

ETFs Prove Their Worth in Turbulent Times

Is Human-AI Advice Better than Human or AI Advice?

What Does Your Personality Reveal
about Your Financial Behavior?
Evidence from a FinTech Experiment

“MiCA” – Regulating the European Markets
in Crypto-Assets



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Editorial

ETFs Prove Their Worth in Turbulent Times

Eric Leupold

If a casual observer were to look at the latest figures for exchange traded funds (ETFs), s/he would not guess that a pandemic and a war hit the global economy hard in the last two years and, at least in the meantime, also the capital markets, because the growth of ETFs is unbroken.

Since their introduction in the 90s, ETFs have become one of the most popular product innovations in the asset and wealth management industry. Demand from private investors, especially for ETF savings plans, is also on the rise. Last year, assets under management in Deutsche Börse's ETF segment exceeded EUR 1 trillion for the first time, 39% higher than in the previous year. A new all-time high.

Market observers even assume that assets under management can continue to achieve

double-digit growth rates in the coming years. In a study, PwC estimates that global ETF assets could grow by an average of 17% per year until 2026.

Their formula for success: ETFs provide investors with an efficient financial instrument for the cost-effective implementation of investment and trading strategies. In addition, ETFs may even improve liquidity conditions in comparatively less liquid asset classes during quiet market phases due to their instant accessibility. But what about a prolonged period of increased market volatility: Are ETFs more liquid than their underlying components?

To investigate this, the bid-ask spread can be applied as a simple measure of market liquidity (the analysis was based on Xetra order book data). This metric is used to assess



Eric Leupold
 Managing Director / Head of Cash Market
 Deutsche Börse AG

whether ETFs are more liquid than their underlying basket of securities.

Xetra is the leading trading venue for DAX shares and ETFs in Europe. Let's, therefore, look for the first four months of the year at the spread development of the most liquid DAX ETF (the spread calculation for the DAX ETF was based on the bid-ask spreads for a simulated order size of EUR 100,000), tradable on Xetra as well as that of the basket of 40 individual DAX stocks considering their index weighting ("DAX basket"; the spread calculation for the DAX basket was based on the best bid-ask spreads of the index stocks according to their index weighting). During this period, the DAX ETF had an average spread of 3.39 basis points (bp), while the DAX basket showed an average spread of 3.71 bp. Accordingly, the average daily spread difference during this period was 0.32 bp or

8.6% in favor of the ETF.

We also examined the impact of the expansion of the DAX index from 30 to 40 individual securities implemented on September 20th, 2021, on the respective spreads in a period of 50 trading days before and after the index expansion. Despite the expansion by less liquid stocks on average, no negative effect on the spread of the most liquid DAX ETF could be determined. In fact, there was even a slight decrease in the average daily spread of the DAX ETF from 2.91 to 2.89 bp, or by 0.5%. In contrast, the average spread of the DAX basket increased from 3.12 to 3.27 bp, or by 5.1%, in the comparison period.

These results impressively underline the high liquidity of ETFs on Europe's leading trading venue Xetra – even in periods of increased market volatility.

Research Report

Is Human-AI Advice Better than Human or AI Advice?

BUSINESS PRACTITIONERS INCREASINGLY USE ARTIFICIAL INTELLIGENCE (AI) APPLICATIONS TO ASSIST CUSTOMERS IN MAKING DECISIONS DUE TO THEIR HIGHER PREDICTION QUALITY. YET, CUSTOMERS ARE FREQUENTLY RELUCTANT TO RELY ON ADVICE GENERATED FROM MACHINES, ESPECIALLY WHEN THEIR DECISION IS AT STAKE. OUR STUDY PROPOSES A SOLUTION, WHICH IS TO BRING A HUMAN EXPERT IN THE LOOP OF MACHINE ADVICE. WE EMPIRICALLY TEST WHETHER CUSTOMERS ARE MORE ACCEPTING EXPERT-AI COLLABORATIVE ADVICE THAN EXPERT OR AI ADVICE.

