BAI REPRESENTING ALTERNATIVE INVESTMENTS

Sondernewsletter

BAI-Wissenschaftspreis 2024

Inhalt

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BAI
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Roland Brooks
Senior Referent
BAI e.V.

Sehr geehrte Damen und Herren,

die Vergabe des diesjährigen BAI-Wissenschaftspreises fand am 03. Dezember 2024 in Frankfurt statt. Die Laudationen wurden von dem Gremiumsmitglied Prof. Dr. Dirk Schiereck von der TU Darmstadt gehalten, die Übergabe der Preise erfolgte durch das BAI Vorstandsmitglied Prof. Dr. Rolf Tilmes.

Der Bundesverband Alternative Investments e.V. entschloss sich bereits vor über einem Jahrzehnt wissenschaftliche Arbeiten im Bereich der Alternativen Investments zu fördern und einen jährlichen Preis für hervorragende Arbeiten in diversen Kategorien zu vergeben. 2010 war die Geburtsstunde des seit vielen Jahren etablierten BAI Wissenschaftspreises! Seit der Einführung erreichten den Verband inzwischen 216 Bewerbungen aus dem Bereich der Alternativen Investments.

Für den BAI war schon damals absehbar, dass das Thema Alternative Investments und deren Bedeutung für institutionelle Investoren, Asset Manager und auch Dienstleister weiter zunehmen wird.

Seit Einführung des Preises entscheidet ausschließlich ein vom Verband völlig unabhängiges mehrköpfiges Gremium über die Gewinnerarbeiten. Die Autorinnen & Autoren erhalten als Auszeichnung und Anerkennung einen BAI-Award sowie ein Preisgeld, insgesamt diesmal iHv. EUR 10.000.

Die Branche hat sich seit damals permanent stark weiterentwickelt, es sind neue Assetklassen hinzugekommen und die Alternativen Investments gehören bei den meisten institutionellen Investoren mit weiterhin steigendem Anteil heutzutage im Portfolio dazu.

Dies wird auch wieder in dem aktuellen BAI Investor Survey 2024 sehr deutlich und nach unserer festen Überzeugung in Zukunft so bleiben.

Wir merken ebenso seit vielen Jahren mit Freude, dass auf der wissenschaftlichen Seite sich immer mehr Studenten, Doktoranden und andere Wissenschaftler dem Gebiet der Alternativen Investments durch intensive Forschungsarbeit widmen. Für uns also weiterhin Ansporn dies zu fördern und zu belohnen!

Nun zu den diesjährigen Gewinnern und deren Arbeiten wozu Sie in diesem Sondernewsletter die Zusammenfassungen finden.

In der Kategorie **Bachelorarbeiten** überzeugte die Arbeit „The Black-Scholes Model versus the Heston-Nandi GARCH Option Pricing Model: A Comparison of Option Pricing Models" von Finn Cuber. Diese vergleicht das Black-Scholes Modell und das Heston-Nandi GARCH Option Pricing Modell hinsichtlich ihrer Leistungsfähigkeit bei der Schätzung von Optionspreisen. Zum Vergleich der Schätzungen mit den tatsächlichen Preisen werden verschiedene Moneyness-Niveaus und Laufzeiten verwendet.

In der Kategorie **Masterarbeiten** gewann die Arbeit „Improving Option Trade Classification with Machine Learning" von Markus Bilz. Die Arbeit untersucht die Potenziale von Machine Learning (ML) für die Klassifizierung von Optionstrades nach dem Initiator des Trades als Alternative zu klassischen Heuristiken wie dem Lee-Ready-Algorithmus. Auf zwei großen Options-Datensets der ISE and CBOE erzielt sie mit den Ansätzen Gradient-Boosted Trees und FT-Transformer eine deutlich höhere Genauigkeit gegenüber klassischen Benchmarks bei zugleich verbesserter Robustheit. Sie zeichnet sich dadurch aus, dass sie erstmalig sowohl das überwachte Lernszenario betrachtet, als auch eine Erweiterung auf das semi-überwachte Szenario vornimmt, welches nur partiell gelabelte Optionstrades erfordert und dabei hohe Performance-Gewinne erzielt. Weiterhin zeigt die Arbeit durch eine auf Shapley-Werten basierende Feature Importance Analyse, dass klassische Heuristiken und die verwendeten ML-Modelle eine gemeinsame Teilmenge an Trade-Informationen für die Klassifikation teilen, die ML-Ansätze diese aber effektiver ausschöpfen.

In der Kategorie **Dissertationen** wurde die Arbeit von Dr. Alexander Jürgens zum Thema: „Essays on Cyclicality and Heterogeneity in Private Equity“ ausgewählt. Die Dissertation beschäftigt sich mit der Zyklizität und Heterogenität der Performance und Wertschöpfungshebel von Private Equity (PE) Investitionen. Die Ergebnisse der Arbeit zeigen, dass PE finanzierte Unternehmen weniger anfällig für Rezessionsphasen sind als vergleichbare börsennotierte Unternehmen. Die Performance und Wertschöpfung von Investmentfirmen in PE weisen allerdings erhebliche systematische Unterschiede auf, die für Anleger schwer erkennbar sein können. Die Arbeit unterstreicht die Bedeutung umfangreicher Daten und stellt neue statistische Methoden vor, um zuverlässig kompetente PE Firmen zu identifizieren.

In der Kategorie **sonstige wissenschaftliche Arbeiten** überzeugte die Arbeit „Book-to-Market, Mispricing, and the Cross-Section of Corporate Bond Returns“ von dem Autorenteam Prof. Dr. Söhnke M. Bartram, Prof. Mark Grinblatt und Prof. Yoshio Nozawa. Zum Inhalt: Die Verhältnisse des Buchwertes zum Marktwert von Unternehmensanleihen prognostizieren aus Transaktionspreisen berechnete Anleihe-Renditen. Vorrangige Anleihen (sogar Investment-Grade-Anleihen) mit den 20 % höchsten Verhältnissen haben 3-4% höhere Renditen pro Jahr als die mit den 20 % niedrigsten nach Berücksichtigung zahlreicher Liquiditäts-, Ausfall-, Mikrostruktur- und Preisrisikoattribute.

Der BAI dankt allen Preisträgern und Gremiumsmitgliedern, ohne deren Mithilfe die Realisierung dieses Preises nicht möglich wäre.

Wir möchten an dieser Stelle darauf hinweisen, dass Arbeiten für den BAI-Wissenschaftspreis 2025 noch bis zum 28. Februar 2025 beim BAI eingereicht werden können.

