Finance 701

Literature Review

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1 Abstract

This paper explores academic literature across multiple theoretical frameworks to inform the following research question: Does socially responsible outcomes contribute to the generation of excess returns in private equity-backed investments? Corporate social responsibility (CSR) is the main theoretical framework underpinning this research. A methodological approach establishes the taxonomy. The literature investigates the relationship between CSR and corporate governance, the contention in private equity performance, CSR's growing influence in private equity and the methodology underpinning the construction of the investor sentiment index. The mitigation of research design issues is satisfactory. The literature sets a foundation to explore the research question.

Contents

2 Introduction

This paper reviewed research associated with Corporate Social Responsibility, Private Equity (PE) performance and impact on CSR and ESG. The purpose of this review is to gain a more comprehensive understanding of the body of literature surrounding the associations above and their relation to the research question: **Does socially responsible outcomes contribute to the generation of excess returns in private equity-backed investments?** This question broadly sits within the theoretical framework of Corporate Social Responsibility (CSR), a self-regulatory model helping a company remain socially accountable. CSR is achieved by practising corporate citizenship, managing the impact the entity has on all areas of society.

Private Equity (PE) continues to influence global capital markets and conventionally takes one, or a combination, of the following forms: Venture capital for early-stage companies. Growth equity for growth-stage companies or Buyout for late-stage companies. These are forms of investment vehicles usually identified by four characteristics. Firstly, funds organised privately, pooling capital from several parties. Secondly, professional investment managers administer the fund, incentivised by performance-based compensation and significant carry in the fund. Thirdly, they are inaccessible to the public. Lastly, they operate externally to securities regulation and registration requirements. A general partner(s) (GP) manage fund operations and make investments using capital contributed by limited partners (LP). LPs make passive investments with little to no control in the operations of the fund. Funds typically charge a 2% annual fee and 20% performance fee on the fund's annual return. They raise capital through private offerings and pursue investment strategies in private assets to generate returns for investors (Brav, Jiang, Partnoy, and Thomas, 2008).

The role of private equity in CSR activity is receiving increased attention from stakeholders. The analysis supports the increased demand by institutional investors for contributions towards CSR from the willingness to sacrifice returns for activist-related causes and ESG-related outcomes from both demand and price perspectives. However, the measurability in CSR-related activity and transparency in outcomes is complex at best. Private equity also may invest in a subset of industries that deliver financial returns but may deliver poor outcomes in alternative metrics within CSR contexts.

The research intends to achieve the following outcome. Firstly, devise a more transparent methodology in evaluating CSR-related activity in the form of socially responsible outcomes (SRO). Secondly, determine the performance incentives for private equity by contributing to these outcomes to improve society. Thirdly, the outcomes' alignment to the United Nations Sustainable Government Goals (UNSDG). In summary, the intention is to determine whether the delivery of socially responsible outcomes generates excess returns for private equity investors using a more rigorous, quantitative methodology.

The nature of this research is new, encompassing several interrelated frameworks and little historical context. Subsequently, this literature review covers the intersection of CSR, legal origins and corporate governance, CSR and value creation, the historical performance of private equity, private equity's impact on CSR and ESG and an empirical methodology detailing the construction of a socially responsible outcome-related index from underlying proxies.

As a caveat, the lack of historical context opens opportunities for new research. Firstly, expand on existing CSR-related proxies by exploring and designing new rigorous quantitative proxies for socially responsible outcomes. Secondly, investigating the relationship between socially responsible outcomes and the returns generated by private investors. Lastly, the feasibility for these socially responsible outcomes to help achieve the United Nations' Sustainable Development Goals.

3 Theoretical Framework(s)

Corporate Social Responsibility (CSR); Corporate Governance; Environmental, Social, Corporate Governance (ESG); Private Equity

4 Empirical Research Studies

This section uses a methodological approach to assess corporate social responsibility and private equity-related literature. Research design issues integrated into these empirical research studies.

4.1 Corporate Social Responsibility

4.1.1 CSR, Legal Origins and Corporate Governance

The evolution of corporate social responsibility commitments continues to influence investment decisions. Liang and Renneboog investigate the role legal origins plays in cross-country variations in corporate social responsibility. Their assessment of CSR using proxies across the global business community found strong correlations between legal origins and CSR scores (Liang and Renneboog, 2017). The findings are relevant on both macro and micro levels. Firstly, the relationship explored between CSR and legal origins contribute to the broader body of literature covering the role legal origins plays in investor protection rights, financial and economic outcomes examined by La Porta et al. (Porta, Lopez-deSilanes, Shleifer, and Vishny, 1999). Furthermore, there is a greater understanding of CSR engagement and CSR compliance drivers on a global level. These findings are relevant for the research question as private equity operations and commitments to socially desirable outcomes cross borders. Previously, the academic community contest that investment through acquisition in assets with corporate social responsibility initiatives creates a dichotomy in value creation: Acquisitions either maximise value for shareholders or stakeholders at the expense of shareholders. These relationships are articulated in one of two ways: 'doing well by doing good' ((Dowell, Hart, and Yeung, 2000),(Orlitzky, Schmidt, and Rynes, 2003),(Guenster, Bauer, Derwall, and Koedijk, 2011)) and 'doing good by doing well' (Hong, Kubik, and Scheinkman, 2012).

4.1.2 Dichotomy of Value: Stakeholders or Shareholders

One paper finds evidence to resolve this contest and the accompanying dichotomy of thought. The maximisation of stakeholder value view predicts high CSR firms complete mergers to benefit other stakeholders. The acquisition impact improves stakeholder satisfaction benefiting shareholders. In contrast, the opposing view is acquisitions reduce shareholder wealth. The paper finds merger activity by high CSR acquirers, in comparison to low CSR acquirers, creates several benefits. Firstly, a higher announcement of stock returns for both acquirers and value-weighted portfolios of the acquirer and target. Secondly, significant increases in long-term operating performance and stock returns. Lastly, higher likelihood and shorter duration of deal completion. Subsequently, the integration of various stakeholder's interests in operations complete investment enhancing long-term profitability and efficiency. These improvements are in favour of stakeholder value maximisation, enhancing shareholder wealth and corporate value. The empirical analysis is rigorous and robust, similar to most articles in this literature review, invalidating research design issues. Endogeneity issues, for example, high-quality management driving profitable mergers and more excellent CSR investment, are addressed using supplementary 2SLS regression analyses with instrumental variables considering religious and political factors, strengthening internal validity. The measurement of CSR is thorough, drawing extensive methodologies using the KLD database implemented in prior research Lev, Petrovits, and Radhakrishnan, 2010, Waddock and Graves, 1997, Jiao, 2010 This database ensures external reliability. Seven major dimensions measure social performance: community, corporate governance, diversity, employee relations, environment, human rights, and product quality and safety. These dimensions may inform the construction of socially responsible outcomes. Several empirical tests investigate the robustness of the statistical significance and magnification of abnormal stock returns, validating research design. In particular, the CSR measures are statistically significant on the 1% level for determining abnormal stock returns on value-weighted portfolios returns (Deng, Kang, and Low, 2013).

4.2 Private Equity Performance

Private equity has a reputation as a lucrative asset for generating returns. however, academics continue to contest the relative performance of private equity in comparison to other asset classes. Several academics juxtapose this ideology by examining returns from different datasets.

An investigation of a commercially available dataset of individual fund returns and cash flows collected over a sample period between 1980 to 1997 found average fund returns, net of fees, generated approximately the same level of returns as the S&P5 500. Additionally, venture funds outperform the S&P 500 while buyout funds underperform when weighted by committed capital. However, both types of funds expect to generate returns above the S&P 500 (Kaplan and Schoar, 2005). There are a few issues associated with this research. Firstly, a lack of control for market risk and sampling bias invalidate these findings, creating replication design issues. Additionally, the VE dataset is not as comprehensive as the datasets subsequently discussed.

One paper further developed the concept of private equity funds generating returns above the market. The analysis of 1400 U.S private equity (buyout and venture capital) funds, which utilised a new dataset sourced from over 200 institutional investors via Burgiss Systems, discovered U.S Buyout funds outperformed the S&P 500 20% to 27% on average over the life of the fund. The performance correlates to 3% per year, highlighting the lucrative nature of private equity in this first instance. Firstly, the results are similar with different proxies for the market. Determining a market proxy is often highly subjective. Secondly, the statistical methods used to determine the results are rigorous, with samples tested across multiple commercial datasets, ensuring to mitigate the likelihood of positive selection bias (Harris, Jenkinson, and Kaplan, 2014).

Conversely, another article published in 2020 offered an alternative perspective. Analysis on PE fund performance across three datasets derived average net multiple on money (MoM) metric range of 1.55 to 1.63. These findings implied an 11% per annum return, consistent with relevant public market proxies calculations. Carry calculations to help determine the net multiple of money calculations used the same dataset as the previous article. The article identifies the potential for agency conflicts to arise based on the existing fee and carry structure. (2% per annum on AUM and 20% on return). Additionally, the statistical analysis is lacking empirical rigour (Phalippou, 2020). Subsequently, the article raises design and methodology issues.

In summary, private equity does generate favourable returns from investors equal to or above the market.

4.3 Private Equity, CSR and ESG

There is an increased interest in CSR and ESG-related activity in the private equity industry based on published literature.

4.3.1 Impact Investing, Utility and Willingness to Pay

Impact investing offers an alternative perspective on investing for performance alone. The article investigated insights on an investors utility/willingness to pay, showing how investors derive non-pecuniary utility from investing in dual-objective venture capital funds. Random willingness-to-pay models indicated investors were willing to accept 2.5 - 3.7 percentage points lower internal rate of return from an impact fund than a traditional venture capital fund. The analysis found impact funds earn an internal rate of return 4.7 percentage points ex-post lower than traditional venture capital funds (Barber, Morse, and Yasuda, 2021). Funds analysed were organised into five industry groups: Information technology and business services. Diversified and consumer discretionary. Health care. Media and communications. Others (energy, industrials, infrastructure, food and agriculture, materials, real estate etc.). The internal rate of returns found in regressions for impact funds was statistically significant on at least the 5% level for the first four of five industry groups. The random utility of the willing-to-pay model, logit specification adoption given the unobservable nature of utility and expected returns formulation are rigorous. Additionally, the model formulation for willingness to pay across every logit model varied for limited partner controls is statistically significant at the 1% level for both homogenous and heterogenous expected returns forecasts. Investor categorisation unpacks issues with heterogeneity. Regression and logit analysis strengthen the statistical validity and rigour of the empirical research design. This article provides some interesting insights. Firstly, a subset of investors in the private equity industry is willing to sacrifice returns to invest in the causes of impact funds. The same effect may occur for socially responsible outcomes. Secondly, the exact derivation of willingness to pay models, logit regressions and performance models may influence the empirical design required to solve the research question. Thirdly, the grouping exercises may inform the methodology for constructing socially responsible outcome categories for exploration.

