Cost-efficient factor investing in emerging equity markets

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ABSTRACT

When factor investing is applied to emerging equity markets, due to the universe's illiquid structure, the market friction must be considered. Risk-adjusted on-paper returns of such strategies look particularly appealing, but significant implementation hurdles stand in their path. While factor investing has been well-examined in literature, research gaps remain. This dissertation undertakes three comprehensive studies to resolve existing research gaps concerning portfolio cost-efficiency regarding the trade-off between return and implementation costs in emerging equity markets. Various approaches for further improvement of this trade-off extend the research.

The first study demonstrates a factor-based strategy in emerging markets and provides a better understanding of the above trade-off. Multiple sensitivity analyses present the benefits of a first cost-mitigation approach. The second study further seeks to understand equity portfolios' return and cost dynamics in a macroeconomic context. Leading indicators from developed and emerging markets are utilized to forecast the near-term factor regime. This prediction is adaptively implemented into the portfolios, adds a timing component, and highly increases the cost-efficiency. The third study extends the efficacy of the researched cost-mitigation strategy by implementing the benefits of a stock liquidity prediction based on state-of-the-art machine learning models.

ZUSAMMENFASSUNG

Bei der Anwendung von Factor Investing auf die Aktienmärkte der Emerging Markets müssen Marktfriktionen aufgrund der illiquiden Struktur des Universums besonders berücksichtigt werden. Die risikobereinigten Renditen solcher Strategien sehen auf dem Papier besonders ansprechend aus, doch stehen ihnen erhebliche Umsetzungshürden im Weg. Obwohl Factor Investing in der Literatur gut untersucht wurde, gibt es immer noch Forschungslücken. In dieser Dissertation werden drei umfassende Studien durchgeführt, um die bestehenden Forschungslücken in Bezug auf die Kosteneffizienz von Aktienportfolios zu schließen. Hierzu wird der Trade-off zwischen Rendite und Implementierungskosten der Portfolien in Emerging Markets sowie verschiedene Verbesserungsansätze untersucht.

Die erste Studie demonstriert eine faktorbasierte Strategie in Emerging Markets und liefert ein besseres Verständnis des oben genannten Trade-offs. Mehrere Sensitivitätsanalysen zeigen die Vorteile eines ersten Ansatzes zur Kostenreduzierung auf. Die zweite Studie zielt darauf ab, die Rendite- und Kostendynamik von Aktienportfolios in einem makroökonomischen Kontext besser zu verstehen. Frühindikatoren aus Industrie- und Schwellenländern werden zur Vorhersage des kurzfristigen Faktorregimes herangezogen. Diese Vorhersage wird adaptiv in die Portfolios implementiert, fügt eine Timing-Komponente hinzu und erhöht die Kosteneffizienz erheblich. Die dritte Studie erweitert die Wirksamkeit der untersuchten Strategie zur Kostenreduzierung, indem sie die Vorteile einer auf modernen maschinellen Lernmodellen basierenden Vorhersage der Aktienliquidität einsetzt.

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LIST OF ABBREVIATIONS

Token	Description
ADF	Augmented Dickey Fuller test
ADV	Average daily volume
BM	Benchmark
Bps	Basis points
CAPM	Capital asset pricing model
DV	Daily volume
EM	Emerging markets
GB	Gradient boosting
GBM	Gradient boosted machine
GFC	Global financial crisis
MAD	Mean absolute deviation
MAPE	Mean absolute percentage error
MASE	Mean absolute scaled error
Mcap	Market capitalisation
MICE	Multiple imputation by chained equations
ML	Machine learning
OLS	Ordinary least squares
PDP	Partial dependence plot
RMSE	Root mean squared error
SR	Sharpe ratio
TRET	Total return
US	United States
VIX	Volatility index

1 GENERAL INTRODUCTION

When it comes to investing, the triangle of return, risk and liquidity has to be considered to determine one's preferred investment vehicle. This dissertation focuses on factor investing in emerging equity markets and seeks to break down the dynamics of the triangle in this universe. Factor investing is a well-examined field of asset pricing that can combine the expectations on various risk premia (Fama and French (1992), Fama and French (2015) and Carhart (1997)) and achieve outstanding performance. Due to their promising risk-reward profile, the emerging stock markets attract more and more quantitative investors' attention (Davis et al. (2010)). On the other hand, it is well-known that this universe is less liquid (Lesmond (2005) and Bekaert et al. (2007)) compared to developed stock markets such as the United States. Therefore, it is unclear if this increased attention is justified in terms of performance net of market friction. While, in general, emerging stock markets have been broadly examined for factor investing (Achour et al. (1998), Kargin (2002) and Bruner et al. (2003)), research gaps remain for this universe regarding the dynamics of the investment triangle. This dissertation undertakes three comprehensive studies to resolve existing research gaps and further advance research regarding the cost-efficiency of factor investing in this less liquid universe. The trade-off between return and implementation costs of factor investing is the main subject of investigation throughout all three examinations. Each study focuses on this from a different angle and contributes to improving net of cost portfolio performance. In the following, I provide a brief overview of the previous research on cost-efficient factor investing and highlight to what extent the dissertation contributes to it.

Since the investigation of the CAPM (Sharpe (1964)), asset pricing literature has been growing concerning quantitative applications such as factor investing. Fundamental risk premia as value (Basu (1977) and Banz (1981)) and quality (Haugen and Baker (1996) and Titman et al. (2004)), as well as well-understood market effects as price momentum (Jegadeesh and Titman (1994)), are known to cross-sectionally explain stock returns through all markets. While most studies on factor investing focus on the developed US stock market, just recent examinations focus on emerging stock markets (Bekaert and Harvey (1997) and Hart et al. (2003)). In general, emerging markets received less attention in all fields of asset pricing as transaction cost modeling (Lesmond et al. (2002) and Frazzini et al. (2018)) and cost-mitigation techniques for rebalancing equity portfolios with an underlying factor investing strategy (Donohue and Yip (2003), Garleanu and Pedersen (2013) and Novy-Marx and Velikov (2018)). With the investors' attention on the growth potential of emerging equity markets, studies also focus on factor investing with respect to transaction costs in this universe (Lesmond (2005)). However, a broad investigation of the return-to-cost trade-off in emerging equity markets based on the well-examined risk premia and suitable cost models is missing. The sparse literature on cost modeling is reasoned by the lack of a sufficiently large trading dataset of this immature universe. As the trade-off between stock returns and implementation costs is not well understood, few results towards cost-mitigation techniques (Novy-Marx and Velikov (2015)) have been carried out. In addition to these gaps, factor timing as a controversial topic in the US stock market (Asness et al. (2000), Tibbs et al. (2008) and Asness et al. (2018)) is only slightly researched (Desrosiers et al. (2006)) and, to my best knowledge and belief, not examined concerning the cost-efficiency of equity portfolios in emerging markets. On the other side, liquidity forecasting has been carried out by various studies in emerging stock markets (Bae and Lee (2016), Khang (2020) and Cui (2021)), but a cross-sectional investigation of the whole universe with machine learning approaches is still missing. Further, such sophisticated liquidity predictions are not examined in addition to a cost-efficient factor investing approach in emerging equity markets.

It comes down to understanding the dynamics of the investment triangle to sufficiently study the cost-efficiency of factor investing. This dissertation does not contribute to novel risk premia but combines its contributions to the above research gaps and provides a comprehensive study on the main research question of the trade-off between risk premia and implementation costs. The groundwork for better understanding the main subject is carried out in the first study, while the following two examinations consecutively extend and improve its findings. This dissertation not only contributes to the above gaps in literature, including factor timing and liquidity prediction in emerging equity markets but also extends the research by combining the findings to increase portfolio cost-efficiency further. Hence, the trade-off between return and costs is also examined in a macroeconomic framework as well as from an additional microeconomic perspective. Here, changes in liquidity are more precisely predicted and successfully implemented into the quantitative investment process of factor investing.

Table 1-1: Key characteristics of the three studies

Study	Cost-mitigation of factor investing in emerging equity markets	Macroeconomic influence on cost-efficient factor investing in emerging equity markets	The benefits of machine learning for predicting stock liquidity in emerging equity markets
Aim & scope	Examines the trade-off between return and costs of equity portfolio constructions and presents a simple cost-mitigation.	Puts the first study's results in a macroeconomic context and utilizes found dependencies in a factor timing framework.	Models the changes of short-term stock liquidity and further increases the efficacy of the cost-mitigation approach.
Research design	Empirical analysis of stock market data of emerging countries from 2000-2020.	Empirical analysis of stock market data of emerging countries from 2000-2020 and macroeconomic time series from the US market as well as emerging markets.	Empirical analysis of stock market data of emerging countries from 2000-2020.

Next, I provide a summary of the three studies and their results. Table 1-1 provides an overview of the studies. It outlines for each study the respective aim & scope and its research design.

The first study demonstrates factor investing in emerging equity markets with a simple and equal-weighted mix of six common risk premia (Carhart (1997), Frazzini and Pedersen (2014) and Fama and French (2015)). The on-paper returns of this strategy are compared to the net of costs performance by applying a liquidity-driven cost model leaned on (Grinold and Kahn (1999) and Frazzini et al. (2018)). Therefore, this examination focuses on a better understanding of the trade-off between portfolio return and implementation costs of factor investing in emerging equity markets under a set of sensitivity analyses and robustness checks. Further, the empirical results are challenged with a cost-mitigation technique following (Novy-Marx and Velikov (2018) and Frazzini et al. (2018)) to increase the cost-efficiency of portfolios in this universe.

The emerging equity markets are researched in terms of the MSCI Emerging Markets Index with underlying stock data from 1999-12-31 to 2019-12-31. The workhorse of portfolio construction throughout this study and the dissertation is a simple portfolio tilting. This methodology incorporates excess return expectations of risk premia into the portfolios. The cost-mitigation approach is analyzed on top of this portfolio construction. It implicitly constrains the size of any trade by its liquidity demand. Therefore, ex-ante implementation costs can be quantified and considered concerning the underlying cost model and observed liquidity. The study finds that on-paper returns largely deviate from realized net performance regarding the invested portfolio size. Much of this spread can be preserved by the cost-mitigation, which outperforms for most cost levels and invested sizes. Eventually, successful factor investing relies on a skilled trading desk reflected by a low cost level or on a sophisticated strategy that mitigates implementation costs without decreasing the on-paper returns. This study contributes to a better understanding of the return to costs trade-off and strategies that improve factor investing implementability in emerging equity markets.

The second study extends the findings on the trade-off between return and costs in a macroeconomic framework. Based on the methodology of the first study, this examination is carried out to identify the macroeconomic influence on risk premia in emerging equity markets. Further, these findings are incorporated into portfolio decisions to increase cost-efficiency with three adaptive factor timings. Factor timing in developed markets (Asness et al. (2000) and Asness et al. (2018)) is controversial but still a young field for emerging equity markets (Bilson et al. (2001) and Desrosiers et al. (2006)).

The MSCI Emerging Markets Index defines the universe with underlying stock data from 1999-12-31 to 2019-12-31. A set of promising macroeconomic time series from emerging and developed markets, such as the fear-index VIX (Copeland and Copeland (1999) and Boscaljon et al. (2011)) and dollar strength (Druck and Mariscal (2018)), completes the underlying data. In a first step, the macroeconomic data is preselected based on its explainability of near-term factor premia. Then, the factor regime is modeled with this data in binary classification (Guidolin and Timmermann (2007), Bae et al. (2013) and Mulvey and Liu (2016)). The machine learning approaches of logistic regression and the gradient boosted machine are compared against a one-step estimate. Lastly, the regime forecasts are incorporated into portfolio construction with three different approaches to exploit macroeconomic information and increase cost-efficiency. The study finds that machine learning approaches highly outperform the one-step prediction of factor regimes. I emphasize that the entanglement between developed and emerging markets certainly contributes to the performance of this prediction. The focus is not to miss a crash regime regarding the portfolio's cost-efficiency. Both machine learning classifications' hyperparameters are tuned accordingly to obtain the best recall on crash regimes. Given the tuned machine learning models, especially the GBM, the macroeconomic time series mostly provide sufficient information to not miss eventual factor underperformance in the following month. Eventually, this study does not only demonstrate that factor timing in emerging markets is possible. Further, incorporating the regime forecast into portfolio construction increases the net performance of the underlying portfolios.

Finally, the third study predicts near-term stock liquidity (Wyss (2004), Khang (2020)). Due to the frequent rebalancing of factor portfolios and a potential implementation lag, predicting future liquidity is essential to improve portfolio implementability. In an illiquid market, the liquidity risk is an enormous burden to investors as unexpected shortfalls of stock liquidity enlarge the implementation hurdle. Emerging equity markets are known to be less liquid, and a better understanding of cross-sectional liquidity changes is remaining. A few studies have already applied and compared machine learning models to predict stock liquidity only in a few emerging markets (Bae and Lee (2016), Khang (2020) and Cui (2021)).

The emerging equity markets are researched in terms of the MSCI Emerging Markets Index with underlying stock data from 1999-12-31 to 2019-12-31. Based on the methodologies of the first study, a range of machine learning applications and tunings on a broad spectrum of market and stock features is carried out to predict near-term changes in stock liquidity. An expanding window tune of a GBM regression outperforms a naïve one-step liquidity forecast by partly over 50% regarding the underlying error metric. Several liquidity change reversals and a seasonality effect are the essential features of this model. This study provides a cross-sectional improvement for predicting stock liquidity in emerging markets. Eventually, the cost-efficiency of the underlying portfolios is significantly increased on top of the cost-mitigation effects.

The following dissertation is structured in five chapters, including this general introduction. Chapters two, three, and four present the three studies outlined in Table 1-1. Each chapter consists of an individual introduction, a section on the theoretical background, a section on the applied methodology and data, a results section, and a section to conclude the results. Chapter five draws a general conclusion. Finally, chapter six presents the references cited throughout the dissertation.

2 COST-MITIGATION OF FACTOR INVESTING IN EMERGING EQUITY MARKETS

2.1 ABSTRACT

Expensive trading costs of factor investing in emerging equity markets influence optimal portfolio decisions. A simple cost-mitigation approach increases net performance based on a total cost estimate of factor-based portfolio tilts. Exploiting the structure of market impact, we indirectly control the costs by limiting order sizes relative to their underlying stocks' short-term liquidity. This cost-efficient strategy yields better implementability and lower-priced turnover while a possible negative effect on gross performance is more than offset.

JEL classification: G11; G12; G15.

Keywords: Investments; Asset Pricing; Trading Costs; Market Impact; Portfolio Construction; Cost-Efficiency.

2.2 Introduction

Investment decisions based on systematic risk premia provide a more transparent alternative to active management that underlies high idiosyncratic risk. Meanwhile, various multi-factor asset pricing models serve to understand the stock market better. Foremost, Fama and French (1992) demonstrate the Arbitrage Pricing Theory and explain the stock market with a 3-factor-model extending the CAPM with the fundamental size and value risk factors, earlier investigated by Banz (1981) for size and Rosenberg et al. (1985) for value. Later, Carhart (1997) extents the Fama and French's (1992) 3-factor-model, adding the prominent momentum factor. In Fama and French (2015), the two quality factors of investment and profitability are added as further systematic risk premia, which were rejected earlier concerning their robustness.

At the beginning of factor investing research, transaction costs were paid little attention. Contemporary research, still focusing on developed markets and mainly covering US stocks, presents several studies that identify the effect of transaction costs on factor-based equity portfolios with different outcomes. On the one hand, Lesmond et al. (2002), who investigate the transaction costs of momentum-based portfolios, find that net premia vanish for this strategy after trading costs. On the other hand, Korajczyk and Sadka (2005), Novy-Marx and Velikov (2015), Ratcliffe et al. (2017) and Patton and Weller (2019), who also focus on the net performance of momentum-based strategies, find different equilibrium sizes of the factor-based excess returns. Another disparity in the implementation cost literature is the shape of the underlying cost function that differs between concave, linear and convex. The intentionally biased data selection can explain this disparity. Lesmond et al. (2002) report high-cost findings based on strong overweights in small- and micro caps. This examination applies the study of Jegadeesh and Titman (1994), who do not consider implementation hurdles for extensive gross spread price momentum results.

In contrast, Frazzini et al. (2018) limit their results to low-cost algorithmic trading approaches in liquid developed markets. Extrapolating these findings to less efficient universes or average trading efforts might result in biased findings. However, most studies, including Frazzini et al. (2018), identify liquidity as the most significant driver of market impact and an essential dimension for successfully implementing factor-based strategies. An active strategy's total costs are commission fees, bid-ask spreads and market impact. Various papers cover market impact modeling, including Loeb (1983), Kyle (1985), Hasbrouck (1991) and Keim and Madhavan (1996). Frazzini et al. (2018) report the impact of crucial model drivers (most importantly liquidity, followed by market capitalization, the idiosyncratic volatility of a firm's equity return and finally, variables that represent the varying market environment) on the market impact in developed markets based on their extensive trading database. Several examinations covering market impact find this implementation hurdle increasing with a strategy's investment size and liquidity demand. Empirical evidence agrees that the demand for trading large order sizes relative to the liquidity level increases market impact as invisible trading costs of adverse price movements.

Further, Lesmond (2005) researches the costs of liquidity risk in emerging markets by explaining the high returns easily exceeding 75% p.a. with their bid-ask spread. Against this, illiquidity is an additional risk factor researched by Pastor and Stambaugh (2003), Acharya and Pedersen (2005) and Watanabe and Watanabe (2008), who develop asset pricing models incorporating expected asset liquidity. Amihud (2002) finds that liquidity risk also significantly explains equity premia, especially the small firm effect. These studies identify the explanatory power of liquidity risk in the cross-section of stock returns and expose its uncertain effect on cost-efficient factor investing. Based on these findings, Donohue and Yip (2003), Garleanu and Pedersen (2013), Frazzini et al. (2018) and Novy-Marx and Velikov (2018) find optimal portfolio decisions in developed markets concerning transaction costs. Albeit the disparity of equilibrium portfolio sizes of factor-based excess returns and cost functions, literature agrees that transaction costs distort optimal portfolio decisions derived from factor investing strategies. Almgren and Chriss (2000) find cost-efficient strategies by identifying permanent and temporary market impact. Garleanu and Pedersen (2013) and Frazzini et al. (2018) find dynamic portfolio policies obtained by constrained optimizations and improve net factor premia. Novy-Marx and Velikov (2018) resume three common cost-mitigations in developed markets and compare their benefits. Despite the extensive cost modeling, studies on liquidity risk and recent investigations on cost-efficient implementations, the trade-off between risk premia and implementation costs in factor investing remains unclear. Especially the emerging equity markets, known as a less liquid stock universe with a significant implementation hurdle, received little attention.

Our work closely relates to Frazzini et al. (2018) but aims to understand emerging equity markets better. With recent progress regarding trading cost models and cost-efficient factor investing, most examinations focus on the liquid US stock market and other developed markets. This paper extends the existing literature in two ways. First, we investigate the net premia of factor investing in the less liquid emerging equity markets. Hence, we report the impact of a one-dimensionally dynamic cost model of three exemplary cost levels concerning portfolio size. In this approach, we provide a sensitivity analysis of implementation costs by constructing portfolios that do not rely on a specific trading pattern nor result in overweights in small- or micro caps. Second, we research the trade-off between risk premia and transaction costs of factor investing in emerging markets. This approach applies an active rebalancing strategy based on well-known risk factors to assess cost- and turnover efficiency. In our investigation of the efficient implementation of fundamental and generic factors, we use a liquidity-driven market impact model based on Grinold and Kahn (1999) and Frazzini et al. (2018). Following and extending the ideas of Almgren and Chriss (2000), Frazzini et al. (2018) and Novy-Marx and Velikov (2018), a cost-efficient rebalancing strategy is presented. This cost-mitigation strategy seeks to limit the relative order sizes by a cap parameter in each rebalancing step concerning the underlying stocks' short-term liquidity. Therefore, transaction costs are treated as another quantitative factor. Doing so leads to cost-efficient performance.

The paper proceeds as follows. The next section describes the underlying market environment and reflects all applied methodologies. Here, the market impact as the cost model's most prominent component is introduced based on three levels to provide sensitivity analysis. Furthermore, this section defines the methodologies for the multi-factor mix and portfolio tilting. The empirical results section outlines cost-inefficient portfolio performances concerning various investment periods. Further, the cost-mitigation approach and its effect are presented. Moreover, we report a sensitivity analysis concerning the portfolio size and more robustness checks to assess the return-to-cost trade-off. This section closes with the cost-mitigation's implications on risk-adjusted performance. The last section concludes the research.

2.3 Data and methodology

2.3.1 The emerging markets universe

We research the emerging markets universe[1] in terms of the countries listed in the MSCI Emerging Markets Index[2] over the last two decades ending in December 2019. Before the millennium, a small range of available data was omitted concerning the quality and coverage of the liquidity data. This

[1]In the following, the emerging markets are denoted as "EM" and also referred to as the "whole universe".

[2]https://www.msci.com/emerging-markets, last visited: 2020-09-30.

study uses data from MSCI to determine the underlying companies in emerging markets and their free-floating market capitalization. Besides MSCI, the Worldscope database from Refinitive is used for the fundamental value, profitability and investment factors. The generic momentum and low beta factors are calculated based on market data from Datastream (Refinitive). Further, Datastream is utilized for most market data such as return indices, liquidity and bid-ask spreads. Referring to the market closing of 2019 as today, this emerging markets universe consists of 26 countries[3] across the five different sub-regions of Emerging Americas, Europe, Middle East, Africa and the Asia Pacific, of which the latter contributes to 79.35% of the emerging markets' size.

In the following, the stocks associated with the MSCI Emerging Markets Index will be referred to as large caps. In contrast, remaining stocks larger than $10 million in market capitalization are denoted as small caps. Large- and small caps together complete the whole universe researched in this study. Today, this emerging markets universe consists of 3480 stocks summing up to $9.2 trillion free-floating market capitalization. These $9.2 trillion represent 15.1% of the developed[4] and emerging equity's free-floating market capitalization with trending growth potential[5]. At year-end 1999, the free-floating market capitalization of the emerging markets stocks was summing up to $1.5 trillion, of which around $1 trillion were related to large caps divided across 761 stocks. Back then, the universe consisted of 1209 assets and the 761 large caps aggregated roughly two-thirds of the universe's market capitalization. At year-end 2019, the number of emerging large caps grew to 1406 constituents, covering $7.2 trillion market capitalization measured in free-floating stocks. Today, these 1406 emerging markets' large caps grew in their share up to 78.3% of the market capitalization. The remainder of 21.7% of the

[3]The MSCI Emerging Markets Index consists of 26 emerging economies, including Argentina, Brazil, Chile, China, Colombia, Czech Republic, Egypt, Greece, Hungary, India, Indonesia, Korea, Malaysia, Mexico, Pakistan, Peru, Philippines, Poland, Qatar, Russia, Saudi Arabia, South Africa, Taiwan, Thailand, Turkey, and the United Arab Emirates.

[4]The developed world universe consists of all countries listed in the MSCI World Index, augmented with the small caps larger than $10 million in market capitalization in each listed country. The developed universe, excluding frontier- and emerging markets, lists the following 23 countries: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Hong Kong, Ireland, Israel, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Singapore, Spain, Sweden, Switzerland, United Kingdom, United States.

[5]Today, the equity market capitalization of emerging markets in the world's investable stock markets (excluding frontier markets) aggregates to 15.1%. This share almost tripled and is constantly growing from 5.4% at year-end 1999. The recent growth of the emerging stock markets is reported with 14.5% at year-end 2018, 13.9% at year-end 2017 and 12.7% of all non-frontier stock universes' market capitalization at year-end 2016. For reference, less than 1 billion people, or approximately 15% of the world's population, live in a developed markets country but developed stock markets still account for around 85% stock market capitalization. ("http://www.ashmoregroup.com/sites/default/files/article-docs/MC_10%20May18_2.pdf", last visited: 2020-09-30).

market capitalization is divided across 2074 small caps that sum up to around \$2 trillion. This composition reflects the trends in the emerging market environment. Although the number of small caps (quadrupled over the last two decades) significantly outnumbers large caps today, their relative market capitalization in the universe dropped by over 11 percentage points compared to the year-end 1999 level. In Figure 2-1 the number of constituents in the emerging universe, also divided into large- and small caps, is reported. This chart shows that large caps only doubled over the last two decades while small caps quadrupled. Further, we compare the emerging market environment with the developed world over the last two decades. The developed world's small caps captured only a fifth (while emerging markets' small caps captured a third) of their universe's market capitalization in year-end 1999. Today, the developed small caps market capitalization only aggregate to 13.5% (while emerging markets small caps still aggregate to 21.7%), unveiling the same trend of dominating large caps in the developed stock markets. Additionally, Figure 2-2 provides the "lifetime" distribution of the stocks concerning their size class over the 240 observation months. This chart displays that, on average small caps keep in their size class less often than large caps for any given duration over the last two decades. Noting that stocks might change their size class during the observation months, this chart reports the fraction of stocks that survived a given time percentile concerning their size class. The universe counts 7531 unique assets, of which 1053 (13.9%) persist for less than a year on the stock market (5%-percentile). Only 223 (2.96%) of these stocks survive the whole two decades, and only 22.8% of the universe is investable for at least 120 months (50% lifetime). From 6846 unique small caps, only four stocks stay in this size class over the full-time span and the remaining 6842 either left the market or are grown into large caps. Comparably, 124 of 2703 unique large caps keep their large-cap status over the 20 years. Another 95 stocks that shift their size class survive the two decades on the EM stock market. From the 6846 unique small caps, more than a third (2018 stocks) have been downgraded from or upgraded to the large caps at least once in the two decades.

2.3.2 Transaction costs model

We need to apply a reasonable metric for the total transaction costs to calculate the trade-off between gross premia and implementation costs in emerging markets. The market impact model is the essential component of the total transaction costs and reflects the implementation hurdle of the illiquid emerging universe[6]. Our study does not rely on a specific trading pattern by providing a sensitivity analysis of the market impact. We reflect the *market impact* costs with a simple square root cost model leaned on Grinold and Kahn (1999) and Frazzini et al. (2018):

$$market\ impact := cost\ parameter \cdot \sqrt{\%ADV} \tag{1}$$

ADV denotes the short-term liquidity calculated as average across primary and secondary stock exchanges over the last 20 trading days. Therefore, $\%ADV$ denotes the stock-wise order size relative to the monthly calculated ADV. We analyze the three cost levels of market impact, specified by the *cost parameter*. Here, we reflect an efficient trading pattern of an institutional practitioner with a local trading desk, followed by a suggestion of average trading results. Lastly, we reflect an expensive cost level by the idea of incorporating issues with EM brokers and a potential time lag. In a recent study, Frazzini et al. (2018) apply a market impact model to their US trading data. This paper's reported relative trade size is limited to below 15%. This low fraction occurs due to the liquid US stock market and an efficient trading pattern. Hence, no large relative order sizes that might occur from monthly portfolio decisions are included. Following the cost approach of this examination and transferring it to emerging markets, we understand the market impact of rebalancing equity to be mainly driven by liquidity demand (relative order size in $\%ADV$). Finally, we define the total transaction costs as follows:

$$TCost := fees + \frac{1}{2} spread + market\ impact \tag{2}$$

Execution fees[7] are comparably small, while the half bid-ask spread can also be expensive in emerging markets, albeit its general decline after the decimalization of the stock tickers. Referring to Figure 2-4, we display the empirical spread data over the last two decades. A declining trend over the last 20 years is observable. Figure 2-3 indicates the three cost parameters (low, medium, high costs) of variable market impact. However, the actual impact of transaction costs of each portfolio crucially depends

[6]Emerging markets stocks, in general, are considered to be executed more expensive than developed markets stocks. Besides the lower market liquidity, the time shift between emerging and developed regions can be an additional hurdle for institutional and individual investors.

