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AN E-FINANCE LAB PUBLICATION

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Encouraging Growth Funding

Asset Allocation versus Security Selection – New Insights from Individual Investors

Analyzing the Relationship between Differentiated Online Sentiment and Company-Specific Stock Prices

Buy-Side Trading – Challenges Today and Tomorrow

GOETHE UNIVERSITÄT FRANKFURT AM MAIN
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Redaktion
Prof. Dr. Peter Gomber
M. Sc. Jascha-Alexander Koch
Dr.-Ing. Christoph Rensing

Herausgeber
Prof. Dr. Wolfgang König
Vorstandsvorsitzender des E-Finance Lab
Frankfurt am Main e. V.
Prof. Dr. Peter Gomber
Stellvertretender Vorstandsvorsitzender des E-Finance Lab
Frankfurt am Main e. V.

Kontakt
info@efinancelab.com
www.efinancelab.com

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Editorial

Encouraging Growth Funding

Martin Reck

Dr. Martin Reck
Managing Director, Cash Market
Deutsche Börse AG

Insufficient availability of venture capital is the most significant weakness of the German innovation system. Compared with international markets, the potential of German venture capital is still far from being fully utilized. While public funding generally covers much of a company's early stage financing needs, there's a lack of venture capital in the growth financing stage. The Deutsche Börse Venture Network contributes to the establishment of a more attractive business environment for the growth financing phase by substantially improving the financing, exit, and IPO channels. The overall objective is to create a comprehensive ecosystem to encourage growth funding and spur innovation. The Venture Network is designed for companies in the growth, late stage, or pre-IPO phase as well as for international venture capital, private equity and fund investors, family offices, and high-net-worth individuals (HNWI). However, this is an invitation-only network. Companies must satisfy proof-of-concept requirements and fulfil three out of six criteria: (1) already received funding above EUR 10 million plus company value above EUR 20 million, (2) yearly turnover above EUR 10 million, (3) yearly turnover growth above 30%, (4) annual net profit over EUR 500,000, (5) equity above EUR 5 million, (6) nomination by a lead investor.

The focus of the Venture Network is on facilitating matching and networking between investors and companies based on three key elements: First, companies and investors may use the exclusive non-public online platform to communicate with each other and to initiate funding rounds. Companies can provide confidential documents to selected investors by using the protected data room. The online offering is amplified by the two offline elements, events and training, to create trustful personal relationships, exchange ideas, transfer knowledge, and prepare for the capital market. The range of events includes exclusive investor meetings and roadshows, granting companies access to growth investors or other supporting facilitators and key people, such as experienced entrepreneurs, mentors, mutual funds, family offices, and politicians. This gives companies the opportunity to present themselves directly to potential investors. The training program has been developed by Deutsche Börse Group's Capital Markets Academy together with Munich's Technical University. The bespoken training program matches with the specific needs of growth companies and imparts valuable know-how in the areas of corporate development, investor relations, and capital markets readiness. The combination of academic knowledge and business practice allows companies to acquire key skills to successfully develop and scale their businesses.

The Venture Network aims at supporting a new spirit for investments and innovation through improved access to a broad pool of capital, accelerating capital market readiness by progressively familiarizing companies with corporate governance and reporting requirements, and providing an intermediate step paving the way to an IPO if this is the desired exit strategy. Pre-IPO investor communication may enhance mutual trust and lead to better valuations.

A reliable network is an important foundation for a well-established ecosystem. The Venture Network brings talent together with capital by creating a curated community that promotes collaboration and constant exchange of views with investors, peers, and competitors, allows companies to receive feedback and to find mentors, technology partners, clients, and employees. The Venture Network aims at supporting a perfect set-up for innovation, strong ideas, and trustful relationships that encourage and improve growth funding in Europe and help companies to successfully grow their businesses internationally.