4.3.2 ESG in Demand

ESG disclosures and demands from investors emphasise additional factors to accompany performance are gaining traction. One paper provides evidence institutional investors, limited partners in various private equity funds, push for stronger environmental and sustainability around the world. The empirical analysis informs investors are demanding environmental and social outcomes with firms delivering (Dyck, Lins, Roth, and Wagner, 2019). Institutional investors have often limited partners in private equity funds. It is plausible these institutional investors may influence general partners to make investments in assets that are driving socially responsible outcomes.

4.3.3 The Price of ESG

The price of environmental, social and governance practice disclosures about professional private equity investors contributes to the growing field of sustainable entrepreneurship and the role in driving socially responsible outcomes. The paper addresses the role socially responsible and irresponsible financing has on private equity financing (Crifo, Forget, and Teyssier, 2015). The paper derives an exciting method to determine the marginal impact of valuation on investors when given ESG-related information, assessed by good and bad outcomes based on market thresholds. The positive or harmful nature of three qualities (soft, hard, impact) for each factor (environment, social and governance) creates an aggregate marginal sign effect on firm valuation. This methodology informs one null and three alternative hypotheses: No effect. Mispricing. Asymmetrical impacts. Irresponsibility risk premium. The hypotheses inform the impact of ESG disclosure on firm valuation. The methodology expressed in this instance may inform the incorporation of ESG disclosure requirements in socially responsible outcomes for the research question. This approach provides an alternative qualitative approach to assessing socially responsible outcomes compared to the other methods explored in this paper. The variation in case studies and the small sample size of private equity investors raises concerns regarding experimental design. However, several methods improve validity. Firstly, soft and hard practices are tested in conjunction to test the accumulated implications of both. The testing procedures were consistent and structured amongst participants, with each given the same sets of data and process. Additionally, investor profiling approaches control for heterogeneity. These implementations mitigate the threats to reliability by addressing errors and biases for both participants and researchers. The approach finds subsets of ESG disclosures are statistically significant at the 5% and 1% level on firm valuation and investment decisions. Additionally, the predictive margins of good and bad ESG practises are statistically significant at the 1% level, impacting investment decisions, highlighting the strength of this study. Conversely, this analysis shows the impact of ESG disclosure on private equity investment, not how disclosures inform returns. Nonetheless, this analysis may frame how to construct quantitative variables from qualitative information related to socially responsible outcomes.

4.4 Empirical Methodology: Investor Sentiment Index

The following article does not relate to private equity. However, it identifies a rigorous modelling approach that may inform empirical methods. The article confirms the significance of behavioural finance, diverging from classical finance theory. It is one of the most popular articles in finance-related academic literature, measured by citation frequency and academic recognition. Briefly, investment sentiment influences the cross-section of returns, validated by theoretical arguments, historical accounts of speculative episodes and sets of novel empirical results (Baker and Wurgler, 2006). The research question seeks to investigate how socially responsible outcomes generate excess returns in entities backed by private investors. The investigation will require the construction of a methodology to measure socially responsible outcomes. The article constructs a sentiment index to measure sentiment, a formulation of a composite index from six underlying proxies, including the number of IPOs and average first-day returns. Principle component analysis isolates common components as idiosyncratic and non-sentiment-related. The formulation of the composite index follows:

1. Estimate the principal component of six proxies and their lags to create first stage index with twelve loadings
2. Compute correlations between first stage index and the current and lagged values of each proxy.
3. Define the sentiment index as the first principal component of the correlation matrix of six variables, lead to lag with the highest correlation to the first index while scaling for unit variance.

Panels display modelling characteristics and return drivers, split into subsets including returns, profitability and growth opportunity. Each underlying proxy is statistically significant results at the 1% level when regressed on the sentiment index. A series of empirical tests, including decile sorting, predictive regressions and time-series regressions, were rigorous. The empirical results aligned with market observations increasingly the validity of the experimental design. Subsequently, the research methods and design were intensive, delivering validity, replicability and reliability. Additionally, this research is critically acclaimed, significantly contributing to behavioural finance and recognition for the authors in the form of a Nobel prize for their contributions to the area. This methodology may inform the construction of a socially responsible outcome index. Both firm-specific and industry-specific socially responsible outcome-related proxies may form the aforementioned composite index. These may include churn rates, employee health statistics, insurance policies, emission reductions, income statistics, energy access and water quality. Additionally, firm and industry drivers would assist in the formulation of panel data. These may include returns, growth, profitability and industry classification. The modelling may use multiple modelling techniques: cross-sectional, time-series regressions, probit regressions, dummy variables to control for industry-specific outcomes and private equity-related investment, including but not limited to investment size, follow on investment, stage of investment, board influence and time horizon. This modelling approach may evaluate how socially responsible outcomes contribute to driving excess returns of an entity backed by private equity. The empirical analysis across time could be compared to societal-related events before, during and after PE investment.

5 Conclusion

This paper explores academic literature across multiple theoretical frameworks to inform the research question. Corporate social responsibility underpins the objective of determining if socially responsible outcomes contribute to the generation of excess returns in private equity-backed investments? The academic literature provided several insights. CSR-related activities play an increasing role in corporate governance, further contributing to a critical piece of literature on legal origins, corporate governance and investor protection. The dissection of the dichotomy between stakeholders and shareholders in CSR-related value creation informs CSR-related activity can both generate returns and benefit both parties. The debate on whether private equity generates excess returns above the market is ongoing between investment professionals. However, investors are demanding CSR-related contributions and are willing to pay for them. The expression of socially responsible outcomes is complex and opaque. However, the robust quantitative methodologies in other applications could reduce this complexity and improve visibility behind their relationship with returns. Most empirical methodologies correct for research design issues, providing suitable frameworks to base modelling and analysis. In summary, the literature provides context for investigating the ability for socially responsible outcomes to generate excess returns in privately-backed investments in further research.

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Pitcher's Name	Connor Robert McDowall	FoR category	Corporate Social Responsibility	Date Completed	19/04/2021
(A) Working Title	"Private Equity, Performance and Socially Responsible Outcomes"				
(B) Basic Research. Question	Does socially responsible outcomes contribute to the generation of excess returns in private equity-backed investments?				
(C) Key Paper(s)	(1) Liang, H., & Renneboog, L. (2017). On the foundations of corporate social responsibility. The Journal of Finance,72(2), 853–910. doi:https://doi.org/10.1111/jofi.12487.eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/jofi.12487 (2) Barber, B. M., Morse, A., & Yasuda, A. (2021). Impact investing. Journal of Financial Economics,139(1), 162–185. doi: https://doi.org/10.1016/j.jfineco.2020.07.008 (3) Baker, M., & Wurgler, J. (2006). Investor sentiment and the cross-section of stock returns. The Journal of Finance,61(4), 1645–1680. doi: https://doi.org/10.1111/j.1540-6261.2006.00885.x.eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1540-6261.2006.00885.x				
(D) Motivation/Puzzle	**Motivation:** Private Equity (PE) continues to play a role in generating returns for investors. Prior evidence suggests PE primarily focuses on delivering returns without assessing broader socially responsible outcomes (SRO). The definition of SRO's for this research proposal is outcomes that contribute to improving society and contributing to the United Nations' Sustainable Development Goals. A subset of outcomes includes economic growth, accessible healthcare, employment, D&I initiatives, energy security and multi-dimensional well-being. Recent movements highlighted the haste to address systemic societal issues (wealth/gender/racial inequality etc.). Currently, the link between PE investment and SRO's is opaque. This research assesses if SRO's drive excess returns, encourage PE firms to invest with a more holistic approach and play a role in tackling systemic issues. **Puzzle:** Determine if socially responsible outcomes contribute to the generation of excess returns in existing or previously privately owned entities.				
Three	**Three** core aspects of any empirical research project i.e. the "**ID**io**T**s" guide				
(E) Idea	**"Core" Idea:** Formulation of a socially responsible outcome (SRO) composite index. This concept follows a similar design methodology to the sentiment index derived in the Investor Sentiment and the Cross-Section of Stock Returns paper. Firm-specific and industry-specific SRO-related proxies would form the aforementioned composite index. A subset of these proxies may include churn rates, employee health statistics, insurance policies, emission reductions, income statistics, energy access and water quality. SROs would contribute towards the United Nations' Sustainable Development Goals. Additionally, firm/industry drivers would assist in the formulation of panel data. These drivers may include return, growth, profitability and industry classification. Multiple techniques would evaluate how SRO's contribute to driving excess returns of an entity backed by PE. Modelling techniques may include cross-sectional, time-series regressions, probit regressions, dummy variables to control industry-specific outcomes, and private equity-related investment factors. A subset of these factors includes investment size, follow on investment, stage of investment, board influence, time horizon etc.). Comparisons between empirical findings and societal-related events, both before and after PE involvement, could validate the methods. **Central Hypothesis(es):** A range of conditional hypotheses capturing the effect of formulated SRO models. **Theoretical "Tension":** Draw on increasing research around multi-dimensional factors and corporate social responsibility driving returns.				
(F) Data	(1) **Country/Setting:** Global – Assess global investment activity to determine both global and localised insights. **Unit of Analysis:** Individual firms. **Sampling:** Annual. **Type:** Firm/industry specific (2) **Expected sample size:** >50,000 firms years. **Cross-sectionally:** Yes. **Time-series/longitudinal:** Yes. **Sample period:** 1950-2021; unbalanced panel data (3) **Data source(s):** Compustat/Capital IQ/Pitchbook/Preqin/ESG-MSCI ESG KLD STATS. Hand collection of data is not required. **Timeframe:** Some data available through Wharton Research Data Services (WRDS) and other related services so no lag or lead time. Others (Preqin/Pitchbook) require access and licensing. SRO related data might be difficult to obtain so assistance required. (4) **Data/observations**: No major issues, expected to work through missing observations, outliers, standard merging issues, data manipulation/cleansing etc. (5) **Adequate variation in test variables for power:** Quality data is expected.				
(G) Tools	**Basic empirical framework:** Regression model methodologies found in critical papers, approaches standard in literature (cross-sectional, time-series, probit etc.). **Required econometric software:** Python-SAS Hybrid/SAS/Stata – licenses held either at UoA or under academic initiatives, e.g. Oracle Virtual Box, SAS 9.4v via remote servers, Jupyter Notebooks. Panel data modelling, endogeneity and clustered-related errors expected to be faced and handled accordingly. **Statistical/econometrical implementation**: Standard using methodologies expressed in literature. Implementation issues addressed using alternative methods. **Data & framework compatibility:** Expected. Address abnormalities on an ad-hoc basis.				
Two	Two key questions				
(H) What's New	IDEA – Translate existing modelling methodology/design to a new application (SRO vs excess returns). IDEA drives the research, and data/tools are passengers: Global setting with over half a century of data is strong; existing model design/methodology using tools is strong.				
(I) So What	Reliable answers will inform the role SROs have in contributing to excess returns.				
One	One bottom line				
(J) Contribution	**Primary source of the contribution:** Assess the feasibility of private equity in driving socially responsible outcomes				
(K) Other Considerations	Assessment of collaboration necessity: - Idea: Not required - Data: Not required unless need access to inaccessible databases - Tools: Not required unless the need to address panel data and endogeneity issues arise **Target Journal(s):** Tier 1 Finance (Journal of Corporate Finance, Journal of Finance, Journal of Economics etc.). Feasible given key papers. **Assessment of Risks:** – **Results:** Moderate – complexity may lead to inconclusive results – **Competition:** Moderate – relevant area, likely other researchers are assessing the opportunity. – **Obsolesce:** Low – PE activity continues to grow, inform investment decisions/institutional behaviour – **Other Risks:** Moderate - Complexity and size may cause issues				

