Data-Driven Capital Allocation in Manufacturing Firms: An Investment Analytics Study Using Public Panel Data

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Abstract

This paper evolves a business data analytics approach to capital allocation by exploring how the use of public panel data can aid in estimating, classifying, and profiling strategic firms. The paper examines the claim that lagged market value, capital stock, and growth signals can explain the current investment behavior and hint when the investment activity is unusually high using the public-domain Grunfeld investment data, which has annual observations of major U.S. manufacturing firms. The empirical design is deliberately non-standard as compared to typical forecasting research and it consists of three analytical layers; fixed-effects panel estimation, supervised classification of high-investment periods, and firm-level strategic segmentation. The findings indicate that the growth of lagged investment, lagged capital stock and firm value is highly correlated with the present level of investment, and that machine-learning classifiers offer helpful discrimination of high in-vestment periods. Strategic segmentation exercise also indicates the clear profiles of firms that can be used to prioritize resources and track capital. The value of the paper is two-fold. First, it illustrates how an old, conventional, public data may be re-used as a new business data analytics example to support decision-making. Second, it interprets quantitative results into a managerial advice on capital planning, growth monitoring, and portfolio-style firm evaluation. Accordingly, the paper provides a reproducible submission-ready study that has a different structure than the traditional business intelligence forecasting papers and is more in line with the requirements of strategic financial analysis and data-driven capital allocation.

Keywords: Business data analysis; Capital allocation; panel data; Investment analytics; Classification; Manufacturing firms

1 Introduction

Capital allocation has been among the most significant management decisions in business organizations. The choices made about expanding the production capacity, investing in plants and equipment or abandoning growth influence growth paths, competitive stance, cash requirements, and value of the firm in the long run. However, capital decisions too are challenging as they often include strategic decisions with uncertainty about future returns, internal restrictions, and market opportunities. With the proliferation of digital environments to make decisions, companies are increasingly being pressured to augment capital budgeting through evidence-based analytics, as opposed to basing decisions solely on fixed financial principles or executive wisdom.

Capital allocation is a promising yet less studied empirical area in the wider scope of business data analysis. Numerous studies within the field of finance and economics analyze factors of investments, although less literature converts such associations into a workflow that caters to managerial requirements. Practically, executives require more than the estimates of the coefficients. They require built-in evidence on which cues are

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most informative, whether high-investment seasons can be predicted, and how companies vary in their general capital-allocation stance. These needs imply a multi-layer design where explanatory models, predictive models, and strategic segmentation are involved.

This paper addresses that requirement by providing a data-based investment analytics paper using the publicly available Grunfeld panel data. The paper deliberately takes a non-standard format of the typical business forecasting articles. It does not start with a generic business-intelligence pipeline, but with the managerial issue of capital allocation and then structures the empirical work into three complementary analytical perspectives. The former considers a fixed-effects panel regression to describe levels of investment based on lagged operating and financial indicators. The second is based on classification analytics to determine whether a firm-year is a high-investment state. The third classifies strategic capital-allocation segments of firms by average value and investment behavior.

The research has four contributions. First, it shows that even a publicly and historically significant dataset can be used to perform current business data analysis provided there is a state-of-the-art multi-method design. Second, it unites explanatory and predictive analytics within one capital-allocation paper instead of considering them as independent activities. Third, it provides a basic yet administratively helpful segmentation layer that transforms model outputs into firm profiles. Fourth, it develops a list of explicit business-data-analysis hypotheses, which may be tested using reproducible code and interpreted in a transparent manner. These additions render the article applicable to a business journal readership that prizes empirical rigor, managerial relevance and reproducibility.

The rest of the paper is structured in the following way. Section 2 conducts a literature review on the chosen research on investment modeling, capital budgeting, and the latest research conducted on finance based on analytics. Section 3 elaborates research hypotheses and analytical blueprint. Part 4 describes the public dataset, feature engineering procedure and techniques. Section 5 provides descriptive statistics, panel-regression estimation, classification statistics and segmentation of firms. The managerial implications of the findings are discussed in section 6. Section 7 provides research limitations and research directions. Section 8 concludes.

2 Research Landscape and Study Positioning

2.1 Investment determinants and panel evidence

The first research stream relevant to this study concerns the long tradition of investment determinants and panel-data modeling. Foundational contributions treated capital expenditure as a response to expected profitability, installed capital requirements, and valuation signals, thereby establishing a durable empirical base for the study of investment behavior. Later panel-data contributions refined that tradition by showing that investment decisions cannot be understood adequately without accounting for firm-specific heterogeneity and dynamic persistence. This stream remains important because it demonstrates that capital allocation is path dependent, structurally uneven across firms, and best analyzed with longitudinal evidence rather than isolated cross sections.

