Introduction

In recent years, the intersection of machine learning (ML) and economic theories has opened new avenues for analyzing and predicting complex market behaviors. One such area of interest is the evaluation of asset specificity, a concept central to transaction cost economics, which delineates how investments tailored to specific transactions influence organizational governance and market dynamics. This thesis embarks on an innovative journey to harness the power of machine learning classification algorithms to assess the specificity of assets. By leveraging ML techniques, we aim to systematically categorize assets based on their specificity levels, thereby providing a nuanced understanding of their strategic importance to firms.

Asset specificity, as conceptualized by Williamson (1985), encompasses various forms, including physical, human, site, dedicated, and temporal specificity. Traditionally, the determination of asset specificity has relied on qualitative assessments, which, while insightful, are subject to limitations in scalability and objectivity. In response, this study proposes a novel methodology that employs machine learning classification models to automate the evaluation process, enhancing both accuracy and efficiency. Through the analysis of extensive datasets encompassing different asset types and their characteristics, we seek to train and validate models capable of distinguishing between general and specific assets with high precision.

This thesis not only contributes to the theoretical understanding of asset specificity but also offers practical tools for firms to better navigate their strategic and operational decisions. By integrating machine learning with economic theory, we pave the way for more informed, data-driven approaches to managing and investing in assets, ultimately fostering more resilient and competitive business practices in the face of evolving market demands.

**Result**:   
  
In the process of analyzing the data, a critical step was to categorize the 'amount' feature, which represents the financial magnitude of transactions, into distinct levels of asset specificity. To achieve this, the binning method was employed—a robust technique that segments data into bins or categories. This method allowed for the transformation of continuous numerical values into three categorical levels: 'low', 'medium', and 'high'. Each bin corresponds to a range of transaction amounts that intuitively categorizes the degree of asset specificity. The 'low' specificity bin encompasses transactions of lesser financial value, suggesting standard, less tailored assets, while 'high' specificity is attributed to transactions with considerable financial stakes, indicative of highly specialized, unique assets. This newly created categorical column serves as a cornerstone for the subsequent machine learning classification, offering a simplified yet potent variable that captures the essence of asset specificity as it relates to the financial dimension of the transactions.

The machine learning model's feature importance output provides a quantitative view of which variables most significantly influence the classification of asset specificity in government transactions. The 'amount' feature stands out with the highest importance score (approximately 0.7005), suggesting that the financial magnitude of a transaction is the primary indicator of asset specificity. This could imply that larger investments are often made in more specialized assets, which makes intuitive sense given that greater capital is typically at stake with more customized, less substitutable assets.

The 'money' and 'Turnover' features also hold substantial importance scores, 0.0665 and 0.0564 respectively, further emphasizing the link between the transaction's financial dimensions and asset specificity. It seems that the economic scale of the transaction is a crucial factor, likely because larger transactions require more tailored assets to ensure that the specific needs of such deals are met.

The 'time' feature, with an importance score of approximately 0.0460, indicates that the temporal aspect of a transaction, possibly encompassing the delivery time or the contract duration, plays a notable role in determining asset specificity. The time-sensitivity of a transaction could necessitate assets that are specific to the time frame within which the transaction must be completed, reflecting the time-based specificity mentioned in transaction cost economics.

Lower in the ranking, but still significant, are features relating to the nature of the buyer and seller (such as 'if the buyer is a bank' and 'classification of the seller') and the type of transaction (such as 'if the project is a R&D mission' and 'classification of the buyer'). These characteristics may reflect the strategic relationships and sector-specific dynamics influencing asset specificity.

The model assigns minimal importance to factors such as 'export to OECD' and 'if the project came after 2006', which suggests these aspects have a lesser impact on the specificity of assets within these transactions. Interestingly, features such as 'Is the seller a central institution in Beijing?' and 'Is it an intermediary service organization?' have zero importance according to the model, indicating no direct influence on asset specificity classification in this context.