Mehr Informationen finden Sie unter:
https://www.bvai.de/ueber-uns/wissenschaft

Wir wünschen Ihnen eine erkenntnisreiche Lektüre!

Roland Brooks
Koordinator des BAI-Wissenschaftspreises

Kontakt:

Bundesverband Alternative Investments e. V.
BAI e.V.
www.bvai.de

Roland Brooks
Senior Referent
Phone: +49-(0)228-96987-16
E-Mail: brooks@bvai.de

Das Gremium

Der Wissenschaftspreis wird vom BAI gesponsert und verliehen. Über die Gewinner entscheidet jedoch allein und unabhängig ein Gremium, welches sich aus sechs anerkannten Experten aus Wissenschaft und Praxis zusammensetzt.

Die Mitglieder des Gremiums sind:

Prof. Dr. Demir Bektić

Prof. Dr. Demir Bektić ist Managing Director und Head of Multi Asset Solutions im Portfolio Management der Commerzbank. Parallel zu seinem Studium der Wirtschaftsinformatik an der Universität Mannheim sammelte er bereits erste praktische Erfahrung an den Kapitalmärkten. Im Rahmen seiner Promotion über faktorbasierte Investmentstrategien an der TU Darmstadt war er zudem Gastwissenschaftler an der University of Chicago Booth School of Business. Nach weiteren Stationen im Portfoliomanagement & Trading bei Lupus alpha sowie als Portfolio Manager bei einem Single Family Office war er Executive Director und Head of Quant Fixed Income bei Deka Investment. Im Anschluss war er Director Absolute Return bei ansa capital management sowie Head of Portfolio Management beim Multi Family Office FINVIA. Er ist außerplanmäßiger Professor für Finance an der International University of Monaco. Zudem war er Gastprofessor an der University of Miami und Lehrbeauftragter an der TU Darmstadt. Er präsentiert sein Research regelmäßig auf internationalen Fachkonferenzen und bekam für eine Publikation zum Thema Factor Investing den Bernstein Fabozzi / Jacobs Levy Outstanding Article Award des Journal of Portfolio Management verliehen.

Dr. Philippe Jost

is a Managing Director and Head of Risk & Solutions. He is a member of our Responsible Investment Committee, of the Global Valuation Committee and he chairs the Risk Committee. With over 15 years of experience in the financial industry, Philippe specialized in portfolio and risk management for private assets. He has authored and co-authored several research papers in this field. Prior to joining Capital Dynamics, Philippe was a quantitative researcher at Fundo, where he developed dynamic risk management solutions for pension funds. Earlier in his career, he was a researcher at the Swiss Federal Institute of Technology, where he wrote his thesis on sparse approximation. Philippe holds a Master's degree in Communication Systems and a PhD in Signal Processing from the Swiss Federal Institute of Technology.

Prof. Dr. Mark Mietzner

ist Rektor der HTWK Leipzig. Nach seinem Studium an der Johann Wolfgang Goethe-Universität Frankfurt promovierte der Ökonom im Jahr 2008 im Bereich Finanzen mit Auszeichnung an der European Business School in Oestrich-Winkel. Im Anschluss wechselte er als wissenschaftlicher Mitarbeiter an das Fachgebiet für Unternehmensfinanzierung der TU Darmstadt, an der er sich 2017 habilitierte und die venia legendi für Betriebswirtschaftslehre verliehen bekam. Bis zu seinem Wechsel an die HTWK Leipzig war Mark Mietzner als Dekan und kaufmännischer Leiter für die Weiterbildungsprogramme der Zeppelin Universität in Friedrichshafen tätig. Dort hatte er die Professur für Bank- und Finanzwirtschaft inne und veröffentlichte zahlreiche Aufsätze in international führenden Fachzeitschriften. Im Rahmen seiner Forschung befasst er sich u.a. mit Fragestellungen aus den Bereichen Corporate Finance & Accounting, Corporate Governance sowie der empirischen Kapitalmarktforschung.

Professor Dr. Dirk Schiereck

ist seit August 2008 Leiter des Fachgebiets Unternehmensfinanzierung an der Technischen Universität Darmstadt. Seine aktuellen Forschungsschwerpunkte an dieser führenden technischen Hochschule liegen im Bereich der (kapitalmarktorientierten) Unternehmensfinanzierung, dem Asset Management und der Digitalisierung der Finanzindustrie. Mit seinen akademischen Erfahrungen im Bereich der Kapitalanlagen wurde er Aufsichtsratsmitglied der BayernInvest und der creditshelf AG sowie Mitglied im Wissenschaftlichen Beirat des Deutschen Investor Relations Verbands, des Deutsche Kreditmarkt Standard e.V. und des Bundesverbands für Strukturierte Wertpapiere (BSW). Die Wirtschaftswoche zählt ihn aktuell zu den 30 forschungsstärksten Betriebswirtschaftlern im deutschsprachigen Raum. Bevor er an seine heutige Wirkungsstätte kam, promovierte (1995) und habilitierte (2000) er an der Universität Mannheim, baute als Inhaber des Lehrstuhls für Kapitalmärkte und Corporate Governance an der Universität Witten/ Herdecke (2000-2002) dort das Institute for Mergers & Acquisitions auf und war Professor für Bank- und Finanzmanagement an der European Business School in Oestrich-Winkel (2002-2008).

Prof. Dr. Denis Schweizer

Professor Dr. Denis Schweizer studied business administration at Johann Wolfgang Goethe-University in Frankfurt/Main and earned his doctorate in 2008 at the European Business School (EBS) in Oestrich-Winkel with a thesis on alternative investments. During his doctoral studies, he worked at the PFI Private Finance Institute/EBS Finance Academy, designing executive education programs and conducting training sessions. He also earned the Financial Risk Manager (FRM) and Certified Financial Planner (CFP) designations. In 2008, he was appointed Assistant Professor of Alternative Investments at WHU – Otto Beisheim School of Management and served as a visiting scholar at New York University in 2011. He joined Concordia University's John Molson School of Business in 2014 as an Associate Professor, becoming Full Professor in 2020. He also serves as a Research Fellow at Zeppelin University in Germany. Dr. Schweizer is the Director of the Desjardins Centre for Innovation in Business Finance and Scientific Director of the Climate Business Institute. He previously directed the Van Berkom Small-Cap Investment Management Program (2016–2019), where the $1M fund outperformed its benchmark by ~40% during the 2017–2018 period. From 2015 to 2021, he held the Manulife Professorship in Financial Planning.