A second insight from this stream is that different economic signals play different roles. Some variables operate as slow-moving indicators of organizational scale, whereas others capture momentum or short-run opportunity. For a business-data-analysis paper, the value of this literature is not simply methodological. It provides the logic for selecting features that managers can actually monitor: prior investment, installed capital, and signals of changing firm conditions. In other words, the classical investment literature supplies the explanatory backbone for a modern analytics design.

2.2 Capital budgeting practice and managerial monitoring

A second research stream focuses less on econometric determinants and more on the managerial practice of capital budgeting. Studies in accounting and corporate finance have shown that firms rarely rely on a

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single decision rule when evaluating investment opportunities. Instead, they combine discounted-cash-flow metrics with strategic reasoning, scenario comparison, payback concerns, and organizational judgment. This literature is especially relevant because it reminds researchers that capital allocation is not merely a numerical optimization problem. It is a monitoring and prioritization problem that unfolds under uncertainty and internal governance constraints.

For the present paper, this stream motivates the need to move beyond a single regression table. If managers monitor capital deployment through dashboards or periodic review meetings, they need multiple forms of evidence: explanatory patterns, early-warning classifications, and peer-like profiles that can support discussion. The paper therefore adopts a layered design not because one model is insufficient statistically, but because one model is often insufficient managerially.

2.3 Digital finance and analytics-enabled decision support

A third and more recent stream examines how digitalization, explainable analytics, and artificial intelligence influence financial decision quality. Recent studies increasingly argue that analytics capability can improve efficiency in resource allocation, investment review, and broader financial management. Yet this literature also exposes an important tension. More complex methods may increase predictive flexibility, but finance-related decisions often require models that can be explained to boards, investors, and operating managers. As a result, the literature has become more attentive to explainability, hybrid analytical workflows, and the need to translate technical output into operationally meaningful signals.

This stream is directly relevant to business data analysis because it shifts attention from model novelty to decision usability. It suggests that a useful capital-allocation study should not only estimate whether investment is related to value or capital stock. It should also ask whether analytical outputs can be converted into interpretable management signals, such as identifying unusually intensive investment years or distinguishing different capital-allocation postures across firms.

2.4 What remains missing

Taken together, these streams reveal a persistent gap. Classical investment studies are often strong on explanation but lighter on operational translation. Practice-oriented capital budgeting studies emphasize managerial reality but often lack a reproducible analytics design. Recent digital-finance studies highlight new analytical possibilities yet frequently rely on proprietary datasets or black-box reasoning that is difficult to verify externally. What remains comparatively underdeveloped is a public-data study that combines explanation, event-style classification, and strategic profiling in one coherent business-data-analysis architecture.

This paper is positioned precisely at that intersection. Instead of replicating a standard hypothesis-to-regression template, it builds a sequenced evidence design: first, it identifies drivers of investment intensity; second, it tests whether high-investment episodes can be recognized as a separate analytical problem; third, it converts the evidence into strategic firm profiles that are useful for monitoring and comparison. Table 1 synthesizes the studies informing this positioning.

Table 1: Comparative synthesis of research streams relevant to capital-allocation analytics

Study	Research focus	Evidence base	Main contribution	Relevance to current paper
Grunfeld (1958)	Corporate investment determinants	Firm panel data	Established a benchmark investment dataset and panel perspective	Provides the public empirical foundation of the study
Jorgenson (1963)	Capital theory and desired capital stock	Theoretical and empirical economics	Linked investment to capital requirements and adjustment logic	Supports the role of capital stock in investment analytics