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Research Critique

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Contents

1 Abstract

This paper critically evaluates the journal article 'A bold move or biting off more than they can chew: examining small acquirers performance for quality and robustness. The critique reviews each section sequentially. Prior literature informs the research process. Several features reduce endogeneity while increasing the validity, verifiability, reliability, and replicability of the analysis: The data/data source(s); methodology investigating H_1 and H_2; econometric techniques; and methods associated with abnormal returns and ROA. It is possible to improve the article by addressing the criticisms around abnormal trading volumes, information environment and methodology exploring H_3 and H_4. Overall, the paper is of suitable quality and robustness.

2 Introduction

This paper critically reviews:

- Harp, N. L., Kim, K. H., & Oler, D. K. (2021). A bold move or biting off more than they can chew: examining the performance of small acquirers. Review of Quantitative Finance and Accounting, 56(2), 393–422.

The purpose of this review is to evaluate the quality and robustness of the article above critically, reviewing the article's design, methodology, and data issues in each section. This review critiques each section sequentially. This paper addresses strengths, weaknesses, reliability, validity, replicability, econometric techniques, and endogeneity concerns. The critique concludes with an overall opinion, summarizing key points and issuing a final verdict on the quality and robustness of the article.

3 Critique

3.1 Research Question

The Authors (Harp, Kim, and Oler, 2021) explore a research question residing in the broader literature associated with M&A acquisitions. Their research focuses on the size effect of a firm in acquisitions, determined by stock price performance, investigating the observations of more significant favourable announcement period and negative post-acquisition period returns to large acquirers. They seek to find explanations for the phenomena above but do not explicitly state their intentions as a question. The prior research on announcement period returns ((Moeller, Schlingemann, and Stulz, 2004) and (Jansen, Sanning, and Stuart, 2015)) is reputable, indicated from their publication in the Journal of Financial Economics. Other researchers cite the former article approximately 2800 times. Two research papers focusing on post-acquisition period returns are reputable given their publication in journals ((Loughran and Ritter, 2000) and (Oler, 2008)). The prior research informs a suitable research question to pursue. This article defines small acquirers as entities with a market capitalisation below the 25th percentile for all NYSE listed firms in the acquisition announcement year. They highlight other factors that may affect the acquisition success. Financing, limits to arbitrage, manager incompetency defined as 'hubris', synergistic acquisition drivers and illiquidity are some of these issues. The prior literature outlines the piece-wise nature of previous explanations. The authors' intentions to provide better reasons for the abnormal returns of small acquirers are validated. The subsequent exploration of the relationships between small acquirers and form of consideration, relative target size and diversification is appropriate.

3.2 Hypothesis Development

The authors propose four alternative hypotheses to explore their research question. We must highlight their conjecture on acquisition experience lacks evidence. Additionally, the authors do not state a null hypothesis (H_0) to find evidence against, deviating from statistical conventions. Their first hypothesis (H_1) does not link to the previous statements on surprise, experience, hubris and value destruction contributing to positive announcement period returns. There is a suggestion of fewer investors downloading 10-K reports after filings, implying a lack of focus on fundamentals (Loughran and McDonald, 2017). It is arguable analysts who cover small acquirers may receive firm fundamentals from other sources, e.g., Refinitiv Eiken - Thomas Reuters Datastream or Bloomberg. I would also assume firms on the NYSE would receive adequate coverage given the exchange's maturity. The statements about mispricing corrections are both valid and supported by research. Subsequently, H_2 investigating the negative association between small acquirers and post-acquisition returns is appropriate. The logic surrounding abnormal trading volume and short sales limits is consistent, aligning with (H_3). Entities partner with Investment Banks to facilitate deal origination and execution. These partners have significant deal experience. There needs to be more evidence surrounding how a relative lack of experience in the selection, valuation, and execution of acquisitions contributes to lower ROA in (H_4).

3.3 Data and Data Source(s)

The selection methods and applied constraints address endogeneity concerns. The Securities Data Corporation's (SDC) U.S Mergers and Acquisitions (M&A), CRSP/Compustat, and Wharton Research Data Services databases are trustworthy sources for both reliable M&A and financial-related information. The exclusions listed in the articles; and considerations around existing ownership, deal completion, deal size and acquirer public listing status; inform a comprehensive dataset for the analysis of the proposed hypotheses. The 22,664 observations over 32 years (January 1st 1984 - December 31st 2016), derived after implementing the processes above, are sufficient for statistical analysis. Additionally, the authors' dataset extends on prior research. However, there is no granularity on the geographies of the mergers and acquisitions, which may factor into acquisition success.

3.4 Methodological Approach & Econometric Techniques

3.4.1 Matching Process

The calculation of abnormal returns follows the same matching methodology as prior research. The formation of peer group portfolios considers size, industry and book-to-market ratios. Matches enable the formation of quintiles, grouped by industry. Same size quintiles and industry based on book-to-market ratios inform the selection of the closest matches. The use of GICS (or SIC if GICS is not available) codes is an excellent way to accurately group by industry. This matching process helps mitigate endogeneity issues and control for industry fixed effects.

3.4.2 Abnormal Returns Calculation

Abnormal returns, measured by buy-and-hold returns (BHR), is calculated using a conventional methodology to other event studies. The authors subtract the BHR of an acquirer from the average BHR for the acquirer's matching peer portfolio, implementing a control portfolio approach from the matching peer group. There is a BHR for three distinct periods; announcement period (-2 to +2 surrounding announcement date), interim (+3 relative to the announcement to the consummation date, missing when no time between announcement and consummation), and post-acquisition (+1 consummation date until 24 months later). This division is thorough, with the interim period included for completeness. The authors describe the mathematical expression of BHR_{Average} correctly as $\text{BHAR}_i = \prod_{t=s}^{e}(1+R_{i,t}) - \prod_{t=s}^{e}(1+R_{mp}) = \text{BHR}_{firm} - \text{BHR}_{mp}$, calculating the cumulative buy-and-hold abnormal returns for each of the three intervals under investigation. This approach is consistent with other event studies.

3.4.3 OLS Regressions

Ordinary least squares (OLS) regressions regress abnormal returns onto small acquirer dummy variables, interactions with the small acquirer dummies, three subset variables, and other control variables. The OLS regressions make suitable adjustments for heteroscedasticity. The acquirer's information environment is proxied using analyst coverage information from IBES summary files. There are issues with this method discussed in later sections.

3.4.4 Abnormal Trading Volumes

The authors use prior research to inform how to estimate abnormal trading volumes to investigate H_3. The measure estimates an abnormal trading volume percentage based on an average trading volume from a pre-announcement period, precisely between 51 to 100 day before announcement day. The recording of abnormal trading volumes occurs across 11 days (-5 to +5 of announcement day). Their summation forms a parsimonious measure while also investigating abnormal trading volumes among the three subsets mentioned above of small acquirers. This methodology for calculating abnormal trading volumes is not as robust or rigorous as abnormal returns. It does not find averages amongst the peer groups or make adjustments for any year fixed effects. There is no supporting explanation justifying the change in methodology either.

3.4.5 Return on Assets & Fundamental Performance

The fourth and final hypothesis investigates ROA (Net Income / Total Assets) as measuring fundamental performance at +1, +2, and +3 yearly intervals post consummation date. Abnormal ROA uses the same matching peer group methodology as abnormal returns, adjusting for industry fixed effects and endogeneity. Abnormal cash-on-cash returns provide an alternative measure of fundamental performance with Abnormal ROA three years before the consummation date used to control regressions.

3.4.6 Dummy and Control Variables

The small acquirer dummy variables, identified as the variable of interest (1 if acquirer in the 25th percentile of market capitalisation or less, 0 otherwise), is an appropriate variable of interest. Dummy variables control the size, acquisition considerations, diversification and private/public status factors. Additionally, the cash level preceding the acquisition is a variable. The insights from prior literature help include acquirer momentum, net operating assets, accruals and sales growth as variables. The logarithm of acquirer market capitalisation is a great approach to address the asymmetry in the spread of market capitalisations. Overall, the research design and variable definition are comprehensive. The matching process mitigates endogeneity as controls for all variables that vary between groups but are constant within groups by implementing various dummy variables. Accurate data sources and the inclusion of relevant variables minimise endogeneity. However, year fixed effects, e.g., the internet bubble, financial crisis etc. or regional effects, e.g., international or domestic impact, have not been controlled. The implementation of effects would improve the research design to address endogeneity further.

3.5 Research Conclusions

3.5.1 Descriptive Statistics

The authors display the dataset's descriptive statistics across four panels; the entire dataset, small acquirers, large acquirers, and univariate comparisons between small and large acquirers. Each panel displays the abnormal returns across the three periods (announcement, interim and post-acquisition), five dummy variables, pre-announcement acquirer cash level and prior consummated acquisitions. The dataset is suitable given that the summary statistics for each variable are very statistically significant (p-value of < 0.001) across all panels, except interim period announcement returns. There is no further investigation of interim period abnormal returns in the hypotheses, so this statistical significance does not matter. In summary, this dataset is appropriate for analysis.

3.5.2 Results, Findings & Evidence: No Interactions

The authors use multivariate analysis across three panels based on the announcement periods. In Panel A (announcement period), the small acquirer dummy is positive (0.017) and highly statistically significant across OLS and clustered p-values. However, only large target, public target and acquirer momentum make statistically significant contributions to abnormal returns. In panel C (post-acquisition), a small acquirer dummy makes a -0.052 contribution to abnormal returns in this period with p-values of 0.006 and 0.011 for OLS and Clustered, respectively. Additionally, stock consideration dummy, diversification dummy, acquirer momentum and acquirer NOA make statistically significant contributions to abnormal returns. In summary, there is reasonable evidence to support H_1.