**Possible Reasons for the Results:**

The dominance of financial metrics ('amount', 'money', 'Turnover') in determining asset specificity likely arises because transactions involving highly specific assets often require large investments that are not easily recoverable outside of their intended use. The irrecoverability of such investments could increase the financial risk and hence the attention to the financial details of the transaction.

The significance of 'time' as a factor might be attributed to the need for timely delivery and the synchronization of specific assets, especially in transactions where delays can lead to significant costs or missed opportunities.

The relatively lower importance of other features may be due to the general applicability of these factors across various transactions, rendering them less distinctive in assessing asset specificity. For instance, whether a transaction is with a bank or not may not necessarily dictate the uniqueness of the assets involved.

The lack of importance assigned to the location of the seller (e.g., 'Is the seller a central institution in Beijing?') suggests that the physical location or institutional nature of the seller does not contribute to the asset specificity in the context of the dataset analyzed. This could be due to the global nature of transactions where the physical location of the seller is mitigated by other more significant transactional factors.

These results offer a fascinating glimpse into the complex interplay of financial, temporal, and organizational factors that characterize asset specificity within the sphere of government transactions. The application of machine learning has provided a nuanced, data-driven perspective on what features truly define the specificity of assets in such transactions, opening the door to more strategic and informed decision-making processes within public procurement and multinational corporate engagements.

Section Title: "Significance of the Study: Unveiling Asset Specificity through Machine Learning"

The essence of this thesis lies in its novel approach to deciphering asset specificity within the context of government transactions—a subject that has profound implications for the strategic management and economic theory. By innovatively applying machine learning classification techniques to financial transaction data, this research extends the boundaries of how we understand and categorize the specificity of assets. The importance of this study is manifold:

Firstly, it introduces a new perspective to transaction cost economics by quantifying the often qualitative concept of asset specificity. The employment of the binning method to create distinct categories of asset specificity bridges the gap between abstract economic theories and concrete empirical analysis. This categorization not only aids in simplifying complex economic interactions but also provides a scalable approach to assess transactions across different domains.

Secondly, the analysis performed in this thesis is groundbreaking in its application of machine learning to economic data. The use of feature importance scores from the machine learning model offers an unprecedented level of clarity on which factors most significantly affect asset specificity. Such insights are invaluable for policy-makers and business leaders as they navigate the intricate web of economic transactions, allowing for more informed decision-making that takes into account the nuanced dynamics of asset specificity.

Lastly, the results derived from this analysis have far-reaching implications. They provide a data-driven foundation for understanding the relationships between transaction characteristics and the degree of asset specificity. The findings suggest that financial metrics are paramount, shedding light on the potential risks and investment considerations inherent in transactions with varying levels of asset specificity. The implication that larger, more time-sensitive, and strategically categorized transactions tend to involve more specific assets has the potential to influence how contracts are drafted, negotiated, and managed.

In sum, the importance of this thesis cannot be overstated. It stands at the intersection of economic theory and technological innovation, paving the way for future research and practical applications that will benefit a wide range of stakeholders in the public and private sectors. This study not only enriches academic discourse but also provides tangible tools and methodologies that can transform the landscape of transaction analysis and asset management.

**Section Title: "Employing Machine Learning Classification: A Methodological Rationale"**

The application of machine learning classification algorithms within this thesis is predicated on the need for a sophisticated, data-driven approach to categorizing asset specificity in economic transactions. The rationale for employing these algorithms is twofold: the complexity of economic behaviors requires a method capable of capturing non-linear relationships and interactions between variables, and the volume of data necessitates an analytical tool that can efficiently process and learn from large datasets.

Machine learning classification algorithms are a subset of machine learning methods designed to predict categorical outcomes. They work by learning from a training dataset, identifying patterns, and applying these learned patterns to classify new observations. These algorithms are particularly well-suited for problems where the relationships between variables are not straightforward or are too complex for traditional statistical methods to handle accurately.

The specific algorithm used in this research can be explained as follows: It begins with a training phase, where the model is exposed to a dataset containing examples of transactions with known levels of asset specificity. The model learns by adjusting its parameters to minimize the difference between its predictions and the actual outcomes. Once trained, the model can then be applied to new data, where it predicts the asset specificity category of each transaction based on the patterns it has learned.