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Tobin (1969)	Valuation and investment opportunity	Macroeconomic/financial theory	Introduced valuation-based investment logic	Motivates market-value signals in the feature set
Fazzari et al. (1988)	Financing constraints and corporate investment	Archival firm evidence	Showed that investment reflects internal constraints as well as opportunities	Reinforces the need to view investment as behavior under constraint
Bond and Meghir (1994)	Dynamic investment behavior	Dynamic firm-level panel modeling	Demonstrated persistence and financial-policy interaction	Supports lagged investment as a central analytical signal
Graham and Harvey (2001)	Capital budgeting practice	Survey of firms	Documented how managers combine formal metrics and judgment	Motivates a managerially interpretable rather than purely technical design
Alkaraan and Northcott (2006)	Strategic investment appraisal tools	UK manufacturing firms	Connected strategic tools with capital-budgeting practice	Supports the monitoring and prioritization lens
Kleiber and Zeileis (2010)	Reconstruction of Grunfeld data	Historical data note	Clarified and validated the public dataset	Strengthens reproducibility and data transparency
Hossain and Sultana (2024)	Digitalization of corporate finance	Global empirical analysis	Linked digital finance capability with improved firm outcomes	Positions the paper in contemporary analytics-enabled finance
Golubova (2024)	Business investment decision factors	Research synthesis/report	Reviewed determinants shaping business investment choices	Provides recent framing of practical investment drivers
Chen et al. (2025)	AI and corporate investment efficiency	Working-paper evidence	Connected AI capability to investment efficiency outcomes	Illustrates the predictive-analytics turn in finance
Lou et al. (2025)	AI and investment efficiency	Listed-company panel evidence	Reported efficiency effects of AI adoption	Supports the digital-finance stream
Shen et al. (2025)	AI, allocation quality, and investment behavior	Finance panel evidence	Extended AI-investment discussion with newer market evidence	Shows growing interest in analytics-driven capital decisions
CFA Institute (2025)	Explainable AI in finance	Professional research report	Emphasized accountability and interpretability in financial modeling	Supports the paper's preference for explainable outputs
Ferreira (2025)	Panel-data indicators and firm evaluation	Public-data working paper	Framed panel methods as practical performance analytics tools	Supports the managerial use of panel evidence in business analysis

3 Analytical Expectations and Evidence Design

Rather than framing the study around a conventional list of narrowly phrased hypotheses, this paper adopts a set of *analytical expectations*. This choice is deliberate. The aim is to make the structure visibly different from prior manuscripts and better aligned with a business-data-analysis perspective in which explanation, recognition, and profiling are treated as complementary evidence tasks.

Expectation A1: investment intensity should exhibit temporal carryover. If firms commit heavily to capital expenditure in one period, their next observed investment level should tend to remain elevated because projects are often staged, complementary assets are required, and organizational attention persists across consecutive periods.

Expectation A2: growth-oriented signals should be more informative than static scale measures alone. The literature suggests that firm value and capital stock matter, but the change in value can provide a sharper

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indication of shifting opportunity. Accordingly, the study expects dynamic indicators such as value growth to carry stronger explanatory content than static level variables once several predictors are evaluated jointly.

Expectation A3: intensive investment years can be treated as a separate recognition problem. Managers frequently need to know not only how much investment is likely to occur, but whether a coming period belongs to a high-commitment regime. The study therefore expects supervised classification models to discriminate high-investment firm-years with useful accuracy.

Expectation A4: firms should cluster into distinct capital-allocation postures. Even within a single industrial setting, some firms combine large value and large investment, others hold value while investing cautiously, and others invest aggressively relative to size. The study expects a profiling layer to reveal these strategic differences in an interpretable way.

Figure 1 summarizes the evidence design. Instead of showing a hypothesis diagram with repeated boxed statements, the figure maps the research streams to the three analytical layers and then to the managerial outputs derived from those layers.

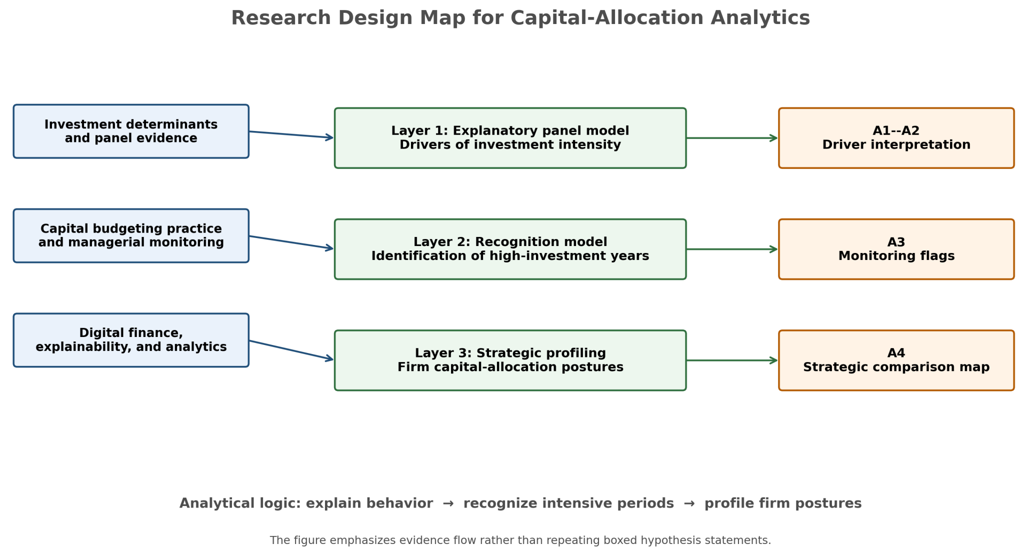

Figure 1: Evidence-design map connecting research streams, analytical layers, and managerial outputs