Cathy Liu Yang

Xitong Li

Kevin Bauer

Oliver Hinz

Introduction

Intelligent machines' support of human decisions is increasingly at the center of corporate strategies, especially in the financial services sector (Gunaratne et al., 2018). Although it is regularly argued that the use of intelligent machines leads to increases in productivity and quality (Rahwan et al., 2019), it is inconclusive whether and how human decision-makers – laypeople and experts alike – internalize advice from machines. The potential downstream consequences are farfetched. There has been a long tradition that customers rely on expert advice when making a

purchase or investment decision. With the increasing use of machines in customers' decision-making process, little is known about (i) whether and when customers are more accepting of advice from a machine than an expert, and (ii) whether customers feel more assured of the expert advice when knowing the advice is an outcome of a human-AI collaboration. Against this background, we aim to understand whether bringing humans into the loop of algorithmic decision-making will potentially benefit customers by increasing the accountability of algorithmic recommendations.

Experimental Design

We conducted an empirical study of the customers of a German savings bank to answer the abovementioned questions regarding private investments in personal loans. To generate AI advice, we trained a state-of-the-art machine-learning model to predict the riskiness and chance of default of individual loan requests from LendingClub, one of the largest peer-to-peer lending platforms in the world. To generate expert-AI collaborative advice, we conducted a study with bank advisors by asking them to make risk assessments and default predictions for their customers on some selected personal loans with the help of machine predictions.

After collecting the advice of the bankers as an outcome of expert-AI collaboration, we conducted a second study with 137 customers who visited the bank store, where advisors work, between October 2021 and December 2021. Each customer who participated in the study was endowed with EUR 1,000 to make ten investment decisions on personal loan requests (i.e., EUR 100 of endowment per investment) with a chance to realize the investment decision by the end of the experiment. In this manner, the participants in the experiment had strong incentives to behave as they would in a real investment decision because their decision would have an influence on the payout.

For each loan request, participants were instructed to make two rounds of risk assessment and investment decision, once before and once after receiving advice, along with seven pieces of information about the loan (i.e., the loan amount, term, purpose, annual percentage rate, monthly installment payment, borrower's current occupation, and annual income). Upon participating in the survey, we randomly assigned each customer to one of the three experimental conditions where the advice source came from an AI, a human bank advisor, or the human-AI collaboration. To account for individual differences in the investment preferences, we also asked each participant about their risk-taking tendency, investment experience, and other demographic information.

Results

We measured the influence of the advice source on customers' investment decisions in multiple ways: (i) the extent to which customers follow the investment recommendation; (ii) the extent to which customers follow the risk assessment; (iii) the final accuracy in predicting a loan's default; (iv) the payoff in EUR value if an investment decision is realized. We show the results in Table 1, benchmarking the results with the AI advisor condition. We find that customers are more likely to follow a banker's than a machine's

	(1)	(2)	(3)	(4)
	Alignment in Final and Advised Investment Decision	Gap in Final and Advised Risk	Investment Prediction Accuracy	Payoff
Expert	0.478**	-0.348***	0.545***	0.058***
	(0.232)	(0.110)	(0.202)	(0.020)
Expert-AI	0.179	-0.253**	0.584***	0.066***
	(0.234)	(0.106)	(0.211)	(0.020)
Observations	1,369	1,369	1,369	1,369
Investor-Investment Time-Varying Controls, Investor-Level Controls, Initial Risk Assessment Fixed-Effects, Advice Risk Fixed-Effects, Investment Fixed-Effects, Date Fixed-Effects, Branch Fixed-Effects	Yes	Yes	Yes	Yes

Table 1: Customers Are More Likely to Follow Advice from Expert than Machine Even If Machine Influences Expert Advice

investment and risk assessment advice. Additionally, we see that customers tend to follow the expert-AI collaborative advice in investment and risk assessment more than the machine advice. Consequently, customers make more accurate default predictions and receive a higher monetary payoff if the investment decision is realized under the condition that the advice is from an expert or expert-AI collaboration.

