Advanced Programming 2025

Working Capital Dynamics and Dividend Policy: Evidence from U.S. Firms

Final Project Report

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Abstract

This project investigates whether working capital dynamics can explain or predict dividend per share variations, beyond traditional financial determinants. The motivation stems from the information gap faced by investors at the end of the fiscal year, when balance sheet data are available but dividend decisions have not yet been announced. In this context, working capital represents an intuitive indicator of short-term liquidity that could potentially inform dividend expectations. The analysis combines two complementary approaches. First, firm fixed-effects panel regressions are estimated on U.S. consumer staples firms over the 2015–2019 period to assess the explanatory power of changes in working capital scaled by total assets, while controlling for profitability, leverage, and firm size. Second, a predictive framework based on Random Forest models is applied to the 2021–2024 period using lagged accounting variables to evaluate out-of-sample forecasting performance.

The results show that working capital dynamics are not statistically significant determinants of dividend changes and do not improve predictive accuracy. In fact, including working capital worsens out-of-sample performance in machine learning models. Overall, the findings suggest that dividend policy is driven by broader strategic and institutional factors rather than short-term liquidity measures. The main contribution of this project is to provide both econometric and predictive evidence on the limited role of working capital in explaining dividend policy.

Keywords: data science, Python, machine learning, dividend policy, working capital, panel data, fixed effects, financial forecasting

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1 Introduction

Dividends constitute a key component of equity returns, especially for long-term investors who rely on regular income streams. In this respect, dividends can be compared to interest payments received on fixed-income securities, as they provide periodic cash flows to investors. However, unlike interest payments, dividends are not contractual and are not capped ex ante. Their amount can vary substantially over time and, in principle, can grow without limit if a firm's financial performance improves. This flexibility makes dividend policy both attractive and complex, as it reflects firms' financial health, strategic choices, and long-term outlook.

The corporate finance literature traditionally emphasizes that dividend payments are primarily driven by profitability, firm size, and earnings stability. Nevertheless, from a more intuitive and practical perspective, liquidity considerations may also play a role in dividend decisions. In particular, working capital, defined as the difference between current assets and current liabilities, captures a firm's short-term financial flexibility and ability to meet near-term obligations. During my studies, I became interested in whether working capital dynamics could serve as a simple and informative indicator for anticipating dividend payments, as firms with higher liquidity might appear better positioned to distribute cash to shareholders.

This question is especially relevant from an investor's point of view. Most publicly listed firms in the United States close their fiscal year on December 31, at which point annual financial statements become available. However, dividend decisions are generally discussed and approved by the board of directors only several months later, typically between February and April of the following year. Consequently, at the end of the fiscal year, investors observe firms' balance sheets but do not yet know the dividend per share that will ultimately be distributed. This timing mismatch creates an information gap during which investors may wish to form expectations about future dividend payments using the accounting information already available.

The objective of this project is therefore to examine whether changes in dividend per share can be explained or predicted using working capital dynamics, and whether working capital provides meaningful information beyond standard financial indicators. By combining econometric panel regressions with machine learning techniques, this study evaluates both the explanatory and predictive power of working capital relative to traditional determinants of dividend policy. More broadly, the analysis seeks to assess whether investors could realistically rely on balance sheet information alone to anticipate dividend outcomes, or whether dividend dynamics remain largely driven by broader firm fundamentals and managerial decisions.

The remainder of this report is organized as follows:

- Section 2 reviews the related literature.
- Section 3 describes the data, methodology, and implementation details.
- Section 4 presents the empirical and predictive results.
- Section 5 discusses the findings and their implications.
- Section 6 concludes and outlines directions for future research.

2 Literature Review / Related Work

Dividend policy has long been a central topic in corporate finance, generating extensive theoretical and empirical research. Early studies established that dividend decisions are not neutral and may convey information about firms' financial conditions and future prospects. One of the most influential contributions is Miller and Modigliani (1961), who argue that under perfect market conditions, dividend policy is irrelevant for firm value. However, subsequent research has shown that once market imperfections such as taxes, agency costs, and information asymmetries are introduced, dividend policy becomes economically meaningful.