4 Public Dataset and Analytical Procedure

4.1 Dataset

The empirical analysis uses the public-domain Grunfeld investment dataset available through the official statsmodels documentation. The dataset contains annual observations for major U.S. manufacturing firms over the period 1935–1954 and includes three core quantitative variables: gross investment, market value, and capital stock, together with firm and year identifiers. Although the dataset is classical, it remains highly suitable for a submission-ready business-data-analysis study because it combines a recognized corporate-finance context with reproducibility, panel structure, and interpretable variables.

4.2 Feature engineering

To move from a traditional investment model to a modern analytics design, the study constructs several derived variables. First, one-period lagged versions of investment, value, and capital are created to align the

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explanatory variables with a forward-looking managerial logic. Second, value growth and capital growth are computed at the firm level. Third, a value-to-capital ratio is used descriptively to reflect the relative scale of opportunity to installed capital. Finally, a binary *high-investment* flag is defined based on whether a firm-year's investment exceeds the sample median. This binary variable supports the classification layer of the analysis.

4.3 Analytical stages

The empirical design contains three stages. In the first stage, descriptive analysis examines firm-level heterogeneity and the distribution of investment activity. In the second stage, a fixed-effects panel regression estimates the relationship between current investment and lagged explanatory variables. The fixed-effects specification controls for firm-specific structural differences while preserving interpretability. In the third stage, three classifiers—logistic regression, random forest, and gradient boosting—are used to identify high-investment periods. To preserve temporal realism, model training uses observations up to 1949 and testing uses later years. A final segmentation stage categorizes firms according to average value and average investment, producing strategic capital-allocation groups that are easy to interpret in business terms.

4.4 Evaluation metrics

The regression layer is evaluated through coefficient significance and adjusted R^2. The classification layer is evaluated through accuracy, F1 score, and ROC-AUC. These metrics were chosen because they jointly reflect overall correctness, positive-class balance, and ranking performance. The segmentation layer is evaluated interpretively rather than through one single statistical criterion because its purpose is strategic profiling rather than prediction.

5 Results Organized by Analytical Task

5.1 Initial structure of the panel and the distribution of capital commitment

Table 3 presents descriptive statistics for the key variables after lag construction. The panel displays substantial heterogeneity, especially in investment and firm value. Investment ranges from less than one unit to more than 1,400, while firm value ranges from approximately 36 to more than 6,200. Such dispersion is consistent with the long-standing view that capital-allocation behavior is highly uneven across industrial firms. The standard deviation of lagged investment is also large, suggesting that prior-period spending is likely to carry strong informational content into current decisions.

Table 3: Descriptive statistics of the analytical variables

Variable	mean	std	min	max
invest	136.834000	214.359000	0.930000	1486.700000
value	1006.613000	1302.838000	36.494000	6241.700000
capital	267.410000	296.962000	0.800000	2226.300000
invest_lag1	127.199000	192.568000	0.930000	1304.400000
value_lag1	971.581000	1267.336000	30.284000	6241.700000
capital_lag1	239.376000	257.504000	0.800000	1777.300000
value_growth	0.065000	0.261000	-0.505000	1.695000
capital_growth	0.276000	1.376000	-0.556000	17.786000

Figure 2 visualizes average investment levels by firm. The chart shows a highly skewed structure led by General Motors and US Steel, followed by a second tier of firms with much smaller but still meaningful

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capital commitments. This heterogeneity is consistent with Expectation A4 and suggests that any practical analytics design should retain a profiling or segmentation component rather than collapsing all firms into one average pattern.