3.5.3 Results, Findings & Evidence: Interactions

The introduction of interactions with stock considerations and large target dummy strengthens the argument for announcement period abnormal returns with more immense positive, statistically significant contributions to abnormal returns. The authors also find statistically significant explanatory power in the interactions between stock consideration and diversification, with a small acquirer dummy, to at least the 5% level. However, the introduction of interactions weakens either the magnitude or statistical significance of contributions by most other explanatory variables to post-acquisition abnormal returns. In summary, there is reasonable evidence to support H_2.

3.5.4 Results, Findings & Evidence: Information Environment

The authors provide statistically significant abnormal trading volume differences for small acquirers larger than large acquirers and between the panel subgroups. They also suggest the subcategories expressed in the panels experience higher abnormal returns in the announcement periods. The differences surrounding abnormal trading volumes have issues with calculating abnormal trading volumes and lack empirical analysis to find statistical evidence considering other factors (e.g., analyst coverage). Panels outlining subsets of small acquirers announcement returns, analyst coverage, logarithms of market capitalisations and announcement abnormal returns give comparisons. The use of multivariate analysis would help investigate and verify the differences associated with abnormal trading volumes. A small group of analyst could be more efficient in covering small acquirers. Further analysis would support how analyst coverage, abnormal trading volumes, and abnormal returns are related.

3.5.5 Results, Findings & Evidence: Fundamental Performance

The authors follow the same process by conducting univariate analysis for post-acquisition fundamental performance across six separate panels. There is no evidence of exploring statistical significance in panels A-E, a solid contrast to previous univariate analysis. Panel F investigates mean performance between three subgroups (small acquirer with stock consideration, large target, diversified) and small acquirers not included in the subset, essentially a control group. Every comparison is highly statistical significant comparison except two instances. There is no comparison between subgroups or combinations between subgroups. Abnormal ROA is tracked from years -3 to +4, as explained previously. The authors robustly test H_4 with multivariate analysis. This analysis is thorough as it finds statistically significant negative associations for abnormal ROA with small acquirer interaction terms with stock considerations and diversification. Most of the other variables are not statistically significant. However, without considering the interaction terms, including a moderate number of small acquirers, there is a positive correlation between abnormal ROA and small acquirers. The trends in abnormal ROA between small and large acquirers are comparable. Additionally, the authors repeated the analysis for abnormal ROA with operating cash flows scaled by assets and unadjusted ROA (or operating assets scaled by assets). Experiments related to cross border acquisitions and different definitions of diversification using Fama-French (1997) industry definition schemes (instead of 2-digit SIC codes) yield similar results, verifying robustness. However, the authors don't provide these results in the paper.

3.6 Author Issues

The authors do not explicitly raise or address issues associated with the design, methodology or data. However, they mostly follow conventions supporting empirical analysis.

3.7 Design, Methodology & Data Issues

3.7.1 Endogeneity

Previous sections outline discussions on how the methods address endogeneity.

3.7.2 Econometric

The primary econometric techniques utilised are peer-group matching processes, OLS regressions, correlation analysis including Spearman and Pearson's methods, interaction modelling and panel use. There is no discussion on the correlations analysis in this critique as the regressions explore these correlations in greater depth. Previous sections raise issues with these techniques.

3.7.3 Biases

The authors ensure reliability as they minimise researcher bias through their design, methods and data. The quantitative nature of this research does not create the need to control the level of bias experienced in more qualitative methods and experimental designs. The authors rely a lot on prior research, which may create bias in their process, preventing the exploration of other methods and may limit creativity.

4 Structure

The in-text citation style is inconsistent at the beginning of the article. One of two citation methods would be best, a full in-text citation in most instances e.g., (Harp et al., 2021) or cite the year e.g., Harp et al. (2021) in instances when explicitly mentioning authors.

5 Opinion

5.1 Compliments

The findings of this study are substantiated but not materially different from prior research. The authors pull insights from existing literature published in respected journals to inform their research. The variable of interest, the small acquirer dummy, is a suitable variable for investigating abnormal returns and abnormal ROA, providing construction validity. The accuracy of analysis and generalisability targeting small acquirers ensure both internal and external validity. The matching process to form peer groups, multivariate analysis modelling and isolation of dummy variables address endogeneity. The industry classification using SIC of GICS codes is a great way to form subsets. The announcement, interim and post-acquisition periods are well-defined. OLS regressions make adjustments for heteroscedasticity. ROA is a suitable measure of fundamental performance. The provision of alternatives validates their selection of ROA as a measure of fundamental performance. The utilization of commercial datasets ensures replicability on the NYSE, other US exchanges, e.g., Nasdaq or other Global Exchanges, e.g., FTSE.

5.2 Criticisms

The hypotheses do not follow conventions for statistical analysis, disproving a null hypothesis (H_0) favouring the alternatives. There are comments on the download history of 10-K filings being a proxy for analyzing fundamental performance. Other resources are well suited for analyzing fundamental performance. The methodology for abnormal trading volumes did not consider peer groups and was not as robust as abnormal returns or abnormal ROA. The variables don't adjust for year effects, e.g. The internet bubble, global financial crisis etc., that may affect acquisitions. Stocks trade at different frequencies 51 to 100 days before the announcement date for several reasons: exogenous events in that period specific to the stock; industry effects; and geography effects. The authors did not raise any of these concerns. The relationship with fundamental performance, abnormal trading volumes, information environment, and analyst coverage must be more robust through conducting more statistical tests and exploring multivariate methods. The assessment of abnormal ROA omits both measures to determine the statistical significance of mean performance in summary statistics and the results from alternative measures. There is no consideration of ROE in fundamental performance comparisons or explanation for the omission. The authors do not critique their analysis or identify their shortcomings. The in-text citation style is inconsistent at the beginning of the article.

5.3 Verdict

In summary, the research follows a due process of both good quality and robust nature. They contribute the findings of small acquirers, who either offer stock or diversification, generating negative post-acquisition returns and confirm previous results of the positive correlation of small acquirer status with announcement period abnormal returns. However, their findings are not a material departure from prior research. Their contributions to the relationship between the information environment, abnormal trading volumes and initial mispricing are plausible. More thorough statistical analysis using multivariate methods would strengthen these findings. Addressing the criticisms in further research would improve the robustness and quality of this research.

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Research Proposal: Data Science in Private Equity

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1 Abstract

This research proposal aims to validate and extend the contributions made by Block et al (2019). They identify seven investment criteria crucial for investment decision making in private equity. We explore if data science can improve screening efficiency in investment due diligence for private equity fund managers when assessing investment and exit opportunities. We propose forming numeral and categorical proxies for the investment criteria from private company data stored in PitchBook. Subsequently, we propose the implementation of the data science process proposed by Aurélien Géron (2017). We will train three supervised learning algorithms to make predictions on investment/exit opportunities. These models are Multi-nominal Logistic Regressions, Random Forests, Multi Layer Perceptrons (MLP). The proposed contributions aim to validate the investment criteria, validate the use of PitchBook for research purposes, and show evidence data science can inform investment due diligence and create efficiencies in screening for investments.

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2 Introduction

Private Equity (PE) is an alternative asset class with similar characteristics to hedge funds. Private equity funds are investment vehicles usually identified by four characteristics. Firstly, they are privately organized, pooling capital from several parties. Secondly, professional investment managers administer the fund. Their incentives are performance-based including compensation and significant carry in the fund. Thirdly, they are inaccessible to the public. Lastly, they operate externally to securities regulation and registration requirements. A private equity fund is managed by general partners (GP) who manage limited partners' (LP) investments in the fund. LPs make passive investments with little to no control in the fund's operations. Private equity funds typically charge a 2% annual fee and 20% performance fee on the fund's annual return. They raise capital through private offerings and pursue investment strategies in private markets based on the funds mandate to generate returns for investors (Brav, Jiang, Partnoy, and Thomas, 2008). Data science combines scientific methods, maths, statistics, specialized programming, advanced analytics, AI, and even storytelling to uncover and explain the business insights buried in data (IBM, 2021b). The number of data science applications are increasing in most industries but there is slow uptake in private equity. This creates opportunities to use emerging technologies to add value in operational and investment processes, exemplified through case studies featuring BCG (2019), Blackstone (2020) and the NZ Super Fund. Section 3 evaluates the prior literature related to private equity and decision processes by fund managers. Section 4 frames hypotheses to extend the contributions by Block et al (2019). In particular, this section explores if data science can improve screening efficiency in investment due diligence for private equity fund managers when assessing investment opportunities? Section 5 outlines the variables of interests with investment criteria and investment decision/exit opportunities, the dependent and independent variables respectively. Furthermore, explanations outline the derivation of investment criteria from the database PitchBook, limitations with the database, and contingency plans on the provision of poor quality data from PitchBook. Section 6 conveys how this research proposal will follow conventional data science processes proposed by Aurélien Géron (2017), and implement the three forms of supervised learning algorithms: Multi-nominal Logistic Regression, Random Forests, and Multi-Layer Perceptrons. Section 7 concludes with the key contributions and a few suggestions for future research.