Research Report

Asset Allocation versus Security Selection – New Insights from Individual Investors

WE DECOMPOSE INDIVIDUAL INVESTORS' PORTFOLIO RETURNS INTO PASSIVE BENCHMARK RETURNS, ACTIVE SECURITY SELECTION RETURNS, AND ACTIVE MARKET TIMING RETURNS. FOR THE AVERAGE INVESTOR IN OUR SAMPLE, PASSIVE BENCHMARK RETURNS EXPLAIN SOME 40% OF VARIATION IN LONGITUDINAL PORTFOLIO RETURNS, SECURITY SELECTION EXPLAINS AN ADDITIONAL 50%, AND MARKET TIMING PLAYS ONLY A MINOR ROLE. THIS STANDS IN STARK CONTRAST TO EARLIER RESULTS ON INSTITUTIONAL INVESTORS WHERE PASSIVE BENCHMARK RETURNS (REFLECTING DIFFERENT ASSET ALLOCATION STRATEGIES) EXPLAIN OVER 90%. THE PREDOMINANCE OF SECURITY SELECTION COMES AT A COST FOR INDIVIDUAL INVESTORS: INVESTORS FROM THE HIGHEST QUINTILE IN TERMS OF SECURITY SELECTION ACTIVITY UNDERPERFORM THEIR PEERS FROM THE LOWEST QUINTILE BY MORE THAN 10 PERCENTAGE POINTS PER YEAR. TRANSACTION COSTS EXPLAIN ONLY PART OF THIS UNDERPERFORMANCE. THE LESS INVESTORS DIVERSIFY, THE WORSE THEY DO.

Benjamin Loos
Steffen Meyer
Andreas Hackethal

Introduction

A large strand of the household finance literature focuses on investment mistakes and the investment performance of individual investors. However, results vary depending on the specific dataset and methodology used. Investment mistakes are often referred to be the potential reasons for the lack of performance among individual investors.

Odean (1999) analyzes the timing of trades made by individual investors. His results show that stocks sold by individuals subsequently outperform the stocks purchased. Barber and Odean (2000) analyze the aggregate performance of all stocks held directly by individual investors. Both studies conclude that individual investors trade too much in single stocks and pay a performance penalty after transactions costs. In our paper, we seek to shed additional light on the investment decisions of individual investors by decomposing their total portfolio returns into three components (Fama, 1972): investment policy (i.e., passive benchmarks from asset allocation strategies), market timing, and security selection.

The classical method to decompose portfolio returns into performance components was developed by Brinson et al. (1986). Investment policy returns correspond to the hypothetical return an investor would achieve if the average asset class weights were kept constant throughout the entire investment period and if the investor invested in the benchmark index of each asset class. Market timing measures the effect of a temporary under- or overweighting of asset classes relative to an investor's average long-term asset class weights. Security selection refers to the active selection of securities within a specific asset class.

According to Brinson et al. (1986), investment policy and thus asset allocation are the key determinants of institutional investors' returns and explains on average 93.6% of the variation in quarterly funds returns across time. So far, research has exclusively focused on institutional investors to determine the importance of investment decisions.

Data and Methodology

In this study, we use a dataset on 7,707 individual investors provided by one of Germany's largest online brokers. We have detailed information on all single securities, demographic data on all individual investors, their monthly holdings, and their daily trading records for the period August 2005 through March 2010. The daily frequency of trading records in combination with monthly holdings allows us to compute the four required return series on a daily basis.

We use the bank's security categorization in conjunction with the Lipper funds database to identify daily asset class weights (investor's actual asset class weights) and to compute individual portfolio returns (investor's actual asset class returns). We use four asset classes: equity, fixed income, cash, and other. The other asset class mainly comprises blended funds that do not belong to any of the other three asset classes, investment certificates, and options. We use the average holding of each asset class for each investor as an approximation of the investment policy weights *(investor's average asset class weights).*

For investment policy returns, we use asset class benchmark returns and, in order to ensure the robustness of our results, we employ three different asset class benchmarks: a German set of benchmark indices, an international set of benchmark indices, and an own-benchmark approach. Our main analysis is based on a German set of benchmarks since investors have 50% of their equity part, which on average makes up 84.8% of investors' portfolios, invested in German securities.