[7]Execution and commissions fees are negotiable and sum up to over 7bps in emerging markets. These fees cover all legal middle office activities of the sell-side and ensure the backup of all trade documentation through a global custodian. These electronic backups are by law completed by carbon copies in case of emergency.

on its size. Furthermore, Almgren and Chriss (2000) research this implementation hurdle of the stock markets by incorporating trading costs that eventually lead to a distorted but cost-efficient portfolio. In this sense, many naive implementations of risk factors might result in high gross premia but fail a successful implementation as exemplary reported in Lesmond et al. (2002). We also researched more complex cost models concerning the effect of stock volatility and a perfectly passive trading model. This approach reflects the costs of waiting that arise by slowly trading towards the desired portfolio in positions of exemplary 10% of the ADV per trading day. While the latter model mitigates the annualized transaction costs, no researched cost model distorts the results presented in this study. Therefore, we apply the one-dimensional market impact model concerning simplicity as the most intuitive implementation. The following section presents a Z-scoring based on six risk factors and a portfolio tilting methodology.

2.3.3 Multi-factor Z-scoring

Based on the asset pricing models of Carhart (1997), Frazzini and Pedersen (2014) and Fama and French (2015), we research tilt portfolios concerning a mix of six well-known equity factors[8]. We include the generic effects of momentum and low beta and the four fundamental risk factors, value, size, profitability and investment. All these six factors[9] are based on sound groundwork. We seek to diversify the factor premia and maintain a more persistent performance by equal-weighted mixing of the six signals. The empirical evidence presented in this examination is robust to alternative factor definitions, different mixes and also different weighting schemes. We decide to present this mix of six factors to cover fundamental factors and market effects and calculate the equal-weighted scheme with respect to simplicity.

[8]A detailed description of the six factors and their calculations is reported in Appendix A.

[9]The fundamental value factor was researched in Basu (1977) and Rosenberg et al. (1985). The size factor is also a systematic risk premium discovered in Banz (1981). Jegadeesh and Titman (1994) and Hurst et al. (2017) researched the generic momentum factor. The operating profitability was researched by Haugen and Baker (1996) and Novy-Marx (2013) and is another systematic risk premium and the investment factor found in Titman et al. (2004), Cooper et al. (2008) and Watanabe et al. (2013). Ang et al. (2006) and Frazzini and Pedersen (2014) examined the generic low beta factor.

2.3.4 Portfolio construction methodology

We apply a factor-tilt portfolio construction as a value-weighted method based on the market capitalization of free-floating stock. This value-weighted approach ensures no strong overweight in small- and micro caps arise. The stock positions in the initial portfolio (at t_0) as well as all the following rebalancing weights (at $t > t_0$) are constructed by screening the positive Z-scores ($Z\text{-}score_i > 0$) from the multi-factor mix. To calculate portfolio weights for each stock i, the universe weights $weight_{universe,i}$ are tilted under several constraints[10] with respect to the following equation:

$$weight_{tilt,i} := \begin{cases} weight_{universe,i} \cdot Z\text{-}score_i, & \forall i \in \{EM : Z\text{-}score_i > 0\} \\ 0, & \text{else} \end{cases} \tag{3}$$

Where the universe weights $weight_{universe,i}$ are determined by free-floating market capitalization. Each stock i is assigned its factor-based return expectation $Z\text{-}score_i$, obtained by the equal-weighted mix of six Z-scores in every monthly rebalancing step. After each rebalancing the portfolio weights $weight_{tilt,i}$ are updated with empirical return indices[11]. This loop continues until the last rebalancing month of 2019-11-29. Later on, this tilting (denoted as "standard" or "uncapped" tilt) is further constrained by the cost-mitigation methodology.

2.4 Empirical results

2.4.1 Net performance

Before implementing the cost-mitigation, this subsection provides a net performance analysis of the tilting construction in emerging equity markets. The illustrations of factor premia in emerging markets are displayed in the upper charts of Figure 2-5 - Figure 2-8. The setting in these four charts builds the foundation of our analysis and is split concerning the investment period to investigate time trends. The initial portfolio size for these periods is chosen heuristically concerning the rising market liquidity and desired comparability. The upper chart of Figure 2-5 displays the factor premia of the uncapped

[10] A detailed description of all (rebalancing) constraints is reported in Appendix B.

[11] Thompson Reuters Datastream return indices for emerging equity represent the empirical stock returns as done by the Center for Research in Security Prices (CRSP) concerning dividend payments and stock splits.

tilt over the last two decades. While its gross performance is higher than the universe's or large caps' return, most excess returns vanish with a medium cost level. The upper chart of Figure 2-6 displays the returns over the last decade. Here, the factor-based tilts even underperform the universe net of costs. The upper chart of Figure 2-7 shows similar results with even more considerable underperformance relative to the universe and large caps over the last five years. The factor premia lost much of their magnitude in the trend of the last two decades. Hence, in the upper chart of Figure 2-8, significant factor premia in emerging markets persist over the first decade after the millennium. Finally, the tilt construction charts display that the gross factor premia in emerging markets have been prominent in this century's first decade but lost most of their potential in current market environments. Especially with this decay in factor premia, the need for a cost-efficient implementation rises. Based on Almgren and Chriss (2000) and Novy-Marx and Velikov (2018), we present a cost-mitigation strategy to assess the trade-off between gross factor premia and transaction costs in the emerging stock markets. By applying this strategy to the above factor-tilts, we report a thorough analysis of its effects.

2.4.2 Cost-mitigation strategy

This section reports the impact of the cost-mitigation strategy on the uncapped tilting portfolios. We examine the additional cost-mitigation constraint based on gross and net factor premia insights to improve its return-to-cost trade-off. We accomplish that by indirectly considering the transaction costs by adding a liquidity constraint to the tilt construction. While the trade execution is treated as entirely exogenous to the monthly portfolio decisions, we implement the market impact function endogenously into the tilting construction. This constraint limits order sizes to exploit the near-term liquidity expectation. Therefore, the total transaction costs are mitigated while expensive turnover is re-distributed concerning sufficiently liquid stocks. The portfolio objective is to maximize the net performance without distorting risk. Eventually, this comes at the cost of lowered return expectation (measured in average portfolio ex-ante Z-score) and, therefore, possibly lowered gross performance. However, the strategy is cost-efficient, while the uncapped tilting maximizes the ex-ante return expectation without considering costs. Keeping all portfolio- and rebalancing constraints equal, various cost-mitigated portfolios are compared to their uncapped tilts and the universe concerning (risk-adjusted) performance. The more recent study of Novy-Marx and Velikov (2018) claims that there is no arbitrage opportunity in harvesting factor premia in developed markets. Factor premia's statistically significant net performance improvement is reportedly based on higher risk exposure. Novy-Marx and Velikov

(2018) report statistically equal Sharpe ratios for factor-based strategies against the universe. We also find mostly statistically insignificant Sharpe ratios of risk premia in recent years. However, improved factor tilts, particularly cost-mitigated portfolios and low-cost implementations, clearly show statistically significant (risk-adjusted) returns against the universe and uncapped tilts. Further, we display the cost-mitigated performances of the factor-tilts in the lower charts of Figure 2-5 - Figure 2-8. These four tilts are constructed by constraining the relative order size in each rebalancing to a limit of 100% of the near-term ADV ($100\%ADV$). All these portfolios show increased net performance in comparison to the upper charts' performance of uncapped tilts. Due to lowered turnover and efficiently lowered costs, the cost-mitigation offsets losses in gross performance. In Figure 2-5 the cost-mitigation alone results in a significant excess return of around 2% p.a. after costs. Over the last ten years, the net underperformance of over 1.5% relative to the large caps can almost be fully recovered in Figure 2-6. Over the last five years, in Figure 2-7, around 2.5% of the net underperformance is recovered by the cap parameter of 100 %ADV. In the lower chart of Figure 2-8, the cost-mitigation outperforms its uncapped tilt by almost 1.5% annualized return after costs (at medium cost level). We remark that the naive ADV expectation of predicting liquidity in the trade execution by its current level is a model assumption. Nonetheless, we apply the cost model concerning the liquidity level after portfolio decisions with perfect foresight. The quality of the ADV expectation relies on this naive forecast. However, the monthly first-order auto-correlation of ADV (no overlap due to the ADV window size) is significantly large. Even in the cross-section of different size classes, the Pearson auto-correlation ranges from 70 to 90% concerning the time periods. Eventually, the cost-mitigation implicitly controls and mitigates expensive turnover. The strategy results in more cost-efficient implementations by applying a suitable order size limit ($100\%ADV$ in the above scenarios) concerning the investment size.

2.4.3 Sensitivity analysis

In this subsection, the effect of the cost-mitigation strategy is analyzed in more detail. The intended improvement in the return-to-cost trade-off seeks to determine net performance efficiency concerning portfolio size. By applying the cost-mitigation strategy, we increase the (risk-adjusted) net premia of portfolios in emerging markets. The charts of Figure 2-9 - Figure 2-12 report the gross and net performances of several cost-mitigations against their uncapped tilts concerning ascending initial portfolio sizes (log-scaled x-axis). Figure 2-9 displays the performances over the last two decades and reveals a sorted picture. No gross performance is lost with cost-mitigated tilts for small initial portfolio sizes.

For initial portfolio sizes above $250 million, increasing parts of the gross performance are sacrificed for most cap parameters. This negative effect is more than offset by most strategies and cost levels. The loss in gross performance is more considerable for strict cap parameters (e.g., for limiting order sizes by 50% of the ADV, in the portfolios denoted as "TradeCap050"). The stricter cap parameters eventually outperform the uncapped tilt at smaller portfolio sizes at a hefty cost level. For larger portfolio sizes, more soft constraints like cap parameter 200% of ADV outperform the uncapped tilt concerning the capacity limits of strict implementations. In Figure 2-10, there is almost no adverse effect on gross performance and almost every cap parameter outperforms the uncapped tilt even concerning the low cost level. More strict cap parameters stand out over this period, especially for large portfolio sizes or high costs. With lower factor premia, the portfolios displayed in Figure 2-11 are less sorted over the last five years. However, cost-mitigation strategies outperform the expensive uncapped tilt with rising cost levels and portfolio size. In the market environment with significant factor premia, as seen in Figure 2-12 after the millennium, the uncapped tilt outperforms the cost-mitigated strategies concerning gross performance. While the strict cap parameters can not increase the net performance, more soft cap parameters can outperform the uncapped tilt at least at a medium cost level. Summing up these results, we often see an inevitable gross performance loss induced by the additional short-term liquidity constraint in many tilt portfolios. Nonetheless, with ascending portfolio size, cost level, or both, a cost-mitigation strategy is found to outperform the uncapped tilt in each investment period. Eventually, determining a cross-sectional optimal strategy parameter is impossible but depends on investment size, cost level and market conditions. We can further conclude the empirical evidence that the cost-mitigation strategy shows increasing profitability with higher cost levels, portfolio sizes, or lower risk premia.

To research the effect of the cost-mitigation on further portfolio characteristics, Table 2-1, Table 2-2 and Table 2-3 exemplary report a thorough performance analysis and descriptive statistics on the four environments. Table 2-1 shows that across all periods, fractions of the excess return expectation (denoted as ex-ante factor Z-score) are sacrificed in the cost-mitigation. Therefore, this effect is in line with the extent of the cost reduction and is larger for strict cap parameters. Table 2-1 also reports the significance in (risk-adjusted) performance differences between any cost-mitigation against the uncapped tilt. Appendix C describes the applied hypothesis testing methodology to determine statistically significant differences in returns and Sharpe ratios. Even small differences can easily be statistically significant due to the high serial correlation between the portfolio tilts. Table 2-1 confirms that for each declared investment period and cost level, at least one cost-mitigation significantly outperforms the uncapped tilt's (risk-adjusted) performance. In Table 2-2 other statistics are presented to better understand the cap parameters' efficacy. We see that more strict cap parameters lead to a broader diversification in average holdings. This effect is mainly affecting small caps. With more strict cost-mitigations, the two-sided turnover shrinks while limiting the expensive trades. This effect, in general, is similar between large- and small caps in the tilted portfolios. For the 20-year and the 10-year periods after the millennium, strict cost-mitigations improve the average position size held in the portfolio relative to its short-term ADV. This portfolio liquidity improvement is reversed for the latest 10- and 5-year periods. Unfortunately, the average portfolio liquidity relative to the universe liquidity worsens for the most strict cap parameters. This negative effect peaks for the first 10-year period after the millennium between the uncapped tilt and cap parameter 50 with a 16 percentage points difference in portfolio liquidity. Nonetheless, the (risk-adjusted) net performance improvement is substantial for these tilts at each cost level. Finally, Table 2-2 reports the average order size of the cost-mitigations and uncapped tilt relative to the short-term liquidity and it is clear that the strict cost-mitigations yield a certainly improved implementability. The "capped trades" statistic shows how many total trades in each portfolio are affected by the cost-mitigations on average per rebalancing. Table 2-3 reports each cost-mitigation's return and Sharpe ratio significance against the universe. The portfolios over the last two decades and the first decade after the millennium outperform the universe significantly. This increase in Sharpe ratio has been much weaker over the last 10 and 5 years. The portfolio tilts often underperform concerning the cost level. For the 5-year period, only the most strict cap parameter outperforms the universe, and the return differences are insignificant for any cost level. This picture again reflects the observed decline in factor premia. The 10-year period portfolios must be strictly cost-mitigated to outperform the universe significantly.

2.4.4 Robustness checks

To obtain robustness-checked results for the performance of the cost-mitigation and to smooth the path dependencies of any initial portfolio, we provide robust statistics by constructing portfolios on a monthly rolling basis. Due to high serial correlations in the constructed portfolios and path dependency to their initial portfolio, geometric means over all possible portfolios (1-month rollings) of different initial dates confirm the overall efficiency of the cost-mitigation strategy. We do not want the results to be conditioned by the market environment or return expectations of the initial portfolio. Therefore, this robustness check corrects for all path dependencies. Hence, we update the monthly rolling initial portfolio sizes by the previous starting month's performance. Table 2-4 reports the (risk-adjusted) excess return significance of cost-mitigated tilts against the uncapped tilts concerning the rolling construction. All return and Sharpe ratio differences are statistically significant concerning many sampled rebalancing months and often high serial correlations. Table 2-5 reports the (risk-adjusted) excess return significance of cost-mitigated portfolios against their universe concerning the rolling construction. Cap parameter $100\%ADV$ emphasizes the statistically significant excess returns against uncapped tilts and the universe for various investment sizes. With the rolling portfolios over the last 20 years, $100\%ADV$ outperforms the universe by 2.5% (the uncapped tilt by around 1%) p.a. with a significantly higher Sharpe ratio of .96 against 0.66 (.88) at only medium cost level.

2.5 Conclusion

While illiquidity can be understood as a long-term factor that causes cyclical near-term risk premia, it is also crucial for transaction costs. We studied this trade-off concerning gross factor premia over various periods. From our analysis, we can draw several conclusions. First, we find it possible to construct factor-based equity tilt portfolios with positive net premia in emerging markets over the last two decades and sub-periods. Second, we see that the high risk premia of factor-tilts in emerging equity markets have vanished in recent years. Therefore, a successful factor-based strategy is often determined by an efficient implementation (cost-mitigation or low cost level). Third, with increasing portfolio size, fractions of short-term portfolio liquidity and excess return expectation are sacrificed. Fortunately, the negative effect on the expected excess return and, eventually, on gross performance is more than offset. Finally, we show that the cost-mitigation improves the (risk-adjusted) net performance of the factor-tilts but can only partially preserve vanished risk premia. A cost-efficient implementation is often the critical component to outperform the market when the uncapped factor strategy solely does not.

As an alternative or addition to an efficient trading pattern, this cost-mitigation approach allocates cost-efficient decisions by incorporating trading costs and limiting expensive turnover. Further, the strategy has certain portfolio size limitations concerning the market environment and cost-mitigation parameters. Before reaching this capacity limit, the efficacy of the cost-mitigation is increasing concerning rising investment sizes and cost levels. Further investigation will focus on the associations between factor investing, cost-mitigation strategies and macroeconomic influences. We researched that risk premia are cyclical in the near term and assume that a macro-adaptive approach might further increase cost-efficiency.

2.6 List of charts and tables

Figure 2-1: Time series of constituents in the emerging markets universe
This chart reports three time series based on monthly data of the number of constituents with respect to the whole universe, large- and small caps.

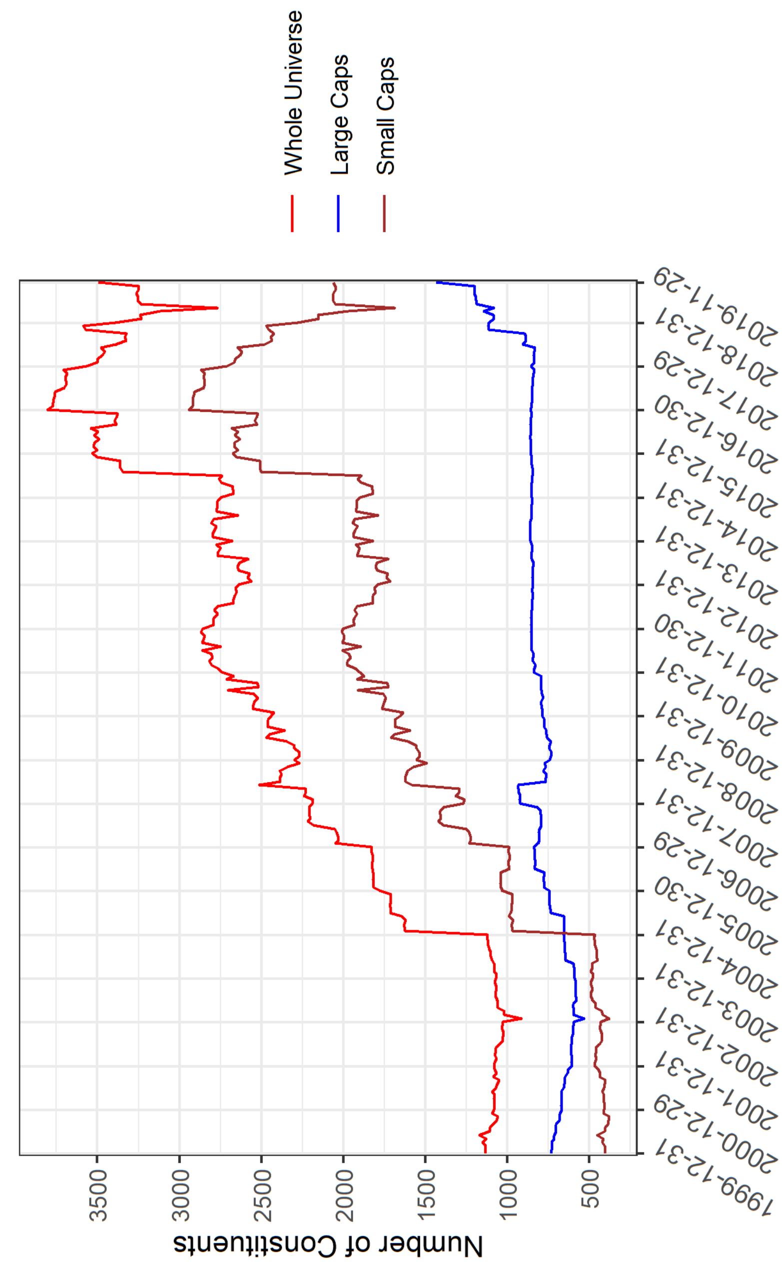


Figure 2-2: Distribution of the lifetime of emerging markets stocks
As we find 7531 individual stocks in our analysis of the last two decades, this chart reports the relative lifetime distributions based on monthly data of the three size classifications. The relative fraction of the size class enduring this percentile is assigned over the percentiles of the stock lifetime (e.g., the 10% percentile denotes a lifetime of 24 months or less).

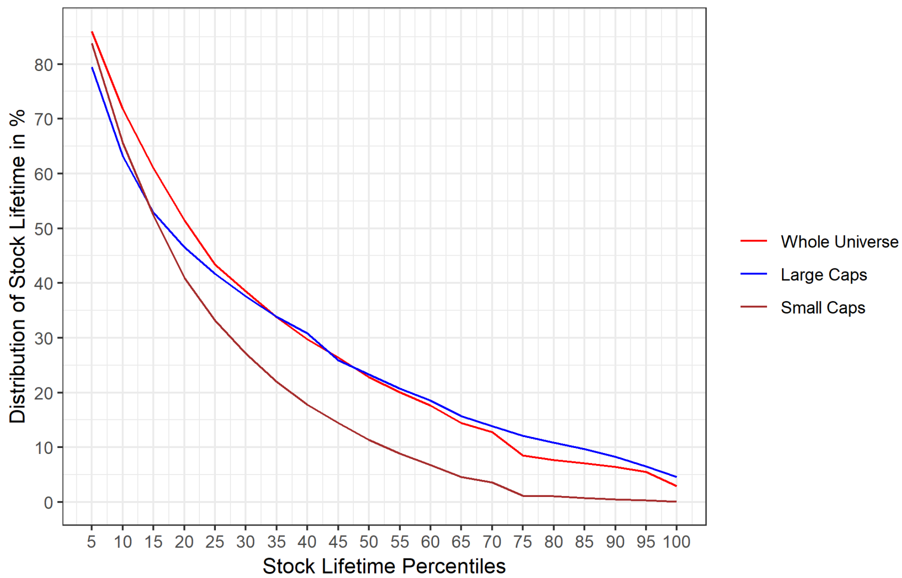


Figure 2-3: Transaction costs square root model
This chart displays the three cost levels of market impact applied in this paper. The three parameters are scaling factors for the square root functionality of order sizes relative to liquidity.

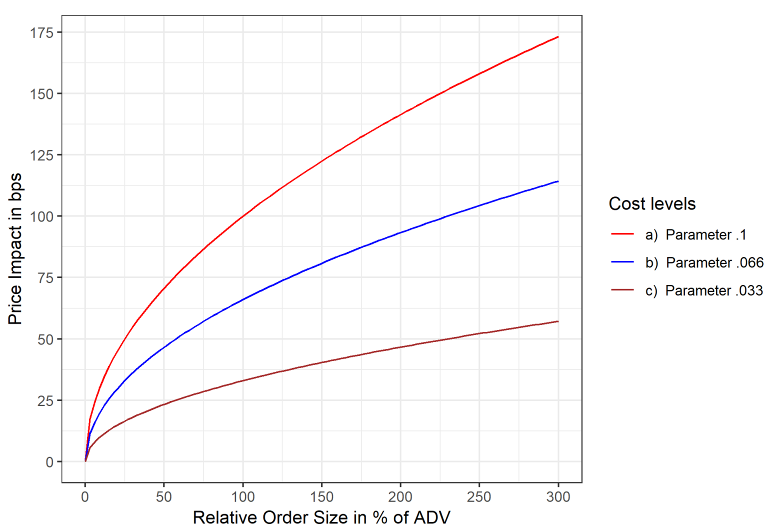


Figure 2-4: Time series statistics of spread data
This chart reports six time series statistics of the emerging markets' positive spread data in bps based on daily data across all stocks.

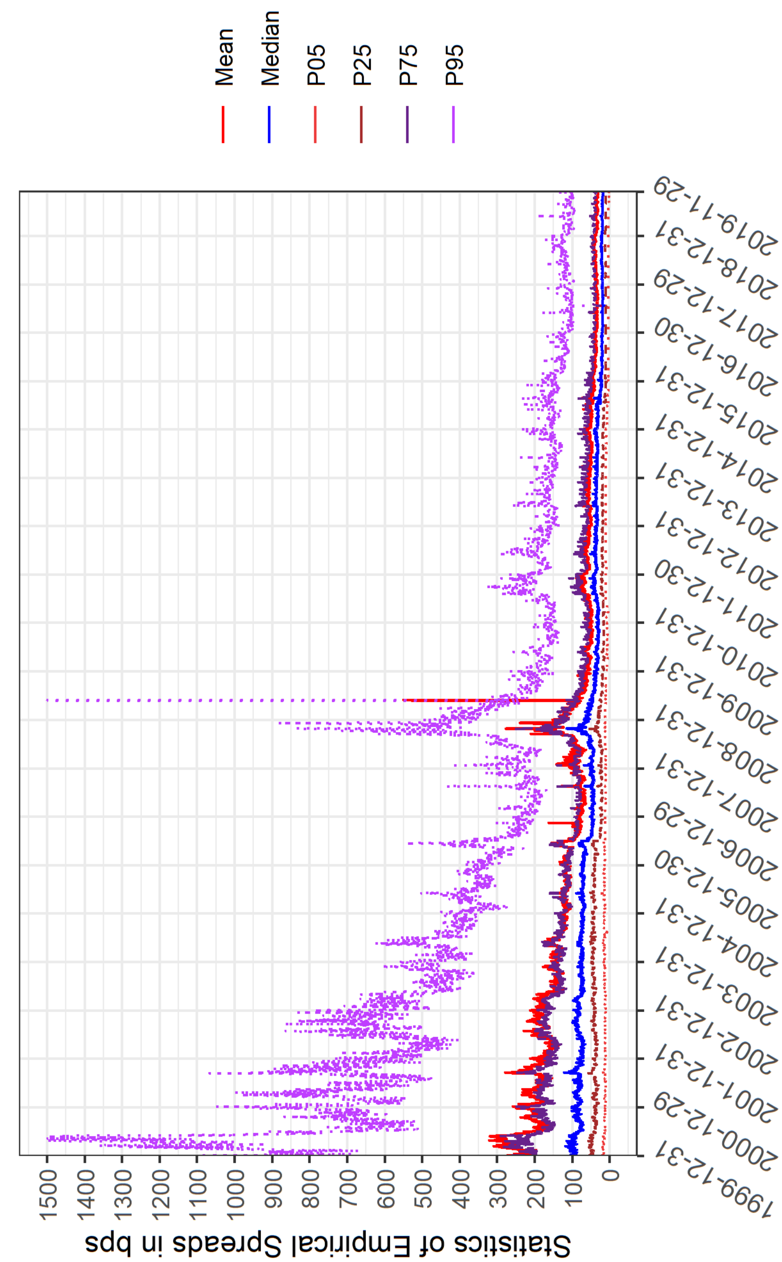
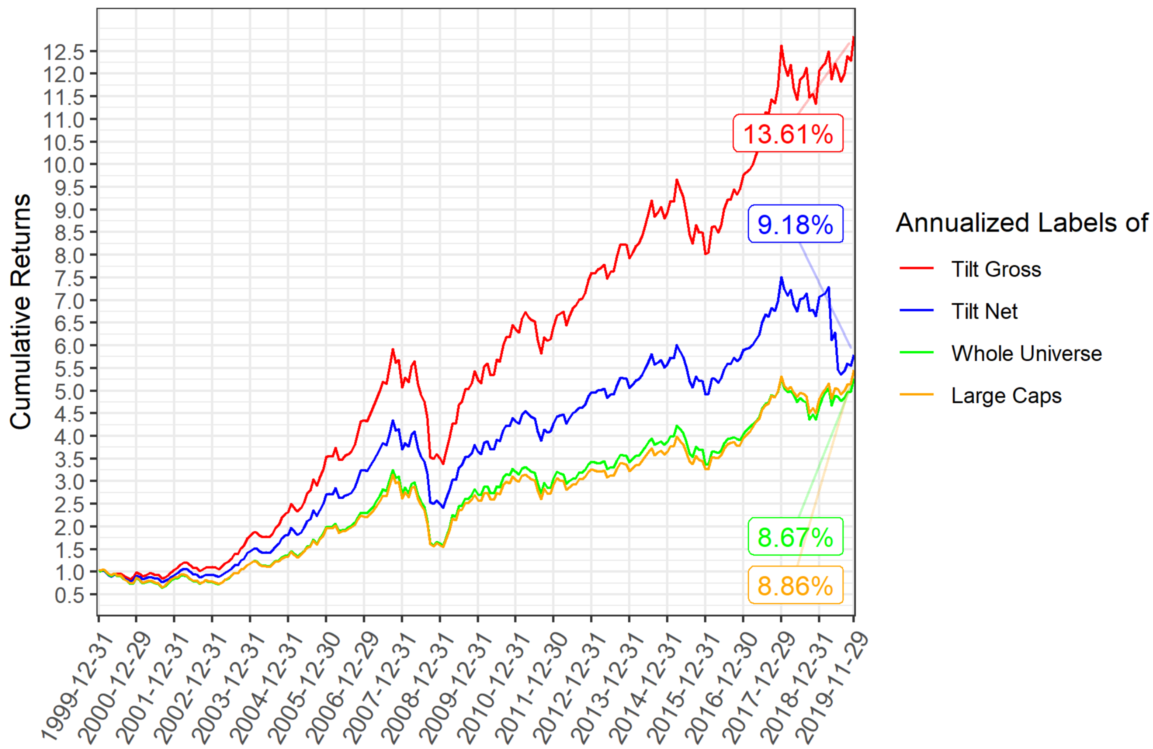


Figure 2-5: These charts report the performance (medium cost level applied) of the factor-based tilt portfolios with $2 billion initial portfolio size over the last two decades. The upper chart displays the uncapped tilt with 295.98% two-sided turnover p.a. The lower charts display the cost-mitigated strategy with order size limiting parameter set to 100% of ADV (190.90% two-sided turnover p.a.).