A large strand of the literature emphasizes the role of profitability, firm size, and earnings stability as key determinants of dividend payments. Lintner (1956) documents that firms tend to smooth dividends over time and adjust payouts gradually in response to changes in earnings. Empirical studies consistently find that more profitable and larger firms are more likely to pay dividends and to maintain stable payout policies, reflecting both greater cash generation capacity and lower uncertainty. These findings have been confirmed in numerous later studies, including Fama and French (2001), who show that dividend-paying firms tend to be larger, more profitable, and less volatile than non-dividend-paying firms.

Beyond profitability-based explanations, liquidity considerations have also received attention in the dividend policy literature. Jensen's (1986) free cash flow theory suggests that firms with excess internal funds may distribute cash to reduce agency costs, while firms facing liquidity constraints may retain earnings instead. From this perspective, short-term financial flexibility plays a crucial role in payout decisions. Working capital, defined as the difference between current assets and current liabilities, provides a natural measure of such short-term liquidity conditions.

Several empirical studies have highlighted the importance of liquidity and cash flow variables in explaining dividend behavior. For instance, studies focusing on cash holdings and operating cash flows show that firms with stronger liquidity positions are more likely to distribute dividends and less likely to cut payouts during periods of financial stress. Although many papers use cash flow or cash holdings as liquidity proxies, fewer studies explicitly focus on changes in working capital as a determinant of dividend policy. This creates room for further investigation, particularly regarding whether working capital dynamics contain information beyond standard accounting measures.

More recent contributions have also explored dividend policy from a predictive perspective, combining traditional econometric models with machine learning techniques. These studies argue that non-linear relationships and complex interactions between financial variables may limit the explanatory power of linear regression models. Machine learning approaches, such as tree-based models, have been shown to improve predictive performance in corporate finance applications, including earnings forecasting and financial distress prediction. However, their use in the context of dividend prediction remains relatively limited.

This project builds on these strands of the literature by combining a traditional panel data approach with firm fixed effects and a machine learning framework. While the econometric analysis follows established methods used to identify within-firm relationships between financial variables and dividend payments, the machine learning component focuses on the predictive relevance of working capital relative to standard determinants such as profitability, leverage, and firm size. By explicitly incorporating working capital dynamics, this study contributes to the literature on dividend policy by highlighting the role of short-term liquidity conditions in both explaining and anticipating dividend payments.

3 Methodology

3.1 Data Description

This project uses a firm-year panel dataset constructed from public and fully reproducible data sources. Accounting information is collected from the SEC EDGAR XBRL "Company Facts" API, which provides annual balance sheet and income statement variables based on U.S. GAAP filings. Dividend data are obtained from Yahoo Finance using the yfinance library, from which annual dividend per share (DPS) is computed by aggregating dividends paid within each calendar year.

Alternative data providers were initially considered to obtain historical accounting data, as Yahoo Finance does not consistently provide complete firm fundamentals prior to 2020. However, subscription-based platforms require paid access and user-specific credentials, which would limit reproducibility and require code modifications by third parties. To ensure that all results can be replicated without restrictions, the final dataset therefore combines SEC filings for financial statements and Yahoo Finance for dividend information.

The initial sample consists of approximately 100 U.S.-listed firms from consumer staples and staples-adjacent industries (e.g., food, beverages, tobacco, retail). The dataset covers the period 2015–2024. To ensure data quality and comparability, the analysis focuses on two subsamples: a regression sample covering 2015–2019, which requires firms to have complete data for all five years, and a machine learning sample covering 2020–2024, which requires at least three complete firm-years.

Key variables include total assets, current assets, current liabilities, total liabilities, and net income from SEC filings, as well as annual dividend per share from Yahoo Finance. Based on these items, standard financial measures are constructed, including working capital, working capital scaled by total assets (WC/TA), return on assets (ROA), and leverage.