Our research strategy is as follows: As a first cut, we look at the returns from investment policy, security selection, and market timing to obtain tentative evidence on how much an investment activity contributes to individual investors' portfolio returns. In a second step, we regress on an investor-by-investor basis each of the three constructed return series on the actual return series. This yields evidence on the relative importance of investment policy, security selection, and market timing in explaining variation in portfolio return time-series.

Empirical Findings

We find that investment policy and security selection are the main determinants of individual investors' performance. On average, each explains about half of the return variation across time. Market timing is negligible. There is, however, considerable cross-sectional variation in the importance of investment policy and therefore also in the importance of security selection among individual investors.

To further investigate this variation, we divide our sample into quintiles based on the importance of investment policy. The individual investors with a low importance of investment policy (quintile 1) have an average R-squared of 10.4%; those with a high importance of investment policy (quintile 5) have an average R-squared of 71.5%. Investors with a low importance of investment policy tend to be younger, poorer, have a slightly shorter relationship with the bank, have smaller investment accounts, trade more, have higher portfolio turnover, a lower share of their portfolio invested in the equity asset class, and a higher share in the other asset classes. Furthermore, the coefficient estimates from a Fama-French & Carhart four-factor model reveal that quintile 1 investors (low importance of investment policy), compared to quintile 5 investors (high importance of investment policy), prefer to tilt their portfolios more heavily toward low-beta, small, value, and momentum stocks.

Importance of Investment Policy and Annual Fama-French & Carhart Intercepts

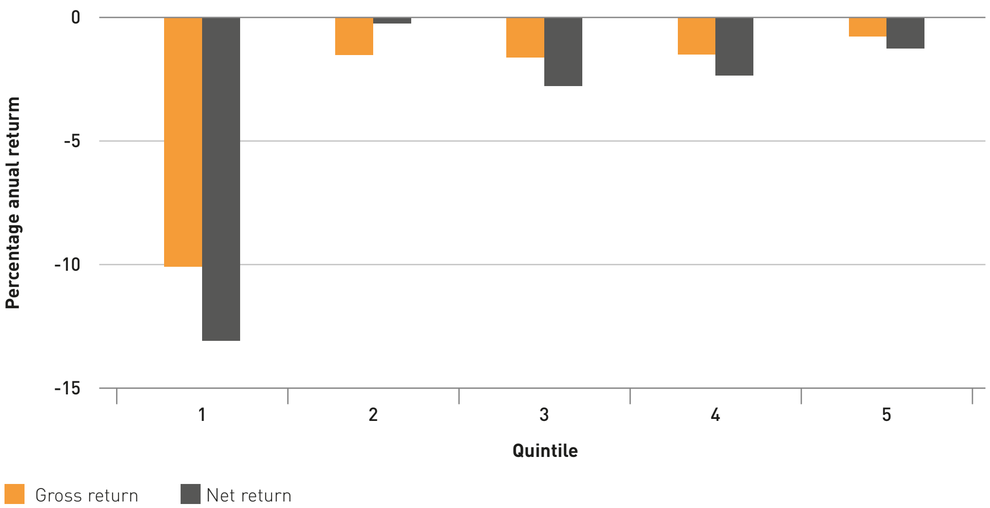

Figure 1: The Dark (Light) Orange Bar Represents the Gross (Net) Annualized Mean Fama-French & Carhart Intercepts for Individual Investor Quintiles Partitioned by Importance of Investment Policy.

The quintile of investors, for whom security selection is relatively important, underperforms all other investors by over 8% per year gross of transactions costs and 10% per year net of transactions costs (see Figure 1). Turnover increases with the importance of security selection, but can only partially explain this underperformance. This result is markedly different from results reported in Barber and Odean (2000), who find almost no underperformance in gross returns, but increasing underperformance with turnover in net returns. Differences in gross returns across quintiles 2 to 5 are small in our sample, too. There is, however, one group of investors with very active security selection (i.e., high unsystematic risk shares), high turnover, a higher share of their portfolio invested in other products like certificates and options, and a portfolio tilted toward low-beta and small stocks that underperforms their peers even before accounting for transactions costs. The other products asset class underperforms the equity asset class of these investors' portfolios by approximately 10% per year. Trading in options and structured products aggravates the effect of bad security selection.