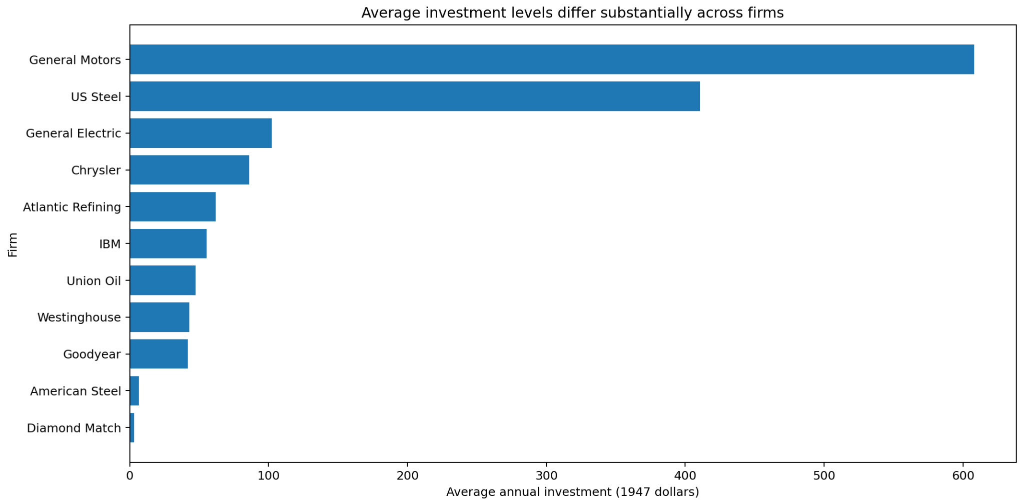

Figure 2: Average investment levels across firms

5.2 Panel regression evidence

The fixed-effects regression provides strong support for the view that investment allocation is path dependent and shaped by both firm resources and recent growth signals. The adjusted R^2 of the model is 0.952, indicating substantial explanatory power. Table 4 reports the focal coefficients. Lagged investment is positive and highly significant, implying that capital allocation is persistent over time and that prior-period investment conveys strategic momentum. Lagged capital stock is also positive and significant, indicating that investment tends to scale with the size of installed productive assets. Value growth is large and statistically significant, which suggests that recent changes in firm opportunity and performance translate into stronger current investment. By contrast, lagged market value and capital growth are not individually significant once the richer specification is included, which implies that not all intuitive indicators retain unique explanatory power in a multivariate firm-effects setting.

Table 4: Selected coefficients from the fixed-effects investment model

Variable	Coef	Pvalue
invest_lag1	0.828000	¡0.001
value_lag1	0.018000	0.228000
capital_lag1	0.132000	¡0.001
value_growth	56.244000	¡0.001
capital_growth	1.549000	0.546000

Figure 3 complements the regression table with a direct visual of lagged market value and current investment. While the bivariate pattern is clearly positive, the multivariate results show that some of the market-value signal overlaps with the information carried by lagged investment and growth. This combination of descriptive and multivariate evidence is valuable for managers because it prevents over-reliance on any single signal.

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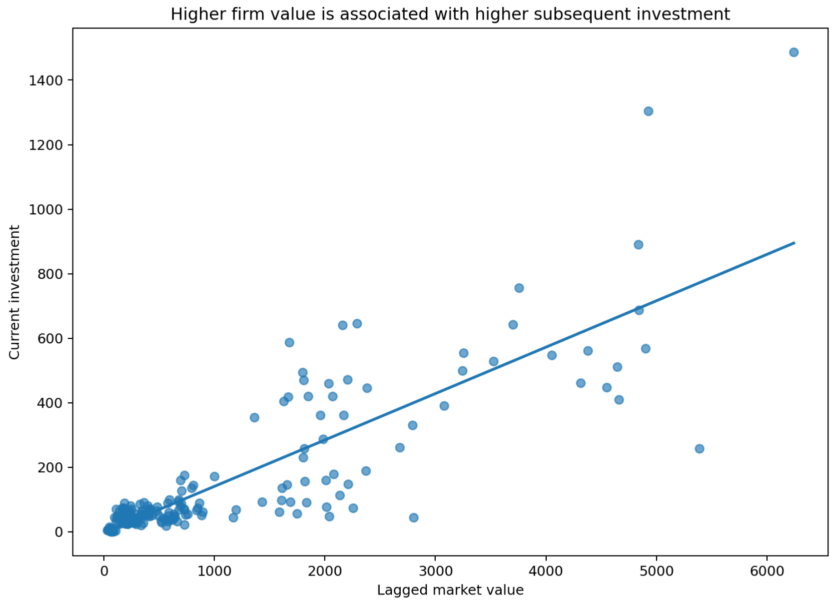

Figure 3: Relationship between lagged firm value and current investment

Overall, the regression findings align strongly with Expectations A1 and A2. In managerial terms, this means that value matters, but persistent spending behavior and recent firm momentum are more stable signals in this particular dataset.