Missing values arise due to heterogeneous reporting practices and incomplete historical coverage, particularly for older years. To address this issue, the dataset retains only firm-years for which a minimum set of accounting and dividend variables is available. This filtering ensures a consistent and reliable panel for both econometric and predictive analyses, while preserving the reproducibility of the data collection process.

3.2 Approach

The empirical strategy of this project combines econometric panel regressions and machine learning techniques to analyze the role of working capital in dividend policy. This dual approach allows the study to assess both the explanatory relationship between financial variables and dividends, as well as the predictive relevance of working capital relative to standard firm fundamentals.

As a first step, the analysis begins with a simple descriptive and econometric baseline. An ordinary least squares (OLS) regression is estimated to examine the raw relationship between dividend growth and changes in working capital scaled by total assets. The baseline specification is given by:

$$\Delta \log(DPS_{it}) = \alpha + \beta \Delta (WC/TA)_{it} + \varepsilon_{it}.$$

This initial regression provides an intuitive benchmark and is used mainly for exploratory purposes. However, it does not account for unobserved firm-specific characteristics that may jointly affect working capital dynamics and dividend policy.

To address this limitation, the explanatory analysis then relies on firm fixed-effects panel regressions estimated on the 2015–2019 sample. Fixed effects allow the model to control for time-invariant firm characteristics, such as business models, management style, or corporate culture. The baseline fixed-effects specification focuses on working capital dynamics only and is defined as:

$$\Delta \log(DPS_{it}) = \alpha_i + \beta\Delta(WC/TA)_{it} + \varepsilon_{it},$$

where α_i denotes firm fixed effects. This specification isolates within-firm variation over time and serves as the reference econometric model.

Building on this baseline, a first comprehensive model is estimated to capture standard determinants of dividend policy without including working capital. This specification allows the analysis to assess how much explanatory power traditional financial variables provide on their own. The model is specified as:

$$\Delta \log(DPS_{it}) = \alpha_i + \gamma_1 ROA_{it} + \gamma_2 Leverage_{it} + \gamma_3 Size_{it} + \varepsilon_{it}.$$

Profitability (ROA), leverage, and firm size are commonly used controls in the dividend literature and reflect firms' capacity and incentives to distribute cash to shareholders.

The second comprehensive model augments this specification by reintroducing working capital dynamics. This final econometric model evaluates whether changes in working capital scaled by total assets provide additional explanatory power beyond standard firm fundamentals:

$$\Delta \log(DPS_{it}) = \alpha_i + \beta\Delta(WC/TA)_{it} + \gamma_1 ROA_{it} + \gamma_2 Leverage_{it} + \gamma_3 Size_{it} + \varepsilon_{it}.$$

Comparing the coefficients and fit of this model with the previous specifications makes it possible to assess whether working capital contains independent information relevant for dividend policy once traditional determinants are controlled for.

In all fixed-effects regressions, standard errors are clustered at the firm level to account for serial correlation within firms over time.

Finally, the predictive analysis uses machine learning methods applied to the 2020–2024 sample. These models focus on forecasting dividend outcomes using accounting information available at the end of the fiscal year. Machine learning techniques are particularly suited to capture potential non-linearities and interaction effects that may not be fully reflected in linear regression models. Model performance is evaluated using out-of-sample prediction metrics, allowing for a comparison between models that include working capital variables and those that rely solely on traditional financial indicators.

Overall, this approach enables a comprehensive assessment of the role of working capital in dividend policy by combining interpretable econometric estimates with predictive modeling. It also reflects the project's objective of evaluating whether balance sheet information can be used by investors to anticipate dividend payments before official announcements.

An important measurement choice concerns the definition of working capital. While working capital in levels provides a simple measure of short-term liquidity, it may fail to capture economically meaningful changes when current assets and current liabilities evolve proportionally. To address this issue and ensure comparability across firms of different sizes, the analysis focuses on working capital scaled by total assets (WC/TA) and its year-to-year changes. This normalization captures relative liquidity dynamics and reduces measurement bias related to firm size.

