropping one of the RHS variables due to perfect multicollinearity. Net dividend is excluded here for its relative stability. In the robustness checks, other variables may be tested for exclusion. The VAR results for Equation 3 are not reported, as the Granger causality test failed to reject any null hypothesis, and very few coefficients were statistically significant. This limited significance may be attributed to the increasing standard deviation, resulting in high heteroskedasticity-robust standard errors.

4.2 Rolling-Window VAR

To mimic the real-life prediction process, rolling-window VAR tests are performed using smaller sets of training data to predict next-quarter corporate profit changes. This approach mitigates the risk of structural changes and, to some extent, the issue of increasing standard deviation. The R^2 values from tests using both level and percentage change data are reported here, with more models using other specifications in the later robustness check section.

R^2 for models using level changes are calculated by transforming the predicted level changes into percentage change predictions using the formula below:

$$\text{PredictedPctChange}_t = \frac{\text{PredictedLevelChange}_t}{\text{CorporateProfit}_{t-1}}$$

The R^2 is then calculated as:

$$R^2 = 1 - \frac{\sum_t \left(\text{ActualPctChange}_t - \text{PredictedPctChange}_t\right)^2}{\sum_t \left(\text{ActualPctChange}_t - \overline{\text{ActualPctChange}}\right)^2}$$

It is important to perform this transformation, as both the series of predicted level changes and actual level changes of corporate profit have increasing standard deviations. Without this adjustment, R^2 could be high but spurious. By converting predicted level changes into percentage terms, the increasing standard deviation could be removed and the predictive power across models can be easily compared.

Table 2: Rolling-Window VARs

	R2
R2 for pct 4-80	.1906034
R2 for pct control 4-80	.0173584
R2 for pct 8-100	.2850141
R2 for pct control 8-100	.019117
R2 for level 4-80	-.0237362
R2 for level 8-100	-.2695254

Table 2 presents R^2 from four rolling-window VAR models and two control models which include only lagged changes in corporate profit and time. Here 'pct 8-100' means that the model uses percentage changes with 8 lags and 100 lookback periods. Notably, the two models using level changes do not possess any predictive power, even though they slightly outperform their control models (not reported). Pct 4-80 predicted 19.1% of the variations of next-quarter corporate profit, and Pct 8-100 predicted 28.5%. Both significantly outperformed their control models, which barely have any predictive power.