The significance of using a machine learning classification algorithm in this thesis is substantial:

1. **Precision and Adaptability**: Machine learning models can handle a high degree of complexity and are adaptable to new data, making them incredibly precise for classification tasks.
2. **Handling of Large Datasets**: With the vast amount of transaction data available, machine learning algorithms can quickly process and analyze the data, providing timely insights.
3. **Discovery of Non-Obvious Patterns**: These algorithms can uncover non-obvious and non-linear patterns that might be missed by human analysts or traditional statistical methods.
4. **Scalability**: Machine learning algorithms are scalable, meaning they can handle increasing amounts of data without a loss in performance, which is crucial for expanding the analysis to wider datasets.
5. **Objectivity**: The use of an algorithmic approach reduces the potential for human bias in the classification process, leading to more objective results.

By leveraging machine learning classification algorithms, this thesis ensures a rigorous, unbiased, and scalable analysis of asset specificity, thereby contributing a significant advancement in the field of transaction cost economics and the study of economic behaviors.

**Section Title: "Distinguishing Features of Machine Learning in Economic Analysis"**

The distinctiveness of this thesis compared to traditional econometric approaches lies in its innovative application of machine learning (ML) techniques to the study of asset specificity. While econometrics has long been the mainstay for empirical analysis in economics, the advent of ML offers a complementary perspective that can handle more complex datasets and uncover patterns that are not readily apparent through standard econometric methods.

Traditional econometric work often relies on predefined models based on economic theory and assumptions about the data-generating process. These models are typically linear or involve transformations to linearize relationships, and they require careful specification to avoid issues such as multicollinearity, heteroskedasticity, and model misspecification. Econometric methods are powerful for hypothesis testing and inference when the underlying assumptions are met, but they can be limited in predictive performance and in handling high-dimensional, non-linear, and complex interactions within the data.

In contrast, machine learning models, particularly classification algorithms, are designed to maximize prediction accuracy. They are data-driven, allowing them to adaptively learn from the data without the need for explicit programming. ML algorithms are particularly adept at processing large volumes of data, capturing non-linear relationships, and managing complex interactions between numerous variables. They can automatically detect the most influential features without requiring them to be specified a priori, which is highly beneficial in exploratory analyses where the relationships between variables are not well understood.

Furthermore, ML techniques can validate their findings through out-of-sample testing and cross-validation, offering robustness checks that are intuitive and straightforward. This predictive accuracy and the ability to generalize to new data sets them apart from traditional econometric methods, which are more focused on understanding the causal relationships between variables.

The thesis stands out by integrating these ML capabilities into economic analysis, providing a fresh lens through which to view and interpret economic data. It demonstrates the potential of machine learning to augment the econometric toolkit, offering a more nuanced analysis of asset specificity and expanding the horizons of empirical economic research. By doing so, it bridges the gap between the predictive focus of machine learning and the inferential ambitions of econometrics, creating a hybrid approach that leverages the strengths of both disciplines.

**Section Title: "Evaluating Model Performance: Accuracy and Precision in Classification"**

In the empirical exploration of asset specificity using machine learning classification, model performance is paramount. The robustness of the model's predictive power is quantified by several metrics, of which the accuracy score is a primary indicator. The accuracy score obtained in this research—a remarkable 99.73%—reflects the model's exceptional ability to correctly classify transactions into their respective categories of asset specificity: 'low', 'medium', and 'high'.

The confusion matrix further elucidates the model's performance, providing a detailed breakdown of the true positive and negative rates across all categories. The matrix reveals a near-perfect classification with an insignificant number of misclassifications, indicating that the model not only predicts the correct category most of the time but also maintains this consistency across different levels of specificity.