3 Literature Review

Prior literature emphasizes generated returns, comparisons to public markets, and value created from private equity. The presence of cyclicality in PE returns differs according to fund type and is consistent with the conjecture that capital market segmentation contributes to private equity returns (Cavagnaro, Sensoy, Wang, and Weisbach, 2019). Institutional investors returns are not from chance alone, but skill leads to outperformance when selecting private equity investors (Ang, Chen, Goetzmann, and Phalippou, 2018). The adaptation of stochastic discount factor valuation methods to evaluate performance for venture capital generalized the Popular Market Equivalent (PME) method to reflect risk-free rates and public returns found abnormal performance (Korteweg and Nagel, 2016). Evidence of differences in skill and exit styles among venture partners investing at the same VC firm at the same time estimates human capital is two to five times more important than a VC firm's organizational capital in explaining performance (Ewens and Rhodes-Kropf, 2015). Classification of risks and post-investment actions inform agency and hold-up problems are important to contract design and monitoring (S. N. Kaplan and Strömberg, 2004). The analysis of firm and VC characteristics, in combination with value-increasing investments post-IPO for both VC's and underlying companies, is an efficient solution to information problems (Iliev and Lowry, 2020). Harris et al (2014) found buyout performance consistently exceeds the public markets (S&P 500) by 3% annually, calculated using the Burgiss data set. The performance in Cambridge Associates and Preqin datasets is qualitatively consistent with Burgiss but lower in Venture Economics. The determinant of leverage in buyouts is variation in economy-wide credit conditions. Higher deal leverage is associated with higher transaction prices and lower buyout fund returns. This suggests that acquirers overpay when access to credit is easier (Axelson, Jenkinson, Strömberg, and Weisbach, 2013). Investments in innovation, measured by patenting activity, informs one form of long-run activity. Based on 472 LBO transactions, there is no evidence that LBOs sacrifice long-term investments (Lerner, Sorensen, and Strömberg, 2011). Phalippou (2020) finds evidence private equity performance does not exceed public markets after considering carry and other factors. The above literature eludes to the presence of multiple factors and investment criteria when making investment decisions. Block et al (2019) explore investment criteria with an experimental conjoint analysis of private equity fund-types to inform how investments are made. There has been a comprehensive investigation on the effects of PE financing in corporate and entrepreneurial finance. Empirical analysis in precedent literature finds evidence of improvements to operating performance from PE investment (S. N. Kaplan and Stromberg, 2009) and public market outperformance ((Ang et al., 2018),(Braun, Jenkinson, and Stoff, 2017), (Harris, Jenkinson, and Kaplan, 2014), (S. N. Kaplan and Schoar, 2005), (S. N. Kaplan and Sensoy, 2015), (Phalippou and Gottschalg, 2009), (Robinson and Sensoy, 2013)). The exploration of PE investments across fund types and size yield consistent results ((S. Kaplan, 1989), (Chemmanur, Krishnan, and Nandy, 2011)). Selection and treatment effects ascribe to increased performance ((Bengtsson and Sensoy, 2011), (Bernstein, Giroud, and Townsend, 2016), (Rin, Hellmann, and Puri, 2013), (Puri and Zarutskie, 2012)). The active investment nature of PE enables portfolio companies the provision of value-added activities, either direct or indirect. Direct benefits include access to coaching or networks. Indirect benefits include certification effects to third parties ((Bottazzi, Da Rin, and Hellmann, 2008), (Gompers and Lerner, 2001), (Hellmann and Puri, 2002), (Korteweg and Sorensen, 2017), (Josh Lerner, 1995)). Portfolio company selection, and the capacity to add value through financial, governance and operational engineering, are the skillsets emphasized by PE investors. Contrary to the importance of investment selection, there is very little literature exploring investment selection and decision making by private equity managers. PE managers expend considerable resources in evaluating and screening investment opportunities ((S. N. Kaplan and Stromberg, 2001), (Gompers, Kaplan, and Mukharlyamov, 2016)). Their investment screening and selection process reviews many companies while only investing in a select few. Gompers et al (Gompers et al., 2016) reports for every hundred investment opportunities, the average PE investor conducts thorough due diligence on 15, enters agreements with eight, and eventually closes fewer than four. Empirical challenges associated with isolating the effect of different company characteristics contribute to the lack of empirical evidence surrounding investment criteria. Block et al (2019) are one of the first groups to investigate the investment criteria of PE investors, given decision making in PE is often debated ((Gompers and Lerner, 2001), (S. N. Kaplan and Strömberg, 2004)). The use of observational data is not feasible as observing investor preferences between two identical companies that vary in predetermined characteristics is not possible. Adopting similar methodologies to Bernstein et al (2017), Block et al (2019) compares decision making across different investor types using a large-scale conjoint analysis of 19,474 screening decisions by 749 PE investors through contacting 15,600 investment professionals listed in PitchBook. The conjoint analysis enables a more accurate representation of actual decision making as captures decisions making trade offs between criteria. Block et al (2019) required participants to make a series of assessments on a set of discrete company attributes. In particular, these attributes are: (1) profitability, (2) revenue growth, (3) track record of management team, (4) reputation of current investors, (5) business model, (6) value-added of product/service, and (7) international scalability. Every participant needed to evaluate multiple companies which differ only in the specifications of the above attributes and recommend investment decisions. A multi-level logistic regression model evaluated and compared the importance of different investment criteria, enabling criteria comparisons across investor types. Lerner et al (Josh Lerner, Schoar, and Wongsunwai, 2007) identifies there are likely differences in decision making between investor types with a broader perspective on investing behaviour underdeveloped (Hellmann, Schure, and Vo, 2013). Block et al (2019) investigates analysis with greater granularity to explore decisions by different investor types. In particular, investor types explored in this analysis are, (1) family offices, (2) business angels, (3) venture capital funds, (4) growth equity funds, and (5) leveraged buyout funds. Firstly, Block et al (2019) identify the relative importance of PE investors' investment criteria. In order of importance, revenue growth, value-added (product/service), and management team track record are the most important criteria. Internationally scalability, current profitability, business model, and reputation of existing investors are relevant but of lower importance. Secondly, Block et al (2019) compare the importance of the respective investment criteria across different investor types. They provide systematic empirical comparison methods of these differences and find family offices, growth equity funds and leveraged buyout funds prefer profitability over revenue growth. Venture capital funds and business angels prefer revenue growth over profitability. These findings imply discrepancies in the risk profiles between investor types. In the case of family offices, the results align with the objective of a family office to preserve wealth in order to maintain financial and social standing. The above literature informs the investment criteria to considered when evaluating investment decisions in PE.

4 Hypotheses Development

4.1 Research Question

This research proposal aims to extend the contributions from Block et al (2019). Gompers et al (Gompers et al., 2016) inform the closure of fewer than four out of hundred investment opportunities. The wrong investment decisions may have serious consequences for both fund returns and manager reputation. Kaplan et al (2001) and Gompers et al (2016) reiterate PE managers expend considerable resources evaluating and screening investment opportunities. Block et al (2019) identified several investment criteria integral to investment decisions: (1) profitability, (2) revenue growth, (3) track record of management team, (4) reputation of current investors, (5) business model, (6) value-added of product/service, and (7) international scalability. Data science can automate manual processes and make predictions considering complex interactions between numerical and categorical variables. Data science methodologies considering the variables proposed by Block et al (2019), after surveying PE managers and their risk profiles, may reduce screening time, reduce due diligence costs, and identify profitable investments aligning with investment mandates. Subsequently, this research proposal will explore:

Can data science improve screening efficiency in investment due diligence for private equity fund managers when assessing investment opportunities?

In layman's terms, improving screening efficiency relates to accurately predicting suitable companies to invest. This process supports company selection when using traditional screening processes and considers the investment criteria proposed by Block et al (2019). Depending on the success of screening models, these practices may replace existing screening methods, adding value to both investment due diligence processes and PE fund managers.

4.2 Hypotheses

The proposition of the below hypotheses aims to investigate the research question:

$$H_0 : \text{Data science models do not predict suitable investment targets.} \tag{1}$$

$$H_1 : \text{Data science models do predict suitable investment targets.} \tag{2}$$

Suitable investment targets are companies that either currently, or are predicted to, align with Block et al (2019). Data science methodologies will also test if the investment criteria proposed by Block et al (2019) after surveying PE managers identify suitable investment targets and/or if there are other unexplained contributing factors/interactions.

5 Data

5.1 Variables: Inputs

Block et al (2019) implemented a two-step process to evaluate the screening criteria. Firstly, prior research informs an investment criteria long-list ((Bernstein, Korteweg, and

Laws, 2017), (Franke, Gruber, Harhoff, and Henkel, 2008), (Puri and Zarutskie, 2012)). Secondly, Block et al (2019) conducted 19 expert interviews with PE investors across Europe and the US, identifying the most relevant criteria After their analysis, they discovered the relative importance of PE investors' investment criteria across multiple investor types. These criteria are, (1) profitability, (2) revenue growth, (3) track record of management team, (4) reputation of current investors, (5) business model, (6) value-added of product/service, and (7) international scalability. One must highlight the definition of business models comes from Amit et al (2001). Block et al (2019) outlined the attributes and attribute levels for the above investment criteria, used in the conjoint analysis, in figure 1. The following subsections include the descriptions of these attributes (figure 1). This proposition aims to explore these criteria paired with common financial, operational and categorical variables displayed in table 1.

5.1.1 Revenue Growth

Revenue growth describes the average yearly revenue growth over the last years. This is a categorical variable with four designations: 10% p.a., 20%p.a., 50%p.a., and 100%p.a. These growth rates will be considered over one, three and five year time periods, assigned to the closest category. Additionally, revenue growth will be included as a numerical variable for comparison purposes.

5.1.2 Value-added (Product/Service)

Value-added services (product/services) describes the value added to the customer from the product or service. Low value represents a marginal improvement (e.g., cost reduction or service quality), whereas high value represents significant improvements. This is a categorical variable with three designations: low, medium, and high. Value-added is a difficult variable to measure. However, using sentiment analysis with Natural Language Processing (IBM, 2021a) with non-financial data (e.g. social media mentions, web traffic, news features and reviews) would enable the categorization of value-added services.

5.1.3 Management Team Track Record

Management team track record describes whether the management team has a relevant track record (e.g. industry and leadership experience). This is a categorical variable with three designations: none of them, some of them, all of them. Multi-nominal logistic regression will consider executive experience and education to create the above categorical variables (Edgar and Manz, 2017).

5.1.4 International Scalability

International scalability describes the difficulty of scaling internationally, in terms of the time and investments needed. This is a categorical variable with three designations: easy, medium and difficult. Multi-nominal logistic regression will consider various features (e.g., industry classification, committed capital, market presence, years since founding etc.) to create the required categorical variables (Edgar and Manz, 2017).

5.1.5 Profitability

Profitability describes the current profitability of the company, a categorical variable with three designations: not profitable, breakeven, and profitable. Multi-nominal logistic regressions will consider the following financial values to form the above categorical variables: Earnings Before Interest, Tax, Depreciation and Amortization (EBITDA); Earnings Before Interest and Tax(EBIT); Net Operating Performance After Tax (NOPAT); Return on Assets (ROA); and Return on Equity (ROE). Additionally, EBIT, EBITDA, NOPAT, ROA, and ROE will be included as numerical variables for comparison.

5.1.6 Business Model

Business model describes the key focus of the company based on prior research (Amit and Zott, 2001) pertaining to four designations: (1) Lock-in, (2) Innovation-centered, (3) Low cost, and (4) Complimentary. The Lock-in model keeps customers attracted and 'locked in', having high switching costs for customers, which prevent them from changing to other providers. The Innovation-centered model offers innovation in the form of new technology, products or services. The Low cost model focusses on reducing costs for customers for already existing products or services. The Complimentary model bundles multiple goods and services to generate more value for customers. This is also a difficult variable to derive. Business descriptions would be input into the text classification functionalities in Natural Language Processing (IBM, 2021a) to categorize models designations. This will be difficult.

5.1.7 Current Investors

Current investors describes the types of investors, if any. This is a categorical variable with three designations: no other current external investors, other current external investors - unfamiliar, and other current external investor - Tier 1. Tier 1 investors are reputable investors. Investor relationships can be modelled using the mathematics behind graph theory and network analysis from geographical applications ((Curtin, 2018), (Faudree, 2003)). Modelling the strength in investor relationships and investment history, in combination with multi-nominal logistic regression analysis, will categorize the necessary designations. However, this will also be difficult.