While it is not surprising that customers rely on expert advice to a greater extent than on

a machine due to the high-stake decision, we find that customers are not deterred from following expert advice knowing it is influenced by a machine. This trend is evident especially when the investment risk and, therefore, the possible return is high (see column 1 of Table 2), and the customer did actually not plan to invest in the first place (see column 3 of Table 2).

Conclusion

Business practitioners increasingly use AI systems to assist customers in making deci-

	(1)	(2)	(3)	(4)
	High-Risk Investment	Low-Risk Investment	High-Risk Investment	
			No Initial Investment	Initial Investment
Expert	1.878***	0.475	6.146***	0.863
	(0.462)	(0.334)	(1.212)	(0.531)
Expert-AI	1.423***	0.347	5.020***	0.386
	(0.413)	(0.330)	(1.231)	(0.483)
Observations	730	639	433	289
Investor-Investment Time-Varying Controls, Investor-Level Controls, Initial Risk Assessment Fixed-Effects, Advice Risk Fixed-Effects, Investment Fixed-Effects, Date Fixed-Effects, Branch Fixed-Effects	Yes	Yes	Yes	Yes

Table 2: Customers Are More Likely to Follow Expert-AI Collaborative Advice When Investment Is Riskier and When They Initially Decided Not to Invest

sions due to their capability to arrive at higher prediction qualities. Yet, customers might be reluctant to rely on advice from machines, possibly because of a lack of trust. In this study, we find that bringing human components into the advice loop could mitigate the reluctance of customers to rely on machine advice. This human factor reassures customers when they feel the decision is more uncertain. We plan to conduct additional laboratory studies to bring further insights into understanding the psychological mechanism underlying our findings.

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Research Report

What Does Your Personality Reveal about Your Financial Behavior? Evidence from a FinTech Experiment

WE CO-OPERATE WITH A GERMAN FINANCIAL ACCOUNT AGGREGATOR (FAA) AND CONDUCT A PERSONALITY SURVEY WITH 1,700 APP USERS. WE COMBINE THE SURVEY RESULTS WITH THEIR ANONYMIZED TRANSACTION DATA AND INVESTIGATE LINKS BETWEEN PERSONALITY TRAITS AND SPENDING BEHAVIOR. OBSERVING MANY LOTTERY WINDFALLS IN OUR DATASET AND TREATING THESE INCIDENTS AS REAL-LIFE EXPERIMENTS, WE ASK: WHAT DO INDIVIDUALS DO WITH UNEXPECTED INCOME CHANGES? OUR FINDINGS SUGGEST THAT HIGHLY EXTRAVERTED INDIVIDUALS TEND TO OVERSPEND IN RESPONSE TO LOTTERY WINDFALLS.

Andreas Hackethal

Fabian Nemecek

Jan Radermacher

Introduction

Financial Account Aggregators (FAA) enable their users to link all financial accounts and to see an exhaustive overview of the entire financial behavior. This opens great opportunities for research since spending behavior can be holistically observed. We make use of such data with our analysis and, additionally, conduct a survey with users of the FAA. This provides us with complete spending behavior in combination with answers to specific questions about personality and consumption patterns. We used these for our studies on saving and consump-

tion propensities, i.e., investigating how people save and spend money.

Hypotheses and Research Question

We are interested in consumption responses after the receipt of lottery windfalls. Lottery windfalls are useful to analyze as they are characterized as exogeneous transitory income shocks (Olafsson and Pagel, 2020).

Understanding how people react to such unexpected one-time income shocks helps policy makers in designing appropriate monetary

policy, e.g., when assessing the effects of inflation or “helicopter money”. Additionally, understanding how different types of personalities drive spending behavior also helps companies and banks in targeting certain people of interest. Therefore, we examine the question whether people with different personality types react differently to the receipt of lottery windfalls.