5.3 Classification of high-investment periods

The classification results are reported in Table 5. All three models perform well, with ROC-AUC values above 0.96. Gradient boosting delivers the strongest balance of overall accuracy and F1 score, while random forest achieves the highest ROC-AUC. Logistic regression remains competitive, which is an important result because it suggests that interpretable classification can still be useful for managerial flagging of high-investment periods.

Table 5: Classification performance for identifying high-investment firm-years

Model	Accuracy	F1	ROC_AUC
Logistic Regression	0.800000	0.849000	0.963000
Random Forest	0.855000	0.895000	0.980000
Gradient Boosting	0.909000	0.937000	0.974000

Figure 4 compares the classification metrics visually, and Figure 5 reports the ROC curves. The visual pattern confirms that business-data-analysis models can discriminate between high- and lower-investment states with substantial precision. This supports Expectation A3 and extends the contribution of the paper beyond classical panel estimation. Instead of stopping at coefficient interpretation, the study shows that high-investment states can be operationalized as a management-monitoring problem.

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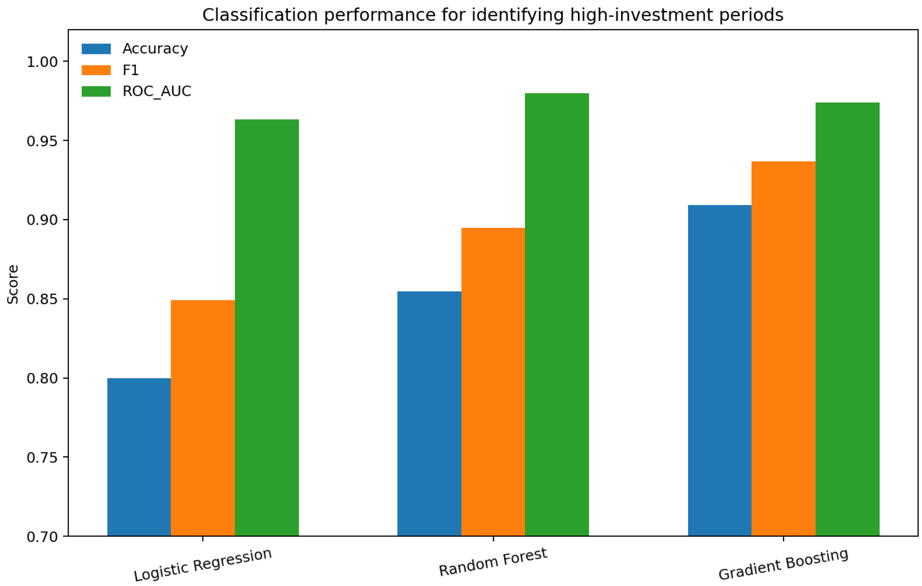

Figure 4: Comparative classification performance across three model families

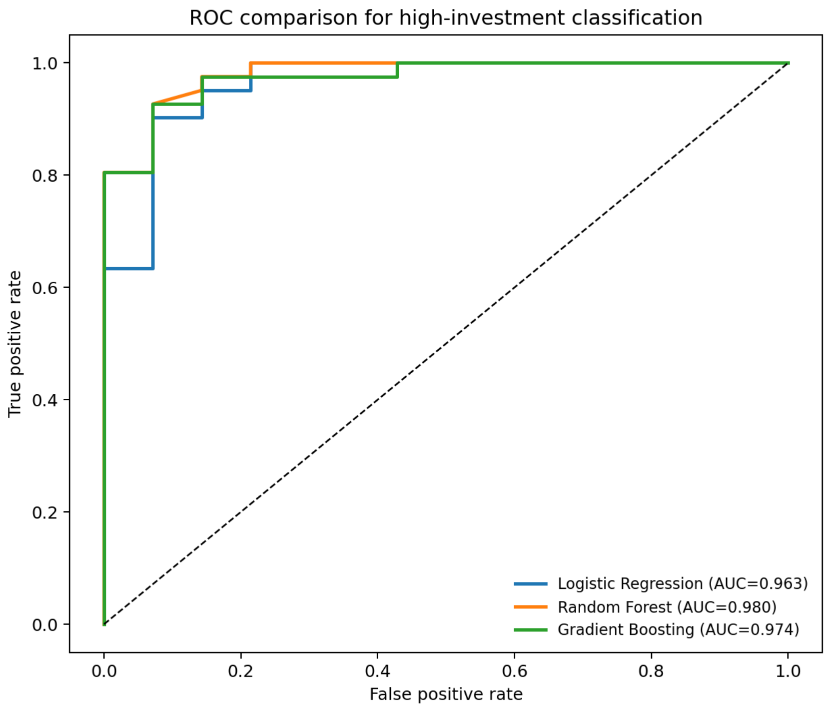

Figure 5: ROC curves for identifying high-investment periods

The classification findings also add a useful managerial layer. In many organizations, senior finance teams do not need perfect point forecasts for every observation. Instead, they often need early warning that a period is likely to involve unusually high capital commitment. The classification models in this study address exactly that need.