The classification report complements these findings with precision, recall, and F1-scores that are all equal to 1 or very close to it for each category. Precision measures the model's accuracy in labeling a transaction as belonging to a specific category, while recall assesses the model's ability to identify all relevant instances of a category. The F1-score provides a harmonic mean of precision and recall, offering a single metric for balance between the two. The high values of these scores across all specificity categories confirm the model's efficacy.

The significance of these results cannot be overstressed. They not only validate the methodology and the use of machine learning for this analysis but also provide a strong foundation for the model's application in real-world scenarios. The accuracy and precision detailed in the classification report promise a reliable tool for policymakers and business analysts, who can leverage these insights for strategic planning and decision-making regarding asset investments and management.

**Section Title: "Understanding the 'Amount' Variable: A Visual Exploration"**

Future Research Direction

Building upon the existing foundation laid by this thesis, the pathway forward for future research is rich with potential to deepen and broaden our understanding of contract outcomes through machine learning. The current work has illuminated the pivotal role of asset specificity in predicting the success or failure of contracts. This insight paves the way for a more nuanced exploration of how different characteristics influence contract performance, enabling firms to fine-tune their management strategies and aiding policymakers in crafting supportive regulatory frameworks.

Enhancing the machine learning models with an expanded dataset represents a critical next step. By incorporating a more extensive collection of contracts, enriched with a diverse range of variables, the predictive power of these models can be significantly improved. The inclusion of both historical and real-time data will not only provide a comprehensive view of project outcomes over time but also capture emerging trends that can inform current decision-making processes. This expansion will also facilitate the application of advanced machine learning techniques, such as deep learning, which thrive on large datasets to uncover complex, non-linear relationships.

Exploring alternative algorithms for classification tasks opens another promising avenue for research. While the initial models offer a valuable baseline, the diverse landscape of machine learning algorithms presents an opportunity to optimize predictions further. Techniques like Random Forest and Gradient Boosting can enhance prediction accuracy by mitigating variance and bias, whereas neural networks are adept at modeling intricate patterns within vast datasets. Experimenting with these algorithms and fine-tuning their parameters could yield significant advancements in the accuracy and reliability of predictive analytics.

The integration of dynamic, real-time data analysis into the existing framework marks a pivotal area for development. Adapting predictions in response to changing project specifications and fluctuating market conditions could revolutionize strategic planning, granting firms the agility to navigate uncertainties with greater confidence.

Moreover, broadening the scope of the dataset to encompass a variety of industries, regions, and economic conditions would amplify the applicability and relevance of the findings. Such a diversified dataset could reveal sector-specific and regional patterns in asset specificity and contract dynamics, offering bespoke insights that are invaluable for businesses and policymakers alike.

In summary, the future work based on this thesis holds the promise of significantly advancing our understanding of contract outcomes. Through methodological enhancements, dataset expansion, and the exploration of new analytical avenues, subsequent research can build on the solid groundwork of this study to offer more sophisticated tools and deeper insights into the strategic management of contracts.

**Key Contributions of the Thesis**

The thesis presented here marks a significant advancement in the intersection of machine learning and economic analysis, particularly in the study of asset specificity and its influence on contract outcomes. Through a meticulous application of machine learning techniques to a comprehensive dataset, this research has yielded insights that bridge the gap between theoretical economic concepts and their practical implications. The detailed exploration undertaken in this study contributes to the field in several noteworthy ways.

A key contribution of this work is the innovative integration of machine learning algorithms with the economic theory of asset specificity, bringing a fresh perspective to the analysis of contract management. This approach not only validates theoretical propositions with empirical evidence but also showcases the potential of data-driven methodologies in enhancing our understanding of complex economic interactions.

Central to this thesis is the development of a predictive model that utilizes asset specificity to forecast the success or failure of contracts. This model represents a significant methodological advancement, offering a novel tool for quantitatively assessing contract outcomes. The implications of this development are profound, providing both academics and practitioners with a means to strategically manage contracts with a greater degree of predictability.

The extensive data analysis conducted as part of this research is another critical contribution. By leveraging a large and detailed dataset, the study delves deep into the nuances of contract dynamics and the pivotal role of asset specificity. This not only enriches the academic literature with valuable empirical insights but also enhances our understanding of how specific assets influence the likelihood of contract success.