Big Five Personality Traits

The “Big Five” personality traits are a psychological model describing personality by five dimensions: openness, conscientiousness, extraversion, agreeableness, and neuroticism (OCEAN). The model is based on the lexical hypothesis postulating that personality differences are encoded in language. Specifically, psychologists have identified personality-describing adjectives and several studies have independently from each other identified the above five stated factors (Borghans et al., 2008).

In Table 1, we display facets of the Big Five traits that describe personality.

Data on personality traits are collected in the form of a personality test that includes several questions per trait, where respondents should answer statements on a Likert scale, such as: “Do you believe in the good of people?”, which elicits the degree of agreeableness. The personality inventory “Revised NEO Personality Inventory (NEO-PI-R)” is the most commonly used questionnaire and was invented by Costa and McCrae in 1978 (Costa and McCrae, 2008). With

240 questionnaire items, it is characterized as a highly precise research instrument. However, as this questionnaire is time-consuming, more recent studies suggest shorter versions of questionnaires, such as the 10-item short version of Rammstedt and John (2007), that can be completed in less than a minute without considerable lack in precision. According to psychological literature, the personality of people is persistent and robust over their lives and, thus, the Big Five only need to be collected once.

In recent decades, the Big Five model has been more frequently incorporated into economic models. However, as Borghans et al. (2008) collate, economists face several limitations, such as the problem with reverse causality: interpreting correlations between personality measures and economic outcomes might be misleading as one cannot per se trace the originated driver from personalities. Economists try to circumvent these causality issues, e.g., by

Openness: Imagination, Emotionality, Adventurousness, Intellect, Liberalism

Conscientiousness: Efficacy, Dutifulness, Achievement-Striving, Self-Discipline, Cautiousness

Extraversion: Friendliness, Activity Level, Excitement-Seeking, Cheerfulness

Agreeableness: Trust, Morality, Altruism, Cooperation, Modesty, Sympathy

Neuroticism: Anxiety, Anger, Depression, Self-Consciousness, Vulnerability

Table 1: Facets of Big Five Personality Traits

further estimating latent factors and disentangling spurious effects – for more details, refer to Borghans et al. (2008).

Financial Account Aggregators

The digitization of different areas of life also reached the private financial budget planning. There are several companies that provide services that help private households and individuals (i) to optimize financial behavior, (ii) to reduce debt, and (iii) with the management of subscriptions. Such a service is called “financial account aggregator”.

FAAs process and aggregate all in- and out-going cash flows from different bank accounts. Doing so, they reveal aggregated income and spending among different categories to provide a unified overview of the user’s financial situation. Such FAAs make use of the EU Payment Services Directive (PSD2) to receive customer data entrusted with other financial service providers.

Spending Behavior and Personality Traits

In recent years, several studies have used FAA data and started to analyze spending behavior of different personality types. For example, Landis and Gladstone (2017) investigate peoples’ spending behavior and reveal that especially extraverts consume more status-related goods. Tovanich et al. (2021) go further and infer Big Five traits from the digital footprints that FAA users left with their transaction data. Specifically, they make use of the rich set of transaction data and apply machine learning

methods to predict the Big Five traits. Doing so, they can identify which spending categories are driving certain personality types.

Survey and Transaction Data

We use data from a German financial account aggregator app that provides a personal money management mobile application where users can connect different bank accounts to reveal aggregated income and spending among different categories in a unified overview.

We surveyed about 2,200 customers, and after filtering uncompleted surveys, we end up with about 1,700 observations. We incentivized respondents by raffling 50 Amazon vouchers. We surveyed the Big Five using the Big Five Inventory (BFI)-10 questionnaire of Rammstedt and John (2007).