3.3 Implementation

The project is implemented in Python and executed as a script-based workflow on macOS (Python 3.14). The full data pipeline, econometric analysis, and machine learning models are implemented in a standalone Python script (`working_capital_dividends.py`), which can be executed sequentially to reproduce all results. A lightweight `main.py` entry point is provided to verify that the repository runs correctly in a standard Python environment.

Data collection and preprocessing are fully automated within the Python scripts. Firm-level accounting information is retrieved from the U.S. Securities and Exchange Commission (SEC) EDGAR XBRL *Company Facts* API, while dividend per share data are obtained from Yahoo Finance using the `yfinance` library. These sources were selected to ensure that all data are publicly accessible and that the analysis can be reproduced without requiring paid subscriptions or proprietary databases. The collected raw data are merged into a firm–year panel structure and exported to an Excel file in the `output/` directory for inspection and reuse in subsequent analysis steps.

The empirical analysis relies on standard Python libraries. Panel regressions with firm fixed effects are estimated using `statsmodels` and `linearmodels`. Machine learning models are implemented using `scikit-learn`, with Random Forest regressors employed for the predictive analysis. Data manipulation and numerical operations are handled using `pandas` and `numpy`, while figures are generated using `matplotlib`.

To avoid look-ahead bias and data leakage, the predictive analysis follows a strictly temporal design. Accounting variables observed at time $t-1$ are used to predict dividend growth at time t. Training and testing samples are separated by calendar years, with earlier periods used for model estimation and later periods reserved for out-of-sample evaluation. Model performance is assessed using standard prediction metrics, including root mean squared error (RMSE), mean absolute error (MAE), and out-of-sample R^2. A fixed random seed is used in the machine learning models to ensure reproducibility.

Final outputs used in the report are exported to the `figures/` directory, including regression tables (Excel and LaTeX formats) and figures (high-resolution PNG files). This implementation ensures that the full analysis can be reproduced by executing the provided Python scripts in sequence.

4 Results

4.1 Experimental Setup

All experiments are conducted on a macOS-based laptop using Python 3.14.2 within a Jupyter Notebook environment. The implementation relies on standard open-source Python libraries, including pandas and numpy for data manipulation, statsmodels and linearmodels for econometric analysis, and scikit-learn for machine learning models.

The econometric results are obtained using panel regressions with firm fixed effects and clustered standard errors. These models do not require hyperparameter tuning, as estimation relies on closed-form or iterative optimization procedures implemented in the respective libraries.

For the machine learning analysis, Random Forest regressors are employed. Hyperparameters are kept fixed across specifications to ensure comparability between models with and without working capital variables. In particular, each Random Forest model uses 500 trees, a minimum of two observations per terminal node, and a fixed random seed. All available CPU cores are utilized through parallel processing.

4.2 Performance Evaluation

	(1) Baseline FE WC only	**(2) Comprehensive FE No WC**	**(3) Comprehensive FE With WC**
Δ(WC/TA)	-1.095 (0.627)		-1.062 (0.578)
ROA		0.394 (1.092)	0.182 (0.862)
Leverage		0.117 (0.153)	-0.012 (0.185)
Size		0.318 (0.142)	0.238 (0.114)
Firm Fixed Effects	Yes	Yes	Yes
SE	Firm clustered	Firm clustered	Firm clustered
Observations	92	115	92

Table 1: Fixed Effects Regression Results (2015–2019)

Model	**RMSE**	**MAE**	$\mathbf{R^2}$	**Train rows**	**Test rows**
RF Controls only	0.507	0.207	-0.142	110	121
RF Controls + Δ(WC/TA)	0.545	0.258	-0.317	110	121

Table 2: Out-of-sample prediction performance (Random Forest, temporal split)