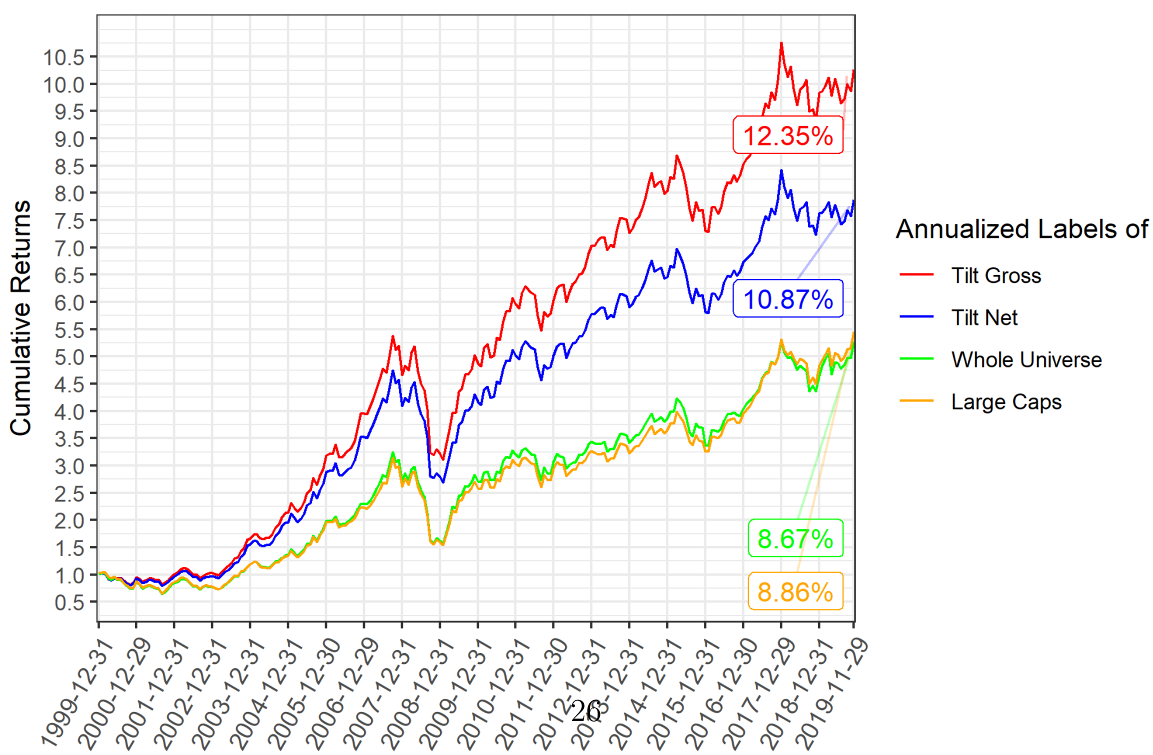
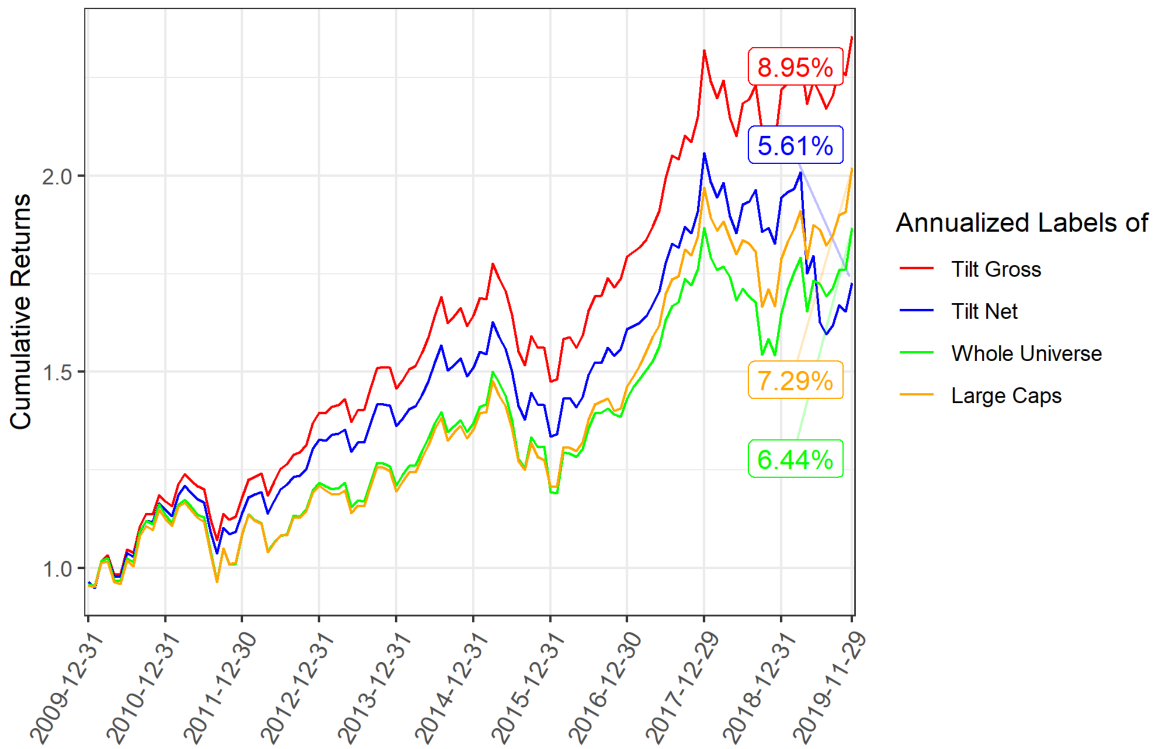


Figure 2-6: These charts report the performance (medium cost level applied) of the factor-based tilt portfolios with $5 billion initial portfolio size over the last decade. The upper chart displays the uncapped tilt with 289.46% two-sided turnover p.a. The lower charts display the cost-mitigated strategy with order size limiting parameter set to 100% of ADV (250.18% two-sided turnover p.a.).



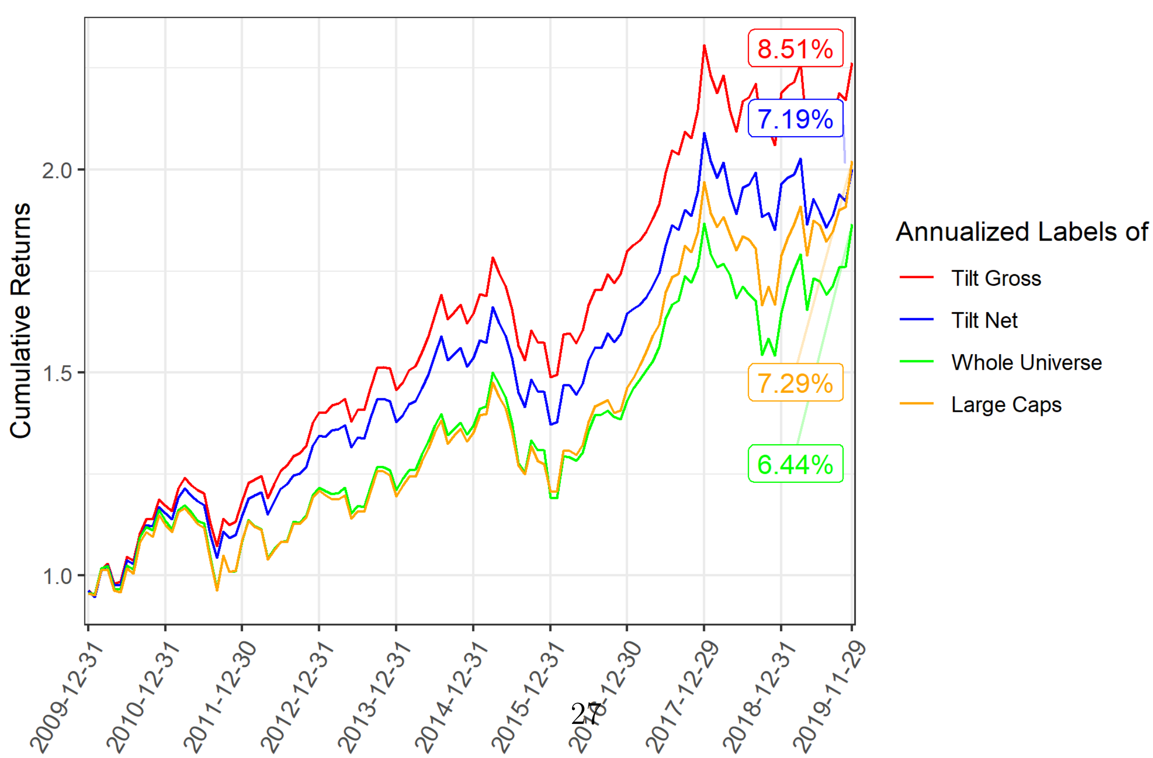


Figure 2-7: These charts report the performance (medium cost level applied) of the factor-based tilt portfolios with \$7.5 billion initial portfolio size over the five years. The upper chart displays the uncapped tilt with 215.12% two-sided turnover p.a. The lower charts display the cost-mitigated strategy with order size limiting parameter set to 100% of ADV (202.23% two-sided turnover p.a.).

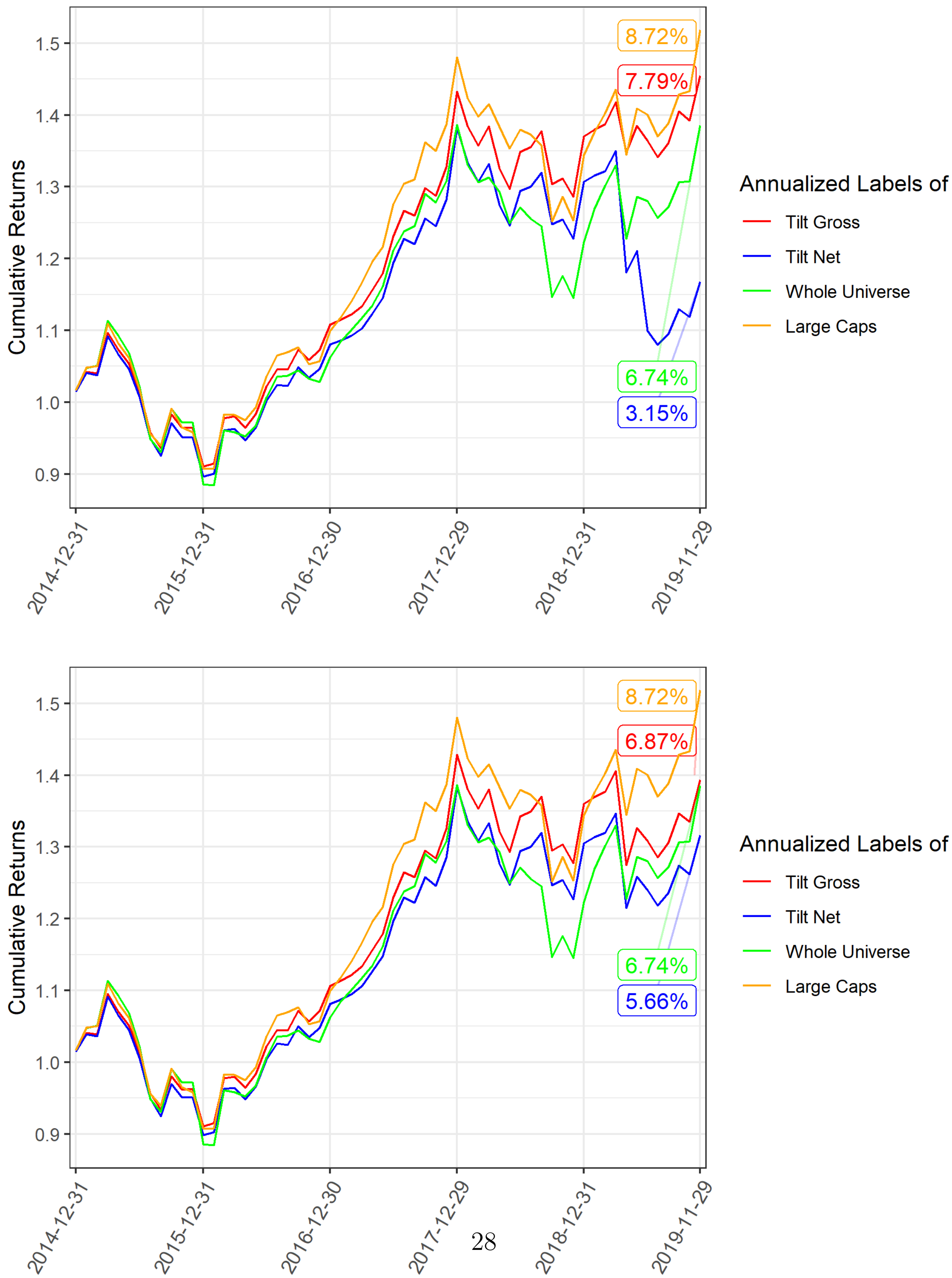
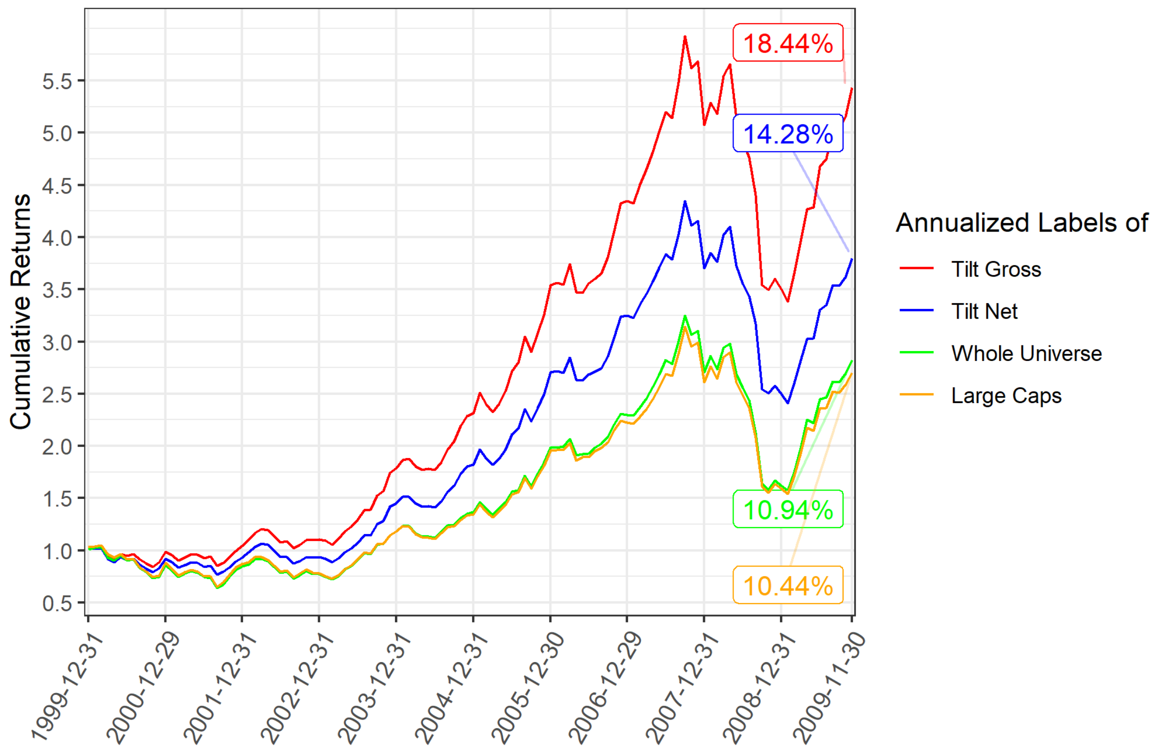


Figure 2-8: These charts report the performance (medium cost level applied) of the factor-based tilt portfolios with \$2 billion initial portfolio size over the first decade only. The upper chart displays the uncapped tilt with 305.90% two-sided turnover p.a. The lower charts display the cost-mitigated strategy with order size limiting parameter set to 100% of ADV (208.21% two-sided turnover p.a.).



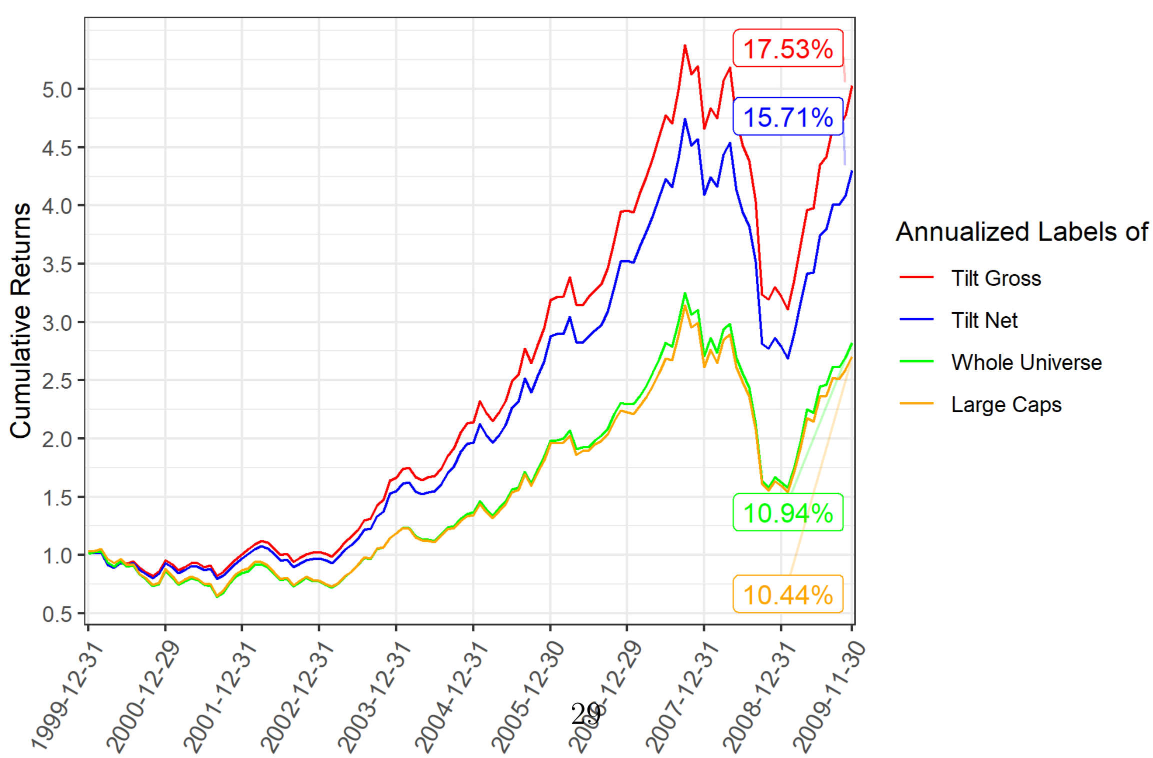
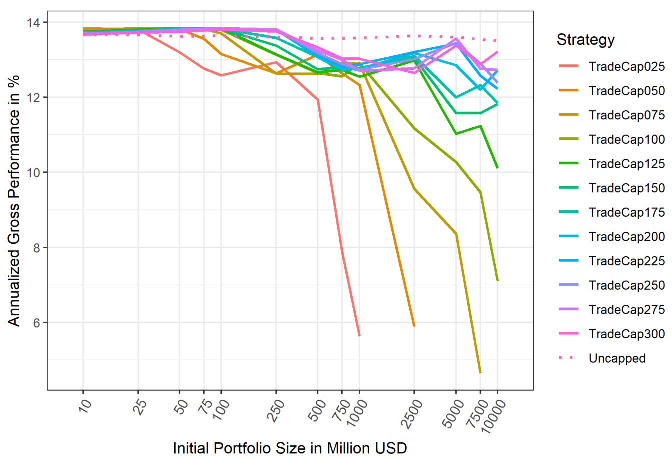


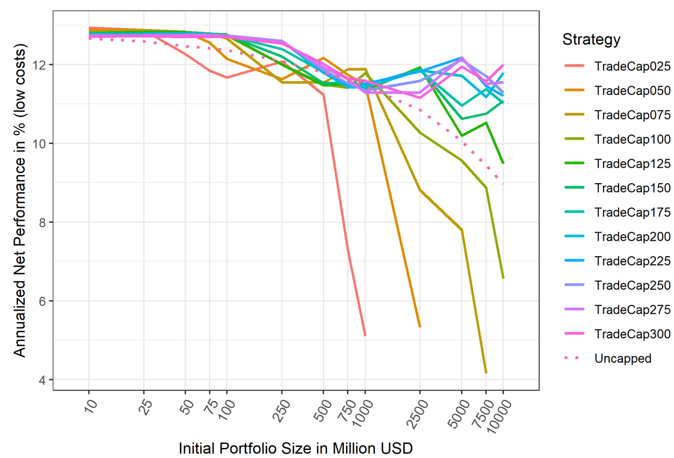
Figure 2-9: These charts report the gross and net performance of various cost-mitigation strategy limitings from 1999-12-31 to 2019-11-29 with respect to initial portfolio size and level of the trading cost model. The base case labeled as "Uncapped" is indicated with a dotted line and a ceased line indicates the reached capacity level of that strategy with respect to the market environment.

Gross Performance



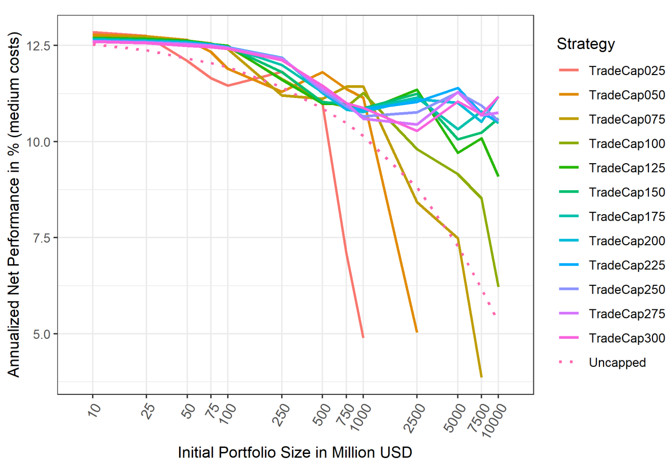
Net Performance

(Low cost level)



Net Performance

(Medium cost level)



Net Performance

(High cost level)

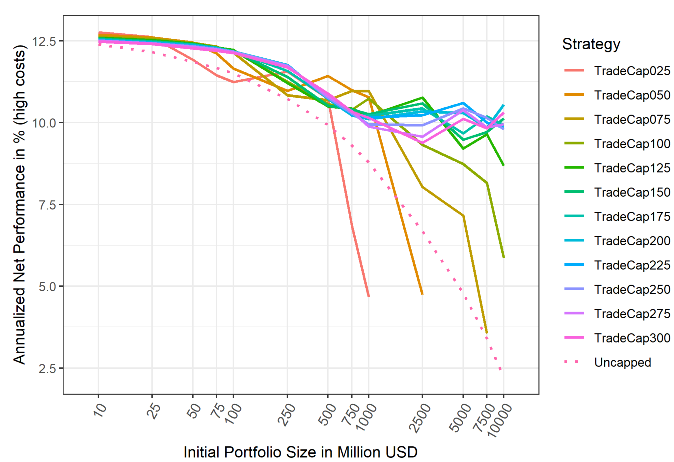


Figure 2-10: These charts report the gross and net performance of various cost-mitigation strategy limitings from 2009-12-31 to 2019-11-29 with respect to initial portfolio size and level of the trading cost model. The base case labeled as "Uncapped" is indicated with a dotted line and a ceased line indicates the reached capacity level of that strategy with respect to the market environment.