In our sample, about 25% of the customers received any type of lottery windfall. Such lottery windfalls emerge, for instance, from sports bets (about 11%, e.g., Tipico, Tipp24.de), from charity lotteries (about 6%, e.g., Aktion Mensch), from classical lotteries (60%, e.g., Toto Lotto), and others (23%).

In Figure 1, we show the averages of some personality traits for lottery players and those that do not. We see that the personality traits are rather pronounced for lottery players. This gives us certainty that personality traits are indeed translated into behavior, saying that individuals with pronounced openness and extraversion are

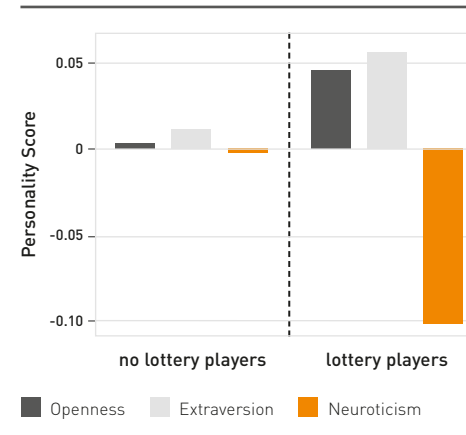


Figure 1: Standardized Personality Traits by Gender and Lottery Windfall

rather lottery players. In addition, they are characterized by a very low degree of neuroticism.

Before we turn to the empirical analysis, we investigate visually whether individuals increase their consumption after the receipt of lottery windfalls. For this, we display in Figure 2 the average monthly total consumption of the customers in a four-month time window around the lottery windfall. We define total consumption as the monthly sum of all accounts’ outflows in the categories: cinema, sports, streaming, tickets, newspaper, virtual goods, pets, toys, etc. We see that before the arrival of the lottery windfall, the average total consumption lies around EUR 2,750 and, then, jumps up to over EUR 3,000 in the month of the windfall and peaks in the month after the arrival. Based on this, we indeed see that individuals react to lottery windfalls.

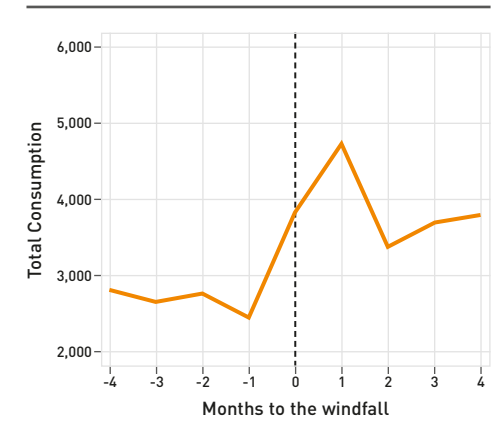


Figure 2: Total Consumption before and after the Receipt of Lottery Windfall

Empirical Investigation

To identify the consumption response of individuals depending on their personality traits, we conduct the following pooled OLS regression:

$$y_{i,t} = \beta_0 + \beta_1 Windfall_{i,t} + \beta_{2,j} BigFive_{i,j} + \sum_{s=-L}^L \beta_{3,t+s} D_{i,t+s} + \beta_4 X_{i,t} + \epsilon_{i,t}$$

In this specification, $y_{i,t}$ stands for total consumption of individual i in time t . In addition, β_1 measures the impact of the windfall in EUR on total consumption and $\beta_{2,j}$ includes the coefficients for the $j=5$ Big Five traits. $D_{i,t+s}$ are dummies that control for the $L=3$ month window around the lottery windfall. $X_{i,t}$ is a vector of control variables such as gender, age, and income. Lastly, $\epsilon_{i,t}$ is the error term and standard errors are clustered on individuals. With this specification, we expect to