Conclusion

In sum, investors trade too much, but transaction costs explain only part of the under-performance. The remainder can be attributed to bad security selection. The less investors diversify, the worse they do. Financial product innovations or professional services that increase self-control and increase portfolio efficiency could be potential solutions.

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Research Report

Analyzing the Relationship between Differentiated Online Sentiment and Company-Specific Stock Prices

PRACTITIONERS AND RESEARCHERS ALIKE INCREASINGLY USE SOCIAL MEDIA MESSAGES AS AN ADDITIONAL SOURCE OF INFORMATION WHEN DEALING WITH STOCKS. BASED ON EMOTION THEORY AND AN ESTABLISHED SENTIMENT LEXICON, WE DEVELOP AND APPLY AN OPEN SOURCE DICTIONARY FOR THE ANALYSIS OF SEVEN DIFFERENT EMOTIONS IN 5.5 MILLION TWITTER MESSAGES ON 33 S&P 100 COMPANIES. WE FIND VARYING EXPLANATORY POWER OF DIFFERENT EMOTIONS (ESP. HAPPINESS, AND DEPRESSION) FOR COMPANY-SPECIFIC STOCK PRICE MOVEMENTS OVER A PERIOD OF THREE MONTHS.

Marten Risius

Fabian Akolk

Roman Beck

Introduction

Comprehensive and immediate information plays a crucial role in stock price analysis. In this regard, researchers and practitioners alike increasingly consider online user-generated content as an additional source of information for investment decision-making. Events like the loss of approximately USD 136 billion in equity market value within three minutes due to a fake tweet from the hacked Associated Press Twitter account demonstrate the interwovenness between Social Media and stock markets. Social Media also affects the stock market on a more regular basis, seeing that the New York Stock Exchange (NYSE) introduced an automated sentiment analysis of Social Media platforms to provide investors with real-time information on indices, industry sectors, and specific companies.

Company-specific tweet sentiments have been found to intervene with investor decision-making, affect market prices through information leakage, and have explanatory power for daily stock price changes (e.g., Bollen et al., 2011). So far, the majority of research has ignored the more complex, multi-dimensional structure of human emotions and only considered aggregated sentiment measures. The few studies that considered differentiated emotions found differential effects for positive and negative messages on stock prices (e.g., Sprenger et al., 2014). However, this research is generally limited to general market indices, included very few emotion words, has neglected the predictive value of specific emotions, and withheld specifics on the operationalization of the emotions.

In this study, we address this research gap by developing an open source emotion-specific dictionary which is derived from the established SentiStrength word list. It enables us to assess seven different emotions whose operationalization is based on the model of the hierarchical structure of the affective domain developed by Ekkekakis (2013). Subsequently, this sentiment analysis is applied to 5.5 million Twitter messages on 33 S&P 100 companies which we collected over a three-month period. Ultimately, we conduct a lagged panel regression of the differentiated emotion strength on the company-specific NYSE stock price movements obtained from Yahoo!Finance. Overall, in this study, we investigate how differential emotions correspond to company-specific stock price movements.

Developing an Emotion-Specific Sentiment Analysis

When applying automated sentiment analysis, Information Systems researchers have predominantly focused on measuring the average emotionality (positive vs. negative). However, the undifferentiated dimensional approach implies a lower degree of specificity which can only be overcome through the assessment of distinct emotional states. In a critical reconsideration of emotion theory research, Ekkekakis (2013) integrated different emotion concepts into one model of the hierarchical structure of the affective domain. In this study, we rely on the model's refined emotional states in addition to the basic valence (positive vs. negative) dimension.

To develop the differentiated sentiment analysis tool, we draw on the established "SentiStrength 2" dictionary which provided the emotion words with over 2,300 sentiment words (Thelwall et al., 2012). Three independent coders classified these words into the seven different emotions (affection, happiness, satisfaction, fear, anger, depression, and contempt) described by Ekkekakis (2013). The underlying description of the classification can be found in Table 1. We provide open access to the differentiated sentiment analysis with the emotion specific coding here: http://bit.ly/1BpocLl.