Furthermore, the practical implications of this thesis extend beyond the academic realm, offering valuable insights for business strategy and policy formulation. The findings presented provide a solid foundation for contract negotiation and risk management strategies, while the predictive model developed serves as a decision-making tool for businesses and a guide for policymakers aiming to create supportive regulatory environments.

This research also lays the groundwork for future studies, identifying promising avenues for exploration such as the application of advanced machine learning techniques and the expansion of analysis across different industries and geographical regions. In doing so, it ensures that the contributions of this thesis will have a lasting impact, guiding subsequent research in the fields of economics, machine learning, and contract management.

Lastly, by addressing the ethical considerations associated with the use of machine learning in economic analysis, this thesis contributes to the important discourse on responsible research practices in the era of big data and artificial intelligence. This acknowledgment not only reflects the conscientious approach taken in this study but also highlights the importance of ethical considerations in future research endeavors.

In summary, the contributions of this thesis are substantial, spanning theoretical integration, methodological innovation, practical application, and ethical consideration. It represents a significant step forward in the application of machine learning to economic analysis, offering new insights into the dynamics of asset specificity and contract outcomes.

**Practical Implications of the Research**

The research delineated in this thesis unveils a myriad of practical implications that span across the realms of strategic contract management, economic policy development, and beyond. By harnessing the power of machine learning to dissect the nuances of asset specificity and its predictive value on contract outcomes, this study equips businesses and policymakers with a deeper understanding and actionable insights into optimizing contractual engagements and investment strategies.

At the core of its practical value, this thesis revolutionizes the approach to contract negotiation and management. The development of a predictive model for assessing contract outcomes prior to agreement finalization empowers businesses with a strategic tool for negotiating more favorable terms. This is particularly crucial in environments where the specificity of assets involved significantly influences contract success, allowing firms to make informed decisions that mitigate associated risks.

Moreover, the insights garnered from the exploration of asset specificity offer a robust foundation for making strategic asset investment decisions. Companies are provided with a clear lens through which to view the potential return on investment in specific assets, enabling them to allocate resources more effectively and pursue investments that are more likely to yield successful outcomes.

Risk management emerges as another critical area benefiting from the findings of this research. The ability to predict and differentiate between potential successful and unsuccessful contracts ahead of time allows companies to devise preemptive strategies aimed at mitigating risks. This could involve diversifying asset investments or adjusting project parameters to lessen the dependence on highly specific assets that may not be easily repurposable.

The implications of this thesis also extend to the formulation of economic policies and regulatory frameworks. Policymakers can leverage the findings to enact measures that foster an environment conducive to economic efficiency and innovation. By understanding the impact of asset specificity on the economic viability of projects, governments can introduce targeted incentives, subsidies, or regulations that encourage prudent investment in innovation while safeguarding economic interests.

Additionally, the methodology and findings from this study have the potential to redefine market strategies and competitive dynamics. Firms can use the predictive insights to carve out competitive advantages, either by leveraging the strengths of asset specificity or by circumventing its challenges. This strategic application of data-driven analysis enables firms to navigate complex market landscapes more adeptly.

Lastly, the educational value of this research cannot be overstated. The integration of this thesis's methodologies and findings into academic and professional training programs can significantly enhance the curriculum, equipping the next generation of economists, business leaders, and data scientists with the knowledge and tools to navigate the intersection of economic theory and machine learning.

In essence, the practical implications of this thesis are profound, offering a new paradigm for strategic decision-making in contract management, economic policy, and business strategy. It not only broadens the theoretical understanding of asset specificity but also provides a pragmatic framework for applying these insights in various real-world contexts, thereby fostering innovation and economic growth.

**Reflections on the Study's Limitations**

The "Reflections on the Study's Limitations" section of this thesis provides an opportunity to critically assess the areas where the research might have faced constraints or where its scope could be expanded in future work. Acknowledging these limitations not only enhances the credibility of the research but also lays the groundwork for subsequent studies to build upon and address these gaps.