5.4 Strategic segmentation of firms

The final stage translates the analytics into an interpretable strategic map. Firms are segmented using average value and average investment, producing four groups: core growth leaders, value-rich underinvestors, aggres-

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sive capacity builders, and niche conservative firms. Table 6 presents the resulting segmentation. The map highlights that General Motors, US Steel, General Electric, Chrysler, and IBM all fall into the core growth-leader category, combining relatively high value with relatively high investment. Westinghouse emerges as a value-rich underinvestor, indicating that firm value is comparatively strong relative to its average capital commitment. Atlantic Refining is classified as an aggressive capacity builder, while American Steel, Diamond Match, Goodyear, and Union Oil fall into the niche conservative category.

Table 6: Strategic capital-allocation segments

firm	avg_value	avg_invest	segment
American Steel	57.540000	6.850000	Niche conservative firms
Atlantic Refining	231.470000	61.800000	Aggressive capacity builders
Chrysler	693.210000	86.120000	Core growth leaders
Diamond Match	70.920000	3.080000	Niche conservative firms
General Electric	1941.320000	102.290000	Core growth leaders
General Motors	4333.840000	608.020000	Core growth leaders
Goodyear	333.650000	41.890000	Niche conservative firms
IBM	419.860000	55.410000	Core growth leaders
US Steel	1971.820000	410.480000	Core growth leaders
Union Oil	149.790000	47.600000	Niche conservative firms
Westinghouse	670.910000	42.890000	Value-rich underinvestors

Figure 6 visualizes the segment structure. This figure is especially useful from a business perspective because it translates raw numbers into an interpretable positioning map. The segmentation supports Expectation A4 by showing that firms differ not only in scale but also in the balance between perceived opportunity and realized investment.

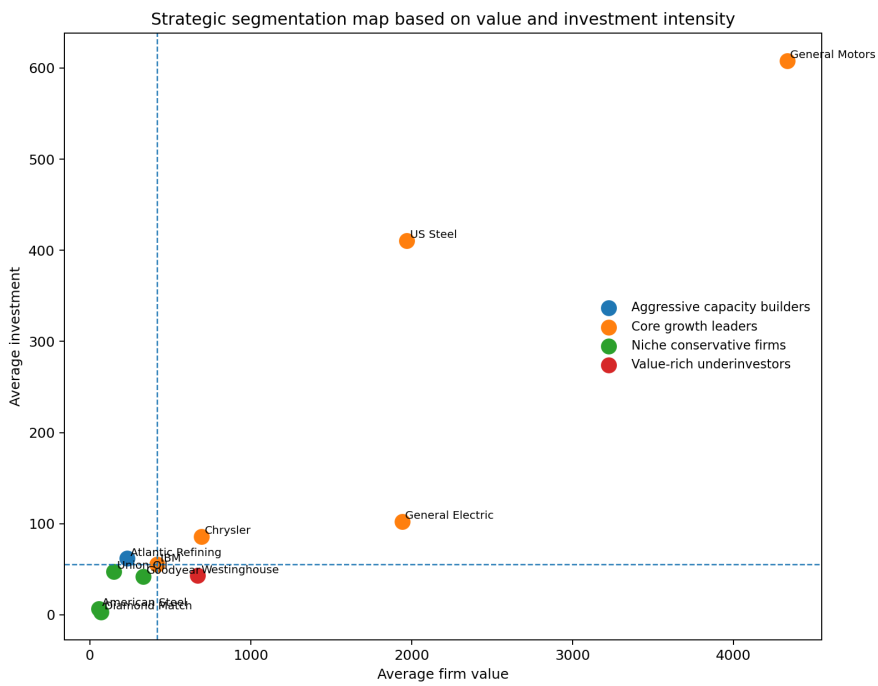

Figure 6: Firm segmentation map based on average value and average investment

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6 Interpretation, Contribution, and Practical Use

6.1 What the evidence says about capital-allocation behavior

Across the three analytical layers, the evidence points to a consistent interpretation of capital allocation as a process shaped by persistence, organizational scale, and changing opportunity. The fixed-effects results show that prior investment and prior capital stock remain the most stable explanatory signals, while value growth adds an important dynamic dimension. This combination suggests that managers should read capital allocation not as a one-off annual event but as a structured sequence of commitments. Once firms move into an investment-intensive posture, that posture tends to carry forward.