Dr. Jan Tille

leitet seit April 2018 das Research Team der Absolut Research GmbH und befasst sich seit seinem Einstig in das Unternehmen im Jahr 2009 intensiv mit der Analyse liquider alternativer Anlagestrategien und Multi-Asset-Konzepten. Daneben ist er als Honorardozent im Bereich Finanzen und Kapitalmärkte an der ISM tätig sowie Practioner Fellow am Hamburg Financial Research Center. Zuvor absolvierte er sein Studium der Betriebswirtschaftslehre an der Universität Hamburg, wo er auch als externer Doktorand am Lehrstuhl für Unternehmensfinanzierung und Portfoliomanagement promovierte.

Jurymitglieder, die in ihrer beruflichen Praxis bzw. wissenschaftlichen Tätigkeit in Bezug auf eine eingereichte wissenschaftliche Arbeit in Kontakt mit dem Autor standen, waren von der Bewertung dieser Arbeit ausgeschlossen.

Bachelorarbeit - The Black-Scholes Model versus the Heston-Nandi GARCH Option Pricing Model: A Comparison of Option Pricing Models

by Finn Cuber

Finn Cuber

Introduction

In recent years, option trading volume has surpassed stock trading volume for the first time, underscoring the growing importance of options in financial markets (Berenberg Research, 2023). In the 1970s, options were not as prevalent, primarily serving as risk management tools for industries like agriculture. This changed in 1973 with the establishment of the Chicago Board Options Exchange (CBOE), which standardized option trading and lowered buyer risk. Additionally, the Black-Scholes Model (BSM) introduced a method for pricing options accessible for practical applications, further contributing to option trading's growth (Black and Scholes, 1973). While widely used, the BSM relies on assumptions that do not fully reflect market realities, such as constant volatility.

To address these limitations, later models like the Heston-Nandi GARCH (HN-GARCH) model were developed. Heston and Nandi (2000) incorporated a GARCH approach, allowing for a more nuanced treatment of volatility, especially during periods of rapid change. This bachelor thesis compares the BSM with two variations of the HN-GARCH model, symmetric and asymmetric, evaluating their accuracy using options on the S&P 500 Index.

Valuation of Options

The BSM is a widely recognized and frequently used option pricing model, which is attributable to its simple application and the short computing time of prices. Although groundbreaking, BSM has limitations, particularly regarding its assumptions of static volatility, and stock prices adhering to a random walk, or "Brownian motion" (Bachelier, 1900).

The Black-Scholes formula for pricing European call options is given as:

$$C(t) = S(t)N(d_1) - Ke^{-rT}N(d_2) \tag{1}$$

where
$$d_1 = \frac{log\left(\frac{S(t)}{K}\right) + \left(r + \frac{1}{2}\sigma^2\right)T}{\sigma\sqrt{T}}, \tag{2}$$

and
$$d_2 = d_1 - \sigma\sqrt{T}\ . \tag{3}$$

C is the premium of the option, S(t) denotes the spot price of the underlying asset at time t and N(d) represents the cumulative normal density function. K is the strike price of the option, r denotes the continuously compounded risk-free interest rate, and σ is the volatility of the underlying asset. T stands for the time until the expiration date (Black and Scholes, 1973).

To address these limitations, Heston and Nandi (2000) developed their GARCH model, which incorporates time-varying volatility by using past returns to model current and future volatility. The HN-GARCH model allows for a more dynamic treatment of volatility, theoretically improving price estimations in scenarios where market volatility fluctuates. Additionally, an asymmetric version of the HN-GARCH model was introduced to capture the effect that negative returns have a greater impact on future volatility than positive ones. Both symmetric and asymmetric HN-GARCH models are valuable in capturing realistic volatility structures and offering more flexible estimates compared to the BSM.

Error measurements for assessing model performance include the Mean Absolute Percentage Error (MAPE), Mean Error (ME), and Root Mean Squared Error (RMSE). These metrics allow for a robust comparison by quantifying each model's deviations from actual market prices.

Data and Methodology

The empirical analysis is based on S&P 500 options data from September 2022 to December 2023, including both in-sample and out-of-sample periods. The in-sample period is September 2022 to September 2023, followed by the out-of-sample period from September to December 2023. Daily data on European call options, risk-free rates, and the underlying asset's closing price were collected and processed using two selection criteria. Only options with less than 3 months to expiration and six different strike prices per quarter were chosen. This selection method ensured a broad analysis of moneyness impacts across options nearing expiration.

For calculating BSM prices, the spot price, volatility, risk-free rate, strike price, and time to maturity are used. The symmetric and asymmetric HN-GARCH models required further estimation of autoregressive and moving average parameters using the autocorrelation (ACF) and partial autocorrelation functions (PACF) based on the S&P 500's log-returns. The evidence suggests that opting for a GARCH (1,1) model appears to be a reasonable choice.

In-Sample Comparison

In the in-sample analysis, all three models' performance was tested for accuracy using the MAPE, ME, and RMSE across categories of moneyness and maturity. The results suggest that the Black-Scholes Model provides the lowest error rates overall, particularly in scenarios with extreme moneyness values (either very low or very high), where it typically performs best. In contrast, the symmetric and asymmetric HN-GARCH models tend to exhibit higher errors, particularly for at-the-money options. Furthermore, the symmetric model tends to be slightly more accurate than the asymmetric one for long maturities, while both GARCH models generally overestimate option prices across various moneyness levels, contrary to the BSM's tendency to underestimate.

These outcomes indicate that the HN-GARCH models' dynamic treatment of volatility does not necessarily translate to improved pricing accuracy. Notably, the BSM's ability to adjust daily volatility might offer it a practical advantage, given the static parameters used by the GARCH models for each three-month estimation period. Overall, although BSM is less complex, its results in the in-sample analysis suggest it may still be preferable for option pricing.

Out-of-Sample Comparison

The out-of-sample period (September–December 2023) presents a unique challenge for model performance, as models are applied to data beyond the period in which parameters were estimated. During this period, the S&P 500 displayed positive growth, increasing the options' moneyness and complicating direct comparisons. Additional strike prices were introduced to extend the range of options in the dataset, enabling more consistent analysis regarding the moneyness of options.