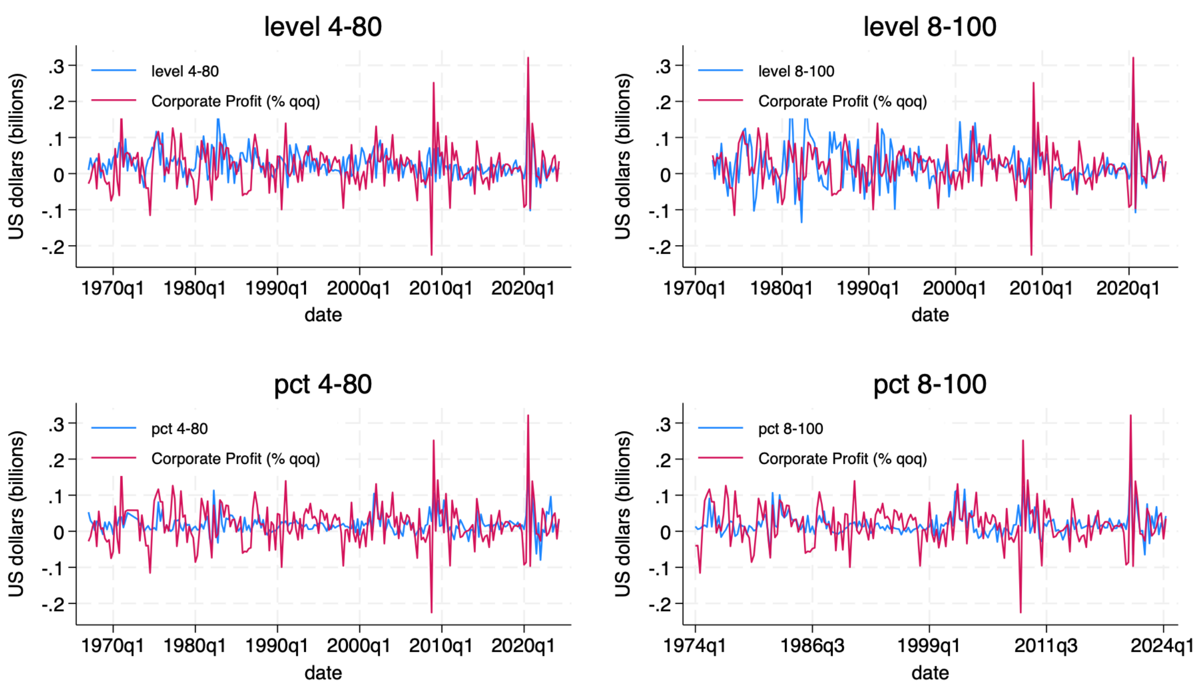

Figure 5: Prediction Series

Figure 5 displays the prediction series of the four models in Table 2 alongside the actual level and percentage change in corporate profit. It shows that the two models using level changes consistently gave volatile predictions. This is expected since the two models have to fit the later part of training models whose standard deviation is larger and thus its prediction for the earlier part of the training data would tend to be more volatile. Meanwhile, the two models using percentage changes could only capture part of the variation in the next-quarter profit, and the prediction series tends to be more stable than the actual series. This observation is consistent with Table 3, even though it turns out that even the perceived volatile series could not match the volatility of the actual series.

Table 3: Summary Statistics

	mean	sd	min	max
level 4-80	.0268783	.0377139	-.1023735	.2760183
level 8-100	.022715	.0555009	-.135033	.2871547
pct 4-80	.0188041	.0272921	-.0796602	.1794075
pct 8-100	.0184845	.0318601	-.0657208	.1939854
Corporate Profit (% qoq)	.0208806	.0659253	-.2722773	.36
Observations	309			

5 Robustness

To enhance the robustness of this study, more models of various specifications are presented in this section, and the application of some models is extended to annual data.

5.1 More Specification

Two more models using percentage changes (12-120 and 16-160) are presented. Two more models using level changes are presented, which dropped net investment as an independent variable instead of a net dividend, for the fact that in Table 1, the Granger causality test could not reject the null hypothesis for net investment.

Table 4: R^2 for more models

	mean
R2 for pct 12-120	.3586333
R2 for pct 16-160	.439759
R2 for alternative level 4-80	-.0127257
R2 for alternative level 8-100	-.0980562
Observations	310

Table 4 shows that the predictive power of the models using percentage changes keeps improving when the number of lags and observations used for model training increases. The pct 16-160 model could predict 44% of the variations of next-quarter profit change. This shows that the impact of the variables in the Kalecki-Levy equation on future corporate profit could be cumulative. Meanwhile, the two models using level changes still could not possess any predictive power with negative R^2.

5.2 Annual Data

Three models using percentage changes are applied to the annual NIPA series, with results presented below.

Table 5: Rolling-window VAR for Annual Data

	mean
R2 for pct 4-40	.0553855
R2 for pct 6-60	.4447948
R2 for pct 4-60	.1291389
Observations	95