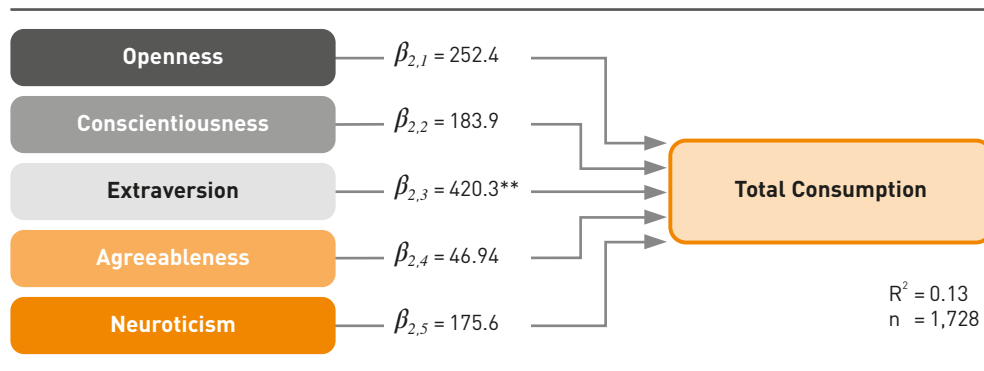


Figure 3: Coefficients of Big Five Personality Traits

see significant effects in the coefficients of the Big Five traits and that the dummy variables $D_{i,t+s}$ indicate significances in the month of or the month after the arrival of the windfall.

Results

The results of the regression are displayed in Figure 3. For the sake of brevity, we only show the coefficients of the Big Five traits, in which we are interested.

The coefficients are interpreted as follows: In the case of extraversion, a one standard deviation increase leads to an increased consumption by about EUR 420. The coefficient of extraversion is the only significant one and the remaining coefficients are all insignificant. We conducted several robustness checks to find further support for this finding.

If we look closer how extraverts in our data set spend money, we see that in addition they spend more for food and clothes shopping.

This finding is in line with Landis and Gladstone (2017) who also identified extraverts as the group that overall spends more, especially on status. In their study, they define spending on high status by elicited preferences for the categories "foreign air travel", "golf", "electronics", and "art institutions".

It is important to mention that, with the underlying sample, we cannot fully generalize our findings to the German population. We compared our dataset with representative samples (e.g., the German Socio-Economic Panel) and found that customers of the FAA only represent younger and wealthier cohorts and were predominantly male.

Methodologically, we could not perform the preferred fixed effects regression because Big Five traits are time invariant and would be omitted. Therefore, we conducted several robustness checks, for instance, we set the traits themselves as fixed effects. By this, we end up with

similar results. Lastly, it is worth mentioning that, for the scope of this analysis, we abstained from more profound endogeneity tests, so that we are limited in providing a full picture on causalities. Nevertheless, our analysis demonstrates that personality traits are indeed relevant determinants that might explain further heterogeneity in consumption behavior.

Conclusion

The co-operation with the German FAA enabled us to study consumption behavior (using transaction data) and personality traits (relying on survey results) in parallel. It allowed us to investigate links between personality and consumption behavior from an economic perspective. Apart from the rich and unique dataset, the setting and research question also form a novel contribution to the literature.

Our finding that extraverted individuals tend to overspend on lottery windfalls confirms our initial hypothesis and can be well embedded in the existing literature. In large groups (e.g., all customers of a bank, all individuals in a country) percentage shares of extraverts are well known thanks to the psychological literature. Combining these insights with our findings could help policy makers to design appropriate policy solutions to help extraverts tackle problematic overspending issues (e.g., by raising awareness through campaigns).

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Insideview

“MiCA” – Regulating the European Markets in Crypto-Assets

INTERVIEW WITH STEFAN BERGER

The new Markets in Crypto-assets Regulation (MiCA) will massively affect European users of distributed ledger technology (DLT) and investors in digital assets. From your perspective as the rapporteur of the European Parliament on MiCA, what are the main targets?