Similar to the in-sample results, the Black-Scholes model generally outperformed the HN-GARCH models in the out-of-sample analysis. BSM showed lower MAPE values across all moneyness categories and error measures. Both GARCH models again tended to overestimate option prices, and the ME revealed that while BSM consistently underestimated prices, both GARCH models frequently overestimated them. Furthermore, while BSM's errors were relatively stable across periods, both GARCH models showed fluctuating errors that grew over time, likely reflecting the disadvantage of their static parameters in adapting to the changing market.

Overall, out-of-sample results reinforce the patterns observed in-sample, suggesting that the simplicity of BSM may confer robustness in practice, especially when models are applied to future, unpredictable data. These findings indicate that even though the HN-GARCH models incorporate past volatility patterns, they may struggle to predict future prices as effectively as BSM in a live trading context.

Conclusion and Evaluation

The findings underscore the ongoing challenges and nuances in option pricing, particularly in comparing simpler models like Black-Scholes (BSM) with more complex approaches, such as the Heston-Nandi GARCH (HN-GARCH) models. While models like HN-GARCH incorporate volatility dynamics that capture historical return patterns, this added complexity does not necessarily yield more accurate pricing estimates compared to simpler methods. In fact, the BSM, with its straightforward assumptions, frequently provides closer estimates to market prices across different conditions of moneyness and time-to-maturity.

One key insight is that both types of models, BSM and HN-GARCH, tend to show systematic tendencies in their estimations: while BSM often underestimates option prices, HN-GARCH models generally overestimate, particularly in the asymmetric version which accounts for negative market shocks. However, the models can still be used by traders differently, for example by extracting the implied volatility from the BSM, to gain insight into the market sentiment.

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Contact

Finn Cuber
E-Mail: finn.cuber@web.de

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BAI e.V. · Poppelsdorfer Allee 106 · D-53115 Bonn
Tel. +49 - (0) 228 - 969870 · Fax +49 - (0) 228 - 9698790
www.bvai.de
info@bvai.de

Haftungsausschluss

Satz & Layout

SimpleThings GmbH
Münsterstraße 1 · 53111 Bonn
www.simplethings.de
info@simplethings.de

from Markus Bilz

Markus Bilz

1 Background and Motivation

Every option trade has a buyer and seller side. For a plethora of problems in option research, it's crucial to determine the party that initiated the transaction. Applications include the study of option demand, of order flow, or of trading costs. Despite the importance for empirical research, the true initiator of the trade is absent in datasets and is typically inferred using trade classification rules. In consequence, the correctness of empirical studies hinges on the algorithm's ability to accurately identify the trade initiator.

Popular heuristics to sign trades are the tick test, quote rule, and hybrids thereof such as the Lee-Ready (LR) algorithm (Lee and Ready, 1991). These rules have initially been proposed and tested in the stock market. For option markets, Savickas and Wilson (2003) and Grauer et al. (2023) raise concerns about the transferability of trade signing rules due to deteriorating classification accuracies and systematic misclassifications. The latter is crucial, as non-random misclassifications bias the dependent research.

A second, growing body of research (Blazejewski and Coggins, 2005; Rosenthal, 2012; Fedenia et al., 2022) advances trade classification performance through machine learning (ML). The scope of current works is yet mainly focused on the stock market and the superficial setting, where supervised models are trained on labeled trades. Then again, labeled trades are difficult to obtain, whereas unlabeled trades are abundant.

The goal of our empirical study is to investigate if a ML-based classifier can improve upon the accuracy of state-of-the-art approaches in option trade classification.

2 Contributions

Our contributions are threefold:

(i) By employing gradient-boosted regression trees (GBRTs) and Transformers we establish a new state-of-the-art in option trade classification. We outperform existing approaches by 3.73% - 6.51% in accuracy on a large sample of International Securities Exchange (ISE) trades. Relative to the ubiquitous LR algorithm, improvements are up to 17.02%. The model's efficacy is demonstrated at an alternative trading venue, in sub-samples, and in an application study.

(ii) Our work is the first to consider trade classification in the semi-supervised scenario, in which trades are only partially-labeled. Our best models classify 74.55% (+ 6.94) of all trades correctly.

(iii) Through a feature importance analysis based on Shapley values, we can consistently attribute performance gains of rule-based and ML-based classifiers to feature groups. We show that both paradigms share common features, but ML-based approaches exploit the data more effectively.

3 Data

We perform the empirical analysis on two large-scale datasets of option trades recorded at the ISE and Chicago Board Options Exchange (CBOE). Our sample construction follows Grauer et al. (2023), which fosters comparability between both works.

Training and validation are performed exclusively on ISE trades. After a time-based train-validation-test split, required by the ML estimators, we are left with a test set spanning from Nov. 2015 – May 2017 at the ISE. CBOE trades between Nov. 2015 – Oct. 2017 are used as a second test set. Each test set contains between 9.8 Mio. – 12.8 Mio. labeled option trades. An additional, unlabeled training set of ISE trades executed between Oct. 2012 – Oct. 2013 is reserved for learning in the semi-supervised setting.

We distinguish three feature sets and apply minimal feature engineering. The first set is based on the data requirements of tick/quote-based rules, the second of hybrid algorithms with additional dependencies on trade size data, and the third feature set adds option characteristics, like the option's Δ or the underlying.

4 Methodology

We model trade classification using GBRTs, a wide tree-based ensemble, and the FT-Transformer, a Transformer-based neural network. We select these approaches for their state-of-the-art performance in tabular modeling (Gorishniy et al., 2021; Grinsztajn et al., 2022) and their extendability to learn on partially-labeled trades. Additionally, Transformers offer some model interpretability through the attention mechanism. An advantage we exploit to derive insights into the classification process of Transformers.

As stated earlier, our goal is to extend ML classifiers for the semi-supervised setting to make use of the abundant, unlabeled trade data. We couple GBRTs with self-training, whereby confident predictions of unlabeled trades are iteratively added into the training set as pseudo-labels. A new classifier is then retrained on labeled and pseudo-labeled instances. Likewise, the Transformer is pre-trained on unlabeled trades with a replaced token detection objective and later finetuned on labeled training instances. Conceptually, the network is tasked to detect randomly replaced tokens or features of transactions. Both techniques are aimed at improving generalization performance. Standard trade classification rules are implemented as a rule-based classifier allowing us to construct arbitrary candidates for benchmarking and support richer evaluation of feature importances.[1]

For a fair comparison, we run an exhaustive Bayesian search, to find a suitable hyperparameter configuration for each of our models. Classical rules have no hyperparameters per se. Akin to tuning the ML classifiers on the validation set, we select classical benchmarks based on their validation performance. The so-selected benchmarks come from Grauer et al. (2023), which we subsequently refer to as Grauer-Schuster-Uhrig-Homburg (GSU) method (small/large). [2]

5 Results and Discussion

Our models establish a new state-of-the-art for trade classification on the ISE and CBOE dataset, as shown in Table 1. For ISE trades, Transformers achieve an accuracy of 63.78% when trained on trade and quoted prices as well as 72.58% when trained on additional quoted sizes, improving over current best of Grauer et al. (2023) by 3.73% and 4.97%. Similarly, GBRTs reach accuracies between 63.67% and 72.34%. We observe performance improvements up to 6.51% for GBRTs and 6.31% for Transformers when models have access to option characteristics. Relative to the ubiquitous tick test, quote rule, and LR algorithm, improvements are 23.88%, 17.11%, and 17.02%. Both architectures generalize well on CBOE data, surpassing the benchmark by 5.26% and 7.86% depending on the model and feature set.