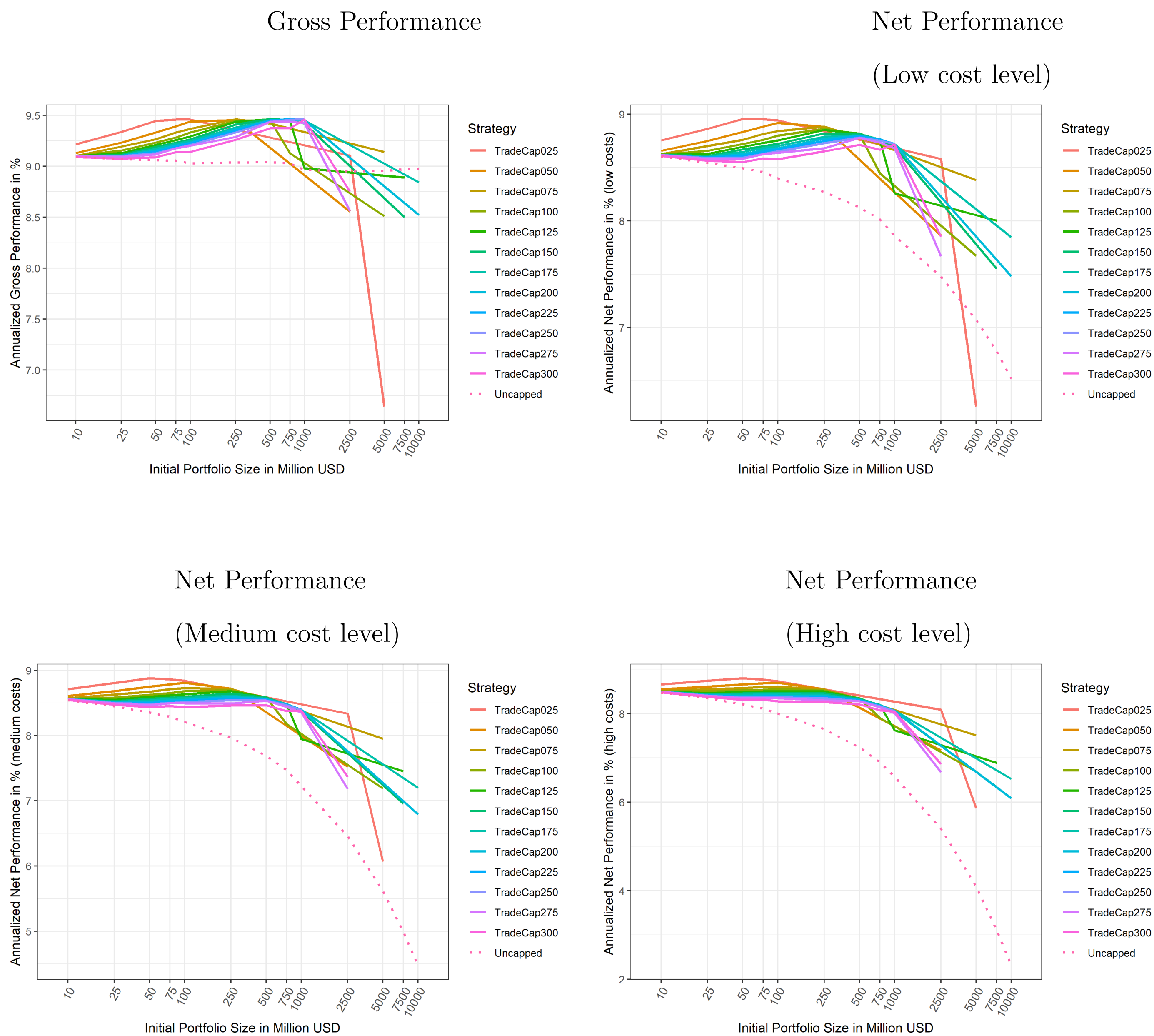


Figure 2-11: These charts report the gross and net performance of various cost-mitigation strategy limitings from 2014-12-31 to 2019-11-29 with respect to initial portfolio size and level of the trading cost model. The base case labeled as "Uncapped" is indicated with a dotted line and a ceased line indicates the reached capacity level of that strategy with respect to the market environment.

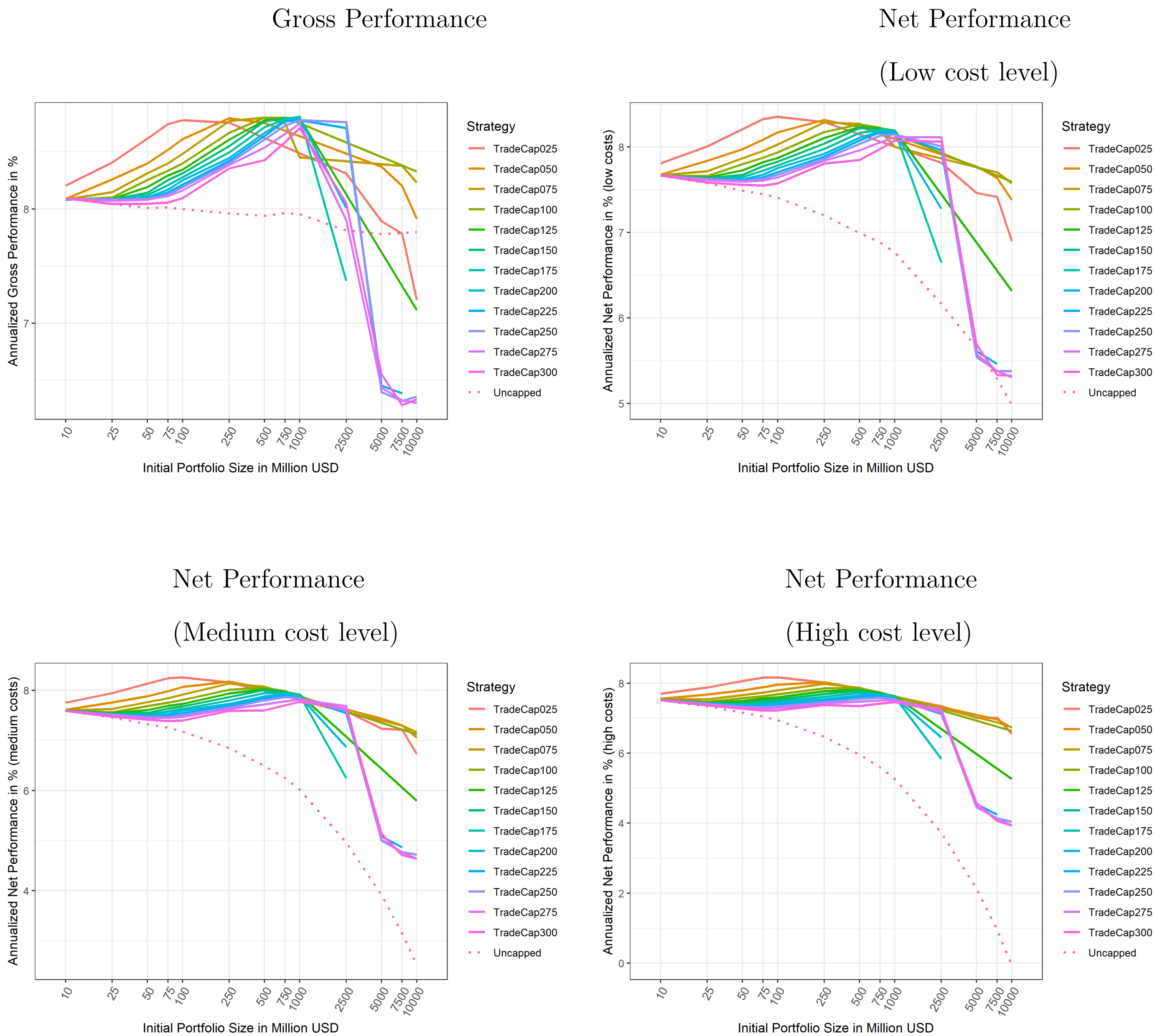


Figure 2-12: These charts report the gross and net performance of various cost-mitigation strategy limitings from 1999-12-31 to 2009-11-23 with respect to initial portfolio size and level of the trading cost model. The base case labeled as "Uncapped" is indicated with a dotted line and a ceased line indicates the reached capacity level of that strategy with respect to the market environment.

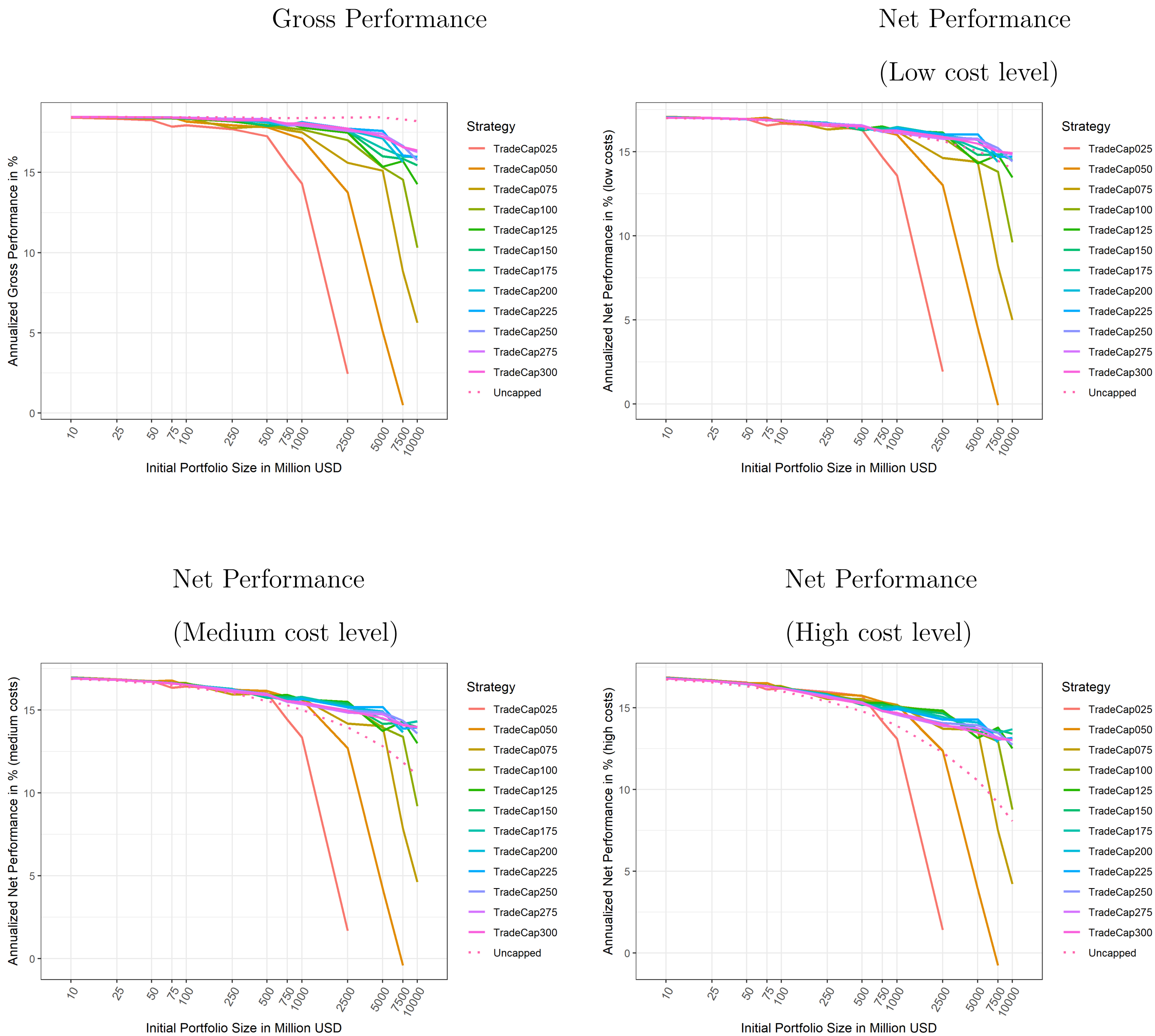


Table 2-1: **Statistical significance (* for p < 0.05, ** for p < 0.01 and *** for p < 0.001) against the uncapped tilts** with respect to the three cost levels: Medium (Low) ((High))
Various cost-mitigation strategies of relative order size limiting are reported based on four investment periods.

	Strategy Param.	Ex Ante Factor Z-score	Gross Return (% p.a.)	Net Return (% p.a.)	Sharpe Ratio
1999-12-31 to 2019-12-31	100% Cap	.81	11.17	9.8*** (10.28**) ((9.32***))	.68*** (.71) ((.64***))
	150% Cap	.92	13.05	11.25*** (11.89***) ((10.59***))	.78*** (.83***) ((.74***))
	200% Cap	.96	13.18	11.11*** (11.86***) ((10.34***))	.77*** (.82***) ((.72***))
	250% Cap	.98	13.08	10.76*** (11.59***) ((9.92***))	.74*** (.80***) ((.69***))
	300% Cap	.99	12.65	10.28*** (11.15**) ((9.39***))	.7*** (.76***) ((.64***))
	Uncapped	1.06	13.64	8.81 (10.85) ((6.68))	.57 (.73) ((.41))
2009-12-31 to 2019-12-31	50% Cap	.94	9.15	8.17*** (8.52***) ((7.82***))	.8*** (.83***) ((.76***))
	100% Cap	1.01	8.51	7.19*** (7.68***) ((6.69***))	.69*** (.73***) ((.64***))
	150% Cap	1.04	8.25	6.76*** (7.32*) ((6.18***))	.62*** (.68*) ((.57***))
	200% Cap	1.06	8.2	6.6*** (7.2***) ((5.98***))	.6*** (.66) ((.54***))
	250% Cap	1.07	8.23	6.56*** (7.2***) ((5.92***))	.59*** (.65) ((.53***))
	300% Cap	1.07	8.16	6.48*** (7.1***) ((5.82***))	.58*** (.64) ((.52***))
	Uncapped	1.07	8.95	5.61 (7.1) ((4.1))	.49 (.65) ((.33))
2014-12-31 to 2019-12-31	50% Cap	1.01	8.2	7.3*** (7.64***) ((6.96***))	.71*** (.74***) ((.67***))
	100% Cap	1.05	6.87	5.66*** (6.12***) ((5.18***))	.5*** (.54**) ((.46***))
	150% Cap	1.06	6.63	5.24*** (5.79) ((4.68***))	.45*** (.5*) ((.4***))
	200% Cap	1.06	6.4	4.92*** (5.51) ((4.32***))	.41*** (.47) ((.36***))
	250% Cap	1.06	6.32	4.77*** (5.38) ((4.14***))	.4*** (.46) ((.34***))
	300% Cap	1.06	6.29	4.71*** (5.33) ((4.07***))	.4*** (.45) ((.34***))
	Uncapped	1.06	7.8	3.15 (5.29) ((.95))	.25 (.46) ((.07))
1999-12-31 to 2009-12-31	50% Cap	.7	13.76	12.7*** (13.02***) ((12.37))	.69*** (.7***) ((.67))
	100% Cap	.85	17.02	15.32*** (15.86) ((14.76***))	.87*** (.9) ((.83***))
	150% Cap	.93	17.59	15.39*** (16.11***) ((14.66***))	.87*** (.91***) ((.83***))
	200% Cap	.95	17.62	15.16*** (15.97**) ((14.33***))	.86*** (.91**) ((.81***))
	250% Cap	.97	17.66	14.99*** (15.88***) ((14.08***))	.85*** (.9**) ((.8***))
	300% Cap	.98	17.74	14.95*** (15.89***) ((13.99***))	.85*** (.9**) ((.79***))
	Uncapped	1.05	18.42	13.97 (15.63) ((12.29))	.78 (.88) ((.69))

Table 2-2: Further statistics of Table 2-1
Various cost-mitigation strategies of relative order size limiting are reported based on four investment periods with medium cost level applied.

	Strategy Param.	Average N (LC) ((SC))	Two-sided Turnover in % p.a. (LC) ((SC))	Mean Position to ADV	PF Liquid. to universe	Order Size (%) Mean (Median)	Cap. Trades (%) Mean (Median)
1999-12-31 to 2019-12-31	100% Cap	508 (304) ((204))	191 (164) ((27))	3.35	.67	53.7 (37.8)	64.3 (59.8)
	150% Cap	475 (290) ((185))	226 (195) ((31))	3.94	.71	70.4 (48.9)	44.8 (44.8)
	200% Cap	450 (282) ((168))	245 (210) ((35))	4.17	.73	82.5 (52.4)	33.6 (33.4)
	250% Cap	432 (277) ((155))	256 (220) ((36))	4.25	.74	92.2 (53.2)	26.3 (25.8)
	300% Cap	423 (275) ((148))	260 (224) ((36))	3.99	.74	100.4 (52.1)	20.8 (19.8)
	Uncapped	374 (263) ((111))	296 (246) ((50))	9.86	.77	1186.7 (49.7)	0 (0)
2009-12-31 to 2019-12-31	50% Cap	570 (342) ((228))	211 (183) ((28))	.74	.68	22.7 (17.5)	45.9 (48.7)
	100% Cap	488 (321) ((167))	250 (218) ((32))	.7	.7	30.4 (19.2)	19.4 (18.4)
	150% Cap	464 (316) ((148))	265 (230) ((35))	.72	.72	36.6 (19.1)	11 (10.4)
	200% Cap	452 (315) ((137))	273 (237) ((36))	.72	.72	38.9 (18.9)	6.8 (5.9)
	250% Cap	445 (314) ((131))	278 (240) ((38))	.73	.73	39.2 (18.7)	4 (2.8)
	300% Cap	442 (314) ((128))	279 (241) ((38))	.73	.73	38.8 (18.4)	2.6 (1.3)
	Uncapped	431 (313) ((118))	289 (240) ((49))	.73	.73	89.1 (18.2)	0 (0)
2014-12-31 to 2019-12-31	50% Cap	548 (365) ((183))	210 (171) ((39))	.32	.59	19 (15)	33.1 (32.4)
	100% Cap	497 (346) ((151))	248 (202) ((46))	.28	.6	26 (15.7)	13.4 (12)
	150% Cap	482 (342) ((140))	262 (213) ((49))	.23	.61	31.1 (15.4)	6.89 (4.8)
	200% Cap	476 (341) ((135))	267 (217) ((50))	.23	.61	33.5 (15.3)	5 (3)
	250% Cap	472 (340) ((132))	270 (219) ((51))	.19	.61	33.7 (15.2)	3.3 (1.4)
	300% Cap	471 (340) ((131))	271 (219) ((52))	.19	.6	33.9 (15)	2.5 (.8)
	Uncapped	460 (339) ((121))	290 (215) ((75))	.29	.6	115.5 (14.8)	0 (0)
1999-12-31 to 2009-12-31	50% Cap	448 (281) ((167))	152 (130) ((22))	4.35	.78	39.59 (23.82)	99.95 (96.3)
	100% Cap	405 (254) ((150))	208 (178) ((30))	5.14	.85	56.7 (39.85)	64.15 (64.71)
	150% Cap	384 (242) ((140))	242 (206) ((36))	5.76	.88	75.11 (51.4)	48.16 (48.73)
	200% Cap	371 (236) ((135))	257 (219) ((38))	6.32	.89	88.45 (56.79)	39.54 (40.77)
	250% Cap	360 (231) ((129))	268 (228) ((40))	6.72	.9	104.44 (58.28)	32.83 (34.08)
	300% Cap	354 (229) ((125))	272 (231) ((41))	6.46	.91	114.57 (56.77)	26.55 (27.81)
	Uncapped	315 (214) ((101))	306 (254) ((52))	18.95	.94	2558.08 (52.91)	0 (0)

Table 2-3: **Statistical significance (* for p < 0.05, ** for p < 0.01 and *** for p < 0.001) against the universe** with respect to the three cost levels: Medium (Low) ((High))
Various cost-mitigation strategies of relative order size limiting are reported based on four investment periods.

	Strategy Param.	Net Return (% p.a.)	Universe Return (% p.a.)	Sharpe Ratio	Universe Sharpe Ratio
1999-12-31 to 2019-12-31	100% Cap	9.8** (11.17***) ((9.32*))	8.67	.68*** (.71***) ((.64***))	.5
	150% Cap	11.25*** (13.05***) ((10.59***))	8.67	.7***8 (.83***) ((.74***))	.5
	200% Cap	11.11*** (13.18***) ((10.34***))	8.67	.77*** (.82***) ((.72***))	.5
	250% Cap	10.76*** (13.02***) ((9.92***))	8.67	.74*** (.8***) ((.69***))	.5
	300% Cap	10.28*** (12.65***) ((9.39*))	8.67	.7*** (.76***) ((.64***))	.5
	Uncapped	8.81 (13.64***) ((6.68***))	8.67	.57** (.73***) ((.41**))	.5
2009-12-31 to 2019-12-31	50%	8.17*** (8.52***) ((7.82***))	6.44	.8*** (.83***) ((.76***))	.52
	100%	7.19* (7.68***) ((6.69))	6.44	.69*** (.73***) ((.64***))	.52
	150%	6.76 (7.32*) ((6.18))	6.44	.62** (.68***) ((.57))	.52
	200%	6.6 (7.2*) ((5.98))	6.44	.6* (.66***) ((.54))	.52
	250%	6.56 (7.2*) ((5.92))	6.44	.59* (.65***) ((.53))	.52
	300%	6.48 (7.1*) ((5.82))	6.44	.58 (.64***) ((.52))	.52
	Uncapped	5.61 (7) ((4.1***))	6.44	.49 (.65***) ((.33***))	.52
2014-12-31 to 2019-12-31	50% Cap	7.3 (7.64) ((6.96))	6.74	.71** (.74**) ((.67*))	.54
	100% Cap	5.66* (6.12) ((5.18***))	6.74	.5 (.54) ((.46))	.54
	150% Cap	5.24** (5.79) ((4.68***))	6.74	.45 (.5) ((.4))	.54
	200% Cap	4.92** (5.51) ((4.32***))	6.74	.41* (.47) ((.36**))	.54
	250% Cap	4.77** (5.38) ((4.14***))	6.74	.4* (.46) ((.34**))	.54
	300% Cap	4.71** (5.33) ((4.07***))	6.74	.4* (.45) ((.34**))	.54
	Uncapped	3.15*** (5.29) ((.95***))	6.74	.25*** (.46) ((.07***))	.54
1999-12-31 to 2009-12-31	50% Cap	12.7** (13.02***) ((12.37**))	10.94	.69*** (.7***) ((.67***))	.52
	100% Cap	15.32*** (15.86***) ((14.76***))	10.94	.87*** (.9***) ((.83***))	.52
	150% Cap	15.39*** (16.11***) ((14.66***))	10.94	.87*** (.91***) ((.83***))	.52
	200% Cap	15.16*** (15.97***) ((14.33***))	10.94	.86*** (.91***) ((.81***))	.52
	250% Cap	14.99*** (15.88***) ((14.08***))	10.94	.85*** (.9***) ((.8***))	.52
	300% Cap	14.95*** (15.89***) ((13.99***))	10.94	.85*** (.9***) ((.79***))	.52
	Uncapped	13.97*** (15.63***) ((12.29*))	10.94	.78*** (.88***) ((.69***))	.52

Table 2-4: **Statistical significance (* for p < 0.05, ** for p < 0.01 and *** for p < 0.001) against the uncapped tilts** of monthly rolling robustness check with respect to the three cost levels: Medium (Low) ((High)) The initial portfolio size refers to the first month of each investment period and the ongoing rolling constructions are based on updated initial portfolio sizes with respect to the back-tested net performance. All returns are reported as geometric means overall rolling portfolio constructions.

	Strategy Param.	Initial Size (billion USD)	Net Return (% p.a.)	Sharpe Ratio
1999-12-31 to 2019-12-31 (rolling 5 years)	50% Cap	2	13.39*** (13.74***) ((13.04***))	.95*** (.98***) ((.93***))
	100% Cap	2	13.49*** (14.04***) ((12.93***))	.96*** (1***) ((.92***))
	150% Cap	2	13.38*** (14.04***) ((12.7***))	.95*** (1***) ((.91***))
	200% Cap	2	13.25*** (13.99***) ((12.5***))	.94*** (.99***) ((.89***))
	250% Cap	2	13.18*** (13.97***) ((12.37***))	.93*** (.99***) ((.88***))
	300% Cap	2	13.12*** (13.94***) ((12.28***))	.93*** (.99***) ((.87***))
	Uncapped	2	12.52 (13.64) ((11.35))	.88 (.91) ((.79))
2009-12-31 to 2019-12-31 (rolling 5 years)	50% Cap	5	7.19*** (7.53***) ((6.84***))	.73*** (.77***) ((.7***))
	100% Cap	5	6.76*** (7.24***) ((6.27***))	.68*** (.73***) ((.63***))
	150% Cap	5	6.61*** (7.15) ((6.06***))	.66*** (.712*) ((.6***))
	200% Cap	5	6.56*** (7.12) ((5.98***))	.65*** (.707*) ((.59***))
	250% Cap	5	6.53*** (7.11***) ((5.94***))	.65*** (7.04***) ((.59***))
	300% Cap	5	6.53*** (7.11***) ((5.93***))	.65*** (7.04***) ((.59***))
	Uncapped	5	6.35 (7.13) ((5.55))	.62 (.71) ((.53))
2014-12-31 to 2019-12-31 (rolling 3 years)	50% Cap	7.5	9.36*** (9.68***) ((9.03***))	.92*** (.95***) ((.88***))
	100% Cap	7.5	9.47*** (9.93***) ((8.99***))	.92*** (.97***) ((.88***))
	150% Cap	7.5	8.66*** (9.19***) ((8.11***))	.8*** (.86***) ((.75***))
	200% Cap	7.5	8.49*** (9.06***) ((7.9***))	.78*** (.83***) ((.72***))
	250% Cap	7.5	8.48*** (9.08***) ((7.87***))	.78*** (.84***) ((.72***))
	300% Cap	7.5	8.32*** (8.92***) ((7.69***))	.75*** (.814***) ((.69***))
	Uncapped	7.5	7.29 (8.82) ((5.68))	.63 (.811) ((.46))
1999-12-31 to 2009-12-31 (rolling 5 years)	50% Cap	2	22.94** (23.3***) ((22.56***))	1.41*** (1.43***) ((1.38***))
	100% Cap	2	24.06*** (24.68***) ((23.43***))	1.5*** (1.54***) ((1.46***))
	150% Cap	2	24.14*** (24.93***) ((23.35***))	1.5*** (1.55***) ((1.45***))
	200% Cap	2	24.14*** (25.04***) ((23.23***))	1.5*** (1.56***) ((1.45***))
	250% Cap	2	24.1*** (25.08***) ((23.11***))	1.5*** (1.56***) ((1.44***))
	300% Cap	2	24.1*** (25.08***) ((23.01***))	1.49*** (1.56***) ((1.43***))
	Uncapped	2	22.73 (24.32) ((21.09))	1.4 (1.5) ((1.29))

Table 2-5: **Statistical significance (* for p < 0.05, ** for p < 0.01 and *** for p < 0.001) against the universe** of monthly rolling robustness check with respect to the three cost levels: Medium (Low) ((High))
The initial portfolio size refers to the first month of each investment period and the ongoing rolling constructions are based on updated initial portfolio sizes with respect to the back-tested net performance. All returns are reported as geometric means overall rolling portfolio constructions.