5.1.8 Year

The consideration of a yearly designation (e.g., 2016, 2017 etc.) related to the collection of investment criteria proposed by Block et al (2019) will inform time-series analysis.

5.2 Variable: Output(s)

Block et al (2019) explored the importance of investment criteria through multi-level logistic regressions models. The investment decision is binary: 0 if no investment, 1 if investment. Multi-level logistic regressions account for both nested investment decisions and multi-level effects. This proposal will explore a similar outcome of an investment decision (0 if no investment, 1 if investment). Additionally, the exploration of three exit outcomes based on investment criteria will contribute to the validation of an investment target. These outcomes are, (1) IPO, (2) Acquisition, and (3) Bankruptcy/failure. In lyman's terms, identify the likely exit outcomes and suitable time to exit a company for a PE manager. Ross et al (2021) explore this phenomena with models trained on a different set of features using a different dataset (Crunchbase, 2021). The inclusion of the desired outcomes in the datasets enables the most appropriate algorithms for this proposal (Section 6.5). It must be highlighted their findings are not published in top ranked journal, they don't consider key financial or operation variables in their feature selection, and lacks rigorous comparisons to traditional empirical methods (e.g., logistic regressions) to cross-validate results. It is poor quality research. This research proposal will explore the above exit outcomes using investment criteria considered by PE investors and cross-validate results with logistic regressions where possible.

5.3 Sources

5.3.1 PitchBook

PitchBook is financial data and software company that provides thousands of professional's comprehensive data on private and public market information (PitchBook, 2021). Block et al (2019) identifies PitchBook as one of the most comprehensive databases in entrepreneurial finance, regularly used for PE related research ((S. N. Kaplan and Lerner, 2016),(Paglia and Harjoto, 2014)). Disclosed information from limited partners, filings of national regulators and other available information are the main contributors to the database. PitchBook has advantages over alternative databases as reports information on investment teams and contact details in addition to information on the investment entity (Brown, Harris, Jenkinson, Kaplan, and Robinson, 2015). The database records comprehensive data on companies, investors, deals, M&A, LPs, funds, financials, advisors, professionals, debt & lenders. In particular:

- Companies of various designations (Publicly traded, Pre-IPO, PE-backed, Startups/Stealth etc.)
- Deal information (Bankruptcies, IPOs, PIPEs, LBO, VC Investments etc.)
- Financial information (calculation transparency, balance sheets, cash flow state-

ments, income statements, consensus information, deal multiples, financial ratios, fundamentals etc.)

Data, both time-series and cross-sectional, is accessible using application programming interfaces (API) or direct downloads to excel formats (e.g., xlsx etc.) Industry widely adopt the platform as the product has high levels of granularity for data science applications. PitchBook continues to grow as industry and PitchBook employees continue to contribute to the platform. An itemized illustration, of the size and scope of available data, as at 03/06/2021 follows:

1. **Deals**: 1,540,549 deals with 45 deals types, evaluate deal histories, get key information and deal multiples, access pre and post money valuations, explore series terms and stock information.
2. **Companies**: 3,096,933 (private), 58,362 (public), get key information, explore financing history, evaluate financials and filings, view executives and board members, follow non-financial metrics.
3. **Financials**: Financials and estimates summary, analyse key metrics, explore balance sheets, income statements, cash flows, ratios & multiples.

PitchBook is an appropriate data source as Block et al (2019) surveyed investors from this database, and it provides all the information required to derive the set of variables described in Section 5.1.

5.4 Limitations: PitchBook

The main contributors to PitchBook are disclosed information from limited partners, filings from national regulators and other publicly available information. Additionally, there is self-selection bias as private companies elect to disclose information-related to their companies. This research proposal is unable to provide descriptive statistics on the data available from PitchBook as requires a service subscription. The derivation of Business Model and Value-added categorical variables will be difficult as require an implementation of a complex algorithm. However, it is feasible. The aforementioned limitations may create poor quality datasets when taking global perspectives. This research proposal will focus on the North American market in an attempt to minimize data issues as data pertaining to this market is the most complete. If the data is unsuitable for analysis after these considerations, we will explore the alternative datasets and sources in Section 5.5.

5.5 Alternative Data Sources

The consideration of alternative data sources will form contingency plans if data issues persist with PitchBook. A consortium of databases is necessary to construct the variables of interest described in MergerMarket (2021) and CB Insights (2021) have a comprehensive M&A database on relevant deals. Crunchbase (2021) contain investment professional, identification and non-financial information on early stage companies. Preqin (2021) includes comprehensive information on PE managers. In addition to the above databases, liaising and partnering with local and global PE managers may help source the required data to create variables. However, PitchBook is more comprehensive than the consortium of alternatives as contains all the required information for investment criteria variable construction. The research proposal may be put on hold until better quality data comes to market on the basis both PitchBook and the consortium of alternatives fail to provide the required data.

6 Methodology

The research methodology will follow the conventional data science process proposed by Aurélien Géron (2017). This process is: (1) Get the "Big picture". (2) Get the Data. (3) Discovery & Visualization. (4) Data Preparation. (5) Model Selection & Training. (6) Model Tuning. (7) Presentation. (8) Launch, Monitor, and Maintain System (Omitted). We explore each step sequentially from Section 6.1 to Section 6.7. and highlight the mathematics pertaining to the methodology is listed in the Appendix (Section 8.1).

6.1 Problem Scoping

6.1.1 Problem Framing

Problem scoping involves three processes: framing the problem, selecting performance measures, and checking data assumptions. Sections 2, 3 and 4 frame the objective of this research proposal. Currently no other solutions or prior literature on using the investment criteria proposed by Block et al (2019) exist to train data science models with the objective of informing and increasing the efficiency of investment screening and selection for PE fund managers.

6.1.2 Performance Measure Selection

Performance measures evaluate the accuracy of machine learning models to validate predictions. The computation of Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) will inform predictability. Both are cost functions and measure the distance between vectors. RMSE calculates the standard deviation of errors between the observed values ($y^{(i)}$) and values predicted by the model ($h(\mathbf{x}^{(i)})$. This performance measure is the preferred the algorithms discussed in Section 6.5. The number of instances in the dataset (m) is comparable to a datapoint with combinations of time-series and cross-sectional data in conventional empirical datasets. $\mathbf{x}^{(i)}$) is a vector of all feature values for the ith instance. In layman's terms, the investment criteria (feature values) are described in Section 5 for the ith company (instance).

6.1.3 Checking Data Assumptions

This research proposal builds on the investigation Block et al (2019). The numerical and categorical variables suggested in 5 are appropriate. The outcomes of this research will inform an end-to-end methodology that do not rely on other systems or processes. Addressing the data limitations in Section 5 enable the implementation of this research proposal.

6.2 Data Acquisition

Firstly, there will be an initialization of a research workspace using the technologies itemized in the Appendix (8.2) and best practise proposed by Wilson et al (2016). The workspace enables a Python implementation, distributed by Anaconda, using several core modules: Numpy, Pandas, Matplotlib, Scikit-learn, and Tensorflow. Microsoft Visual Code (IDE), complete with Git functionalities, will facilitate software development. The hardware in use will be a MacBook Pro (2019) with macOS Mojave as the chosen operating system. The use of IBM Watson and AWS technologies depends on hardware capabilities and the computational complexity of this methodology. PitchBook, a subscription-based product, will provide the raw data pertaining to private companies. Subsequently, collaboration with subscription holders is necessary. A screening for US companies sorts US company-related information into one data source. This sheet contains the relevant information to derive the required numerical and categorical investment criteria. Downloading the results from the screening grants access to the data. This is the matrix for feature values for all instances. PitchBook grows iteratively as there are over 3 million private companies registered on the database. It is important to automate a data pipeline to retrain models and provide up to date information. This will be accomplished through controlling PitchBook's excel application programming interface (API) with a custom python module. If the above data limitations related to PitchBook persist, industry collaboration enables the access to relevant data from their internal and external sources. Additionally, the division of the feature matrix ($\mathbf{X}$) into three sets is necessary to mitigate bias in both model selection and data snooping. Random sampling will form three subsets: training, validation and testing respectively.

6.3 Discovery & Visualization

Following on from data acquisition, it is important to get a general understanding of the data prior to manipulation and preparation. Exploratory analysis will take place on the training set investigating a number of features pertaining to the dataset. This analysis will explore geographical visualizations per US State to show concentrations of private entities, correlations between numerical and categorical variables pertaining to unprocessed investment criteria and explore the correlations between combinations of numerical and categorical variables.

6.4 Data Preparation

A series of transformation functions will be written for reproducibility on updated datasets and test variation in data transformations. This will take the form of a transformation pipeline to apply to the training set feature matrix (**X**). The pipeline will first incorporate cleansing functionalities to: remove missing variables, isolate the required variables in the feature matrix in order to derive investment criteria in Section 5, Numerical revenue and profitability values are converted to the designated categorical investment criteria proposed by Block et al (2019). Value-added (Product/Service) and Business Model categorical variables will require Natural Language Processing techniques to derive the attribute levels within these investment criteria. The use of sentiment analysis with non-financial data (Section 5) using Tensorflow's Word2Vec & Seq2Seq tutorials will derive Value-added (Product/Services) categories. The use of NLP's text classification functionalities with company descriptions (Section 5) will categorize business models. Variations in generalized multi-level logistic regressions (Section **??**) using the relevant data to the desired investment criteria (Section 5) will categorize the variables needed for International Scalability, Management Team Track Record and Current Investors investment criteria. The categorization of desired outcomes (outputs) for screening processes (investments and exits) will be binary (1 for each of a present outcome (investment, IPO, acquisition, bankruptcy/failure), 0 otherwise). After, missing variables will be filled with median values on a case-by-case basis in order to include critical instances. Thirdly, the transformation pipeline will convert text and categorical attributes to numerical values stored as SCiPy sparse matrices using scikit-learn's OneHotEncoder function. Lastly, the transformation pipeline will implement feature scaling to rescale all input attributes to the same scale using scikit-learn's StandardScaler function. Standardization subtracts the mean value and divides by the variance so the resulting distribution has unit variance. This procedure does not bound values to a specific range (unlike normalization) but is much less affected by outliers. Rescaling is required to optimize algorithm performance.

6.5 Model Selection & Training

Data preparation is the most difficult section of the methodology. Methods become elementary (my dear Watson) after data preparation. Machine learning methods have a reputation for being 'blackboxes' with decision making opaque to users. This generally creates adoption issues which may extend to PE managers given the lack of understanding in how the algorithms function. Subsequently, this research proposal suggests three supervised learning, model-based methodologies: (1) Multi-nominal Logistic Regression, (2) Random Forests, and (3) Multi Layer Perceptrons (MLP). Supervised machine learning algorithms include desired outcomes (labels) in the training sets and are the most transparent to PE managers e.g., these investment criteria contribute to this investment or exit decision. These models enable predictions across both time-series and cross-sectional contexts. These algorithm require nested mathematical functions. We include their expression in the Appendix (8.1).