Table 1: Accuracy of supervised GBRTs and Transformers for different feature combinations on the ISE and CBOE datasets. The improvement is estimated as the absolute change in accuracy between the classifier and the benchmark. For the feature set classic GSU (small) is the benchmark and otherwise GSU (large). Models are trained on the ISE training set. The best classifier per dataset is in bold.

		Classic		Size		Option	
Dataset	Classifier	Acc. in %	+/-	Acc. in %	+/-	Acc. in %	+/-
ISE	GBRT	63.67	3.62	72.34	4.73	**74.12**	**6.51**
	Transformer	**63.78**	**3.73**	**72.58**	**4.97**	73.92	6.31
CBOE	GBRT	66.00	5.26	71.95	5.43	**74.38**	**7.86**
	Transformer	**66.18**	**5.44**	**72.15**	**5.64**	74.28	7.76

We derive from exhaustive robustness tests, that performance is stable across multiple subsets. Outperformance is strongest for in-the-money options, options with a long maturity, as well as options traded at the quotes.

1 Our implementation is publicly available under https://pypi.org/project/tclf/.

2 All of our source code and experiments are publicly available under https://github.com/KarelZe/thesis/.

Advancements in classical trade classification have been fueled by more complex decision boundaries, e.g., by fragmenting the spread as in the case of the Ellis-Michaely-O'Hara rule and Chakrabarty-Li-Nguyen-Van-Ness method or by stacking multiple heuristics as with the GSU rules. It is thus likely, that the outperformance of our ML estimators is due to the more complex, learned decision boundaries. The strong results of Transformers sharply contradict those of Fedenia et al. (2022), who benchmark random forests and feed-forward networks (FFNs) for trade classification in the equity and bond market and find clear dominance of the tree-based approach. First, unlike FFN, the FT-Transformer is tailored to learn on tabular data through being a non-rotationally-invariant learner. Second, our data preprocessing and feature engineering are adapted to the requirements of neural networks. Without these measures, tree-based approaches excel due to their robustness in handling skewed and missing data.

In the semi-supervised setting, as visualized in Table 2, Transformers on ISE trades profit from pretraining on unlabeled trades with accuracies up to 74.55%, but the performance gains diminish on the CBOE test set. Vice versa, we observe no benefits from semi-supervised training of GBRTs.

Table 2: Accuracy of semi-supervised GBRTs and Transformers for different feature combinations on the ISE and CBOE datasets. The improvement is estimated as the absolute change in accuracy between the classifier and the benchmark. For the feature set classic GSU (small) is the benchmark and otherwise GSU (large). Models are trained on the ISE training set. The best classifier per dataset is in bold.

		Classic		Size		Option	
Dataset	Classifier	Acc. in %	+/-	Acc. in %	+/-	Acc. in %	+/-
ISE	GBRT	63.40	3.35	72.16	4.55	73.54	5.93
	Transformer	**64.66**	**4.60**	**72.86**	**5.25**	**74.55**	**6.94**
CBOE	GBRT	**66.19**	**5.44**	**71.92**	**5.41**	73.95	7.44
	Transformer	65.67	4.92	71.78	5.27	**74.10**	**7.58**

An explanation as to why pre-training improves performance on ISE but not CBOE trades, may be found in the pre-training data and setup. It is conceivable, that pre-training encodes exchange-specific knowledge, such as trading regimes. Trades used for pre-training are recorded at the ISE only and are repeatedly shown to the model. While our pre-training objective is stochastic with different features being masked in each step, past research has shown that repeatedly presenting the same tokens in conjunction with a small-sized pre-training dataset, can degrade performance on the downstream classification task. For instance, Raffel et al. (2020) document in the context of language modeling that a high degree of repetition encourages memorization in the Transformer, but few repetitions are not harmful.

Self-training with GBRTs as a base learner generally performs worse than GBRTs trained on labeled trades. With the pseudo labels derived from high-confident predictions, the success of self-training hinges on the reliability of the predicted class probabilities. In an analysis of the GBRT, we observe that the validation loss in terms of sample-wise loss stagnates due to a growing number of overconfident but erroneous predictions. It is conceivable, that the increased number of confident yet incorrect predictions, affects the generated pseudo labels. Given these observations, we recommend using GBRTs for supervised trade classification only.

For an evaluation of feature importances, that suffices for a cross-model comparison, we use Shapley Additive Global importancE (SAGE). It is a global feature importance measure based on Shapley values and is capable of handling complex feature interactions, such as highly correlated quotes and prices. We estimate SAGE values in terms of improvement in zero-one loss per feature set, complementing our accuracy-based evaluation.

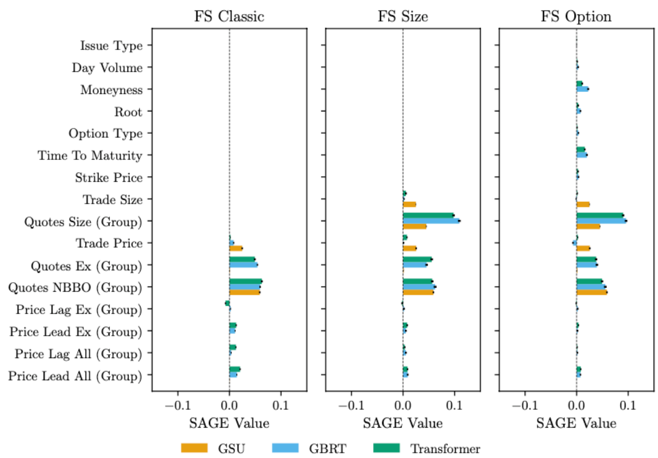

Figure 1: SAGE feature importances of rule-based and ML-based classifiers. Importances estimated on ISE test set with zero-one loss. Bigger feature importances are better. For the feature set classical the GSU method (small) is used and otherwise the GSU method (large).