Differential Sentiment Analysis and Stock Price Movements

Online user-generated content is increasingly relevant as a source of information for investment decision-making. Social Media content in general and company-specific tweet sentiments in particular have been found to inter-

Emotion		Description	Emotion Word
Valence	State		
Positive	Affection	Genuine fondness and liking that is attributed to a particular person or object.	Love, Adoration
	Happiness	Amplified enthusiasm and excitement about attaining something desired or desirable.	Joy, Terrific
	Satisfaction	Proud acknowledgement of and contentment with reaching a predetermined goal.	Pride, Contentment
Negative	Fear	Anticipatory horror or anxiety in unpredictable or potentially harmful situations.	Horror, Anxiety
	Anger	Animated animosity towards malice that can motivate rectification.	Hate, Outrage
	Depression	Impeding sadness evoked by an aversive event that may hinder activity.	Sadness, Hopeless
	Contempt	Revulsion to something considered socially offensive or unpleasant.	Guilt, Disgust

Table 1: Overview of the Seven Different Emotions and Their Operationalization

vene with investor decision-making, affect market prices through information leakage, and have predictive power for daily stock price changes (e.g., Li et al., 2014). However, recently researchers discovered differential effects for positive and negative messages on stock prices and an improvement of the predictive validity on global market indices by considering specific emotions while the undifferentiated sentiment only shows a poor correlation with company stocks (e.g., Sprenger et al., 2014). Thus, we hypothesize:

Hypothesis 1: The average message sentiment about a company is unrelated to the company's stock prices.

Comparisons of the differential effects of positive and negative sentiment valence on Social Media platforms show that negative messages spread more easily than positive news and receive more attention. Consequently, company-specific negative user-generated content is more thoroughly processed and has more explanatory power of abnormal returns than positive information. Accordingly, we conclude:

Hypothesis 2: The stronger the negative valence of the message sentiment about a company, the lower its stock prices, whereas the positive sentiment is unrelated to company stock prices.

Only a small share of research has investigated the specific effects of different emotions on stock prices. These findings, however, can be generally summarized in the sense that different emotions (mostly the negative ones) have differential effects on stock prices. Especially fear, depression, and anger have been linked with a downward pressure on stock prices and trading volume. We therefore expect:

Hypothesis 3: The strength of the differentiated message sentiment about a company is related to company stock price variations.

Empirical Investigation

In order to empirically analyze the relationship between different emotions and company-specific stock prices, we collected 5.5 million tweets and 61 NYSE daily closing values on a random sample of 33 S&P 100 companies over a three-month period. We computed the average sentiment (Model 1), the average strength of positive and negative emotions (Model 2), and the average strength of the differentiated emotions (Model 3) as well as the daily closing value difference per company for each day. Afterwards, we conducted fixed effects panel regressions with robust standard errors to test our hypotheses (Table 2).

The average sentiment (Hypothesis 1) of company-related tweets showed no explanatory power for the stock price movements.

The emotional valence specific analysis (Hypothesis 2) shows that the stronger the negative sentiment towards a company, the lower its stock price, while the strength of the positive sentiment was unrelated to stock price movements. This finding – as opposed to the case of an aggregated sentiment – shows the necessity for a more differentiated sentiment analysis especially when analyzing company-specific effects.

The subsequent simultaneous consideration of the distinct emotions (Hypothesis 3) shows more precisely that depression and happiness are significantly associated with stock price movements. Considering that happiness has a significant effect while the average positivity is not associated with stock prices shows again the importance of investigating single emotions separately.

Generally, our results support our underlying assumption that the differentiated sentiment offers additional explanatory power for the company-specific stock price developments.