4.3 Visualizations

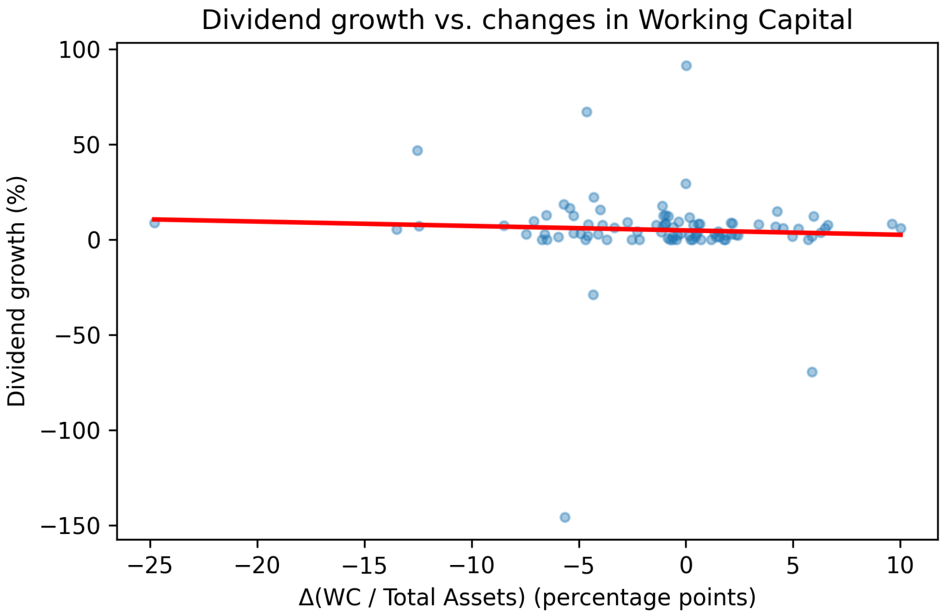

Figure 1: Relationship between changes in working capital scaled by total assets and dividend growth. The fitted line represents a simple linear trend.

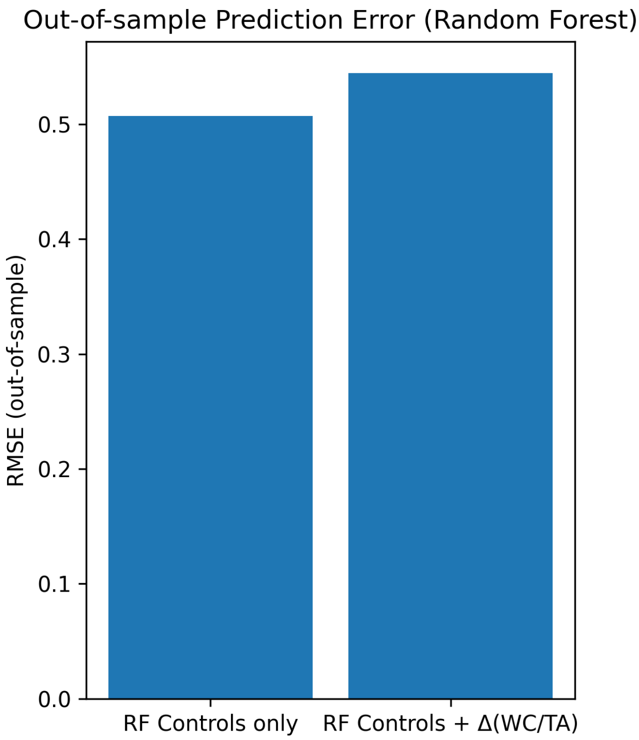

Figure 2: Out-of-sample RMSE comparison between Random Forest models with and without working capital dynamics.

5 Discussion

The results of this project can be considered conclusive, even though they do not fully align with the initial expectations formulated at the outset of the analysis. The primary objective was to assess whether working capital dynamics could explain or predict dividend changes, beyond standard financial determinants. The empirical findings, both from an econometric and a predictive perspective, suggest that working capital plays a much more limited role than initially anticipated.