As evident from Figure 1 we find that all models attain the largest improvement in loss from quoted prices and if provided from the quoted sizes. The contribution of the national best bid and offer (NBBO) to performance is roughly equal for all models, suggesting that even simple heuristics effectively exploit the data. For ML-based predictors, quotes at the exchange level hold equal importance in classification. This contrasts with GSU methods, which rely less on exchange level quotes. Transformers and GBRTs slightly benefit from the addition of option features, i. e., moneyness and time to maturity.

Regardless of the method used, changes in trade price, central to the tick test, are irrelevant for classification and can even impede performance. This result aligns with earlier studies of Savickas and Wilson (2003) and Grauer et al. (2023).

6 Conclusion

In summary, our study showcases the efficacy of machine learning as a viable alternative to existing trade signing algorithms for classifying option trades, if partially-labeled or labeled trades are available for training. Compared to existing approaches, our classifiers also improve robustness, which together reduces noise and bias in option research dependent on reliable trade initiator estimates.

The out-of-sample results are particularly strong for the pre-trained FT-Transformer, indicating that unsupervised pre-training can encode a generalizable knowledge about the trades in the model. An interesting venue for future research is to revisit training Transformers on a larger corpus of unlabeled trades through pre-training objectives and study the effects from exchange-specific finetuning.

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Contact

Markus Bilz
E-Mail: web@markusbilz.com

from Dr. Alexander Jürgens

Dr. Alexander Jürgens

Introduction and Motivation

The Private Equity (PE) industry has become an integral part of the global economy over the past decades. The continuous growth in assets managed by PE investors highlights the increasing interest of investors in the asset class. However, PE research still faces major challenges today due to limited access to large-scale and granular data in private markets. Consequently, a wide range of research gaps and challenges remain in existing research that motivate this dissertation. Particularly, the vast majority of studies on the performance of PE rely on fund-level data, which induces significant shortcomings for empirical investigations. Further, standard methodologies from public market research cannot easily be applied in this context since funds and transactions are not publicly traded and data is not readily available (Korteweg and Westerfield (2022)).

The primary goal of this dissertation is to contribute to the understanding of PE value creation and performance as well as the separation of investment skills and luck of PE managers.

Resilience and Cyclicality in Private Equity: Value Creation and Investment Flows in Economic Cycles

The first paper of the dissertation investigates the effects of economic cycles on abnormal value creation of buyouts (BOs) and on the investment activity of the corresponding PE funds. Implementing the methodology by Achleitner et al. (2010) and Puche et al. (2015), the study decomposes the overall value generated in financial, market, and operational components. In particular, the study implements a matching procedure that identifies publicly listed benchmark transactions and calculates the abnormally generated value for each BO transaction against a portfolio of matched benchmarks. To understand the effects of economic cycles on value creation outcomes, recession scores are computed from indicator variables provided by the National Bureau of Economic Research (NBER). The recession score measures the exposure to recessionary cycles over the holding period of a transaction.

The findings suggest that BOs create substantially more overall value than public benchmark transactions. Leverage, multiple expansion, and free cash flow are the central components of abnormal value creation in BO transactions. Nonetheless, value creation in BOs has noticeably declined over the years, resulting in similar outcomes as the matched public benchmark transactions for the latest years. The decline mainly stems from decreasing leverage and multiple effects, whereas operational components of BOs and benchmarks remain similar over time. Moreover, the results from hierarchical linear regressions show that the negative effects of recessionary cycles on value creation are substantially less severe for BO transactions than public benchmarks. The result remains robust when controlling for the financial risk component.

Analyzing the time series of cash flows between PE funds and their portfolio companies, the study further shows that initial investment flows of PE funds are slightly pro-cyclical (counter-cyclical) towards the beginning (end) of their investment cycle. However, reinvestment flows remain counter-cyclical, with PE funds reinvesting between 45.2% and 48.6% more capital during recessions, irrespective of remaining investable capital. Further, probabilities of initial investments and reinvestments are 2.46 to 3.66 and 12.34 to 14.77 percentage points higher during economic downturns. Thus, PE funds reinvest more and more frequently during recessions, thereby potentially relieving financial constraints of their portfolio companies, whereas evidence on initial investments is mixed.

The study contributes to the literature in multiple ways. It is one of the first studies directly identifying publicly listed benchmark companies for a large set of BO transactions to analyze abnormal value creation of BO transactions. Further, the study provides initial evidence on co-movements of value creation in PE with public benchmarks and the economy. The findings also provide new insights into the investment behavior of PE funds in economic cycles. In particular, analyses of cash flows between PE funds and their portfolio companies are new to the literature.

Does Skill Persist Beyond Leverage in Buyouts? Investigating Abnormal Effects in Private Equity Value Creation

This study examines the persistency of abnormal value creation outcomes of BOs. The study starts with a model-free approach to examine heterogeneity in abnormal effects of value creation components in BO transactions across PE firms. The results show that all quartiles except the bottom quartile of PE firms generate substantial abnormal levered value creation. When adjusting for financial risk, abnormal effects are only found for the top half of PE firms. Considering only the operational components, the abnormal effect decreases for the second-top quartile, while the top quartile remains significant and large.

However, the heterogeneity found in the model-free approach cannot accurately capture expected abnormal value creation outcomes as abnormal value components are noisy. Therefore, the study implements Bayesian multivariate mixed-effects models to quantify the systematic differences in expected levered, unlevered, and operational value creation outcomes across PE firms. The framework in this essay further allows for estimating the correlations of the firm ranks across the value creation components. The results imply substantial cross-sectional heterogeneity in all three value creation components and highly correlated PE-firm ranks. Nonetheless, abnormal effects in unlevered and operational value components are only achieved by around 32% of the PE firms. The correlations of PE-firm ranks across the value components emphasize that investors can expect substantial gains from identifying PE managers with investment skills beyond the financial risk component.

The contributions of this essay are manifold. The study presents new evidence on abnormal value creation and persistence of value components in PE. Assessing not only PE-firm-specific skills on different value components but also how persistent effects in these components relate to each other is novel to the literature. Further, the methodology established in the study allows for controlling systematic differences in risk-taking across PE firms and their relation to the expected value creation outcomes.