6.5.1 Multi-nominal Logistic Regression (Softmax Regression)

?? Logistic regression estimates the probability that an instance belongs to a particular class. This research proposal will consider the investment criteria of each instance to determine the probability of investment and exit outcomes. The use of this algorithm is intuitive as enables cross-validation with the logistic regressions performed by Block et al (2019). This proposal suggests using two multi-nominal logistic regression, generalizations to support one investment decision and three exit outcomes respectively. This algorithm computes a score, then estimates the probability of each class by applying the normalised exponential. After calculating the scores for every class for the instance $\mathbf{x}$, the probability $\hat{p}_k$ that the instance belongs to class k is calculated by running the scores through a softmax function. This function computes the exponential of every score then normalizes them. The softmax regression classifier predicts the class with the highest estimate probability. The models aims to estimate a high probability for the target class (and low probabilities for the other classes) through the minimization of a cross entropy cost function. The computation of a gradient vector from the cross entropy cost function enables optimisation techniques, in this instance gradient descent, to find the parameter matrix Θ that minimizes the cost function. Therefore the investment or exit decision. Sckit-learn's LogisticRegression function applies this algorithm with the equation pertaining to the method in the Appendix ().

6.5.2 Random Forests

The second algorithm is a Random Forest, an ensemble of decision trees. Decision trees are an algorithm suitable for classification tasks. They make predictions based on a branching structure and are relatively simple. This research proposal suggests decision trees can estimate the probability an instance (company) belongs to a particular investment decision or exit opportunity. Estimation starts at the root node. Each node explores two outcomes e.g., revenue growth is less than 20% p.a. or 20% and greater. The algorithm will divide the training instances based on the binary criteria. A node will have three attributes: (1) samples, (2) value, and (3) gini. Sample counts how many instances the node applies to e.g, 100,000 companies. Value informs the number of instances per class applies to the node e.g, 40,000 invested, 60,000 not invested. Gini is an impurity measure with purity (gini = 0) representing all training instances it applies to belong to the same class. There are two forms of impurity measure: gini and entropy. Decisions at nodes form boundaries, forming partitions of instance groupings. Decision trees can continue to form new nodes based investment criteria until it settles on the max depth or each leaf node is 'pure'. Subsequently, a decision tree can estimate the probability that an instance belongs to an investment decision or exit opportunity. Firstly, it traverses the tree to find the leaf node for this instance, then returns the ratio of training instances of class k in this node. Requesting a prediction will return the class with the highest probability at this node. The Classification And Regression Training (CART) algorithm trains the decision trees. Firstly, it splits the training set in two subsets using a single feature k and threshold t_k, searching for the pair producing the purest subsets (weighted by their size). This process is recursive until either the user-defined max depth is reached or there are no further splits that will reduce impurity. The 'optimal solution' is difficult to find as the optimal tree is a NP-Complete problem, requiring O(exp(m)) time causing intractability for fairly small trees. Gini impurity measures leads to faster computations but entropy measures tend to produce more balanced tree. Random forests are ensembles of decisions trees, combining combinations of decision trees trained using the same training algorithms with varying subsets of the training data. This process forms a diverse set of classifiers with predictions, when aggregated, This proposal suggests using Scikit-learn's RandomForestClassifier to implement ensembles of decisions trees, applying the above process, to compute the equations in the Appendix (8.1.4). Random forests are the most appropriate for PE-related decision making as they are the most intuitive and transparent of the three proposed supervised machine learning algorithms.

6.5.3 Multi Layer Perceptron (MLP)

Artificial Neural Nets (ANN) are versatile, powerful, and scalable. They sit at the heart of deep learning as frequently outperform other machine learning algorithms on large and complex problems. This research proposal suggests implementing two sets of multi-layer perceptron, a form of ANN, to predict investment decisions and exit opportunities from investment criteria. A linear threshold unit (LTU) feeds the weighted sum of input values ($z = \mathbf{w}^T \cdot \mathbf{x}$) into a step function ($h_w(\mathbf{x}) = step(z)$). A perceptron is a single layer of LTUs where each LTU is connected to every input. Perceptrons are suitable for classification as output the positive investment decision or exit opportunity if a threshold is met. Perceptrons utilize a training algorithm assessing the strength of connections between perceptrons while considering errors. A perceptron is fed one training instance at a time, making predictions for each instance. For every output LTU that produced a wrong prediction, it re-enforces the connection weights using the perception learning rule (Appendix (8.1.5)) from the inputs that would have contributed to the right prediction. A Multi Layer Perceptron is composed of one LTU input layer, multiple LTU hidden layers and an output LTU layer. The step functions in each LTU are replaced by a logistic or ReLU function ($\sigma(z) = \frac{1}{1+exp(-z)}$ or $ReLU(z) = max(0, z)$ respectively) to enable gradient descent for optimisation. A shared softmax function replaces the individual activation functions in the output layer to enable exclusive classification. In this instance, the classification of investment decisions, or exit opportunties, from investment criteria. Tensorflow's DNNClassifier function facilitates the implementation of MLPs in this proposal.

6.5.4 Evaluation

This proposal will utilise performance measures outlined in Section 6.1.2 and cross-validation techniques with validation sets to inform the prediction proposed models. Transparency decreases and complexity increases with Random Forests, Multi-nominal Logistic Regression and Multi Layer Perceptrons (MLP) respectively.

6.6 Model Tuning

Each model has a set of hyper parameters integral to performance. This proposal will conduct grid search, randomized search, error analysis and evaluations using test sets to find the best combination of hyper parameters to optimise model performance.

6.7 Solution Presentation

This research proposal will inform the feasibility of data science applications in private equity to assist with investment screening due diligence. The above methodology will be converted to a custom python package distributed on the open-source Python Package Index (2021) containing source code, package documentation, this research proposal, accompanying dissertation and technical guides to inform proposed algorithms. Lastly, demonstrations will be made to private equity managers.

7 Conclusions

7.1 Contributions

This proposal is a very difficult to implement but has the potential to add tremendous value to investment screening and due diligence. There are three key contributions in this research proposal: Firstly, this proposal aims to validate the investment decision criteria proposed by surveyed PE managers gathered by Block et al (2019). Secondly, support arguments on PitchBook being a suitable database for future empirical research, especially with intersections between data science and private equity. Lastly, provide evidence to PE managers data science can inform investment due diligence and create efficiencies in screening for investments.

7.2 Future Research

There are several new avenues for research depending on a successive outcome(s) from this proposal. Firstly, this proposal only considers relative performance of investment criteria from the perspective of the average PE investor. Further research could explore the segmentation of PE investor types (family office, business angel, venture capital, growth equity, leveraged buyout). Lastly, this proposal could explore the implications of screening different industry segmentations and their alignment with different fund mandates.

7.3 Research Timetable

The implementation of this proposal will take place over a 14 week window, starting the July 19th 2021 and ending October 22nd 2021. The timetable in 2 in the Appendix (8.5) outlines the time taken to implement each step of the methodology outlined in Section 6. Additionally, the research timetable includes expectations on time commitments to report writing, reviewing, editing and meetings with supervisors.

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8 Appendix

8.1 Mathematics

This subsection informs the mathematical expressions pertaining to data preparation and algorithm implementation.

8.1.1 Performance Measures

Root Mean Square Error

$$RMSE(\mathbf{X}, h) = \sqrt{\frac{1}{m}\sum_{i=1}^{m}(h(\mathbf{x}^{(i)}) - y^{(i)})^2} \tag{3}$$

$$\tag{4}$$

Mean Absolute Error

$$MAE(\mathbf{X}, h) = \frac{1}{m}\sum_{i=1}^{m}|(h(\mathbf{x}^{(i)}) - y^{(i)})| \tag{5}$$

$\mathbf{X}$ is a matrix containing all feature values, of all instances, from the dataset.

8.1.2 Multi-level Logistic Regression

Generalised Multi-level Logistic Regression

$$ln(\frac{\hat{p}}{1-\hat{p}}) = \beta \cdot X + \mathcal{E} \tag{6}$$

- $\hat{p}$: The expected probability that the outcome is present.
- β: The vector of co-efficient related to sensitivities
- X: The vector of distinct independent variables.
- $\mathcal{E}$: The vector of error terms.

8.1.3 Multi-nominal Logistic Regression (Softmax Regression)

Softmax Score for Class K

$$s_k(\mathbf{x}) = \theta_k^T \cdot \mathbf{x} \tag{7}$$

$$\tag{8}$$

Softmax Function

$$\hat{p}_k = \frac{exp(s_k(\mathbf{x}))}{\sum_{j=1}^{K} exp(s_k(\mathbf{x}))} \tag{9}$$

$$\tag{10}$$

Softmax Regression Classifier Prediction

$$\hat{y}_{\cdot()} = \text{argmax}_k \ \sigma(s_k(\mathbf{x})) = \text{argmax}_k \ \sigma(\theta_k^T \cdot \mathbf{x}) \tag{11}$$

$$\tag{12}$$

Cross Entrophy Cost Function

$$J(\Theta) = -\frac{1}{m} \sum_{i=1}^{m} \sum_{k=1}^{K} y_k^{(i)} log(\hat{p}_k^{(i)}) \tag{13}$$

$$\tag{14}$$

Cross Entropy Gradient Vector for Class K

$$\nabla_{\theta_k} J(\Theta) = \frac{1}{m} \sum_{i=1}^{m} (\hat{p}_k^{(i)} - y_k^{(i)}) \mathbf{x}^{(i)} \tag{15}$$

$$\tag{16}$$

There are two sets of classes: k_1 ϵ{Investment (1,0)} and k_2 ϵ{IPO, Acquistion, Bankrutpcy (1,0)}. $s_k(\mathbf{x})$ is the score for each class k. $\hat{p}_k$ that the instance belongs to class k. θ_k is the parameter vector for class k. Θ is the parameter matrix containing all parameter vectors.

K is the number of classes. $s(\mathbf{x})$ is the vector containing all scores of each class for the instance $\mathbf{x}$. $\sigma(s(\mathbf{x}))_k$ is the estimated probability probability that the instance $\mathbf{x}$ belongs to class k given the scores of each class for that class. Argmax$_k$ returns the value of k that maximises the estimated probability of $\sigma(s(\mathbf{x}))_k$. $y_k^{(i)} = 1$ if the target class for the ith instance is k, 0 otherwise.