5.1 Interpretation of Econometric Results

The firm fixed-effects regressions estimated over the 2015–2019 period, reported in Table 1, indicate that changes in working capital scaled by total assets ($\Delta(WC/TA)$) do not have a statistically significant effect on dividend growth. In the baseline fixed-effects specification, which includes only working capital dynamics, the estimated coefficient on $\Delta(WC/TA)$ is negative (-1.095) with a standard error of 0.627, resulting in a t-statistic well below conventional significance thresholds. This result remains unchanged in the comprehensive fixed-effects model that includes standard control variables such as profitability (ROA), leverage, and firm size, where the coefficient on working capital remains negative (-1.062) and statistically insignificant.

These findings suggest that, contrary to the initial intuition of the project, increases in working capital relative to firm size are not associated with higher dividend growth. The negative sign of the coefficient even points toward a potential inverse relationship. However, the absence of statistical significance prevents any causal interpretation of this effect.

Interestingly, traditional determinants of dividend policy, such as profitability, also do not appear to be statistically significant in these specifications. This result highlights the limited explanatory power of annual accounting variables when dividend dynamics are analyzed through within-firm year-to-year variation. Dividend policies are often characterized by smoothing behavior and long-term considerations, which may not be fully captured by short-run changes in balance sheet variables.

The use of firm fixed effects constitutes an important methodological choice in this context. By controlling for unobserved, time-invariant firm characteristics—such as managerial culture, long-term strategy, or sectoral positioning—the fixed-effects approach identifies the effects of interest from within-firm variation over time. Although this design reduces statistical power, it enhances the credibility of the estimates by mitigating omitted variable bias and strengthening the internal validity of the results.

5.2 Predictive Performance and Machine Learning Results

The predictive analysis using Random Forest models over the 2021–2024 period, summarized in Table 2, reinforces the conclusions drawn from the econometric approach.The model relying solely on traditional control variables exhibits weak out-of-sample performance, with a Root Mean Squared Error (RMSE) of 0.507, a Mean Absolute Error (MAE) of 0.207, and a negative out-of-sample R^2 of -0.142. These values indicate that the model fails to outperform a naïve benchmark based on historical averages.

Adding working capital dynamics further deteriorates predictive performance. The model including Δ(WC/TA) yields a higher RMSE (0.545), a higher MAE (0.258), and an even more negative out-of-sample R^2 of -0.317. Thus, working capital does not provide additional predictive signal and instead introduces noise into the model. Even when allowing for non-linearities and complex interactions, working capital does not appear to be a relevant predictor of dividend changes. These differences in predictive accuracy are visually summarized in Figure 2, which highlights the deterioration in out-of-sample performance when working capital dynamics are included.

5.3 Comparison with Initial Expectations

At the beginning of the project, a relatively intuitive hypothesis guided the analysis: firms with greater short-term liquidity would be better positioned to distribute higher dividends to shareholders. This view implicitly assumes that working capital reflects readily available cash. However, the empirical results do not support this hypothesis.

Several explanations may account for this discrepancy. Working capital can be allocated to multiple competing uses, such as financing operations, managing inventory, reducing liquidity risk, or servicing short-term debt. In addition, dividend decisions are often driven by long-term strategic considerations and managerial discretion, making them less sensitive to short-term fluctuations in liquidity.

5.4 Limitations of the Approach

This study faces several important limitations.

First, data availability significantly constrained the sample size. Out of nearly one hundred firms initially considered, only 23 firms exhibited sufficiently complete data to be included in the fixed-effects regressions. This limitation reduces statistical power and may partially explain the absence of significant results.

Second, many potentially relevant determinants of dividend policy could not be incorporated, including changes in corporate governance, tax policy, regulatory environments, or financing decisions such as debt issuance and equity offerings. These factors may have a substantial impact on dividend decisions but are difficult to measure systematically.

Finally, the predictive analysis covers a period that includes the aftermath of the COVID-19 crisis, which was characterized by heightened uncertainty and structural disruptions. Although the crisis did not persist through 2024, its lingering effects may have weakened the stability of historical relationships between financial variables and dividends.