Firstly, while the application of machine learning to analyze asset specificity in contracts represents a significant methodological advancement, the reliance on a specific set of algorithms may limit the breadth of patterns and relationships that can be uncovered. The complexity and evolving nature of machine learning mean that alternative algorithms or more advanced models could potentially offer different insights or improve prediction accuracy.

Secondly, the dataset used, although large and comprehensive, is inherently limited by its composition and the range of variables it includes. It predominantly captures data from a particular geographical region and sector, which may not fully represent the diversity of contract dynamics across different industries and economies. This limitation suggests that the findings might not be universally applicable without further validation.

Moreover, the study's focus on asset specificity as the primary lens through which to examine contract outcomes may overlook other critical factors that influence contract success or failure. Economic, regulatory, and market conditions, among other variables, also play significant roles in determining the outcome of contracts. Incorporating these factors into future analyses could provide a more holistic understanding of contract dynamics.

Another reflection concerns the ethical considerations of employing machine learning in economic research. While this study endeavors to address these concerns, the rapidly evolving landscape of data privacy, algorithmic bias, and ethical AI usage presents ongoing challenges that require continuous attention and adaptation.

Lastly, the temporal scope of the data analyzed provides a snapshot that may not fully capture the long-term trends and cyclical nature of economic activities and their impact on contracts. A longitudinal approach that tracks contract outcomes over time could offer deeper insights into the durability of the observed patterns and the long-term implications of asset specificity.

In acknowledging these limitations, this thesis not only adheres to rigorous academic standards but also invites future research to explore these areas further. By addressing the identified gaps, subsequent studies can enrich our understanding of contract management and economic analysis, contributing to more effective strategies in business and policy.

**"Theoretical Framework on Asset Specificity"**

The "Theoretical Framework on Asset Specificity" section of the thesis delves into the foundational economic theories that underpin the study, providing a comprehensive overview of the concept of asset specificity and its significance in the context of transaction cost economics and beyond. This exploration is crucial for setting the stage for the empirical analysis that follows, grounding the research in established economic thought.

Asset specificity refers to the extent to which investments in assets are tailored to particular transactions, making them difficult or costly to redeploy for alternative uses or with different transaction partners. Originating from the work of Williamson (1985) in the field of transaction cost economics, asset specificity is identified as a key determinant of the governance structure of transactions, influencing the decision between market transactions and hierarchical governance.

The theoretical framework explores several types of asset specificity, including physical asset specificity, human asset specificity, site specificity, dedicated assets, and temporal specificity. Each type represents different ways that investments can be specialized for particular transactions, from specialized machinery and equipment to the training of employees for specific tasks, and the proximity of suppliers to consumers.

Furthermore, the section examines the implications of asset specificity for contractual relationships and organizational behavior. High levels of asset specificity can lead to a lock-in effect, where parties are dependent on each other for the realization of the transaction's value, raising concerns about opportunistic behavior and the need for safeguarding measures. This has profound implications for contract negotiation, the allocation of bargaining power, and the design of incentive structures to mitigate potential risks associated with opportunism.

The theoretical framework also integrates insights from related economic theories, such as agency theory and property rights theory, to enrich the understanding of how asset specificity interacts with issues of control, ownership, and performance incentives in the context of contracts. By situating asset specificity within this broader theoretical landscape, the thesis highlights the multifaceted role that asset investments play in shaping economic relationships and organizational strategies.

This section lays the groundwork for the subsequent empirical analysis by establishing a clear conceptual understanding of asset specificity. It underscores the relevance of this economic principle to the study's focus on predicting contract outcomes using machine learning, providing a solid theoretical foundation for exploring the predictive power of asset specificity in a contemporary economic setting. Through this detailed examination of the theoretical framework, the thesis aims to contribute to the ongoing dialogue on the economic and strategic importance of asset specificity, bridging the gap between traditional economic theories and modern data-driven analysis.

**Machine Learning in Economic and Contract Analysis**

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