Discussion of the Results

The goal of this study was to analyze the explanatory power of differentiated emotions expressed in tweets for company-specific stock prices. Specifically, we focused separately on emotions with positive (affection, happiness, satisfaction) and negative valence (fear, anger, depression, contempt). Based on established emotion research (Ekkekakis, 2013) and sentiment analysis (Thelwall et al., 2012), we developed and applied an open source emotion-specific dictionary that also considers the underlying valence and activity dimensions. By analyzing daily closing values of 33 S&P 100 companies over the period of three months, this study provides three key findings: (1) the differentiated emotions are more strongly associated with company-specific stock price changes than the undifferentiated average sentiment, (2) negative emotions generally have a higher explanatory power, and (3) especially the strength of emotions referring to specific events

Predictor Variables	Model Statistics		
	Coefficient	Standard error	t-Value
Model 1	$F_{10,32} = 63.81^{***}$, $R^2_{within} = 35.8\%$		
Average	.002	(.001)	1.55
Model 2	$F_{11,32} = 56.46^{***}$, $R^2_{within} = 36\%$		
Positive	.0001	(.002)	-0.12
Negative	-.003**	(.002)	2.11
Model 3	$F_{16,32} = 58.24^{***}$, $R^2_{within} = 36.26\%$		
Affection	.0003	(.003)	0.1
Happiness	-.007*	(.004)	-1.83
Satisfaction	.004	(.003)	1.29
Fear	.0006	(.002)	0.29
Anger	.001	(.002)	0.66
Depression	.009***	(.003)	2.89
Contempt	.003	(.004)	0.79

Notes: Model 1 = Average Sentiment; Model 2 = Average Strength of Positive and Negative Sentiment;
Model 3 = Average Strength of Differentiated Emotions
Each model controlled for weekdays, mean S&P 500 return, pre-holidays, and earnings releases

Table 2: Results of the Fixed Effects Panel Regressions to Test our Hypotheses

(depression and happiness) account for price movements.

Considering the theoretical foundation of these measures, it seems that – while general stock market indices are influenced by the anticipation of hypothetical aversive events (i.e., fear) – company stocks are only influenced by events that have actually occurred. This would also explain why happiness – which constitutes the conceptual opposite of depression – also affects stock prices significantly. The surprisingly negative effect of happiness could be explained by the distinction between immediate and expected emotions. The respective literature suggests that positive emotions might make investors more risk-avoidant by trying to avoid a disturbance of positive feelings. In a similar vein, researchers found evidence that the amount of expressed emotions and not the specific type (i.e., fear, worry, and hope) causes a market index decrease.

Our study offers substantial contributions to research and practitioners alike. The differentiated sentiment analysis developed in this work overcomes existent limitations of the few other differentiated sentiment analyses which have not considered the strength of an emotion, do not respect the exclusiveness of emotion states, or withhold detailed insights into the classification of emotions (e.g., Bollen et al., 2011). On the contrary, we provide access to the dictionary for practitioners to apply.

The evidence presented for the necessity of a more differentiated sentiment analysis is equally relevant for practice considering that NYSE does provide sentiment scores on stocks and industry branches which, however, are limited to the binary emotional valence.

The implications of this study must be considered in the light of their limitations that also provide a basis for future research. The results are limited in their generalizability to microblogging platforms and to the western culture since we only considered tweets in English and NYSE stock prices. Moreover, it could be assumed that the larger number of negative than positive words present on our dictionary might cause bias towards the bigger influence of negative emotionality (e.g., Nielsen, 2011). Future research will need to compare the impact of single actually identified words and the number of words within sets of message.

Furthermore, Sprenger et al. (2014) found time-related effects for positive and negative emotions. Future research should analyze potential intraday and day outlasting effects of differential emotions. Also, the interplay of different emotions needs to be considered as, for example, depression has been found to have a competing effect to anger on risk-taking. Lastly, we intend to analyze whether different emotions are more important in other environments such as customer care, where anger might be expressed more openly.

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Insideview

Buy-Side Trading – Challenges Today and Tomorrow

INTERVIEW WITH CHRISTOPH HOCK

Christoph Hock
Head of Trading
Union Investment

While in the past many buy-side institutions, e.g., asset management firms, outsourced the order execution responsibility to brokers (the sell-side of the industry), today, they handle major parts of the order execution process themselves based on sophisticated technology and quantitative techniques. How has the search for liquidity changed and what is the role of the broker today?

A key element of our philosophy to deliver a best-in-class service to our clients – internally our portfolio managers, externally our investors – is having access to all possible forms of liquidity. A sophisticated electronic trading platform with smart order routing, broker algorithms, and program trading is as essential as block liquidity seeking strategies. I would describe our relationship with brokers in this context as a very well-established partnership.