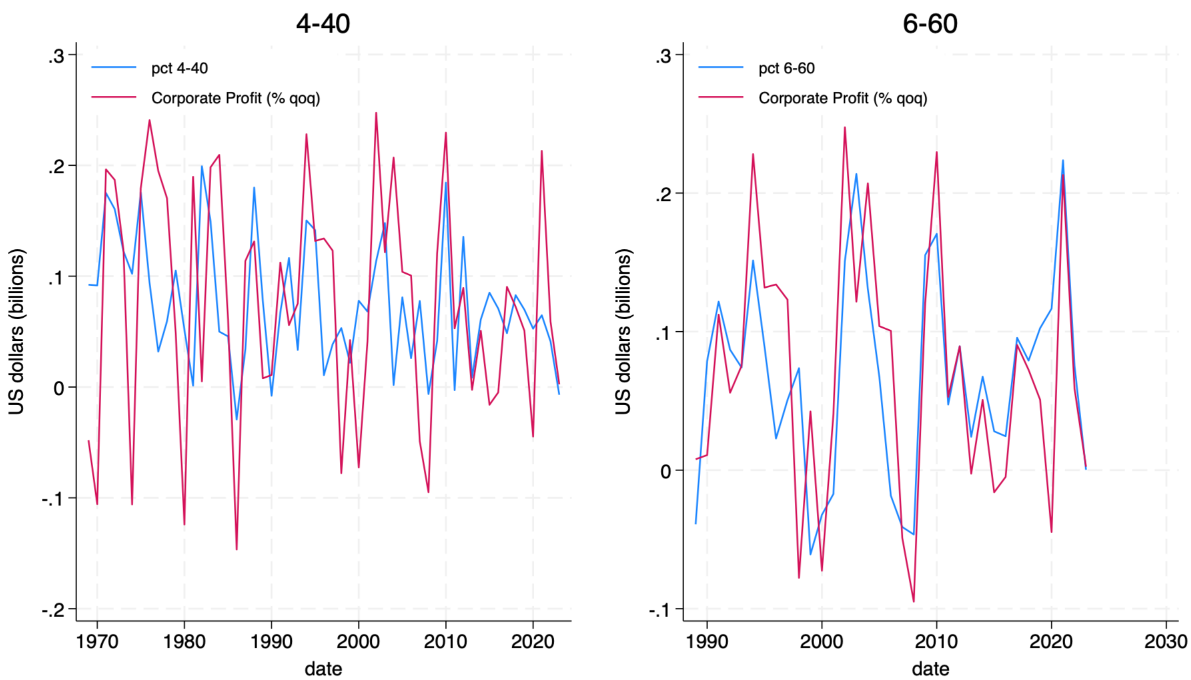

Figure 6: Prediction Series for Annual Data

Table 5 shows that the 6-60 model has a very high R^2, and Figure 6 shows that it got almost all the major directional moves correct. However, for the 4-40 model, the result is unsatisfactory. Compared to the slightly improved result of 4-60 and the findings in Table 4, it is speculated that 40 obs for model training might be insufficient. A large enough number of lags and observations for model training is essential for the success of the models.

6 Conclusion

This project has conducted VAR and Granger causality tests to investigate whether the variables in the Kalecki-Levy equation have lead-lag relations, which turned out to be complicated and have no straightforward interpretation. This project designed rolling-window VAR models to mimic real-life prediction processes and gained considerable success. It has shown that using percentage changes is much more effective than using level differences in rolling-window VAR prediction.

The high R^2 of the rolling-window VAR models indicates considerable predictive power for such a model. If simply analyzing past data can yield positive results, combining this approach with external forecasts and macroeconomic insights could produce an even more effective predictive model. The findings from this study demonstrate that approaching corporate profit from a *macro perspective* holds great potential compared to the bottom-up approach, which merely aggregates the expected profits of individual firms.

This project has some limitations. For example, by using a rolling-window model, there is limited information on *how* the lagged variables predict next-quarter corporate profit, aside from their overall effectiveness. Additionally, this project can extend to building models to predict second-next quarter profit changes, for which VAR could predict the next quarter change first, and then use them as input to predict the second-next quarter change. In this study, I used autoregressive distributed lags (ADL) models to mimic VAR for rolling-window VAR tests (for predicting one variable and one period they are the same), which reduced 90% of the computation time. However, predicting further away future is possible with the power of VAR.

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