	Strategy Param.	Net Return (% p.a.)	Universe Return (% p.a.)	Sharpe Ratio	Universe Sharpe Ratio
1999-12-31 to 2019-12-31 (rolling 5 years)	50% Cap	13.39*** (13.74***) ((13.04***))	10.99	.95*** (.98***) ((.93***))	.66
	100% Cap	13.49*** (14.04***) ((12.93***))	10.99	.96*** (1***) ((.92***))	.66
	150% Cap	13.38*** (14.04***) ((12.7***))	10.99	.95*** (1***) ((.91***))	.66
	200% Cap	13.25*** (13.99***) ((12.5***))	10.99	.94*** (.99***) ((.89***))	.66
	250% Cap	13.18*** (13.97***) ((12.37***))	10.99	.93*** (.99***) ((.88***))	.66
	300% Cap	13.12*** (13.94***) ((12.28***))	10.99	.93*** (.99***) ((.87***))	.66
	Uncapped	12.52*** (13.64***) ((11.35***))	10.99	.88*** (.91***) ((.79))	.66
2009-12-31 to 2019-12-31 (rolling 5 years)	50% Cap	7.19*** (7.53***) ((6.84***))	5.97	.73*** (.77***) ((.7***))	.51
	100% Cap	6.76*** (7.24***) ((6.27))	5.97	.68*** (.73***) ((.63***))	.51
	150% Cap	6.61** (7.15***) ((6.06))	5.97	.66*** (.71***) ((.6***))	.51
	200% Cap	6.56** (7.12***) ((5.98))	5.97	.65*** (.71***) ((.59***))	.51
	250% Cap	6.53** (7.11***) ((5.94))	5.97	.65*** (.7***) ((.59***))	.51
	300% Cap	6.53** (7.11***) ((5.93))	5.97	.65*** (.7***) ((.59***))	.51
	Uncapped	6.35* (7.13***) ((5.55*))	5.97	.62*** (.71***) ((.53))	.51
2014-12-31 to 2019-12-31 (rolling 3 years)	50% Cap	9.36* (9.68*) ((9.03))	8.43	.92*** (.95***) ((.88**))	.74
	100% Cap	9.47* (9.93**) ((8.99))	8.43	.92*** (.97***) ((.88***))	.74
	150% Cap	8.66 (9.19) ((8.11))	8.43	.8 (.86*) ((.75))	.74
	200% Cap	8.49 (9.06) ((7.9))	8.43	.78 (.83*) ((.72))	.74
	250% Cap	8.48 (9.08) ((7.87))	8.43	.78 (.84*) ((.72))	.74
	300% Cap	8.32 (8.92) ((7.69))	8.43	.75 (.81) ((.69))	.74
	Uncapped	7.29* (8.82) ((5.68))	8.43	.63* (.81) ((.46***))	.74
1999-12-31 to 2009-12-31 (rolling 5 years)	50% Cap	22.94*** (23.3***) ((22.56***))	18.18	1.41*** (1.43***) ((1.38***))	1.02
	100% Cap	24.06*** (24.68***) ((23.43***))	18.18	1.5*** (1.54***) ((1.46***))	1.02
	150% Cap	24.14*** (24.93***) ((23.35***))	18.18	1.5*** (1.55***) ((1.45***))	1.02
	200% Cap	24.14*** (25.04***) ((23.23***))	18.18	1.5*** (1.56***) ((1.45***))	1.02
	250% Cap	24.1*** (25.08***) ((23.11***))	18.18	1.5*** (1.56***) ((1.44***))	1.02
	300% Cap	24.1*** (25.08***) ((23.01***))	18.18	1.49*** (1.56***) ((1.43***))	1.02
	Uncapped	22.73*** (24.32***) ((21.09***))	18.18	1.4*** (1.5***) ((1.29***))	1.02

2.7 Appendix

2.7.1 Appendix A

2.7.1.1 Descriptions of factors

Factor	
Momentum	Logarithmic price momentum is calculated as the sentiment of the stock price 12 months ago up to the previous month's end price based on Jegadeesh and Titman (1994). The so-called $12X1$ momentum omits the last month concerning the reversal effect for long-term investments. It is the supreme example of a generic market factor and a superior long-term alpha driver in the cross-section of sectors and regions. The persistence of this factor can be reasoned by the behavioral traits of investors that follow strong-performing stocks. These investors' attention leads to a crowding effect that fosters the price sentiment until a macroeconomic event, earnings miss, or other incident stops the trend. In this paper, the price momentum is determined as $$Mom12X1_t := log(\frac{pClose_{t-12}}{pClose_{t-1}}) \qquad (4)$$

Factor	
Value	As researched in Rosenberg et al. (1985), the value factor denotes a common book-to-price multiple that compares an asset's book value to the actual market price. An immense book-to-price value represents a cheap stock and therefore assigns a buy signal with respect to factor investing approaches. The origin of this fundamental risk premium dates back to the investigations of Benjamin Graham and David L. Dodd and has behavioral-based characteristics beneath its systematic and fundamental nature. A possible explanation of the persistence of this systematic risk premium lies in the investors' optimism about bargains and pessimistic overreactions, often resulting in bargains when poor financials are reported.
Beta	The low beta factor investigated by Ang et al. (2006) and Frazzini and Pedersen (2014) describes how stock returns co-vary with market returns. Empirical research proves that low beta stocks explain cross-sectional premia in the long run and, by construction, serve as a cushion in drawdowns. In this study, $$Beta := \frac{cov(r_i, r_{uni})}{\sigma^2(r_{uni})} \quad (5)$$ is calculated with weekly data over the last 250 business days and the $cov()$ is exponentially weighted with a 125 business days half-life.

Factor	
Size	The size factor researched in Banz (1981) shows that smaller stocks in market capitalization explain cross-sectional excess return as an investor's compensation for taking additional risk. The efficacy of the size factor can be economically explained as a systematic risk premium based on the volatile nature and higher risk of bankruptcy of small caps. This examination calculates the size factor as the logarithmic free-floating market capitalization.
Operating Profit (Profitability)	Operating profit (commonly known as EBIT) denotes the profitability of the company's business before interest and taxes and is widely applied as another quality factor. To determine operating profit, the operating expenses are subtracted from the gross profit. Haugen and Baker (1996) and Novy-Marx (2013) find an additional risk premium with this factor. Financially healthy companies tend to continue their good business in the future. Therefore, economically justifies this risk factor.
Total Assets Growth (Investment)	This risk factor measures the growth of the total assets to forecast future excess return as a second quality factor. Titman et al. (2004), Cooper et al. (2008) and Watanabe et al. (2013) find that stocks with lower recent total assets growth tend to outperform the market. In this paper, we compute the growth of the total assets over the last 500 business days.

2.7.2 Appendix B

2.7.2.1 Descriptions of rebalancing and tilting constraints (applied values in parentheses)

In the following table, all applied constraints are listed. The first constraint listed is the essential additional constraint that defines the cost-mitigation strategy. While all tilt-portfolios are equally initialized, all cost-mitigated portfolios hold this additional constraint in all time steps $t_{>0}$.

Constraint	
Relative Maximum Order Size Cap (25%-300% of ADV)	This parameter distinguishes cost-mitigated portfolios from their base case. This sets a limit for the relative order sizes in the rebalancing steps.
Initial Threshold (Top 50%)	This threshold determines the lower bound for the mixed factor exposure at portfolio initialization. It controls the number of titles in the initial portfolio. This constraint represents the banding constraint from Novy-Marx and Velikov (2018).
Rebalancing Threshold (Top 50%)	Alike the initial threshold constraint, a lower bound for the factor exposures is set for each rebalancing step. This banding constraint controls turnover and guides the number of holdings in the portfolio with respect to the trade-off of diversification and excess return expectation.
Relative Minimum Order Size (10%)	This constraint manages the minimum size of position changes of already held assets in the rebalancing. It can be utilized to control turnover.

Constraint	
Absolute Minimum Order Size (1 basis point of portfolio size)	Alike the relative minimum order size in absolute terms. This constraint prohibits the factor-tilt from generating economically insignificant orders that would artificially raise the average holdings.
Absolute Minimum Holding Size (5 basis points of portfolio size)	Declares the smallest permitted size of weight in the constructed portfolio that a position might have.
Absolute Maximum Holding Size (2% of portfolio size)	Concerning implementability and diversification, a maximum holding constraint limits portfolio weights to a certain fraction of the whole portfolio size. Each asset's total market capitalization is additionally taken care of in this constraint.

2.7.3 Appendix C

2.7.3.1 Pairwise portfolio significance testing for differences in annualized (excess) returns and Sharpe ratios

Due to strong serial correlations between portfolios, auto-correlation in the tiltings, and a stochastic dependency in the portfolios, an ordinary t-test can not be applied. To test the statistical significance of our presented evidence, we apply the following test statistic Z_μ as a two-sided t-test on the return differences for stochastically dependent, identically distributed portfolios:

$$Z_\mu = \frac{\sqrt{N}(\hat{\mu_1} - \hat{\mu_2})}{\sqrt{\hat{\sigma_1}^2 - 2\hat{\rho_{1,2}}\hat{\sigma_1}\hat{\sigma_2} + \hat{\sigma_2}^2}} \tag{6}$$

With N degrees of freedom ($\#rebalancing\ months - 2$; because portfolio initialization is cost-mitigation independent) and μ_i, σ_i assigning the estimated annualized means and standard deviations of both observations.

We also report the statistical significance of the Sharpe Ratio (SR) difference between two stochastically dependent portfolios with the following test statistic from Ledoit and Wolf (2008):

$$Z_{SR} = \frac{\sqrt{N}(\hat{SR}_1 - \hat{SR}_2)}{\sqrt{2 - 2\hat{\rho_{1,2}} + \frac{1}{2}[\hat{SR}_1^2 + \hat{SR}_2^2 - 2\hat{SR}_1\hat{SR}_2\hat{\rho_{1,2}}^2]}} \tag{7}$$

Based on these test statistics, all hypothesis tests check the alternatives: $H_0 : \mu_1 = \mu_2 \quad (SR_1 = SR_2)$, $H_1 : \mu_1 \neq \mu_2 \quad (SR_1 \neq SR_2)$ and report the p-value to the error levels $p < 0.05$, $p < 0.01$ and $p < 0.001$.

To account for the auto-correlation of the tilts, we do not just report the results of the above hypothesis tests. Still, we perform a bootstrap that is explained as follows.

2.7.3.2 Stationary Circular Block-Bootstrapping

The hypothesis tests above are robustness-checked with a block-bootstrap to correct for auto-correlation as researched in Efron and Tibshirani (1993). Politis and Romano (1992) proved that randomization of the block length in the circular block-bootstrapping maintains the stationarity of the observations in the bootstrapped samples. Therefore the reported p-values are finally calculated as follows:

- Calculate the Z-statistic as Z once for return- or Sharpe ratio testing
- To apply the stationary circular block-bootstrap to test H_0, transform the data so that H_0 is true.
  - For return testing this transformation is given by $\tilde{X_i} := X_i - \hat{\mu_i} + \hat{\mu}_{combinedsample}$ for both time series.
  - For sharpe ratio testing it is: $\tilde{X_i} := [\frac{X_i - \hat{\mu_i}}{\hat{\sigma_i}} \hat{\sigma}_{combinedsample}] + \hat{\mu}_{combinedsample}$ for both time series.
- The robustness-checked hypothesis test works by simulating the distribution of the Z-statistic with block-bootstrapping under a true H_0. We do that by generating $M = 10000$ block-bootstrap samples for both time series of forced length N (circular) with uniformly randomized block-length $b \in \{1, 2, ..., \lfloor \frac{N}{2} \rfloor\}$ to maintain stationarity. The Z-statistic is calculated for each of the M bootstrap samples as $\tilde{Z_i}$.
- Now we sum $\frac{\sum_{i=1}^{M=10000} I(|\tilde{Z}_i| \geq |Z|)}{M} =: p$ where $I()$ denotes the indicator function (that equals 1 if its argument is true and 0 otherwise) to get the p-value of our hypothesis test given H_0 is true. This p-value is the reported statistic for each hypothesis test in the results section.

3 MACROECONOMIC INFLUENCE ON COST-EFFICIENT FACTOR INVESTING IN EMERGING EQUITY MARKETS

3.1 ABSTRACT

We research the explainability of near-term macroeconomic influence on factor investing in emerging equity markets. First, we identify leading indicators that are significantly connected to equity risk premia. Based on this association and by incorporating machine learning classification, three macro-adaptive approaches implement factor regime forecasts into cost-efficient portfolio decisions. Incorporating macroeconomic indicators increases the risk-adjusted net performance of equity portfolios in emerging markets.

JEL classification: E44; G11; G12; G15.

Keywords: Investments; Asset Pricing; Trading Costs; Adaptive Rebalancing; Machine Learning; Regime-Shifting.

3.2 Introduction

Systematic risk premia are widely studied and understood in the long run, whereas short-term behavior remains unclear and noisy. Therefore, it is a subject of interest to understand better the near-term connection between macroeconomic influence and the cyclicality of factor premia. Numerous studies have investigated the macroeconomic integration of fundamental risk factors and generic market effects into the business cycle. Fama and French (1989)[12] examine the macroeconomic connection to factor allocation and find that risk premia are based on macroeconomic risks in the long run. Empirical evidence shows that size and value are the most cyclical risk factors, while low beta and quality are the most defensive. Different approaches to macroeconomic influence can be found in Tibbs et al. (2008) and Alighanbari (2016), who investigate factor momentum[13] in style indices and identify a connection to the factor premia. While Aretz et al. (2010) confirm that momentum contains incremental information for asset pricing, they find that most macroeconomic indicators are already priced. On the other hand, Ahmerkamp et al. (2012) also studied predictability in momentum strategies and found that business cycle indicators are strongly connected to risk premia. Wang and Xu (2015) confirm this, demonstrate the cyclicality of momentum profitability and provide empirical evidence of a significant and robust connection to market volatility. Furthermore, many examinations focus on factor timing from a different perspective, addressing market sentiment. Copeland and Copeland (1999) report that the VIX and changes in the VIX are significant leading indicators of factor performance. Doran et al. (2007) confirm this association between VIX-related variables and various fundamental factor portfolios. Further, Boscaljon et al. (2011) point out that the findings of Copeland and Copeland (1999) also hold for near-term holding periods of 30 days. Another approach has been carried out by Bonne et al. (2018), who reported an association between factor crowding[14] and low risk premia. Rising investors' attraction can explain this crowding effect to systematic and transparent asset allocation after the failure of active management in the global financial crisis (GFC). Lately, Boven (2020) has found a significant entanglement between fundamental factor premia and the current macroeconomic context in the US market. Boven (2020) explains the lost potential of factor premia since the GFC by quantitative easing and stagnation. Eventually, the explainability of near-term factor premia by the

[12] Chen et al. (1986), Barro (1990) and Campbell and Diebold (2009), among others.

[13] With factor momentum, we denote the trend observed in the risk premia of any factor concerning consecutive time steps.

[14] For instance, factor crowding can be measured in (prolonged) liquidity spikes of a particular factor's associated stocks. The recent growth and popularity of factor investing increase the potential for factor crowding. If a factor does become too crowded, there is an increased risk of a drawdown event.

business cycle or leading indicators remains controversial.

Recent examinations have been carried out to demonstrate the impact of transaction costs on factor investing. According to Lesmond et al. (2002), who investigate the transaction costs of momentum-based portfolios, net factor premia disappear for this high turnover strategy. Korajczyk and Sadka (2005), Novy-Marx and Velikov (2015), Ratcliffe et al. (2017) and Patton and Weller (2019), who also examine momentum-based strategies, find different equilibrium sizes[15] of factor-based excess returns. Most studies on transaction costs identify liquidity as the costs' most crucial driver. Based on these investigations, Garleanu and Pedersen (2013), Frazzini et al. (2018) and Novy-Marx and Velikov (2018) find optimal portfolio decisions and present different approaches to cost-efficient portfolio constructions. With investors' growing attraction to emerging equity markets, earlier examinations such as Bekaert and Harvey (1997) and Achour et al. (1998) contribute to factor investing in this market environment. Furthermore, the studies of Kargin (2002), Bruner et al. (2003) and Davis et al. (2010) extend these investigations to a more current market environment. Since Lesmond (2005), little research has been devoted to trading costs in emerging equity markets. The role of factor timing in emerging markets has also received less attention than in the US and other developed markets. Leastwise, Bilson et al. (2001) and Desrosiers et al. (2006) research the connection between macroeconomic indicators and risk premia concerning factor investing in emerging equity markets. Druck and Mariscal (2018) outline the association between dollar strength and emerging market growth as one of the tightest macroeconomic bonds.

While the trade-off between complexity and benefit of macroeconomic factor timing remains controversial in developed markets, emerging equity markets received less attention. We examine the association between near-term leading indicators and risk premia in emerging markets based on the outlined studies on macroeconomic indicators and cost-efficiency in factor investing. For this purpose, we identify significant indicators and research the trade-off between factor premia and trading costs with three macro-adaptive strategies. Eventually, we outline a consideration for using machine learning[16] techniques to estimate the emerging markets' factor regime. With these forecasts, the macroeconomic

[15]We denote a theoretical portfolio size measured in currency with equilibrium size. At this portfolio size, trading costs empirically net out with factor premia. This entity allows comparing the net efficacy of various investment strategies and asset classes concerning their implementability. In other words, portfolios outreaching their equilibrium size underperform the market.

[16]We draw on the findings of Guidolin and Timmermann (2007), Bae et al. (2013) and Mulvey and Liu (2016), who established machine learning models to allocate assets under regime-switching. These studies suggest classification models such as penalized logistic regression, gradient boosted trees and gaussian-kernel-based support vector machines to forecast changes in the market environment.

influence can be successfully implemented in cost-efficient factor investing strategies.

The paper proceeds as follows. The next section outlines the investment universe, a methodology for cross-sectional factor valuation and identifies significant macroeconomic influences on this factor valuation. Later, these macroeconomic indicators are utilized to construct three adaptive factor investing strategies. In the empirical results section, we review the theoretical benefits of the macroeconomic association with factor premia in portfolio implementations and discuss machine learning approaches' role in this context. This section closes with the implications of the risk-adjusted net performance of macro-adaptive strategies in emerging equity markets. The last section concludes our research.

3.3 Data and methodology

3.3.1 The emerging markets universe

To assess the macroeconomic influence on factor premia in emerging equity markets, we apply a general valuation methodology for the excess return of an equal-weighted risk factor mix. Therefore, we conducted our analysis on an emerging markets data set[17] concerning the country listings of the MSCI Emerging Markets Index[18] over the last two decades ending in December 2019. A small range of available data before the millennium is omitted concerning the quality and coverage of the liquidity data and the macroeconomic time series. This study uses data from MSCI to determine the underlying companies in emerging markets and their free-floating market capitalization. Besides MSCI, the Worldscope database from Refinitive is used for the remaining fundamental factors of value, profitability and investment. The generic factors of momentum and low beta are calculated based on market data from Datastream (Refinitive). Further, Datastream is utilized for most market data such as return indices, liquidity, bid-ask spreads, and macroeconomic time series. Referring to the market closing of 2019 as today, this emerging markets universe consists of 26 countries[19] across the five different sub-regions of Emerging Americas, Europe, Middle East, Africa and the Asia Pacific, of which the latter contributes to 79.35% of the emerging markets' size. The MSCI Emerging Markets Index's underlying stocks are

[17]In the following, the emerging markets are denoted as "EM" and also referred to as the "whole universe".

[18]https://www.msci.com/emerging-markets, last visited: 2020-09-30.

[19]The MSCI Emerging Markets Index consists of 26 emerging economies, including Argentina, Brazil, Chile, China, Colombia, Czech Republic, Egypt, Greece, Hungary, India, Indonesia, Korea, Malaysia, Mexico, Pakistan, Peru, Philippines, Poland, Qatar, Russia, Saudi Arabia, South Africa, Taiwan, Thailand, Turkey, and the United Arab Emirates.

considered large caps, whereas all other stocks larger than \$10 million in market capitalization are denoted as small caps. Today, this emerging markets universe consists of 3480 stocks summing up to \$9.2 trillion free-floating market capitalization.

3.3.2 Factor valuation methodology

In this study, we focus on six risk premia. The first is the fundamental value factor researched in Basu (1977) and Rosenberg et al. (1985). The size factor embodied another systematic risk premium and was discovered by Banz (1981). Further, two systematic quality factors are added. The operating profitability, which is researched by Haugen and Baker (1996) and Novy-Marx (2013), and the investment factor found in Titman et al. (2004), Cooper et al. (2008) Watanabe et al. (2013) augment our choice. Jegadeesh and Titman (1994) and Hurst et al. (2017) research the decisive generic momentum factor. Lastly, Ang et al. (2006) and Frazzini and Pedersen (2014) examine the generic low beta factor that completes our selection. A straightforward multi-factor mix based on these six risk factors is explained in Appendix A and B. The empirical evidence presented in this examination is robust to alternative factor definitions, different mixes and also different weighting schemes. We decide to present this mix of six well-known factors to cover fundamental factors and market effects and apply an equal-weighted scheme with respect to simplicity. We calculate its long risk premium at time t in terms of:

$$\begin{aligned} Long\ Premium_t = \frac{\sum_i (weight_{i,t} \cdot Z\text{-}score_{i,t} \cdot return_{i,t})}{\sum_i (weight_{i,t} \cdot Z\text{-}score_{i,t})} - \frac{\sum_j (weight_{j,t} \cdot return_{j,t})}{\sum_j weight_{j,t}} \\ \forall i \in \{EM : Z\text{-}score_i > 0\},\ \forall j \in \{EM\} \end{aligned} \tag{8}$$

weight denotes the free-floating market capitalization and *return* reflects the return index over the next business month. In the following, we utilize this value-weighted methodology to assess the risk premia of the multi-factor mix (as displayed in Figure 3-1 and Figure 3-2) and illiquidity (as in Figure 3-3 and Figure 3-4). We have already remarked on the distinct decline of factor valuation in recent market environments, which is well perceptible in the charts above. Further and concerning long-short factor valuation, we analogously calculate:

$$Long - Short\ Premium_t = \frac{\sum_i (weight_{i,t} \cdot Z\text{-}score_{i,t} \cdot return_{i,t})}{\sum_i (weight_{i,t} \cdot Z\text{-}score_{i,t})} - \frac{\sum_j (weight_{j,t} \cdot return_{j,t})}{\sum_j weight_{j,t}} \tag{9}$$
$$\forall i \in \{EM : |Z\text{-}score_i| > 0.5\},\ \forall j \in \{EM\}$$

And compare the cumulative long-only versus long-short multi-factor premia in Figure 3-5. These simple valuation methodologies (Equation 8 and Equation 9) assess the empirical monthly excess return concerning the market (EM). With these simple valuations that generalize portfolio tiltings, omitting trading costs and constraints, we research the association between macroeconomic influence and factor premia.

3.3.3 The role of macroeconomic indicators

This subsection examines the connection between smoothed[20] multi-factor (and illiquidity) premia to the macroeconomic environment. Inspired by previous investigations on macroeconomic influence in factor investing, we expect significant connections between the factor premia in emerging equity markets and dollar strength (Druck and Mariscal (2018)), VIX (Copeland and Copeland (1999) and Doran et al. (2007)) as well as market momentum. Druck and Mariscal (2018) report an association between dollar strength and GDP growth in EM as one of the tightest macroeconomic connections in the long run. This association is reasoned by a long-term income effect as follows. With rising dollar strength, the relative price of local EM commodities falls. Falling commodity prices lead to a lowered demand for the required labor, leading to lower income. The lowered income inhibits GDP growth and vice versa. Drawing on this, we also expect a significant near-term connection between dollar strength and factor premia that we reason with respect to earnings expectations. A rising dollar strength leads to financial distress in EM companies with a significant stake in USD-denominated debt. The risen value of the USD relative to local EM currencies increases the debt burden's value and leads to lowered earnings expectations. A decrease in earnings expectations leads to a near-term stock price correction. Vice versa, falling dollar strength makes USD-denominated debt relatively cheaper, leading to relatively expensive commodity prices in USD that benefit the production-oriented EM. The fact that USD-denominated debt is typically denoted with a lower interest rate than local credit tightens

[20]We choose a 3-month smoothing window for both time series of premia in the factor valuation concerning their signal decay.

this cycle. In favorable business and market conditions, EM companies might be tempted to raise their debt with cheaper US credit concerning any growth opportunity but not considering an increase in dollar strength. With the burden on a foreign currency, no local central bank correction is possible and the EM companies are exposed to the market condition. Therefore, we expect a cyclicality that might be well connected to the inevitable cyclicality of factor premia in EM. As a caveat, we remark a possible distortion in this connection as very high dollar strength could increase stock prices in EM. Such an increase might happen due to a bargain opportunity for US investors. However, we do not expect this to be an issue in the subsequent investigation. Further, a large absolute VIX and its increase tend to mitigate the following factor premia. Doran et al. (2007) find that this also holds in the near term. The VIX can be interpreted as a fear index. Opposing the pessimistic expectations in line with a high VIX and jumps in the VIX, we assume optimistic expectations on factor premia that accompany consecutive months of solid market performance.

Following these initial presumptions, we collect a selected range of promising macroeconomic time series of the US and EM economies. Based on these raw indicators, we also calculate mid-term change rates (3 months and six months) as possible leading indicators for factor premia. In the first place, considering the issue of possible reporting lags[21] in the data, we naïvely investigate pairwise Pearson correlations between each indicator and the risk premia. For this purpose, we calculate the thresholds of statistical significance with the following T-statistic:

$$T = \frac{R \cdot \sqrt{N-2}}{\sqrt{1-R^2}} \tag{10}$$

Where $N-2$ represents 238 degrees of freedom from 20 years of monthly data. To obtain the minimum Pearson correlation R to hold a certain level of statistical significance, we rearrange Equation 10 to:

$$R = \pm \frac{T}{\sqrt{T^2 + N - 2}} \tag{11}$$

[21] All investigated time series are collected from the database of Thompson Reuters Datastream. We restrict the research in this section to these indicators that can be utilized in real-time without any look-ahead bias induced by reporting lags. By dealing with macroeconomic data, some time series naturally hold reporting lags of up to several months. These indicators had to be excluded from our research.

And display the curve in absolute terms in Figure 3-7 with respect to the p-values resulting from the T-values under the t-distribution. We precondition all indicators by detrending them in an expanding window fashion. Further and concerning required normality for the correlation tests, we also calculate expanding Z-scores. Both premia are tested for stationarity with an ADF. The null hypothesis is rejected at the 1% level for both time series. In Table 3-1 we report all significant macroeconomic indicators concerning both factor premia. The table also provides a detailed overview of the issuer of the macroeconomic time series and a description of their calculation metric. Furthermore, the heatmaps displayed in Figure 3-8 (for illiquidity premia) and Figure 3-9 (for multi-factor premia) also show the Pearson correlations between the macroeconomic indicators. By deriving significant leading indicators, we correct possible ill-conditioning concerning multicollinearity. We estimate possible multicollinearity in the data with the design matrix's condition number[22] on all indicators, including the unit vector. The visualizations of Figure 3-8 and Figure 3-9 also show that the Pearson correlations between the indicators tend to be low and negative. Concerning the robustness of this approach, Spearman rank-correlations also confirm the statistical significance of these indicators. Here, we can confirm the empirical evidence of Copeland and Copeland (1999) that identifies the VIX and changes in the VIX as leading indicators of factor premia in emerging markets. Most EM countries have similar risk exposures with respect to the US and EM VIX. Therefore, we decide to average both signals. This aggregation slightly increases the connection to near-term risk premia for most non-European stocks. For the emerging countries of the Czech Republic, Greece, Hungary and Poland, we research a stronger connection to the VSTOXX. Furthermore, we also confirm the findings of Wang and Xu (2015) for the emerging equity markets and report a significant connection between changes in market volatility and factor premia. To tie on the discussion of Boven (2020), we find high significance between factor premia and changes in quantitative easing in the US economy, measured in FED M2 money growth. The evidence provided by Bonne et al. (2018) is also confirmed for the emerging markets by identifying the connection between risk premia and short-term (20 business days) factor crowding. Further and as expected, we research that the connection between the factor premia and dollar strength (as well as changes in dollar strength for multi-factor premia) is one of the tightest bonds. While the VIX and changes in the VIX are also confirmed as significant leading indicators, the connection with market

[22]We derive the condition number in terms of the spectral norm. This is calculated as the square rooted fraction of the absolute largest and smallest eigenvalue. Further, we remark that the condition number of a well-conditioned design matrix does not exceed 30. Concerning the heatmaps in Figure 3-8 and Figure 3-9, we report a condition number of 4.64 for the leading indicators of illiquidity premia. The indicators for multi-factor premia result in a condition number of 7.83.

momentum is surprisingly weaker. Additional USD-denominated debt burden of EM companies is also identified as a positive signal. This connection can be interpreted as the issuer's expectation of a growth opportunity. Market momentum is measured quarterly and debt growth is calculated on the rolling changes over a semester. We also find significant leading indicators in US Retail Sales changes, Real EM GDP Growth, and Citi's EM Surprise Index for multi-factor premia. We outline the oil price, the US CEO Confidence Index, and a recession indicator of US bond rates[23] as significant leading indicators for the illiquidity premia. While we do not find significance between factor premia and market liquidity changes, we remark that this insufficient connection is satisfactory. Therefore, liquidity effects on factor premia and trading costs do not net out in adaptive strategy approaches. Trading becomes cheaper at a given cost level and with higher market liquidity in EM. The total effect would remain unclear if we simultaneously observe inferior multi-factor premia. Further, we find that US Consumer Confidence, Citi's US Surprise Index and US Unemployment Rates (as well as their change rate) are no leading indicators for neither multi-factor nor illiquidity premia. In general, we remark that our study reveals a strong connection of US macroeconomic indicators with factor premia in emerging markets.