The most challenging task you're facing is the search for block liquidity especially in mid and small cap stocks. How do you handle this difficult task?

In a highly fragmented environment, where the average traded execution size is around EUR 10,000, accessing block liquidity is essential to deliver a best execution and to generate additional alpha for our clients. How do we manage this process and what methods do we use? Just to name some: In the electronic space, there are services like Turquoise Block Discovery enhancing opportunities for block trading. And we are involved in initiatives like Plato in Europe and Luminex in the US, which are designed to execute larger trade sizes and to give investors more influence on market structure. We also source block liquidity via IPOs and accelerated bookbuilds.

What is the role of trading venues, especially of dark pools, in your search for block liquidity?

We expect the use of dark pools to change significantly with the regulation of MiFID II/MiFIR coming into place in 2017. Given the double volume caps of 4% and 8%, respectively, we expect that average trade sizes in dark pools will increase significantly as block trading evolves to utilize the so-called Large-In-Scale waiver (LIS), which is not subject to the above mentioned caps. As a result, dark pools will continue to play a key role for trading block sizes.

How do you assess the performance in order execution provided to you by brokers or trading venues?

To ensure that we fulfill the highest standards of our best execution policy, we carry out regular transaction cost analysis to monitor the quality of our executions. This allows us to analyze and to optimize the decision-making process as well as our trading strategies around our order execution. We are in the process of implementing new capabilities to measure the quality of brokers, algorithms, and venues in a very detailed and granular way focusing on each individual order fill on a microsecond level – this allows for a more sophisticated dialogue with brokers.

How do you see your desk advancing in the future?

The regulatory environment under MiFID II/MiFIR, further electronification, the challenge of liquidity, and transaction cost measurement are key drivers for the development in trading. As a best-in-class trading desk, we deliver both execution and market intelligence to our portfolio managers. So, we understand our role as a service and solutions desk, where we leverage a deep understanding of our clients, our external providers, and the market landscape to achieve the best results with the top priority of knowing and understanding our clients in the best way.

Thank you for this interesting conversation.

Infopool

News

Invitation as Visiting Scholars at the Social Media Listening Center

Janek Benthaus and Marten Risius (layer 1) were invited to join the Social Media Listening Center at Clemson University for two months. The Listening Center was founded in 2012 as an interdisciplinary research lab and teaching facility. In cooperation with Salesforce Radian6, the center monitors and engages in conversations across the Web by capturing more than 150 million sources of Social Media conversations (e.g., Facebook, Twitter, YouTube, LinkedIn, blogs). The two researchers were invited to set up joint future research projects.

Collaborative Research Center MAKI Honored as "Landmarks in the Land of Ideas"

The MAKI Collaborative Research Center headed by Prof. Steinmetz (layer 1) has been honored as "Landmarks in the Land of Ideas 2015". "Germany – Land of Ideas" is the place-branding initiative encompassing both politics and business. The initiative "Germany – Land of Ideas" and our EFL partner Deutsche Bank acknowledge in this year "Innovations for a digital world".

Best Paper Award of IJRM's 2015 Special Issue on Marketing and Innovation

Fabian Schulz, Christian Schlereth, Nina Mažar, and Bernd Skiera were selected as the winners of the Best Paper Award of International Journal of Research in Marketing's (IJRM) 2015 Special Issue on Marketing and Innovation with their paper "Advance Payment Systems: Paying Too Much Today and Being Satisfied Tomorrow" by the Erasmus Center for Marketing of Innovations of Erasmus University Rotterdam, the American Marketing Association, and the European Marketing Academy (EMAC).

Successful Disputation

Benjamin Loos (layer 3) has received his doctoral degree on March 30th, 2015 with his dissertation on "Potential Solutions to Individual Investors' Investment Mistakes". Congratulations!

Selected E-Finance Lab Publications

Clapham, B.; Zimmermann, K.:
Price Discovery and Convergence in Fragmented Securities Markets.
Forthcoming in: International Journal of Managerial Finance, 2015.