8.1.4 Random Forests

Gini Impurity

$$G_i = 1 - \sum_{k=1}^{n} p_{i,k}^2 \tag{17}$$

$$\tag{18}$$

Entropy

$$H_i = 1 - \sum_{k=1, P_{i,k} \neq 0}^{n} p_{i,k} log(p_{i,k}) \tag{19}$$

$$\tag{20}$$

CART Cost Function (Gini)

$$J(k, t_k) = \frac{m_{left}}{m} G_{left} + \frac{m_{right}}{m} G_{right} \tag{21}$$

$$\tag{22}$$

CART Cost Function (Entropy)

$$J(k, t_k) = \frac{m_{left}}{m} H_{left} + \frac{m_{right}}{m} H_{right} \tag{23}$$

$$\tag{24}$$

Variables

- $p_{i,k}$ is the ratio of class k instances among the training instances in the i^{th} node.

- $G/H_{left/right}$ measures the impurity of the left.right subset using gini or entropy measure respectively.
- $m_{left/right}$ is the number of instances in the left/right subset.

8.1.5 Multi Layer Perceptron (MLP)

Perceptron Learning Rule

$$w_{i,j}^{\text{next step}} = w_{i,j} + \eta(\hat{y}_j - y_j)x_i \tag{25}$$

Variables

- $w_{i,j}$ is the connection weights between the ith input neuron and the jth output neuron.
- x_i is the ith input value of the current training instance.
- $\hat{y}_j$ is the output of the jth output neuron for the current training instance.
- y_j is the output of the jth output neuron for the current training instance.
- η is the rate.

8.2 Technology

The subsequent technologies enable the creation a project workspace and the implementation of the research methodology.

- Python: open-source, interpreted programming language
  - **Numpy**: large, multi-dimensional arrays and matrices, along with a large collection of high-level mathematical functions to operate on these arrays.
  - **Pandas**: data analysis and manipulation functionalities.
  - **Scikit-Learn**: software machine learning library for the Python programming language.

  - **TensorFlow**: open-source software library for machine learning with a focus on training and inference of deep neural nets.
  - **Matplotlib**: plotting functionalities ported from MatLab.
  - Additional libraries when required.
- **Anaconda**: distribution service of the Python and R programming languages
- **macOS Mojave (OS)**: operating system.
- **MacBook Pro 2019**: hardware.
  - 13inch
  - 1.4 GHz Intel Core i5
  - 8 GB 2133 MHz LPDDR3
- **Microsoft Visual Studio Code**: integrated programming environment (IDE).
- **Git & GitHub**: version control.
- **IBM Watson**: suite of AI-related products and functionalities
- **Amazon Web Services**: provides cloud computing technologies, platforms and APIs.

8.3 Case Studies

A couple of case studies inform the the practicality of data science in PE. BCG (2019) published analysis on creating value in Private Equity with Advanced Data and Analytics, providing three key examples: geo-analytics, predictive maintenance, and workforce optimisation. Geo-analytics identifies profitable locations for vending machines. Predictive maintenance prioritizes repairing machines with higher failure risks to mitigate repair and replacement costs. Workforce optimisation matches the skillsets of technicians with customer requirements. Blackstone employ data scientists to inform both portfolio operations and investment practices. The buyout fund has the unique ability to sell data of portfolio companies and create value for the owner (Bloomberg, 2020). From an investing perspective, NZ Super Fund are exploring data science applications in equities selection methods to compare against traditionally equity selection processes. The comments on BCG and Blackstone inform operational applications of data science while the comments on NZ Super Fund inform investment applications. These case studies frame inform applications on how data science can add value to PE.

8.4 Investor Criteria, Attributes & Variables

Table 6
Attributes and attribute levels used in our conjoint analysis.
This table describes and defines the attributes and attribute levels presented to participants in our conjoint analysis. We use a choice-based-conjoint (CBC) analysis, in which the participants are presented with investment opportunities and are asked to select the one company that better matches their preferences. The two companies are only described in terms of the attributes displayed in this table ("attributes") and only differ from each other in the respective specification of these criteria ("attribute levels").

Attribute	Attribute levels	Attribute description
(1) Profitability (3 levels, ordinal)	1. *Not profitable* 2. *Break-even* 3. *Profitable*	Describes the current profitability of the company.
(2) Revenue growth (4 levels, ordinal)	1. *10% p.a.* 2. *20% p.a.* 3. *50% p.a.* 4. *100% p.a.*	Represents the company's average yearly revenue growth rate over the last years.
(3) Track record management team (3 levels, ordinal)	1. *None of them* 2. *Some of them* 3. *All of them*	Describes whether the management team has a relevant track record (e.g., industry experience or leadership experience).
(4) Current investors (3 levels, nominal)	1. *No other current external investors* 2. *Other current external investor - Unfamiliar* 3. *Other current external investor - Tier 1*	Describes the type of current investor, if any.
(5) Business model (4 levels, nominal)	1. *Lock-in* 2. *Innovation-centered* 3. *Low cost* 4. *Complementary offering*	Describes the key focus of the business model of the company: 1. Lock-in: Business model that keeps customers attracted and "locked-in", having high switching costs for customers, which prevent them from changing to other providers. 2. Innovation-centered: Business model that offers innovation in the form of new technology, products or services. 3. Low cost: Business model focusing on reducing costs for customers for already existing products or services. 4. Complementary offering: Business model that bundles multiple goods or services to generate more value for customers.
(6) Value-added of product/ service (3 levels, ordinal)	1. *Low* 2. *Medium* 3. *High*	Describes the value added for the customer through the product or service. Low value-added represents a marginal improvement (e.g., in cost-reduction or service quality), whereas high value-added represents significant improvements.
(7) International scalability (3 levels, ordinal)	1. *Easy* 2. *Moderate* 3. *Difficult*	Describes the difficulty of scaling the company internationally, in terms of the time and investment needed.

Figure 1: Investment criteria and attributes from Block et al (2019)

Criteria	Relative Importance (Attributes,%)	Rank (#)	Variables
Revenue Growth	23.4	1	Revenue Growth (t-1, t-3, t-5) 10%, 20%, 50%, 100% (p.a)
Value-added (Product/Service)	20.4	2	Low (1), Med (2), High (3)
Management Team Track Record	15.7	3	None (1), Some (2) , All (3)
International Scalability	13.0	4	Easy (1), Moderate (2), Difficult (3)
Profitability	11.8	5	EBITDA, EBIT, NOPAT, ROA, ROE ($) Not profitable (1), Breakeven (2), Profitable (3)
Business Model	8.3	6	Lock in (1), Innovation-centered (2), Low Cost (3), Complimentary Offering (4)
Current Investors	7.3	7	No Other Current External Investors (1), Other Current Investors - Unfamiliar (2) Other Current Investors - Tier 1 (3)

Table 1: Variables mapping investment criteria

8.5 Research Timetable

This section of the appendix displays the proposed timeline for the research proposal. The timetable displays the implementation of the proposal's methodology through time.

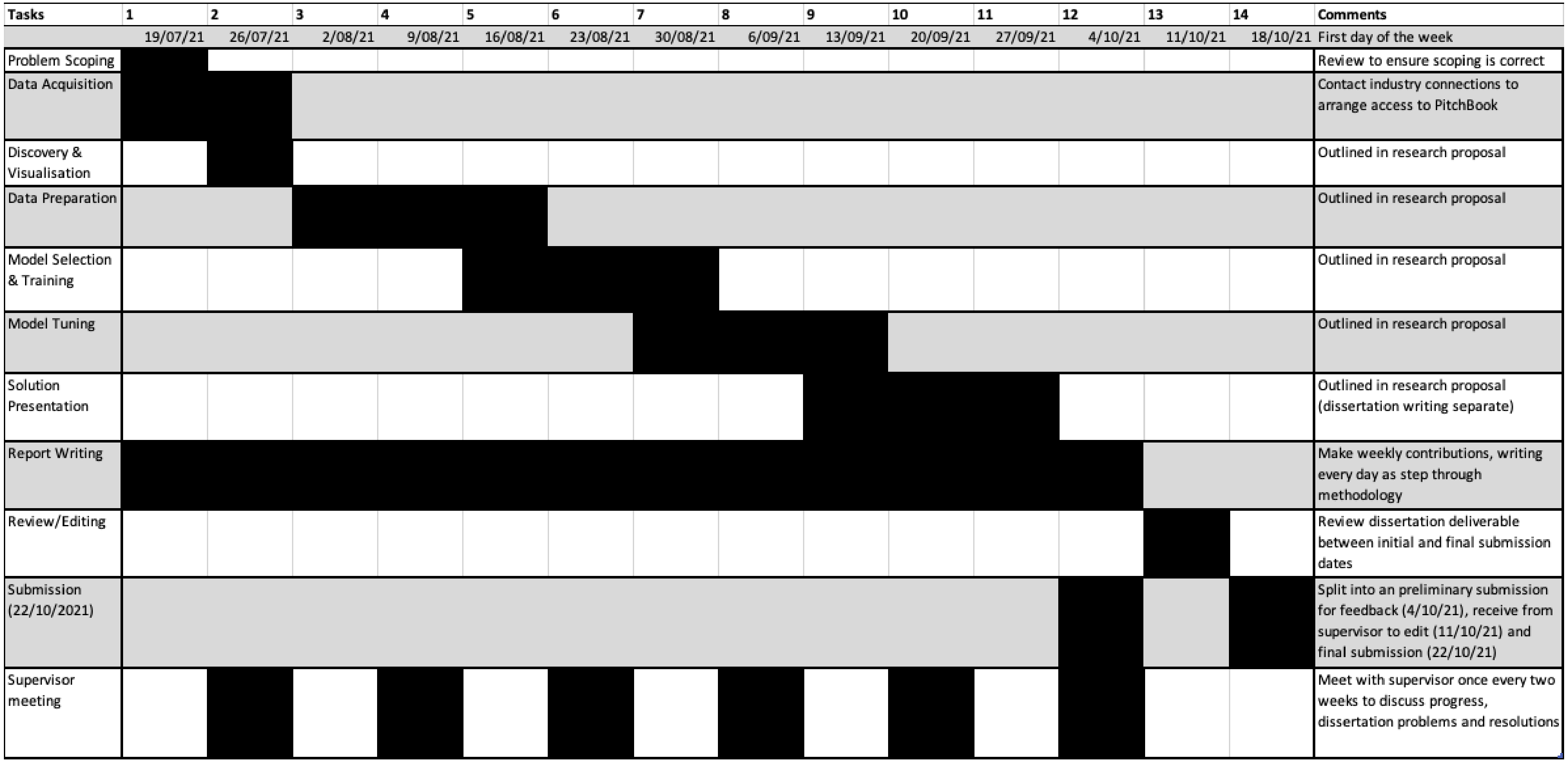

Figure 2: Research Timetable