3.4 Empirical results

3.4.1 Macro-adaptive portfolio strategies

Based on the findings from the previous subsection, we examine three macro-adaptive strategies. The first approach is the adaptive choice of whether or not to suspend a monthly rebalancing step to save its trading costs entirely. Second, we also research the effect of a more aggressive long versus long-short (130/30) strategy concerning the expected factor regime. In the last approach, we adaptively apply a cost-mitigation strategy with respect to limiting the relative trade size[24]. Here, we mitigate turnover

[23]The bond rate indicator is detailed in Table 3-1 and reflects a comparison between short- and long-term US bond rates. A relatively large short-term bond rate versus a long-term bond rate is a negative signal for the US market environment. Our analysis confirms that this macroeconomic connection even holds for the emerging markets.

[24]We measure the stock liquidity in terms of executed average daily volumes across primary and secondary stock exchanges in USD. The average daily volume, denoted as "ADV", is calculated based on a short-term rolling window of 20 business days. Furthermore, we calculate the relative trade size concerning this ADV.

and, therefore, trading costs of multi-factor investing concerning the expected illiquidity regime[25]. As we observe cyclical illiquidity premia, we assume the profitability of the adaptive cost-mitigation approach by incorporating expectations on illiquidity premia. With respect to the macro-adaptivity, we tighten the trade size limiting from 300% of the ADV to 100% of the ADV every time the expectations on illiquidity premia fall short. Each strategy exploits macroeconomic association concerning the return-to-cost dualism in the emerging stock universe. Our main goal is to determine whether or not the macroeconomic links to factor premia can be utilized in cost-efficient equity allocations. Further, we provide a ceiling analysis to understand the impact of macroeconomic association with risk premia in portfolio implementations. We can validate the strategies by implementing adaptivity concerning perfect foresight of the risk premia, a naïve approach and more sophisticated regime models. First, we construct reference portfolios based on the whole period of 1999-12-31 to 2019-12-31 with an initial cash position of 1 billion USD at 1999-12-31 and apply a medium cost level (Figure 3-6 and Appendix C for details). Based on this setting, we calculate the time series of a cost-mitigated portfolio tilting with "cap300" (trade size per rebalancing capped by 300% of ADV) minus its less strict alternative of cap100. Analogously, we build a long-short (130/30) portfolio minus a long-only construction. We find a Pearson correlation of 0.251 between the former time series of cap300 cost-mitigation minus a strict strategy and the smoothed illiquidity premia. Furthermore, we find a 0.461 Pearson correlation with the smoothed multi-factor premia for the latter time series of the long-short minus long-only strategy. Therefore, our initial considerations are supported. We see that the profitabilities of both adaptive strategies are significantly connected with factor premia under perfect foresight. These validations led to the investigations outlined in the following.

3.4.2 Naïve versus ML-based regime estimates

The next step in successfully implementing the macro-adaptive strategies is eliminating any other look-ahead bias. Hence, we formulate the problem of forecasting the factor regime in terms of a binary classification problem. Therefore, we associate a "crash regime" with negative (forecasted) multi-factor or illiquidity premia in the next business month. We can detect crash regimes without making

[25] This cost-mitigation strategy of limiting trade size to a good fraction of the average stock liquidity benefits the cross-section of EM factor investing. Interestingly, this net performance increase does not solely rely on lowered trading costs. This liquidity constraint is quasi-periodically not much of a constraint at all. While illiquidity is a fundamental risk premium, we have already displayed its short-term cyclicality in the long run. Summing up, the efficacy of this cost-mitigation strategy is borne by mitigated implementation costs and recurring liquidity premia.

expensive mistakes by approaching this as a binary classification problem. With the expectation of a crash regime, we can either entirely suspend a non-profitable rebalancing or tightly restrict illiquid and expensive trades. Vice versa, in the absence of an expected crash, a more aggressive investor could be prone to an adaptive long-short positioning. We engineer two machine learning models for the factor regime forecast and compare them against a naïve one-step estimate. At this point, we remark that an improved near-term forecast for the factor regime does not necessarily result in a beneficial adaptive strategy concerning portfolio constraints and path dependency. However, we assume that ML-based factor regime forecasts outperform the naïve estimate concerning standard error measurements. The great advantage of machine learning classifications is training and tuning their efficacy on one binary case. In our problem, this translates into not missing a crash regime. Therefore, we tune the models on the crash's recall because a wrong decision might be more expensive than the profitability of not missing an opportunity.

We decide to model the binary classification of the multi-factor and illiquidity regimes twofold. Therefore, we choose a penalized logistic regression (Logit) and gradient boosted trees (GB) to compare their forecasts. These supervised learning models were chosen to compare two classes of ML methods concerning the Logit's (linear model) penalization term and the GB's (ensemble method) ability to map non-linearities. To account for the missingness in the macroeconomic data[26], we apply a MICE imputation after expanding window Z-scoring all independent features from 1999-12-31 to 2009-12-31. Therefore, we initialize all portfolio tiltings at 2009-12-31 with respect to this minor look-ahead bias induced by the data cleaning. Further, we model the Logit and GB based on monthly expanding window tunes and fits. In this sense and concerning the stationary responses, we omit response scaling. For all independent features, we choose to apply a feature-wise Yeo-Johnson power transform concerning non-positive data. This transformation makes the data more Gaussian-like and potential heteroscedasticity might be cured. Here, the optimal transform parameter for stabilizing the variance and minimizing skewness is estimated through maximum likelihood. Finally, the normalization of all independent features is applied to the transformed data by expanding window zero-mean and unit-variance normalization.

We start the expanding window modeling after an initial tune and fit covering data from 1999-12-31 to 2004-12-31. The initial and subsequent monthly tunings are based on a 5-fold time series split trained on the crash's recall for both ML models (Logit and GB). The tuned hyperparameters consist of only

[26] Fortunately, there are no data gaps after the business year of 2008.

the penalizing parameter for the Logit and number of tree estimators, learning rate, minimum samples per leaf and maximum tree depth for the GB. All hyperparameter tunings have been carried out on sufficiently fine grids so that each parameter's interval limits are never chosen as optimal. Table 3-2 compares the error metrics of both ML estimates based on the indicators listed in Table 3-1 with the one-step estimate. Especially for multi-factor premia, the one-step estimate is not a weak forecast but not outstanding either. Unfortunately, the critical crash recall is low, which is not satisfying for our purpose. While the Logit's accuracy is distinctly higher than the one-step, precision, recall, and therefore f1 score are superior. Further, the GB's accuracy is slightly worse than the one-step's accuracy and notably worse than the Logit's accuracy. Remarkably, the GB responses were better on the recall training than the Logit. Here, we report a 2.5 times stronger recall for the GB, while its precision is slightly worse than the Logits. The one-step forecast for illiquidity premia has similar accuracy to multi-factor premia but distinctly higher precision, recall and, therefore, f1 score. Also, similar to the multi-factor premia, the Logit classifier's error metrics outperform the one-step's. Further, the GB has a superior recall again, but the relative improvement is much smaller than the multi-factor premia comparison. The GB's accuracy for illiquidity premia is more substantial than for multi-factor premia and lower than Logit's estimate. Furthermore, these results assume that one-step estimated regime forecasts might benefit macro-adaptive portfolio tiltings. We further assume that machine learning forecasts outperform this naïve adaptivity due to the remarkable increases in recall and precision metrics concerning detecting crash regimes. We engineered solid forecasts for the multi-factor (and illiquidity) regime in emerging markets that do not guarantee macro-adaptive efficacy but certainly set a milestone in this investigation.

3.4.3 Sensitivity analysis on portfolio decisions

With these machine learning forecasts, we validate macro-adaptive portfolio tiltings' efficacy. We examine the three strategies regarding sensitivity analysis concerning portfolio size and cost level. Machine learning forecasts, the one-step estimate and perfect foresight of the factor regime are utilized to adaptively implement macroeconomic influence in portfolio decisions to provide the ceiling analysis. We consider a successful implementation outperforming its non-adaptive portfolio concerning significant risk-adjusted net performance or at least significant excess return. Table 3-3 to Table 3-8 report the performance statistics of all portfolio constructions in terms of the two-dimensional sensitivity analysis. Here, we research all combinations of six ascending portfolio sizes (250 million, 500 million, 1 billion, 2.5 billion, 5 billion and 10 billion USD) and the three cost levels visualized in Figure 3-6. Each portfolio is priced with respect to the trading cost model detailed in Appendix C.

In general, we see that the success of factor investing relies on a cost-efficient implementation. However, for smaller portfolios up to 1 billion USD, we find strategies with significant excess returns even for the highest cost level. The adaptive long-short strategy has a strong performance for the smallest portfolio size of 250 million USD but depends on the small size and low trading costs. Unfortunately, no macro-adaptive long-short construction with a larger initial size than 250 million USD can outperform its non-adaptive strategy. This lack of outperformance is the case because of its enormous turnover that arises by liquidating the short positions when a regime change is expected. The factor regime's expectations often switch enough to make the macro-adaptive long-short strategy unprofitable for larger investment sizes. Hence, an initial portfolio size of 500 million USD is large enough to make the adaptive long-short strategy unprofitable concerning its high turnover. Contrary to our expectations, we have to reject the efficacy of an ML-based adaptive cost-mitigation strategy. The Logit-based constructions align with the cap300 strategy for portfolio sizes up to 2.5 billion USD but never outperform the more strict cap100 strategy for larger sizes concerning statistical significance. Here, we remark that the efficacy of a cost-efficient implementation is more substantial for larger initial portfolio sizes due to an increased implementation hurdle. However, with a size larger than 1 billion USD invested in 2009-12-31, we emphasize the benefits of the cost-mitigation strategy even at the lowest cost level. Another exciting side finding is that the long-short strategy outperforms the base strategy for each investigated size despite distinctly higher annualized trading costs. Further, at a portfolio size of only 1 billion USD and a high cost level, the non-adaptive base strategy reaches its equilibrium with an annualized net return of 6.58%. At the medium cost level, this can be expanded to a 2.5 billion USD portfolio size, while in both cases, the Sharpe ratios remain significantly higher concerning the market. The equilibrium size of the non-adaptive long-short strategy at the lowest cost level is located beyond the base strategy's equilibrium size at over 10 billion USD. While the base strategy's excess return at the lowest cost level seems to be exhausted at the 10 billion USD initial size, the strategy of suspending rebalancings based on GB forecasts still outperforms the market with over 2.5% p.a. at 9.14% annualized net return. Surprisingly, we find that the adaptive suspending of rebalancing steps is a consistently outperforming strategy with respect to the GB-based regime forecast (remember that the GB responds best to the crash's recall). Compared to the market, these findings hold for the base strategy and one-step estimate for all investigated size and cost combinations. We remark that this macro-adaptive strategy outperforms its perfect foresight implementation concerning the high implementation costs in emerging markets. As an additional robustness check for this strategy, we report that its efficacy is robust to randomly skipping the same amount of rebalancings. Therefore, especially by the construction of suspending rebalancings, we find that even in the absence of a crash regime, high trading costs can often not be offset by risk premia. Concerning its relatively low annualized trading costs and even for the most expensive implementation, this adaptive strategy's equilibrium size might be far beyond the 10 billion USD initially invested in 2009-12-31. This finding underlines the importance of cost-efficiency for a successful implementation of factor investing twofold. First, the most passive and simple strategy outperforms the most promising and aggressive implementations. The adaptive long-short strategy with perfect foresight and the mediocre adaptive cost-mitigation approach fail to outperform significantly at each portfolio size of at least 500 million USD. Second, a macro-adaptive strategy can implement the investors' need to prevent mistakes by omitting expensive and unprofitable turnover.

In Appendix D the hypothesis testing methodology is described to determine statistically significant differences in returns, costs and Sharpe ratios concerning auto-correlated return series. Even the most negligible differences can be statistically significant due to the naturally high serial correlations between the portfolio returns. Further, this method serves as a robustness check and empirically proves that the reported statistical significance does not rely on certain sub-periods but is stable along time.

3.5 Conclusion

In this study, we investigated the success of factor investing in emerging markets regarding trading costs and researched the impact of implementing macroeconomic influence in equity allocations. The simplest way to successfully implement factor investing strategies lies in the cost-efficiency found at a low cost level. Unfortunately, many reasons inhibit individual and smaller investors from achieving a sufficiently small cost level in the stock execution at EM exchanges and therefore, alternative methods are required. From our analysis, we can draw several conclusions.

First, we find empirical evidence for a significant macroeconomic association with factor premia in the near term. Second, we identify that under perfect foresight, aggressive and mediocre macro-adaptive strategies appear to be beneficial before costs and constraints. Third, we research that ML-based models exceed a naïve estimate in forecasting the factor regime. Eventually, this leads to a successful implementation of macroeconomic indicators in factor investing. While no sophisticated regime forecast can be successfully implemented for an aggressive or mediocre strategy with respect to costs and constraints, a passive approach highly benefits from macro-adaptivity. With growing portfolio size and cost, cost-efficient implementation becomes increasingly essential. The adaptive strategy of suspending rebalancings expands the equilibrium size of a simple factor investing framework. A more cost-efficient implementation is often the critical component to outperforming the market when the non-adaptive strategy solely does not. To the best of our knowledge and belief, cost-efficiency is necessary to implement factor investing successfully with investors' recent and ongoing attraction to the emerging equity markets. Finally, we emphasize the tight connection between emerging markets and the US economy that can be utilized in portfolio decisions to increase the risk-adjusted net performance of non-adaptive strategies.

3.6 List of Charts and Tables

Figure 3-1: Multi-Factor Premia
This chart displays the monthly multi-factor valuation from 1999-12-31 to 2019-11-29 based on the long-only valuation methodology.

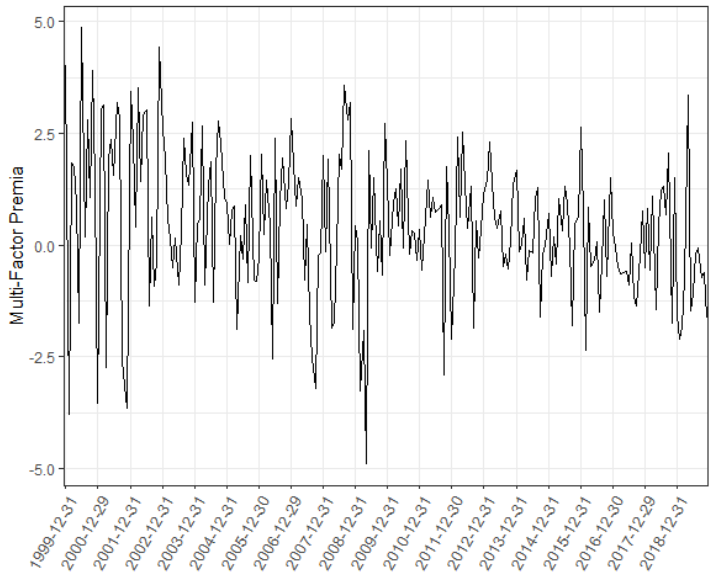


Figure 3-2: Cumulative Multi-Factor Premia
This chart displays the cumulative multi-factor valuation from 1999-12-31 to 2019-11-29 based on the long-only valuation methodology.

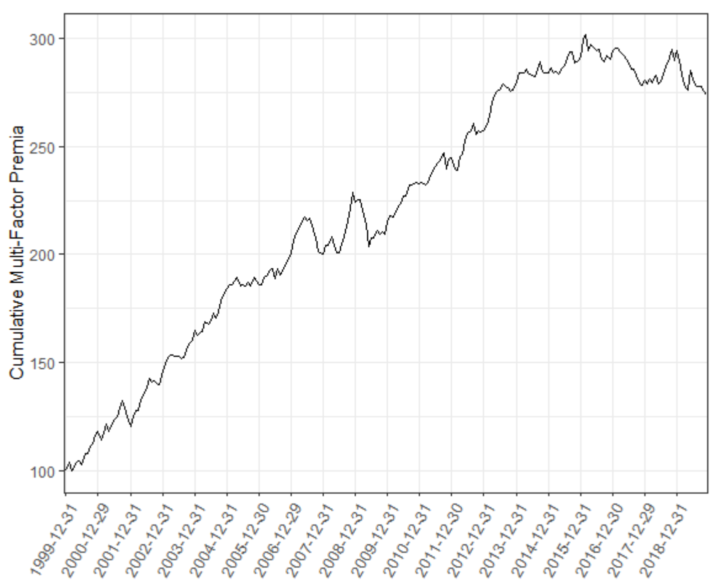


Figure 3-3: Illiquidity Premia
This chart displays the monthly illiquidity valuation from 1999-12-31 to 2019-11-29 based on the long-only valuation methodology. The underlying illiquidity factor is calculated as inverted Z-scores of ADV measured in USD.

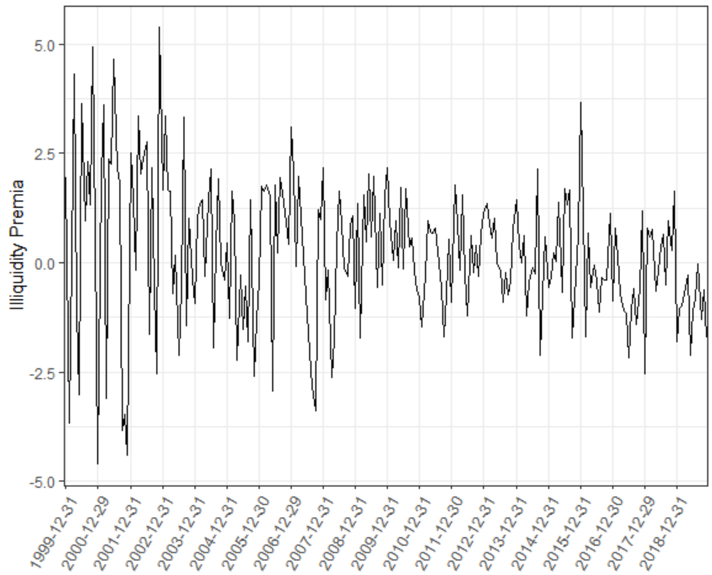


Figure 3-4: Cumulative Illiquidity Premia
This chart displays the cumulative illiquidity valuation from 1999-12-31 to 2019-11-29 based on the long-only valuation methodology. The underlying illiquidity factor is calculated as inverted Z-scores of ADV measured in USD.

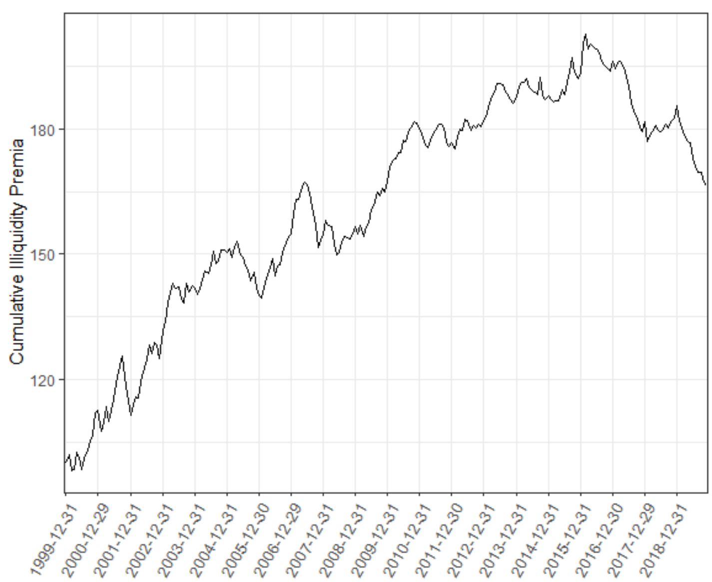


Figure 3-5: Cumulative Multi-Factor Premia Long-Only vs. Long-Short
This chart displays the cumulative multi-factor valuation from 1999-12-31 to 2019-11-29 based on both valuation methodologies.

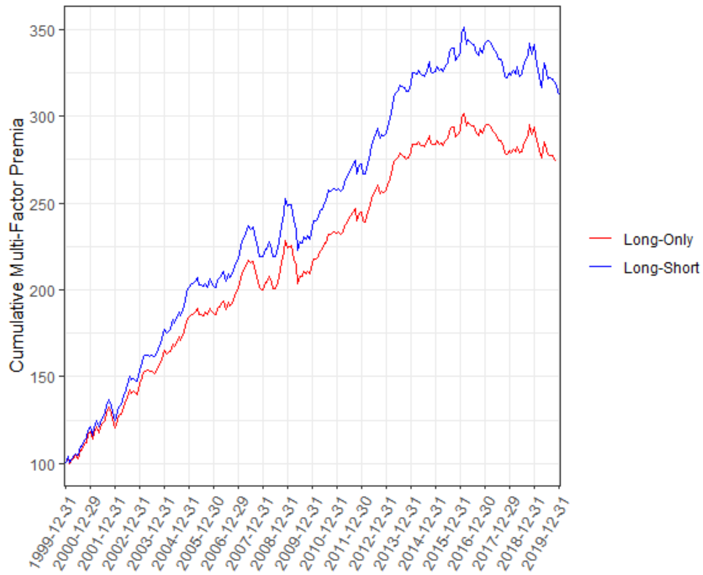


Figure 3-6: Transaction costs square root model
This chart displays the three cost levels of market impact applied in this paper. The three parameters are scaling factors for the square root functionality of order sizes relative to liquidity.

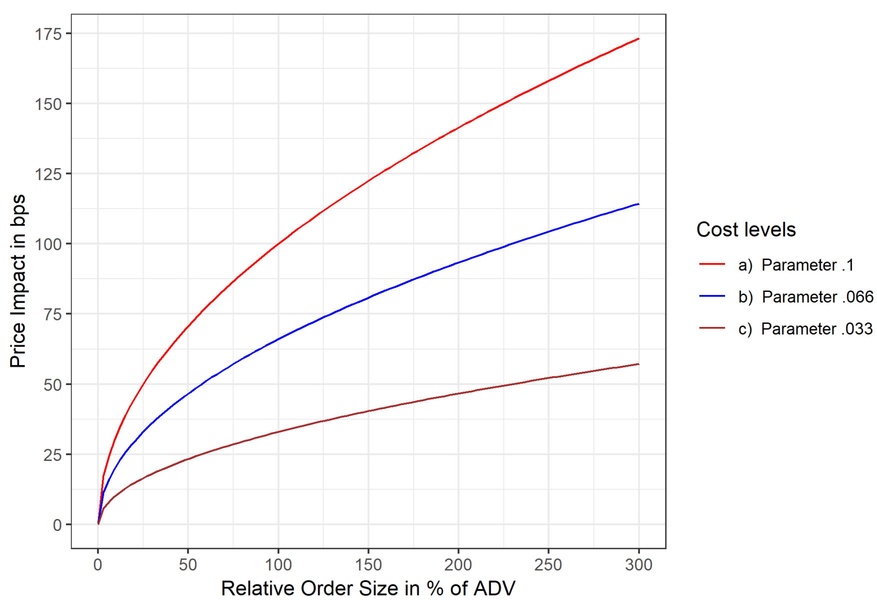


Figure 3-7: Statistical Significance
This chart displays the minimum Pearson correlation necessary for a specific level of statistical significance. The curve is derived by Equation 11 with 238 degrees of freedom.

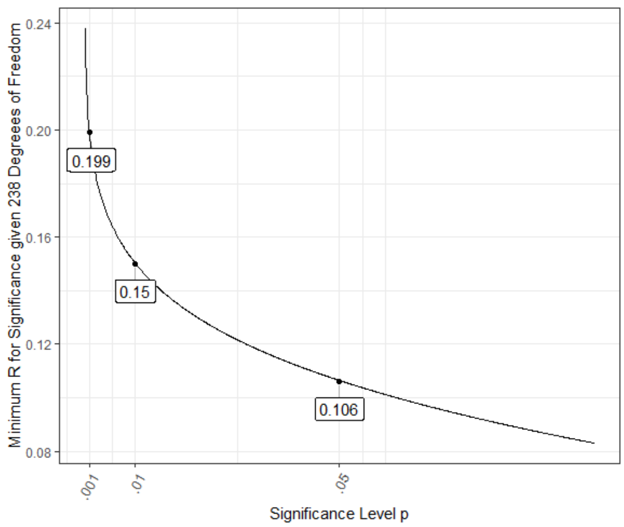


Figure 3-8: Illiquidity Premia Heatmap
This chart displays a heatmap based on Pearson correlations between each significant macroeconomic indicator and the smoothed illiquidity premia.

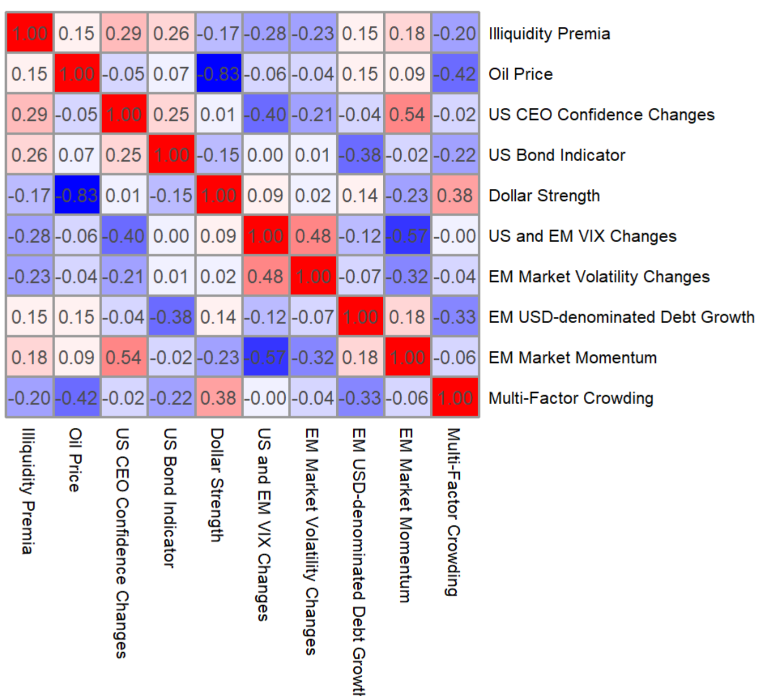


Figure 3-9: Multi-Factor Premia Heatmap
This chart displays a heatmap based on Pearson correlations between each significant macroeconomic indicator and the smoothed multi-factor premia.