Haferkorn, M.:
High-Frequency Trading and its Role in Fragmented Markets.
In: Proceedings of the 23rd European Conference on Information Systems (ECIS), 2015.

Hans, R.; Steffen, D.; Lampe, U.; Richerzhagen, B.; Steinmetz, R.:
Setting Priorities: A Heuristic Approach for Cloud Data Center Selection.
In: Proceedings of the 5th International Conference on Cloud Computing and Services Science (CLOSER 2015), Lisbon, Portugal, 2015.

Risius, M.; Akolk, F.:
Differentiated Sentiment Analysis of Corporate Social Media Accounts.
In: Proceedings of the 21st Americas Conference on Information Systems (AMCIS 2015), Fajardo, Puerto Rico, 2015.

Schulz, F.; Schlereth, C.; Skiera, B.; Mazar, N.:
Advance Payment Systems: Paying Too Much Today and Being Satisfied Tomorrow.
Forthcoming in: International Journal of Research in Marketing (2015).

Skiera, B.; Hinz, O.; Spann, M.:
Social Media and Academic Performance: Does Facebook Activity Relate to Good Grades?
In: Schmalenbach Business Review, 67 (2015) 1, pp. 54-72.

Skodda, C.; Benthaus, J.:
Investigating Consumer Information Search Behavior and Consumer Emotions to Improve Sales Forecasting.
In: Proceedings of the 21st Americas Conference on Information Systems (AMCIS 2015), Fajardo, Puerto Rico, 2015.

For a comprehensive list of all E-Finance Lab publications see *http://www.efinancelab.com/publications*

Infopool

RESEARCH PAPER: HOW DOES HOUSEHOLD PORTFOLIO DIVERSIFICATION VARY WITH FINANCIAL LITERACY AND FINANCIAL ADVICE?

Household investment mistakes are an important concern for researchers and policymakers alike. Portfolio under-diversification ranks among those mistakes that are potentially most costly. However, its roots and empirical importance are poorly understood. The author estimates quantitatively meaningful diversification statistics and investigates their relationship with key variables. Nearly all households that score high on financial literacy or rely on professionals or private contacts for advice achieve reasonable investment outcomes. Compared to these groups, households with below-median financial literacy that trust their own decision-making capabilities lose an expected 50 bps on average. All group differences stem from the top of the loss distribution.

Gaudecker, H.-M.
In: Journal of Finance, 70 (2015) 2, pp. 489-507.

RESEARCH PAPER: AGENT-BASED INTERACTIONS AND ECONOMIC ENCOUNTERS IN AN INTELLIGENT INTERCLOUD

Although Cloud Computing promises to provide an infinite pool of computing resources, each cloud has only a limited physical resource supply. Therefore, Sim presents an agent-based economic model for a so-called InterCloud, which represents a global cooperation for resource sharing among different clouds. Concerning consumer-to-cloud interactions, he proposes a novel negotiation mechanism, based on adaptive concession rates, that achieves significantly higher utilities than time-dependent strategies with fixed concession rates. Sim also describes a novel mechanism for coalition formation in an InterCloud and mathematically proofs that every agent in such a coalition receives a payoff equal to its Shapley value.

Sim, K.
In: IEEE Transactions on Cloud Computing, PP (2015) 99, pp. 1.

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Prof. Dr. Peter Gomber
Vice Chairman of the E-Finance Lab
Goethe University Frankfurt
Theodor-W.-Adorno-Platz 4
D-60629 Frankfurt am Main

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For further information please contact:

Prof. Dr. Peter Gomber
Vice Chairman of the
E-Finance Lab
Goethe University Frankfurt
Theodor-W.-Adorno-Platz 4
D-60629 Frankfurt am Main

Phone +49 (0)69 / 798 - 346 82
Fax +49 (0)69 / 798 - 350 07
E-mail gomber@wiwi.uni-frankfurt.de

Press contact
Phone +49 (0)69 / 798 - 338 62
Fax +49 (0)69 / 798 - 339 10
E-mail presse@efinancelab.com

or visit our website
http://www.efinancelab.com