Do You Get What You See in Private Equity? A Bayesian Decomposition of Investment Skills

The third essay evaluates systematic differences in expected returns, idiosyncratic risk-taking, and default risk of PE firms. The study extends the framework of Korteweg and Sorensen (2017) and presents a Bayesian hierarchical mixture model that accurately captures the intricate distributional features of performance measures in PE. In particular, return measures in PE are heavily right-skewed, left-censored, and characterized by concentrated densities at zero from defaulted transactions. Hence, standard estimation techniques that rely on Gaussian distributions potentially lead to erroneous conclusions in this context. Further, the Bayesian hierarchical model in this study simultaneously estimates not only the expected average performance but also the GP-specific idiosyncratic risk and default risk.

Utilizing a large sample of BO transactions, the findings suggest substantial differences in expected returns, idiosyncratic risk, and default risk across PE firms. First, fund-level results show that the expected fund return of the marginal top-quartile GP is 17% to 21% higher than the marginal bottom-quartile GP, relative to the market. Idiosyncratic risk is not significantly different across GPs on the fund level, and the variation of the PE-firm-specific effect in fund returns explains only 5% to 8% of the overall variance.

Second, the deal-level findings indicate similar levels of performance persistence, with top-quartile GPs generating 23% to 26% higher expected returns than bottom-quartile GPs. However, idiosyncratic risk in deal-level returns is significantly heterogeneous, with an interquartile range of 10% to 13% on the log scale. Similarly, the bottom quartile defaulting GP is 5% to 7% less likely to produce a write-off than the marginal top-quartile defaulting GP. Further, simulation results highlight the challenges of LPs to identify GPs with top-quartile expected returns from observing their past performance. LPs require many observations to obtain a relatively high probability of correctly identifying a top-quartile GP.

The study contributes to the literature by providing an extended framework to incorporate the empirical features of return distributions in PE and estimate the systematic differences across GPs in expected returns, idiosyncratic risk, and default risk. The study is among the first to estimate the heterogeneity across GPs in these dimensions with fund-level and deal-level gross returns. Moreover, the findings show what LPs can learn about the investment skills of GPs from their historic track records.

Conclusion

The findings of this dissertation have meaningful implications for managerial practice and investors in the asset class and offer guidance concerning cyclicality and heterogeneity in PE. The evidence on the cyclicality of value creation outcomes of BOs and publicly listed benchmarks is of pivotal relevance for the portfolio diversification of investors and a potential factor in the successful fundraising efforts of PE firms in the past decade. Further, understanding the effect of economic cycles on the investment behavior of GPs is relevant for both investors and managers of portfolio companies. The behavioral patterns highlight how GPs allocate the capital of their LPs in certain market environments and potentially support their portfolio companies in distressed periods when financing from other sources is restricted. Moreover, the implications of the heterogeneity of abnormal value creation outcomes and performance are manifold. First, superior abnormal operational skills of PE firms appear to be a useful proxy for LPs in identifying GPs that persistently generate abnormal overall value. Similarly, it is relevant for co-investors and managers to understand whether a PE firm has the ability to generate substantial operational value to increase the chances of an overall successful outcome. Secondly, the findings suggest that heterogeneity in PE is not competed away. Hence, LPs that are able to select PE funds of persistently well-performing GPs can expect to earn excess returns. This highlights the importance of correctly identifying skilled PE firms. However, a considerable challenge in practice is the number of fully realized transactions that an LP needs to observe to achieve a reasonable chance of correctly identifying a skilled GP. Consequently, investors need to collect additional information on further elements, such as networks or human capital components of PE firms.

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Contact

Dr. Alexander Jürgens
E-Mail: alexander.juergens@tum.de

from Söhnke M. Bartram, Mark Grinblatt, Yoshio Nozawa

1 Motivation and Previous Research

One of modern finance's greatest puzzles is why the book-to-market ratio of a firm's equity plays such a central role in the cross-section of equity returns. One view is that the book-to-market ratio, a scaling of a firm's share price, proxies for priced risk. For example, Berk (1995) points out that high risk firms discount future cash flows at higher rates, implying that high risk firms should have both low market prices and high book-to-market ratios other things equal. Thus, whenever alpha measurement imperfectly controls for risk, book-to-market will proxy for omitted risk factors and spuriously generate alpha.

An alternative and equally plausible explanation is that high book-to-market ratios reflect underpriced shares and vice versa. This interpretation of book-to-market as a mispricing metric views book equity a crude measure of equity fair value. Here, high book-to-market firms' high equity returns express rates that translate excessively low prices into future payoffs. A similar perspective, with time's arrow in reverse, is that share prices require irrationally high discount rates to undervalue the firm's future payoffs. If investor mistakes rather than omitted risk factors account for the relation between book-to-market and returns, alpha's correlation with book-to-market warrants active management that profits from the valuation errors of market participants.

To better understand book-to-market's role in asset pricing, we focus on another asset class: corporate bonds. As an asset class, corporate bonds rival stocks in importance, yet little is known about their cross-section of returns. Book-to-market's importance in equity pricing makes the ratio a natural starting point for studying the drivers of corporate bond returns and the informational efficiency of the corporate bond market.

The corporate bond market possesses unique attributes that aid understanding of why book-to-market influences asset returns, like equities. In contrast to equities, bond cash flow streams tend to be finite, are contractual, and of relatively shorter duration. These factors make the magnitude and timing of bonds' future cash flows more transparent than those of equities. Indeed, the future cash flows of many bonds are known with relative certainty, as it is only the more extreme and infrequent outcomes for the economy or a company's prospects that materially affect the likelihood of the bonds' promised payments being made.

Prof. Dr. Söhnke Bartmann

Prof. Dr. Mark Grinblatt

Prof. Dr. Yoshio Nozawa

2 Empirical Methodology

We define the "bond book-to-market ratio" ("BBM") as the bond's book (or carrying) value per unit of face amount divided by the bond's market price per unit of face amount. At the time a bond is issued, BBM starts at one. Indeed, for most bonds, the coupons are set so that bond's book value at issue and face amount paid at maturity are approximately the same—referred to as a par bond if the two amounts are identical. Over time, the book-to-market ratios of formerly par bonds then rise above one (becoming discount bonds) or fall below one (premium bonds). Likewise, bonds issued at discounts or premia evolve to have greater or lesser discounts and premia than their amortization schedules would indicate. As with par bond issues, changing economic forces and perhaps sentiment generate price deviations from those schedules.