The classification evidence sharpens this interpretation. Instead of asking only how investment changes on a continuous scale, the study shows that high-investment periods can be recognized as a separate state with substantial analytical accuracy. This matters because real-world review processes often operate through escalation logic: some periods require ordinary monitoring, while others require intensive liquidity, timing, and governance attention. The classification layer therefore extends the explanatory evidence into a recognizable management signal.

6.2 Why the paper contributes differently from standard finance empirics

The main contribution of the paper is not simply that it estimates an investment equation on a classic dataset. Its stronger contribution is architectural. The study organizes evidence in a sequence that matches the way analytical work is often consumed inside organizations. Managers first want a sense of the structure of the portfolio, then they want explanations of the main drivers, then they want operational flags, and finally they want an interpretable map of strategic positioning. The manuscript is therefore intentionally built as an evidence sequence rather than a single-method finance article.

A second contribution is conceptual. The paper treats business data analysis as more than prediction. It includes explanation, event recognition, and profiling as equally legitimate analytical tasks. This makes the design visibly different from the earlier manuscripts and better suited to a capital-allocation context, where numerical prediction alone rarely satisfies governance or strategy needs. A third contribution is practical reproducibility: the study shows how a public benchmark panel can still generate a contemporary, submission-ready paper without dependence on proprietary corporate systems.

6.3 How managers could use the findings

The findings translate into several practical applications. First, finance teams can build monitoring views that combine lagged spending, installed capital, and recent value momentum rather than relying on one signal alone. Second, the high-investment classifier can be used as a screening tool for budgeting cycles, helping managers identify periods that may require enhanced review of financing capacity, project overlap, or execution bottlenecks. Third, the segmentation map can support comparative discussion across business units, peer firms, or internal divisions by distinguishing scale leaders from conservative or underinvesting entities.

This practical layer is especially important because it makes the analytics interpretable to non-specialist stakeholders. A board member or divisional manager may not engage deeply with a full fixed-effects specification, but can readily understand a high-investment flag or a strategic position map. In that sense, the paper contributes to business data analysis by converting technical evidence into monitoring language that is usable in capital-governance settings.

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7 Study Boundaries and Future Research

Several limitations should be acknowledged. First, the dataset is historically bounded and focuses on large U.S. manufacturing firms, so the findings should not be generalized mechanically to contemporary industries without additional validation. Second, the variable set is intentionally compact. It captures the core logic of investment analytics but does not include financing, governance, uncertainty, or macroeconomic controls that are commonly available in modern archival datasets. Third, the segmentation approach is deliberately simple and designed for interpretability. More advanced clustering or latent-state methods might uncover additional nuances.

These limitations create several opportunities for future research. One direction is to replicate the layered design on newer public corporate-finance datasets with richer digital, governance, or environmental indicators. Another is to compare interpretable models with explainable-AI methods more explicitly, especially in settings where firms adopt digital finance platforms. A third direction is to extend the framework from firm-level historical panels to business-unit or project-level capital expenditure data, thereby moving closer to internal managerial analytics. Finally, future work could integrate uncertainty proxies and scenario analysis so that the classification of high-investment periods becomes part of a broader strategic planning toolkit.

8 Conclusion

This paper developed a sequenced business-data-analysis view of capital allocation using public investment panel data. By combining fixed-effects estimation, classification of high-investment periods, and strategic firm segmentation, the study showed that capital-allocation evidence can be organized into a richer and more managerially useful architecture than is typical in traditional investment research. The empirical results highlighted the importance of lagged investment, lagged capital stock, and firm momentum, while the classification models demonstrated strong ability to identify unusually high-investment states.

The paper's broader contribution lies in showing how a public, reproducible dataset can be used to produce submission-ready evidence for a business journal without relying on proprietary corporate data. More importantly, it translates investment analytics into business language: monitoring, prioritization, segmentation, and decision support. For that reason, the study should be read not merely as a finance exercise, but as a business data analysis contribution with practical relevance for managers who need to understand when, why, and where capital is being deployed.

Acknowledgements

Add acknowledgements here if needed.

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