The financial world is facing a development as groundbreaking as the introduction of the joint-stock company in the 17th century – the tokenization. What is tradable today could be tokenized on the blockchain tomorrow. The World Economic Forum predicts that 10% of global gross domestic product (GDP) will be tokenized by 2029; an estimated USD 10 trillion. For Europe, the challenge is to create a regulatory framework with reliable authorization and supervisory structures for tokens, while balancing consumer protection and innovation-friendliness.

What changes will MiCA bring for institutions and firms (e.g., crypto exchanges) on the one hand – and for the end users and investors on the other hand?

The different frameworks and regulations that exist across the European Union regarding crypto-assets limit the possibilities for service providers to expand their activities at EU level. As a result, providers of cross-border products and services are obliged to deal with the laws of several Member States, obtain different national authorizations or registrations, and comply with often divergent national laws. This may lead to high costs, legal complexity, and uncertainty for crypto service providers, limiting the development and expansion of crypto-asset-related activities in the European Union. We see locational inequalities for crypto service providers, which may hinder the smooth functioning of the internal market. The introduction of a common EU framework aims to create



Dr. Stefan Berger
Member of the European Parliament
Committee on Economic and Monetary Affairs

uniform operating conditions for companies within the EU. On the other hand, MiCA is also setting high standards for consumer and investor protection.

Bitcoin was established in the year 2009. Why did the proposal for this substantial regulation come up in the year 2020 – and not much earlier?

First of all, it should be mentioned that bitcoin does not fall under MiCA and enjoys so-called “grandfathering”. The urgency of the approval and supervision of new tokens has become evident when Meta (formerly Facebook) announced that it planned to release its own stablecoin named “Diem”. With around 2.5 billion users of Meta’s apps, by Diem, Mark Zuckerberg could have become a central bank overnight. I believe this kind of power should not be in the hand of a private company. This is why we need MiCA.

What have been the most critical discussion points in the European Parliament and how did you manage to solve them?

Within the parliament, the political groups have intensively discussed the environment and energy consumption of bitcoin. For me as rapporteur, it has always been clear that a ban on proof-of-work is out of the question if we want to create a European innovation hub. On June 30th, MiCA’s last trilogue took place. On behalf of the Parliament, I was in negotiation with the Commission and Council, among other topics, on environmental aspects of crypto-assets. In the end, we took the path of technology openness together, instead of the path of ban. We have agreed that crypto-asset providers should in future disclose the energy consumption and environmental impact of assets. The basis for this will be regulatory technical standards (RTS).

Thank you for this interesting conversation.

Infopool

News

EFL ANNUAL CONFERENCE 2022

The efl – the Data Science Institute invites you to the 2022 edition of the Annual Conference on “Democratization of Data Science & AI”. The event will take place on October 11th, 2022, at Goethe University Frankfurt, Campus Westend, and is organized by Prof. Binnig and his team. The conference will commence at 14:30. Further information will be available soon via: <https://www.eflab.de/annual-conference-2022/>. The registration form is available via: <https://goto.dm.informatik.tu-darmstadt.de/efl/annualconf2022/>. As always, the participation is free of charge.

Prof. Dr. Wolfgang König Retired and Left the efl after 20 Successful Years

We thank Prof. Dr. Wolfgang König for his extraordinary work as the initiator and long-time chairman of the efl. Prof. Dr. Oliver Hinz has taken over his role in February 2022. We wish Wolfgang all the best for his future and hope that he will stay in close contact with the efl!

Dr. Jascha-Alexander Koch Accepted Position as Junior Professor

Dr. Koch will join the University of Siegen as a tenured junior professor of Finance in Business Administration, in particular Digitalization. He joined the Chair of e-Finance (Prof. Dr. Gomber) in August 2013 and received his doctoral degree in July 2019. Since January 2014, he was in the editor team of the “efl insights”. We thank Dr. Koch and wish him all the best for his career!

Prof. Dr. Oliver Hinz Will Be Member of AI Quality & Testing Hub

Prof. Dr. Oliver Hinz joins the expert council of the AI Quality & Testing Hub, which was founded by the Hessian Ministry for Digitization, the Association for Electrical, Electronic & Information Technologies (VDE) and the Technical Inspection Association (TÜV).