If sentiment plays any role, it tends to mean revert. Hence, low book-to-market ratios that are driven by optimistic sentiment tend to rise, making risk-adjusted returns abnormally low. Likewise, sentiment-driven high book-to-market ratios tend to fall, making returns abnormally high. The abnormal returns generated by sentiment's tendency to mean revert generates bond prices with proclivities to converge towards their fair values. Most of BBM's variation depends on a bond's price path since issuance. If the price path has generated returns that closely track the bond's initial yield-to-maturity, BBM remains close to one. However, if the bond's return has exceeded its initial yield-to-maturity, its past return will be high, and its yield-to-maturity will fall.

A primary deterrent to the study of corporate bond returns is their relatively thin trading. While many corporate bonds trade more than once per day, quite a few do not trade for days or even weeks at a time. We apply the martingale property of informationally efficient asset prices to overcome the obstacle of infrequent trading. This property enables imputation of the hypothetical mid-market prices one would trade at from transactions on other dates. While the imputed prices represent noisy estimates, the lower volatility of bonds offsets the enhanced return noise from measurement error, facilitating detection of significant pricing inefficiencies.

We investigate whether the bond book-to-market and bond mispricing signals contain distinct information that is not subsumed by other known predictors of bond returns. To this end, we run Fama-MacBeth monthly cross-sectional regressions of next months' bond returns on our BBM signal and other lagged bond and firm characteristics, including industry fixed effects. We also examine whether the trading profits to the bond mispricing strategy simply capture risk premia as compensation for a list of known risk factors. We focus on returns to five equal- and value-weighted portfolios sorted on BBM in excess of risk-free rates and run time-series regressions of portfolio returns on a set of risk factors. If the returns on the long-short mispricing strategy can be explained by systematic risk factors, the risk-adjusted returns on the long-short portfolio should be indistinguishable from zero.

3 Data and Sample

The sample is initially limited to USD-denominated, senior, unsecured corporate bonds in the Trade Reporting and Compliance Engine (TRACE) database issued by non-financial firms with no embedded options other than call provisions. Robustness tests also study all corporate bonds with fixed coupon rates. We exclude cancelled transactions, those that TRACE specifies as occurring before the issue date or after the maturity date of a bond, and transactions in the bonds of financial firms (SIC codes 60-69). We modify prices to be TRACE's corrected prices (or any other trade terms) when TRACE indicates the trading counterparties retroactively corrected the prices (or other trade terms). Following Bai, Bali, and Wen (2019), we also remove observations with a transaction price below 1/20 or above 10 times their face amount, as well as bonds with remaining maturity of less than one year and bonds in default at the time of the signal.

Our study of bond returns and their cross-sectional relationship with book-to-market is the most extensive study of corporate bond returns to date. The sample period comprises 212 calendar months from January 2003 to August 2020 for trading signals, and from February 2003 to September 2020 for returns, covering 8,925 different bonds, 838 firms, and 459,040 bond-month observations. The large sample is facilitated by the paper's key methodological contribution—showing how to utilize the martingale property to construct monthly returns when trading is thin. Prior studies largely focus on the most liquid bonds in the TRACE database. However, studies of such bonds cannot easily draw unbiased conclusions about the corporate bond market as a whole.

4 Main Findings

The paper documents an alpha difference between extreme BBM quintile portfolios of 3-4% per year with the most extensive controls that is sizable considering the volatility of corporate bond returns compared to stock returns. The BBM trading strategy's alpha is unlikely to stem from an omitted risk control. For one, it is difficult to conceive of omitted risk controls with sufficient risk premia when cross-sectional FM regressions already control for most of the return-related bond and equity characteristics studied in the literature. Moreover, time series factor model regressions confirm a similar alpha. Alpha spreads are of larger economic magnitude when the sample include junior bonds and bonds with exotic options.

This leaves mispricing as the best explanation for the BBM anomaly. That explanation is reinforced by the pattern of profits earned when the BBM signal is delayed, calibrations from yield spreads, similar BBM signal efficacy for bonds with more default risk, and the inability of factor betas to explain BBM profits, even with an additional HML-like factor for bonds. Moreover, the term structure of riskless interest rates cannot explain BBM, as the BBM signal does not predict U.S. Treasury returns. The latter is true even when artificially forcing Treasury prices to mimic the sparse data structure of corporate bonds.

In both reported and unreported analyses, we contemplated the possibility that the illiquidity of bonds could account for our findings. Reported results suggest that the Jensen's inequality bias in returns makes the reported magnitude of the BBM alpha spread conservative. BBM Q1 portfolio bonds trade less frequently than the BBM Q5 bonds. Thus, if bond returns are upwardly biased due to Jensen's inequality, they are more upwardly biased for the short leg (Q1) than the long leg (Q5) of the BBM strategy. We also find that there are more ask than bid transaction initiating our long positions, and more bid transactions initiating our short positions. Finally, our results are not driven by customers receiving off-market deals or a correlation between BBM and the proportion of bid and asks. The results are also insensitive to market microstructure controls.

The BBM anomaly's mispricing explanation may explain the book-to-market effects for other asset classes. If bonds, which have adequate risk controls, favor the mispricing explanation for BBM's effect, we need to take mispricing more seriously in other asset classes, like equity, where risk controls are harder to come by. Consistent with the equity mispricing explanation is the decline in equity HML since 2002 as trading frictions in equities declined and the equity book-to-market anomaly became widely known in hedge fund circles.

Contacts:

Prof. Dr. Söhnke M. Bartram (Corresponding Author)
CEPR Research Fellow
Professor of Finance
University of Warwick
Warwick Business School
Finance Group
Coventry CV4 7AL
United Kingdom

Phone: +44 (24) 7657 4168
E-Mail: s.m.bartram@wbs.ac.uk

Prof. Dr. Mark Grinblatt
Distinguished Professor of Finance
Alumni Chair in International Finance
UCLA Anderson School of Management
110 Westwood Plaza
Los Angeles CA 90095-1481

Prof. Dr. Yoshio Nozawa
Assistant Professor of Finance
University of Toronto
105 St. George Street
Toronto, ON M5S 2E8
Canada

BAI-Wissenschaftspreis 2024


Prof. Dr. Rolf Tilmes (BAI)


Prof. Dr. Dirk Schiereck (TU Darmstadt)


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Gewinnerteam Kategorie
Sonstige wissenschaftliche Arbeiten
Prof. Dr. Söhnke M. Bartram, Prof. Dr. Mark Grinblatt, Prof. Dr. Yoshio Nozawa

Roland Brooks,
Koordinator BAI-Wissenschaftspreis