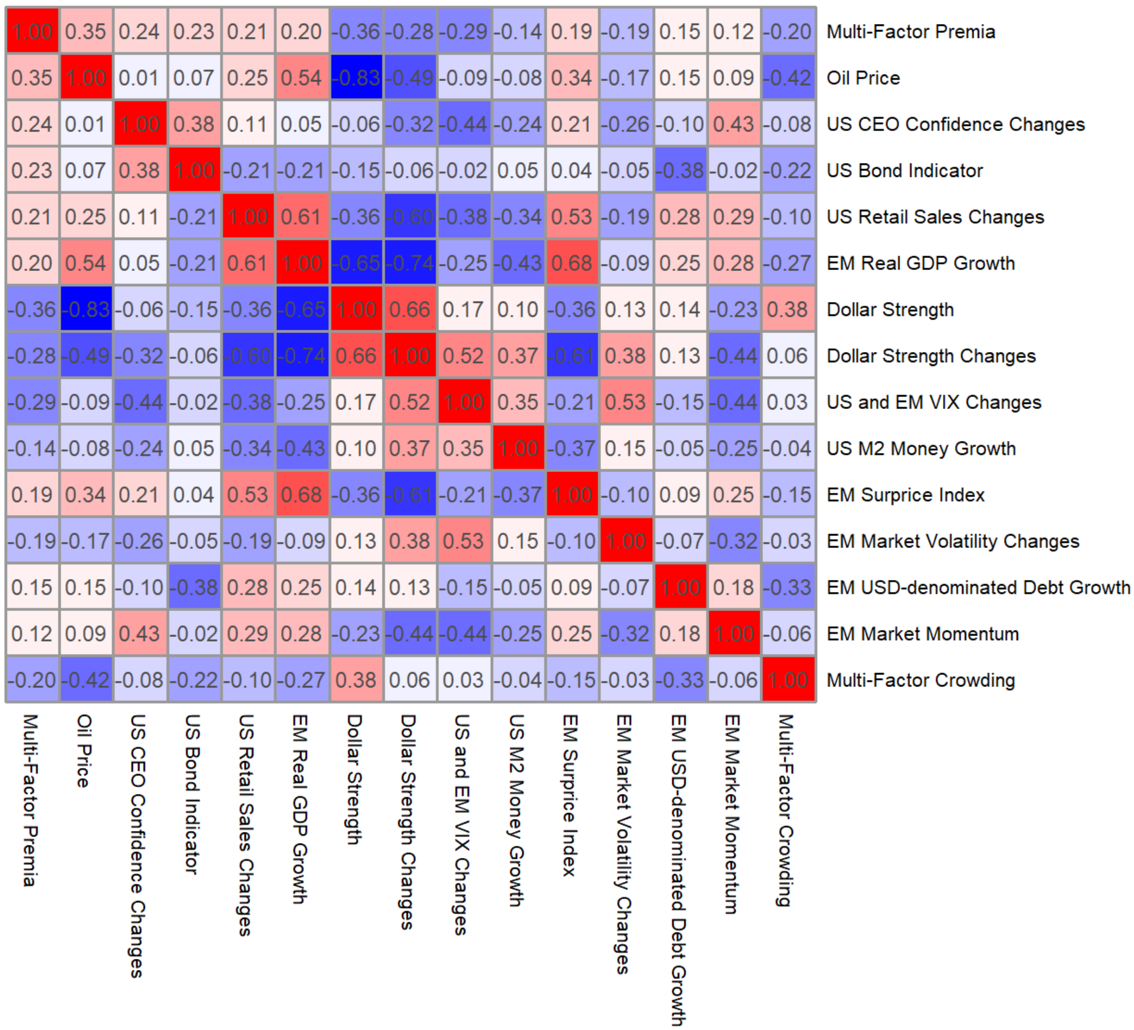


Table 3-1: Detailed description of relevant macroeconomic indicators
Statistical significance (* for $p < 0.05$, ** for $p < 0.01$ and *** for $p < 0.001$) is reported with respect to multi-factor premia (and to illiquidity premia in parentheses).

Macro Indicator	Underlying DS_Name	Underlying DS_Mnemonic	Reported by	Reporting Frequency	Description
Oil Price in USD***(**)	Cushing OK WTI Spt Price FOB U$/BBL	EIARWTC	EIA - Energy Information Administration	Daily	Oil Price of NY 1 Barrel, West Texas Spot Price.
US CEO Confidence***(***)	TOTAL MEASURE OF CEO CONFIDENCE	USCNFCONQ	The Conference Board	Quarterly	US CEO Confidence over following 6 Business Months. Quarterly reported.
US Bond Indicator***(***)	US T-BILL SEC MARKET 3 MONTH (D) - MIDDLE RATE US TREAS.BENCHMARK BOND 10 YR (DS) - RED. YIELD	FRTBS3M USBD10Y	Federal Reserve Federal Reserve	Daily Daily	Based on the Rates of the US 3 Month and the 10 Year Government Bond, we build: $(rate_{US,3M} - rate_{US,10Y})^2$
US Retail Sales***	US RETAIL SALES & FOOD SERVICES, TOTAL CURA	USRETTOTB	US Census Bureau	Monthly	US Retail Sales, Conversion Method 'Sum'.
EM Real GDP Growth***	TB GDP (CON USD) (SA) CONA	TBXGD$S.C	Oxford Economics	Quarterly	GDP EM, Conversion Method 'Sum'.
Dollar Strength***(**)	US Nominal Dollar Emerging MKT IDX	US$CWON	Federal Reserve	Daily	US Dollar Strength to Largest 19 EM Currencies ('OITP'), Weighted by US Import and Export Shares.
VSTOXX, US and EM VIX***(***)	CBOE SPX VOLATILITY VIX -	CBOEVIX VXEEMCLS	CBOE CBOE Statistics	Daily Daily	US Volatility Index. Forecast over next Business Month Volatility Index of EM Equity ETFs. Forecast over next Business Month.
US M2 Money Growth*	US MONEY SUPPLY M2 CURA	USM2..B	Federal Reserve	Monthly	FED M2 Money Supply, Conversion Method 'Average'.
EM Surprise Index**	CESI - EMERGING MARKETS	TBCESIR	Citygroup Inc.	Daily	EM Citigroup Economic Surprise Index. It reflects the Deviations from the Expectations for Economic Development.
EM Market Volatility Changes**(***)	-	-	-	Daily	Based on Daily Returns over the Rolling Window of the last Business Month.
EM USD denominated Debt Growth** (**)	Debt Securities, Denominated in US Dollars	JRTUWDA	IMF - Coordinated Portfolio Investment Survey	Daily	Dollar denominated Debt by EM Country, Conversion Method 'Sum'.
EM Market Momentum*(**)	-	-	-	Daily	Consecutive Return over the Rolling Window of 3 Business Months.
Multi-Factor Crowding***(***)	-	-	-	Daily	Z-score-weighted Liquidity of Multi-Factor Stocks (*Z-score* > 0) versus the Z-score-weighted Liquidity of the Market calculated in ADV (in USD) over the last Business Month. A large Spread in these reflects Factor Crowding and leads to inferior Factor Premia.

Table 3-2: Overview of the error metrics in the binary classification problem for factor regime shifts. The table reports the precision, recall, f1 score and accuracy of the two ML forecasts and the one-step estimator for multi-factor and illiquidity valuations.

	Accuracy	Crash Precision	Crash Recall	Crash F1 Score	Non-Crash Precision	Non-Crash Recall	Non-Crash F1 Score
One-step Multi-Factor Forecast	0.534	0.357	0.349	0.353	0.632	0.64	0.636
Logit Multi-Factor Forecast	0.631	0.493	0.419	0.453	0.693	0.753	0.722
GB Multi-Factor Forecast	0.521	0.424	0.872	0.57	0.814	0.32	0.459
One-step Illiquidity Forecast	0.555	0.5	0.486	0.493	0.597	0.611	0.604
Logit Illiquidity Forecast	0.678	0.675	0.533	0.596	0.68	0.794	0.732
GB Illiquidity Forecast	0.657	0.585	0.79	0.672	0.766	0.55	0.64

Table 3-3: **Statistical significance (* for p < 0.05, ** for p < 0.01 and *** for p < 0.001) against the market (for the base and one-step strategies and against the related one-step otherwise)** with respect to an initial portfolio size of 250 million USD and to the three cost levels: Medium (Low) ((High))
We report an annualized market return of 6.44% and Sharpe ratio of 0.52.

	Strategy	Net Return (% p.a.)	Trading Costs (% p.a.)	Sharpe Ratio
2009-12-31 to 2019-12-31	Base	7.97*** (8.28***) ((7.66***))	1.07 (0.77) ((1.39))	0.75*** (0.78***) ((0.71***))
2009-12-31 to 2019-12-31	Adaptive Cap (Foresight)	7.57*** (7.8***) ((7.34***))	0.88 (0.65) ((1.11))	0.71*** (0.74) ((0.69))
2009-12-31 to 2019-12-31	Adaptive Cap (One-Step)	7.6*** (7.83***) ((7.36***))	0.88 (0.65) ((1.12))	0.72*** (0.74***) ((0.69***))
2009-12-31 to 2019-12-31	Adaptive Cap (Logit)	7.69*** (7.93***) ((7.44***))	0.91 (0.67) ((1.15))	0.73*** (0.75***) ((0.7***))
2009-12-31 to 2019-12-31	Adaptive Cap (GB)	7.55*** (7.78***) ((7.32***))	0.88 (0.66) ((1.12))	0.71*** (0.74***) ((0.55***))
2009-12-31 to 2019-12-31	Cap100	7.56*** (7.79***) ((7.33***))	0.88 (0.65) ((1.11))	0.71*** (0.74***) ((0.69***))
2009-12-31 to 2019-12-31	Cap300	7.75*** (7.99***) ((7.49***))	0.92 (0.68) ((1.18))	0.73*** (0.76***) ((0.7***))
2009-12-31 to 2019-12-31	Adaptive Long-Short (Foresight)	9.56*** (9.96***) ((9.14***))	2.01 (1.61) ((2.43))	0.93*** (0.97***) ((0.88***))
2009-12-31 to 2019-12-31	Adaptive Long-Short (One-Step)	7.96*** (8.3***) ((7.61***))	1.88 (1.54) ((2.23))	0.8*** (0.84***) ((0.76***))
2009-12-31 to 2019-12-31	Adaptive Long-Short (Logit)	8.21*** (8.6***) ((7.8***))	1.91 (1.52) ((2.32))	0.81*** (0.86***) ((0.77))
2009-12-31 to 2019-12-31	Adaptive Long-Short (GB)	8.16*** (8.51***) ((7.8***))	1.4*** (1.05***) ((1.76*))	0.78*** (0.81***) ((0.73***))
2009-12-31 to 2019-12-31	Long-Short	8.49*** (8.85***) ((8.12***))	2.4*** (2.04***) ((2.77***))	0.86*** (0.9***) ((0.81***))
2009-12-31 to 2019-12-31	Adaptive Rebalancing (Foresight)	7.56*** (7.75***) ((7.36***))	0.69 (0.5) ((0.56))	0.71*** (0.73***) ((0.69))
2009-12-31 to 2019-12-31	Adaptive Rebalancing (One-Step)	8.69*** (8.79***) ((8.59***))	0.48 (0.38) ((0.59))	0.82*** (0.83***) ((0.81***))
2009-12-31 to 2019-12-31	Adaptive Rebalancing (Logit)	7.26*** (7.52***) ((6.99***))	0.83 (0.57) ((0.6))	0.67*** (0.69***) ((0.64***))
2009-12-31 to 2019-12-31	Adaptive Rebalancing (GB)	9.37*** (9.43***) ((9.31***))	0.26 (0.2) ((0.32))	0.91*** (0.91***) ((0.9***))

Table 3-4: **Statistical significance (* for p < 0.05, ** for p < 0.01 and *** for p < 0.001) against the market (for the base and one-step strategies and against the related one-step otherwise)** with respect to an initial portfolio size of 500 million USD and to the three cost levels: Medium (Low) ((High))
We report an annualized market return of 6.44% and Sharpe ratio of 0.52.

	Strategy	Net Return (% p.a.)	Trading Costs (% p.a.)	Sharpe Ratio
2009-12-31 to 2019-12-31	Base	7.69*** (8.13***) ((7.24***))	1.35 (0.91) ((1.8))	0.72*** (0.77***) ((0.67***))
2009-12-31 to 2019-12-31	Adaptive Cap (Foresight)	7.26*** (7.58***) ((6.94***))	1.05 (0.74) ((1.38))	0.68*** (0.71***) ((0.64***))
2009-12-31 to 2019-12-31	Adaptive Cap (One-Step)	7.3*** (7.61***) ((6.97***))	1.06 (0.74) ((1.38))	0.68*** (0.72***) ((0.65***))
2009-12-31 to 2019-12-31	Adaptive Cap (Logit)	7.39*** (7.71***) ((7.05***))	1.08 (0.75) ((1.41))	0.69*** (0.73***) ((0.66***))
2009-12-31 to 2019-12-31	Adaptive Cap (GB)	7.25*** (7.57***) ((6.92***))	1.06 (0.74) ((1.39))	0.68*** (0.71***) ((0.64***))
2009-12-31 to 2019-12-31	Cap100	7.26*** (7.57***) ((6.94***))	1.05 (0.74) ((1.38))	0.68*** (0.71***) ((0.64***))
2009-12-31 to 2019-12-31	Cap300	7.42*** (7.75***) ((7.08***))	1.09 (0.76) ((1.44))	0.69*** (0.73***) ((0.66***))
2009-12-31 to 2019-12-31	Adaptive Long-Short (Foresight)	8.81*** (9.56***) ((8.04***))	2.7*** (1.96***) ((3.47***))	0.84*** (0.93***) ((0.74***))
2009-12-31 to 2019-12-31	Adaptive Long-Short (One-Step)	6.22** (7.37***) ((5.04***))	3.59 (2.44) ((4.77))	0.58*** (0.72***) ((0.44***))
2009-12-31 to 2019-12-31	Adaptive Long-Short (Logit)	6.61*** (7.82***) ((5.34***))	3.55** (2.35*) ((4.82))	0.62*** (0.77***) ((0.69***))
2009-12-31 to 2019-12-31	Adaptive Long-Short (GB)	5.54*** (7.17***) ((3.8***))	4.02** (2.39) ((5.77***))	0.5*** (0.69***) ((0.31***))
2009-12-31 to 2019-12-31	Long-Short	8.2*** (8.71***) ((7.67***))	2.72*** (2.21***) ((3.24***))	0.82*** (0.88***) ((0.76***))
2009-12-31 to 2019-12-31	Adaptive Rebalancing (Foresight)	7.39*** (7.66***) ((7.11***))	0.85 (0.58) ((1.14))	0.69*** (0.72***) ((0.66***))
2009-12-31 to 2019-12-31	Adaptive Rebalancing (One-Step)	8.61*** (8.75***) ((8.47***))	0.57 (0.42) ((0.71))	0.81*** (0.82***) ((0.8***))
2009-12-31 to 2019-12-31	Adaptive Rebalancing (Logit)	7.08*** (7.46***) ((6.69***))	1.08 (0.7) ((1.47))	0.65*** (0.69***) ((0.61***))
2009-12-31 to 2019-12-31	Adaptive Rebalancing (GB)	9.32*** (9.41***) ((9.23***))	0.31 (0.22) ((0.39))	0.9*** (0.91***) ((0.89***))

Table 3-5: **Statistical significance (* for p < 0.05, ** for p < 0.01 and *** for p < 0.001) against the market (for the base and one-step strategies and against the related one-step otherwise)** with respect to an initial portfolio size of 1 billion USD and to the three cost levels: Medium (Low) ((High))
We report an annualized market return of 6.44% and Sharpe ratio of 0.52.

	Strategy	Net Return (% p.a.)	Trading Costs (% p.a.)	Sharpe Ratio
2009-12-31 to 2019-12-31	Base	7.23*** (7.87***) ((6.58*))	1.74 (1.1) ((2.39))	0.67*** (0.74***) ((0.59***))
2009-12-31 to 2019-12-31	Adaptive Cap (Foresight)	6.97*** (7.42***) ((6.51***))	1.31 (0.87) ((1.77))	0.65*** (0.7***) ((0.6***))
2009-12-31 to 2019-12-31	Adaptive Cap (One-Step)	6.96*** (7.41***) ((6.51))	1.31 (0.87) ((1.77))	0.65*** (0.7***) ((0.6***))
2009-12-31 to 2019-12-31	Adaptive Cap (Logit)	7*** (7.45***) ((6.53***))	1.32 (0.87) ((1.79))	0.65*** (0.7***) ((0.6***))
2009-12-31 to 2019-12-31	Adaptive Cap (GB)	6.97* (7.41***) ((6.51))	1.31 (0.87) ((1.77))	0.65*** (0.7***) ((0.6))
2009-12-31 to 2019-12-31	Cap100	6.98*** (7.42***) ((6.53***))	1.31*** (0.86***) ((1.76**))	0.65*** (0.7***) ((0.6***))
2009-12-31 to 2019-12-31	Cap300	7*** (7.45***) ((6.52***))	1.34 (0.88) ((1.81))	0.65*** (0.7***) ((0.6***))
2009-12-31 to 2019-12-31	Adaptive Long-Short (Foresight)	5.43*** (7.87***) ((6.45***))	5.98 (3.54) ((4.96***))	0.4 (0.7***) ((0.56***))
2009-12-31 to 2019-12-31	Adaptive Long-Short (One-Step)	4.68*** (6.62**) ((2.64***))	5.17 (3.24) ((7.21))	0.41*** (0.63***) ((0.2***))
2009-12-31 to 2019-12-31	Adaptive Long-Short (Logit)	5.86*** (7.41***) ((4.24***))	4.28*** (2.73***) ((5.91***))	0.54*** (0.72***) ((0.36***))
2009-12-31 to 2019-12-31	Adaptive Long-Short (GB)	3.12*** (6***) ((3.74***))	6.45*** (3.56***) ((5.83**))	0.23*** (0.53***) ((0.31***))
2009-12-31 to 2019-12-31	Long-Short	7.67*** (8.4***) ((6.93***))	3.15*** (2.43***) ((3.9***))	0.76*** (0.85***) ((0.68***))
2009-12-31 to 2019-12-31	Adaptive Rebalancing (Foresight)	7.16*** (7.55***) ((6.76***))	1.09 (0.7) ((1.49))	0.66*** (0.71***) ((0.62***))
2009-12-31 to 2019-12-31	Adaptive Rebalancing (One-Step)	8.5*** (8.7***) ((8.3***))	0.68 (0.48) ((0.89))	0.8*** (0.82***) ((0.78))
2009-12-31 to 2019-12-31	Adaptive Rebalancing (Logit)	6.62*** (7.17***) ((6.06***))	1.42* (0.87*) ((1.98*))	0.6*** (0.66***) ((0.54***))
2009-12-31 to 2019-12-31	Adaptive Rebalancing (GB)	9.25*** (9.37***) ((9.12***))	0.38 (0.26) ((0.5))	0.89*** (0.91***) ((0.88))

Table 3-6: **Statistical significance (* for p < 0.05, ** for p < 0.01 and *** for p < 0.001) against the market (for the base and one-step strategies and against the related one-step otherwise)** with respect to an initial portfolio size of 2.5 billion USD and to the three cost levels: Medium (Low) ((High))
We report an annualized market return of 6.44% and Sharpe ratio of 0.52.

	Strategy	Net Return (% p.a.)	Trading Costs (% p.a.)	Sharpe Ratio
2009-12-31 to 2019-12-31	Base	6.46 (7.48***) ((5.41***))	2.5 (1.47) ((3.55))	0.58*** (0.7***) ((0.46***))
2009-12-31 to 2019-12-31	Adaptive Cap (Foresight)	6.72*** (7.45***) ((5.97***))	1.87 (1.14) ((2.62))	0.62*** (0.7***) ((0.54***))
2009-12-31 to 2019-12-31	Adaptive Cap (One-Step)	6.7*** (7.44***) ((5.95***))	1.88 (1.15) ((2.63))	0.62*** (0.7***) ((0.53))
2009-12-31 to 2019-12-31	Adaptive Cap (Logit)	6.61*** (7.38***) ((5.82***))	1.95*** (1.18**) ((2.75**))	0.6*** (0.69***) ((0.52***))
2009-12-31 to 2019-12-31	Adaptive Cap (GB)	6.74*** (7.47***) ((5.99***))	1.87 (1.13*) ((2.62))	0.62*** (0.7***) ((0.54***))
2009-12-31 to 2019-12-31	Cap100	6.77*** (7.47***) ((6.05***))	1.81 (1.1) ((2.53))	0.63*** (0.71***) ((0.55***))
2009-12-31 to 2019-12-31	Cap300	6.57*** (7.34***) ((5.77***))	1.97** (1.19***) ((2.77**))	0.6*** (0.69***) ((0.51***))
2009-12-31 to 2019-12-31	Adaptive Long-Short (Foresight)	6.05*** (6.89***) ((3.98***))	5.34*** (4.5) ((7.42***))	0.55*** (0.61***) ((0.33***))
2009-12-31 to 2019-12-31	Adaptive Long-Short (One-Step)	3.19*** (5.85***) ((0.41***))	6.65 (3.99) ((9.43))	0.26*** (0.55***) ((0.03***))
2009-12-31 to 2019-12-31	Adaptive Long-Short (Logit)	1.08*** (5.04***) ((1.58***))	9.06*** (5.09***) ((8.55***))	0.07*** (0.44***) ((0.12***))
2009-12-31 to 2019-12-31	Adaptive Long-Short (GB)	0.68*** (4.77***) ((-0.06**))	8.88*** (4.79***) ((9.63))	0.04*** (0.39***) ((-))
2009-12-31 to 2019-12-31	Long-Short	6.84*** (8***) ((5.65***))	4.01*** (2.85***) ((5.19***))	0.67*** (0.8***) ((0.54***))
2009-12-31 to 2019-12-31	Adaptive Rebalancing (Foresight)	6.7*** (7.33***) ((6.06***))	1.55 (0.93) ((2.2))	0.61*** (0.68***) ((0.54***))
2009-12-31 to 2019-12-31	Adaptive Rebalancing (One-Step)	8.26*** (8.58***) ((7.94***))	0.91 (0.6) ((1.23))	0.78*** (0.81***) ((0.75***))
2009-12-31 to 2019-12-31	Adaptive Rebalancing (Logit)	5.96*** (6.85***) ((5.04***))	2.07** (1.18*) ((2.99**))	0.53*** (0.62***) ((0.43***))
2009-12-31 to 2019-12-31	Adaptive Rebalancing (GB)	9.11*** (9.31***) ((8.92***))	0.52 (0.33) ((0.71))	0.88*** (0.9***) ((0.86***))

Table 3-7: **Statistical significance (* for p < 0.05, ** for p < 0.01 and *** for p < 0.001) against the market (for the base and one-step strategies and against the related one-step otherwise)** with respect to an initial portfolio size of 5 billion USD and to the three cost levels: Medium (Low) ((High))
We report an annualized market return of 6.44% and Sharpe ratio of 0.52.

	Strategy	Net Return (% p.a.)	Trading Costs (% p.a.)	Sharpe Ratio
2009-12-31 to 2019-12-31	Base	5.62*** (7.08***) ((4.1***))	3.34 (1.88) ((4.85))	0.49*** (0.65***) ((0.33***))
2009-12-31 to 2019-12-31	Adaptive Cap (Foresight)	6.46*** (7.47***) ((5.43***))	2.4 (1.39) ((3.43))	0.59*** (0.7***) ((0.48))
2009-12-31 to 2019-12-31	Adaptive Cap (One-Step)	6.48 (7.48***) ((5.44***))	2.4 (1.4) ((3.44))	0.59*** (0.71***) ((0.48***))
2009-12-31 to 2019-12-31	Adaptive Cap (Logit)	6.06*** (7.22***) ((4.87***))	2.71*** (1.55***) ((3.9**))	0.54*** (0.67***) ((0.41***))
2009-12-31 to 2019-12-31	Adaptive Cap (GB)	6.41*** (7.4***) ((5.38***))	2.37 (1.37) ((3.4))	0.59*** (0.70***) ((0.48***))
2009-12-31 to 2019-12-31	Cap100	6.53*** (7.44***) ((5.58***))	2.2 (1.28***) ((3.14))	0.61*** (0.71***) ((0.51***))
2009-12-31 to 2019-12-31	Cap300	6.02*** (7.2***) ((4.79***))	2.77*** (1.59***) ((4**))	0.54*** (0.67***) ((0.41***))
2009-12-31 to 2019-12-31	Adaptive Long-Short (Foresight)	4.62*** (6.14***) ((1.86***))	6.74 (5.22***) ((9.5***))	0.41*** (0.54***) ((0.15***))
2009-12-31 to 2019-12-31	Adaptive Long-Short (One-Step)	1.26*** (4.87***) ((-2.52***))	8.56 (4.96) ((12.34))	0.1*** (0.47***) ((-))
2009-12-31 to 2019-12-31	Adaptive Long-Short (Logit)	0.49*** (2.83***) ((0.87***))	9.62 (7.28***) ((9.24***))	0.03*** (0.23***) ((0.06***))
2009-12-31 to 2019-12-31	Adaptive Long-Short (GB)	2.47*** (3.05***) ((-0.75***))	7.08*** (6.5***) ((10.3***))	0.2*** (0.22***) ((-))
2009-12-31 to 2019-12-31	Long-Short	5.94*** (7.57***) ((4.26***))	4.95*** (3.32***) ((6.63***))	0.57*** (0.75***) ((0.39***))
2009-12-31 to 2019-12-31	Adaptive Rebalancing (Foresight)	6.18*** (7.07***) ((5.25***))	2.06 (1.18) ((2.99))	0.55*** (0.65***) ((0.45***))
2009-12-31 to 2019-12-31	Adaptive Rebalancing (One-Step)	8.02*** (8.45***) ((7.56***))	1.17 (0.73) ((1.62))	0.75*** (0.8***) ((0.71***))
2009-12-31 to 2019-12-31	Adaptive Rebalancing (Logit)	5.25*** (6.51***) ((3.93***))	2.8* (1.53*) ((4.12*))	0.45*** (0.59***) ((0.32***))
2009-12-31 to 2019-12-31	Adaptive Rebalancing (GB)	8.97*** (9.24***) ((8.69***))	0.67 (0.41) ((0.95))	0.87*** (0.89***) ((0.84***))

Table 3-8: **Statistical significance (* for $p < 0.05$, ** for $p < 0.01$ and *** for $p < 0.001$) against the market (for the base and one-step strategies and against the related one-step otherwise)** with respect to an initial portfolio size of 10 billion USD and to the three cost levels: Medium (Low) ((High))
We report an annualized market return of 6.44% and Sharpe ratio of 0.52.