Prof. Dr. Bernd Skiera Hosted Data Science Session

Prof. Dr. Bernd Skiera hosted a half-day session on “Static and Dynamic Mapping Method for Uncovering Competitive Positions” at the “European Association for Data Science (EuADS Summer School) – Data Science for Social Media” on June 15th, 2022, in Luxembourg. More information: <https://www.euads.org/fjkdslasjdiglsmgdkcxjhvckh/euads-summer-school/>

TechConference Took Place in June

On June 17th and 18th, the student-run organization TechAcademy at Goethe University, supported by Prof. Dr. Bernd Skiera, organized the “TechConference 2022 – Together for Digital Change.” Representatives from more than 17 non-profit organizations from all over Germany discussed voluntary engagement and didactic concepts for better technology education. Students used the opportunity to interact with leading representatives from academia, industry, and politics. More information: <https://conference.tech-academy.io/>

Selected efl Publications

Bender, M.; Cestonaro, T.; Gomber, P.:

Research Unbundling and COVID-19: Will Europe’s Capital Markets Recovery Package Help?
In: Journal of Investing, 31 (2021) 1, pp. 96–107.

Bender, M.; Frank, S.; Panz, S.:

Dynamics of Trending Topics between Social Media, News, and Scientific Literature.
In: Proceedings of the 30th European Conference on Information Systems (ECIS); Timisoara, Romania, 2022.

El-Hindi, M.; Zhao, Z.; Binnig, C.:

ACID-V: Towards a New Class of DBMSs for Data Sharing.
In: Lecture Notes in Computer Science (LNSC), 12921 (2022), pp. 60–64.

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In: Proceedings of the 30th European Conference on Information Systems (ECIS); Timisoara, Romania, 2022.

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Siering, M.:

Explainability and Fairness of RegTech for Regulatory Enforcement: Automated Monitoring of Consumer Complaints.
In: Decision Support Systems, 158 (2022), Article No. 113782.

Yan, S.; Miller, K.; Skiera, B.:

Do Ads Harm News Consumption?
Forthcoming in: Journal of Marketing Research, 2022.

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RESEARCH PAPER: BIAS IN THE EFFECTIVE BID-ASK SPREAD

The effective bid-ask spread measured relative to the spread midpoint overstates the true effective bid-ask spread in markets with discrete prices and elastic liquidity demand. The use of the midpoint also undermines liquidity timing and trading performance evaluations, and can lead non-sophisticated investors to overpay for liquidity. To overcome these problems, the author proposes new estimators of the effective bid-ask spread, incorporating two proxies for the fundamental value: the weighted midpoint and the micro-price. Both proxies factor in the order book imbalance, measured by the relative depth quoted at the best bid and ask prices. The resulting bias reduction in the liquidity measurement reduces transaction costs of traders by 43–44% in a simulated liquidity demand strategy.

Hagströmer, B.

In: *Journal of Financial Economics*, 142 (2021) 1, pp. 314–337.

RESEARCH PAPER: THE VALUE OF DESCRIPTIVE ANALYTICS: EVIDENCE FROM ONLINE RETAILERS

Researchers and practitioners often focus on the latest statistics and machine learning methods for their projects. However, a new study shows that even the simple implementation of descriptive analytics leads to significantly higher revenues. In the context of online retailing, the authors use a staggered rollout of descriptive analytics dashboards to measure the impact on seller performance. The study finds that those sellers who adopt a comprehensive descriptive analytics dashboard generate 4%–10% higher revenues and explains possible mechanisms behind that increase. While significant in the specific context, those findings suggest that descriptive analytics – without any modeling through statistical methods or machine learning – provide significant value to businesses.

Berman, R.; Israeli, A.

Forthcoming in: *Marketing Science*, 2022.

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