5.5 Overall Assessment

Overall, this project highlights the limitations of relying solely on short-term accounting information to explain or predict dividend policy. While working capital is an intuitively appealing measure of liquidity, it does not appear to significantly explain dividend changes nor improve predictive performance. These findings emphasize the fundamentally strategic and discretionary nature of dividend decisions and suggest that future research should integrate institutional, governance-related, and qualitative information to better understand dividend dynamics.

6 Conclusion and Future Work

6.1 Summary of Key Findings

The objective of this project was to assess whether working capital dynamics can explain or predict changes in dividend per share, beyond standard financial determinants. By combining firm fixed-effects panel regressions with machine learning techniques, the study provides both an explanatory and a predictive evaluation of the role of working capital in dividend policy.

The econometric results indicate that changes in working capital scaled by total assets do not have a statistically significant effect on dividend changes. This finding remains robust when controlling for profitability, leverage, and firm size, and when accounting for unobserved firm-specific heterogeneity through fixed effects. Consequently, working capital does not appear to provide meaningful incremental information for explaining short-term dividend decisions.

The predictive analysis further reinforces this conclusion. Random Forest models exhibit weak out-of-sample performance, and the inclusion of working capital systematically worsens prediction accuracy. Even in a flexible, non-linear framework, working capital does not improve dividend forecasts and instead introduces additional noise. Taken together, the results suggest that working capital is neither a reliable explanatory variable nor a useful predictive indicator for dividend policy.

Overall, this project highlights the limitations of relying solely on short-term accounting information to analyze dividend decisions. While working capital is an intuitively appealing measure of liquidity, dividend policy appears to be driven by broader strategic considerations that are not fully captured by balance sheet dynamics alone.

6.2 Future Directions

Several avenues for future research emerge from this study.From a methodological perspective, future work could extend the analysis by incorporating additional explanatory variables related to corporate governance, financing decisions, or regulatory constraints. Dynamic models that explicitly account for dividend smoothing and persistence may also provide further insights into dividend behavior.

Additional experiments could focus on extending the analysis to other sectors and countries. The consumer staples sector is characterized by relatively stable dividend policies, which may limit observable variation. Examining firms in other industries, as well as in different institutional environments, would help assess the generality of the findings and identify potential cross-sector or cross-country differences.

Regarding real-world applications, the initial motivation of this project was to determine whether investors could use information available at the fiscal year-end, particularly balance sheet data, to anticipate future dividend income before official announcements. Although working capital does not fulfill this role, the approach remains relevant. Future research could explore other balance sheet components or combine accounting information with historical dividend patterns to identify more effective predictors.

Finally, the empirical framework developed in this project is easily replicable for U.S. firms due to the public availability of SEC data. Extending the analysis to non-U.S. firms would require adapting the data collection process using comparable public sources or reliable financial databases. Once suitable data are obtained, the same econometric and machine learning methodologies could be applied without major modifications.

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A Additional Figures

No additional figures are included, as the main results are fully captured by the tables and figures presented in Section 4.

B Code Repository

GitHub Repository: `https://github.com/Ad1020/working_capital_dividends`
The repository is organized as follows:

- `proposal.md`: initial project proposal outlining the research question and methodology
- `README.md`: instructions to install dependencies and run the project
- `requirements.txt`: list of required Python dependencies
- `main.py`: main entry point of the project; running this file reproduces the full analysis
- `working_capital_dividends.py`: core Python script containing data collection, econometric analysis, and machine learning models
- `figures/`: figures and LaTeX tables generated by the analysis and reported in the paper
- `Working_Capital_Dividends_Report.pdf`: final report submitted for the course

To reproduce the results, install the dependencies listed in `requirements.txt` and run the main Python script `main.py`, which executes the full data collection, analysis, and estimation pipeline.

The `output/` directory, containing datasets (Excel files), is automatically created when running `main.py` and is therefore not included in the GitHub repository.