	Strategy	Net Return (% p.a.)	Trading Costs (% p.a.)	Sharpe Ratio
2009-12-31 to 2019-12-31	Base	4.48^{***} (6.53^{***}) ((2.32^{***}))	4.5 (2.45) ((6.66))	0.37^{***} (0.59^{***}) ((0.17^{***}))
2009-12-31 to 2019-12-31	Adaptive Cap (Foresight)	6.28^{***} (7.41^{**}) ((5.12^{***}))	2.6 (1.47) ((3.76))	0.58^{***} (0.71^{***}) ((0.46^{***}))
2009-12-31 to 2019-12-31	Adaptive Cap (One-Step)	6.27^{*} (7.42^{***}) ((5.08^{***}))	2.66 (1.51) ((3.84))	0.58^{***} (0.71^{***}) ((0.45^{***}))
2009-12-31 to 2019-12-31	Adaptive Cap (Logit)	5.61^{***} (7.09^{***}) ((4.07^{***}))	3.31 (1.83) ((4.85))	0.5^{***} (0.66^{***}) ((0.34^{***}))
2009-12-31 to 2019-12-31	Adaptive Cap (GB)	6.32^{***} (7.43^{*}) ((5.17^{***}))	2.56 (1.45) ((3.7))	0.59^{***} (0.71^{***}) ((0.46^{***}))
2009-12-31 to 2019-12-31	Cap100	6.87^{***} (7.82^{***}) ((5.89^{***}))	2.2 (1.25) ((3.18))	0.64^{***} (0.75^{***}) ((0.54^{***}))
2009-12-31 to 2019-12-31	Cap300	5.53^{***} (7.07^{***}) ((3.92^{***}))	3.47 (1.92) ((5.08))	0.49^{***} (0.66^{***}) ((0.32^{***}))
2009-12-31 to 2019-12-31	Adaptive Long-Short (Foresight)	1.45^{***} (3.01^{***}) ((-1.1^{***}))	9.87^{***} (8.3^{***}) ((12.42^{*}))	0.11^{***} (0.23^{***}) ((-))
2009-12-31 to 2019-12-31	Adaptive Long-Short (One-Step)	-1.21^{***} (3.63^{***}) ((-2.74^{***}))	11 (6.17) ((12.53))	- (0.33^{***}) ((-))
2009-12-31 to 2019-12-31	Adaptive Long-Short (Logit)	-2.4^{***} (2.08^{***}) ((-1^{***}))	12.49^{**} (8^{***}) ((11.08^{**}))	- (0.17^{***}) ((-))
2009-12-31 to 2019-12-31	Adaptive Long-Short (GB)	-0.61^{**} (1.68^{***}) ((-0.73^{***}))	10.15 (7.85^{***}) ((10.26))	- (0.12^{***}) ((-))
2009-12-31 to 2019-12-31	Long-Short	4.75^{***} (7.03^{***}) ((2.4^{***}))	6.25^{***} (3.97^{***}) ((8.6^{***}))	0.44^{***} (0.69^{***}) ((0.2^{***}))
2009-12-31 to 2019-12-31	Adaptive Rebalancing (Foresight)	5.45^{***} (6.71^{***}) ((4.12^{***}))	2.79 (1.54) ((4.12))	0.47^{***} (0.61^{***}) ((0.33^{***}))
2009-12-31 to 2019-12-31	Adaptive Rebalancing (One-Step)	7.65^{***} (8.27^{***}) ((7.02^{***}))	1.52 (0.9) ((2.15))	0.72^{***} (0.78^{***}) ((0.66^{***}))
2009-12-31 to 2019-12-31	Adaptive Rebalancing (Logit)	4.29^{***} (6.08^{***}) ((2.39^{***}))	0.68^{**} (0.65^{*}) ((0.7^{**}))	0.35^{***} (0.54^{***}) ((0.18^{***}))
2009-12-31 to 2019-12-31	Adaptive Rebalancing (GB)	8.75^{***} (9.12^{***}) ((8.36^{***}))	0.89 (0.52) ((1.28))	0.85^{***} (0.88^{***}) ((0.81))

3.7 Appendix

3.7.1 Appendix A

3.7.1.1 Descriptions of factors

Factor	
Momentum	Logarithmic price momentum is calculated as the sentiment of the stock price 12 months ago up to the previous month's end price based on Jegadeesh and Titman (1994). The so-called $12X1$ momentum omits the last month concerning the reversal effect for long-term investments. It is the supreme example of a generic market factor and a superior long-term alpha driver in the cross-section of sectors and regions. The persistence of this factor can be reasoned by the behavioral traits of investors that follow strong-performing stocks. These investors' attention leads to a crowding effect that fosters the price sentiment until a macroeconomic event, earnings miss, or other incident stops the trend. In this paper, the price momentum is determined as $$Mom12X1_t := log(\frac{pClose_{t-12}}{pClose_{t-1}}) \qquad (12)$$

Factor	
Value	As researched in Rosenberg et al. (1985), the value factor denotes a common book-to-price multiple that compares an asset's book value to the actual market price. An immense book-to-price value represents a cheap stock and therefore assigns a buy signal concerning factor investing approaches. The origin of this fundamental risk premium dates back to the investigations of Benjamin Graham and David L. Dodd and has behavioral-based characteristics beneath its systematic and fundamental nature. A possible explanation of the persistence of this systematic risk premium lies in the investors' optimism about bargains and pessimistic overreactions, often resulting in bargains when poor financials are reported.
Beta	The low beta factor investigated by Ang et al. (2006) and Frazzini and Pedersen (2014) describes how stock returns co-vary with market returns. Empirical research proves that low beta stocks explain cross-sectional premia in the long run and, by construction, serve as a cushion in drawdowns. In this study, $$Beta := \frac{cov(r_i, r_{uni})}{\sigma^2(r_{uni})} \quad (13)$$ is calculated with weekly data over the last 250 business days and the $cov()$ is exponentially weighted with a 125 business days half-life.

Factor	
Size	The size factor researched in Banz (1981) shows that smaller stocks in market capitalization explain cross-sectional excess return as an investor's compensation for taking additional risk. The efficacy of the size factor can be economically explained as a systematic risk premium based on the volatile nature and higher risk of bankruptcy of small caps. This examination calculates the size factor as the logarithmic free-floating market capitalization.
Operating Profit (Profitability)	Operating profit (commonly known as EBIT) denotes the profitability of the company's business before interest and taxes and is widely applied as another quality factor. The operating expenses are subtracted from the gross profit to determine operating profit. Haugen and Baker (1996) and Novy-Marx (2013) find an additional risk premium with this factor. Financially healthy companies tend to continue their good business in the future. Therefore, economically justifies this risk factor.
Total Assets Growth (Investment)	This risk factor measures the growth of the total assets to forecast future excess return as a second quality factor. Titman et al. (2004), Cooper et al. (2008) and Watanabe et al. (2013) find that stocks with lower recent total assets growth tend to outperform the market. In this paper, we compute the growth of the total assets over the last 500 business days.

3.7.2 Appendix B

3.7.2.1 Multi-factor tilting construction methodology

Concerning single factor cyclicality, we seek to diversify the excess return expectation to maintain more persistent premia. With the six factors outlined in Appendix A, we build an equal-weighted Z-score. The stock positions in the initial portfolio (at t_0) as well as all the following rebalancing weights (at $t > t_0$) are constructed by screening the positive Z-scores ($\textit{Z-score}_i > 0$) from the multi-factor mix. To calculate portfolio weights for each stock i, the universe weights $weight_{universe,i}$ are tilted under several constraints as follows:

$$weight_{tilt,i} := \begin{cases} weight_{universe,i} \cdot \textit{Z-score}_i, & \forall i \in \{EM : \textit{Z-score}_i > 0\} \\ 0, & \text{else} \end{cases} \tag{14}$$

Where the market weights $weight_{universe,i}$ are determined by free-floating market capitalization. In every monthly rebalancing each stock i is assigned its return expectation $\textit{Z-score}_i$. After each rebalancing, the portfolio weights $weight_{tilt,i}$ are updated with empirical return indices[27] to the next rebalancing until this loop terminates.

[27] Thompson Reuters Datastream return indices for emerging equity represent the empirical stock returns as done by the Center for Research in Security Prices (CRSP) concerning dividend payments and stock splits.

3.7.2.2 Descriptions of rebalancing and tilting constraints (applied values in parentheses)

Constraint	
Long-Short (130/30)	This parameter determines the allocation of long and short positions. While the former value depicts the investment grade of the long positions based on a theoretical 100% cash balance, the latter corresponds to the scale of short positions. In this tilting construction, short positions are deducted with the same trading cost model as long positions with respect to both sides of monthly turnover. Additional annualized short-selling costs are priced at conservative 30bps.
Relative Maximum Order Size Cap (300% / 100% of ADV)	This parameter distinguishes cost-mitigated portfolios from their base case. This sets a limit for the relative order sizes in the rebalancing steps.
Initial Threshold (Top 50%)	This threshold determines the lower bound for the mixed factor exposure at portfolio initialization. It controls the number of titles in the initial portfolio. This constraint represents the banding constraint from Novy-Marx and Velikov (2018).
Rebalancing Threshold (Top 50%)	Alike the initial threshold constraint, a lower bound for the factor exposures is set for each rebalancing step. This banding constraint controls turnover and guides the number of holdings in the portfolio concerning the trade-off of diversification and return expectation.

Constraint	
Relative Minimum Order Size (10%)	This constraint manages the minimum size of position changes of already held assets in the rebalancing. It can be utilized to control turnover.
Absolute Minimum Order Size (1 basis point of portfolio size)	Alike the relative minimum order size in absolute terms. This constraint prohibits the factor-tilt from generating economically insignificant orders that would artificially raise the average holdings.
Absolute Minimum Holding Size (5 basis points of portfolio size)	Declares the smallest permitted size of weight in the constructed portfolio that a position might have.
Absolute Maximum Holding Size (2% of portfolio size)	Concerning implementability and diversification, a maximum holding constraint limits portfolio weights to a certain fraction of the whole portfolio size. Each asset's total market capitalization is additionally considered in this constraint.

3.7.3 Appendix C

3.7.3.1 Transaction cost model

The applied liquidity-driven cost model is drawn on the findings of Grinold and Kahn (1999) and Frazzini et al. (2018), who found their models to be less dependent on varying market environments. We build on the finding that the market impact of trading equities is stable concerning regime shifts. The total costs applied in this study are composed of three components. Execution fees and the half bid-ask spread form the basis of this decomposition. The third and most important part is the market impact that reflects the implementation hurdle of the illiquid emerging markets. We model *market impact* with a one-dimensional square root functionality drawing on Grinold and Kahn (1999):

$$market\ impact := cost\ parameter \cdot \sqrt{\%ADV} \tag{15}$$

ADV denotes the short-term liquidity, calculated as average liquidity across primary and secondary stock exchanges over the last 20 trading days. finally denotes the stock-wise order size relative to the monthly calculated ADV. We analyze the impact of three exemplary cost levels of market impact specified by the *cost parameter* (displayed in Figure 3-6). These reflect an efficient trade timing by an institutional practitioner with a local trading desk, followed by an estimate for average trading results. Finally, expensive trading costs are embodied by the idea of incorporating issues with EM brokers and a possible time lag. We define the total transaction costs as a sum of fees (which we conservatively fix at 10bps) and the empirical half bid-ask spread as explicit costs[28] as well as the liquidity-driven market impact as follows:

$$TCost := fees + \frac{1}{2} spread + market\ impact \tag{16}$$

More complex cost models were also researched with respect to incorporating stock volatility and a perfectly passive trading model. This approach reflects the costs of waiting that arise by slowly trading towards the desired portfolio in positions of exemplary 10% of the ADV per trading day. While the latter model mitigates the annualized transaction costs, no researched cost model distorts the results

[28]Execution and commission fees are negotiable and equal to over 7bps in emerging markets. These fees cover all legal middle office activities of the sell-side and ensure the backup of all trade documentation through a global custodian. These electronic backups are by law completed by carbon copies in case of emergency.

presented in this study. Therefore, we apply the one-dimensional market impact model concerning simplicity as the most intuitive implementation.

3.7.4 Appendix D

3.7.4.1 Pairwise portfolio significance testing for differences in annualized (excess) returns, trading costs and Sharpe ratios

Due to strong serial correlations between portfolios, auto-correlation in the tiltings, and a stochastic dependency in the portfolios, an ordinary t-test can not be applied. To test the statistical significance of our presented evidence, we apply the following test statistic Z_μ as a two-sided t-test on the return differences for stochastically dependent, identically distributed portfolios:

$$Z_\mu = \frac{\sqrt{N}(\hat{\mu_1} - \hat{\mu_2})}{\sqrt{\hat{\sigma_1}^2 - 2\hat{\rho_{1,2}}\hat{\sigma_1}\hat{\sigma_2} + \hat{\sigma_2}^2}} \tag{17}$$

With N degrees of freedom ($\#rebalancing\ months - 2$; because portfolio initialization is cost-mitigation independent) and μ_i, σ_i assigning the estimated annualized means and standard deviations of both observations.

We also report the statistical significance of the Sharpe Ratio (SR) difference between two stochastically dependent portfolios with the following test statistic from Ledoit and Wolf (2008):

$$Z_{SR} = \frac{\sqrt{N}(\hat{SR_1} - \hat{SR_2})}{\sqrt{2 - 2\hat{\rho_{1,2}} + \frac{1}{2}[\hat{SR}_1^2 + \hat{SR}_2^2 - 2\hat{SR}_1\hat{SR}_2\hat{\rho_{1,2}}^2]}} \tag{18}$$

Based on these test statistics, all hypothesis tests check the alternatives: $H_0 : \mu_1 = \mu_2 \quad (SR_1 = SR_2)$, $H_1 : \mu_1 \neq \mu_2 \quad (SR_1 \neq SR_2)$ and report the p-value to the error levels $p < 0.05$, $p < 0.01$ and $p < 0.001$.

To account for the auto-correlation of the tiltings, we do not just report the results of the above hypothesis tests. Still, we perform a bootstrap that is explained as follows.

3.7.4.2 Stationary Circular Block-Bootstrapping

The hypothesis tests above are robustness-checked with a block-bootstrap to correct for auto-correlation as researched in Efron and Tibshirani (1993). Politis and Romano (1992) proved that randomization of the block length in the circular block-bootstrapping maintains the stationarity of the observations in the bootstrapped samples. Therefore the reported p-values are finally calculated as follows:

- Calculate the Z-statistic as Z once for return- or Sharpe ratio testing
- To apply the stationary circular block-bootstrap to test H_0, transform the data so that H_0 is true.
  - For return testing this transformation is given by $\tilde{X}_i := X_i - \hat{\mu_i} + \hat{\mu}_{combinedsample}$ for both time series.
  - For sharpe ratio testing it is: $\tilde{X}_i := [\frac{X_i - \hat{\mu_i}}{\hat{\sigma_i}}\hat{\sigma}_{combinedsample}] + \hat{\mu}_{combinedsample}$ for both time series.
- The robustness-checked hypothesis test works by simulating the distribution of the Z-statistic with block-bootstrapping under a true H_0. We do that by generating $M = 10000$ block-bootstrap samples for both time series of forced length N (circular) with uniformly randomized block-length $b \in \{1, 2, ..., \lfloor \frac{N}{2} \rfloor\}$ to maintain stationarity. The Z-statistic is calculated for each of the M bootstrap samples as $\tilde{Z}_i$.
- Now we sum $\frac{\sum_{i=1}^{M=10000} I(|\tilde{Z}_i| \geq |Z|)}{M} =: p$ where $I()$ denotes the indicator function (that equals 1 if its argument is true and 0 otherwise) to get the p-value of our hypothesis test given H_0 is true. This p-value is the reported statistic for each hypothesis test in the results section.

4 THE BENEFITS OF MACHINE LEARNING FOR PREDICTING STOCK LIQUIDITY IN EMERGING EQUITY MARKETS

4.1 ABSTRACT

We research machine learning models for predicting stock liquidity in emerging equity markets based on a broad spectrum of 190 stock and market characteristics. By exposing seasonality and reversal effects, we evaluate the statistical advantage of machine learning predictions compared to naïve estimates. Despite a strong statistical advantage, the economic benefits in portfolios tend to be limited. However, empirical evidence exhibits the significant benefits of the machine learning forecasts in cost-efficient factor investing with respect to the extremes of aggressive and passive trading cost models.

JEL classification: G11; G12; G14; G15; G17.

Keywords: Interpretable Machine Learning, Data Science, Liquidity Prediction, Gradient Boosting, Factor Investing, Portfolio Construction, Cost-Efficiency.

4.2 Introduction

In general, systematic risk premia and factor investing are well understood, but especially in emerging markets, their net trade-off with implementation costs remains less clear. Most studies on transaction costs identify liquidity beneath the costs' most essential drivers (Grinold and Kahn (1999), Lesmond et al. (1999) and Frazzini et al. (2018)). Empirical evidence shows that the demand for trading large order sizes relative to the stock liquidity increases the market impact. This market impact is embodied in invisible trading costs of adverse price movements, as explained in Frazzini et al. (2018). On the other hand, Amihud (2002) finds that liquidity risk significantly explains equity premia, especially the small firm effect. Pastor and Stambaugh (2003), Acharya and Pedersen (2005) and Watanabe and Watanabe (2008) also identify illiquidity as an additional risk premium and develop asset pricing models that incorporate expected asset liquidity. This extension demonstrates the explanatory power of liquidity risk in the cross-section of stock returns. Contrary to the practical importance, little research has been devoted to trading costs in emerging equity markets. Lesmond (2005) examines the costs of liquidity risk in emerging markets by explaining the high returns easily exceeding 75% p.a. with their bid-ask spread. Despite the extensive cost modeling, studies on liquidity risk and recent investigations on cost-efficient implementations, the trade-off between risk premia and implementation costs in factor investing remains unclear. Especially the emerging equity markets, known as a less liquid stock universe with a significant implementation hurdle, received little attention.

Illiquidity is broadly identified as a critical driver for implementing portfolio decisions. Therefore, a better understanding of it and its near-term behavior is mandatory to increase the efficacy of investment strategies. Wyss (2004) ties on the risen attention on the market and stock liquidity. The measuring and prediction approaches for stock liquidity are discussed based on a selection of Swiss stocks. Breen et al. (2002) also studied regression models for predicting stock liquidity in the developed US market. More recently, Cui (2021) provided a macroeconomic view on the US market liquidity based on implications from option prices. While the research on liquidity risk mainly covers developed markets, stock liquidity prediction in emerging countries received more attention for investment decisions. However, the coverage of emerging markets stock liquidity prediction and liquidity risk primarily focuses on single countries. Lischewski and Voronkova (2012) investigate liquidity risk in the Polish stock market as one of the most advanced emerging markets at this time and Altay and Calgici (2019) confirms the illiquidity risk premium for the emerging stock market of Turkey. Further, Khang (2020) predicts stock liquidity in the Vietnamese stock market using state-of-the-art deep learning methods. Bae and Lee (2016) apply and compare five machine learning (ML) techniques, including Bayesian networks, support vector machines, decision trees, neural networks, and ensemble methods on a selection of Korean manufacturing companies. Hence, predicting stock liquidity is a recent field of interest in finance concerning the application of machine learning. Before this, the prediction of stock returns is recently investigated by Leung (2021). Obviously, the application of ML methods for predicting stock returns is closely related to the problem of predicting stock liquidity. This is underlined by the successful implementation of black-box models by Mulvey and Liu (2016) in the classification of factor regimes.

Inspired by the examination of Bae and Lee (2016), this study extends the existing literature twofold. First, we apply ML-based liquidity prediction concerning a broad emerging markets universe and assess the statistical advantage with various error metrics. Second, we implement the sophisticated machine learning prediction of stock liquidity as a cost-mitigation approach for equity factor investing. Our ML model of choice throughout this study is the Gradient Boosting Machine (GBM), which we apply to shallow regression trees. To analyze the GBM's black-box character, we use methods (variable importance and partial dependence plots) from the interpretable machine learning literature. We assume that the cost-efficiency of factor investing can be increased by reducing the exposure of stock liquidity overestimating in portfolio decisions. Based on this methodology, we seek to answer several research questions. The superordinate question is how to implement risk premia in emerging markets cost-efficiently. First, we investigate whether or not it is beneficial to predict cross-sectional stock liquidity non-naïvely. After replicating and extending the ideas of former studies to the whole emerging market universe, we are interested in whether and how ML-based liquidity predictions improve or distort portfolio characteristics. Moreover, we research the effect of the ML-based liquidity predictions on portfolio cost-efficiency over time and with respect to two opposing trading strategies. Lastly, we investigate the practical relevance for small and large institutional investors.

The paper proceeds as follows. The next section outlines the investment universe, a methodology for tilted portfolio constructions, the applied machine learning model and contrasts trading cost models. Later, the ML approach is utilized to improve factor investing strategies and is compared to a naïve estimate. In the empirical results section, we review the accuracy benefits of ML-based liquidity prediction and finally discuss the role of the machine learning approach in this context. This section closes with the implications of the risk-adjusted net performance of ML-predicted stock liquidity in emerging equity markets. The last section concludes our research.

4.3 Data and methodology

4.3.1 The emerging markets universe

To assess the relevance of ML-based stock liquidity predictions, we conducted our analysis on an emerging markets data set[29] concerning the country listings of the MSCI Emerging Markets Index[30] over the last two decades ending in December 2019. A small range of available data prior to the millennium is omitted with respect to the quality and coverage of the liquidity data. This study uses data from MSCI to determine the underlying companies in emerging markets and their free-floating market capitalization. Besides MSCI, the Worldscope database from Refinitive is used for the additional fundamental factors of value, profitability and investment. The generic factors of momentum and low beta are calculated based on market data from Datastream (Refinitive). Further, Datastream is also utilized for the remaining market data of return indices, liquidity, and bid-ask spreads. Referring to the market closing of 2019 as today, this emerging markets universe consists of 26 countries[31] across the five different sub-regions. These regions include Emerging Americas, Europe, Middle East, Africa and the Asia Pacific, of which the latter contributes to 79.35% of the emerging markets' size. The MSCI Emerging Markets Index's underlying stocks are considered large caps, whereas all other stocks larger than $10 million in market capitalization are denoted as small caps. Today, this emerging markets universe consists of 3480 stocks summing up to $9.2 trillion free-floating market capitalization.

4.3.2 Machine learning with boosted regression trees

We use the applied machine learning model (GBM) to predict changes in stock liquidity. After comparing the statistical advantage of the various models researched in Bae and Lee (2016) over the whole

[29]In the following, the emerging markets are denoted as "EM" and also referred to as the "whole universe".

[30]https://www.msci.com/emerging-markets, last visited: 2020-09-30.

[31]The MSCI Emerging Markets Index consists of 26 emerging economies, including Argentina, Brazil, Chile, China, Colombia, Czech Republic, Egypt, Greece, Hungary, India, Indonesia, Korea, Malaysia, Mexico, Pakistan, Peru, Philippines, Poland, Qatar, Russia, Saudi Arabia, South Africa, Taiwan, Thailand, Turkey, and the United Arab Emirates.

emerging markets universe, we decided to implement gradient boosted regression trees as the outperforming method[32]. We build the GBM on the weak learner class of shallow regression trees. The virtual extension by the GBM on these decision trees is the successive splitting of the predictor space. The iterative application of the weak learners is applied so that the residuals of the formerly fitted model are corrected. These corrections eventually combine the weak learners into a more complex prediction algorithm.

As with most machine learning algorithms, the GBM needs to be specified by hyperparameters to adjust model complexity. In this case, the most critical hyperparameters are the number and depth of the trees, the learning rate, and the minimum number of observations for each leaf. We use a specific variation of GBM, the stochastic gradient boosting, which expands the list of relevant hyperparameters by the number of observations and columns to sample each residual tree. In machine learning, the tuning of a model describes searching for hyperparameters that maximize the out-of-sample prediction performance. For tuning purposes, we also use a randomized concept of hyperparameter search over a sufficiently large parameter space. These randomized hyperparameter vectors are evaluated on the R-squared of the validation sets in a time series split cross-validation. The training and validation of models are performed sequentially so that validation sets always come after training sets, never attempting to explain the past with the future. This method's cleaning, tuning and fitting are applied in an expanding window fashion to predict the next month's stock liquidity changes with the most available data without a look-ahead bias.

The underlying data consists of the broad spectrum of 190[33] firm-specific and macroeconomic indicators completed by the response y of monthly liquidity change. Due to the non-stationarity of liquidity data measured in currency (USD), we seek to predict the first-order liquidity changes with the GBM, which are tested and accepted for stationarity[34]. To calculate the percentage change of stock liquidity, we construct two responses concerning two opposing trade execution approaches, which the trading cost models reflect. These cost models are rigorously defined in the next subsection. Both change rates are calculated based on the equal-weighted average liquidity over the past 20 business days. The first

[32]Our research also includes OLS regressions, the applications of LASSO, Ridge and elastic nets over sufficiently fine tuning vectors. We further investigated the more sophisticated implementations of neural nets, random forests and gradient boosted regression trees, of which the latter outstand concerning out-of-sample overestimations.

[33]Detailed description of all implemented features and their lags in Appendix C.

[34]We tested the liquidity changes for stationarity with an Augmented Dickey-Fuller Test and reported stationarity at the 0.1% level.

variable measures the change rate to linear-weighted future daily volumes over the following business month. The second measure reflects the change rate to the equal-weighted future liquidity over the following 20 business days. The first approach reflects the traders' incentive to quickly trade towards the desired position. Here, the most extensive parts of the order might be executed in the following days after the rebalancing. In the second approach, the equal weighting accounts for a reasonable non-instantaneous implementation. The prediction of equal-weighted liquidity changes over the next business month suffices for this slow trade execution. A linear weighting is not meaningful when the trade execution is purposely delayed to mitigate the market impact.

Based on the available data, we chose the first five business years as an initial training set and therefore constructed all portfolios starting in 2005 to omit a look-ahead bias. The cleaning and pre-processing of the entire data set are also conducted in monthly expanding windows. For the cleaning, we apply a MICE imputation and further apply the Yeo-Johnson power transform to make all features more Gaussian. The main goal of the ML-based stock liquidity prediction is an accuracy improvement in the harmful overestimates. While liquidity overestimates might hurt the efficacy of cost-mitigation approaches or investment strategies in general, we tune the GBM respectively. By overestimating the stocks' future liquidity over the assumed trade duration, realized trading costs are hard to control with implicit methods. To run less into these liquidity traps, we implement an asymmetric loss function and fit the GBM on the first tercile of the response instead of its mean. We also add a conservative weighting to the loss function to further focus on the problematic overestimates while keeping underestimate errors at least as stable as possible. Here, we weigh the loss function concerning the decreasing rank of observed average liquidity over the past business month[35].

4.3.2.1 Multi-factor Z-scoring and tilting

This study takes a focus on six common risk premia, combining the examinations of Carhart (1997), Frazzini and Pedersen (2014) and Fama and French (2015). Here, we combine the fundamental risk premia of Fama and French (2015) with the robust market effects found by Carhart (1997) and Frazzini and Pedersen (2014) to demonstrate our ideas with a broadly diversified factor mix. The first factor is the fundamental value factor researched in Basu (1977) and Rosenberg et al. (1985). The size factor embodies another systematic risk premium and is discovered by Banz (1981). Further, two systematic

[35]Weighting by the inverse of observed average liquidity did not result in a meaningful forecast as it is too extreme.

quality factors are added. The operating profitability was researched by Haugen and Baker (1996) and Novy-Marx (2013). The investment factor was researched by Titman et al. (2004), Cooper et al. (2008) and Watanabe et al. (2013) and augmented our choice. Jegadeesh and Titman (1994) and Hurst et al. (2017) researched the generic momentum factor. Lastly, Ang et al. (2006) and Frazzini and Pedersen (2014) examine the generic low beta factor that completes our selection. Appendix A and B explain an equal-weighted multi-factor tilt based on these six Z-scored risk factors which is displayed in Figure 4-4. The empirical evidence presented in this examination is robust to alternative factor definitions, different mixes and also different weighting schemes. We decided to present this mix of six well-known factors to cover fundamental factors and market effects and apply the equal-weighted scheme with respect to simplicity. This decision not only results in a robust factor mix that explains several sources of risk premia but also mitigates portfolio risk by incorporating the low beta factor from Frazzini and Pedersen (2014).

4.3.3 Applied Cost Models

Ideologically, the portfolio rebalancing happens instantaneous at every month-end. In fact, implementing portfolio decisions at a monthly rebalancing take time over the following business days concerning the investment universe, invested size and liquidity demand. While in developed markets this is mostly a matter of one trading day, in emerging markets the trading process can take days up to weeks. This issue is displayed in Figure 4-5. The stock liquidity over these following trading days and weeks is unknown and therefore has to be predicted. The more accurate these liquidity predictions, the better the implicit cost control which is regulated by the tilting constraints shown in Figure 4-4. We twofold model the trade execution after a rebalancing step with respect to two extremes. First, we implement a quick and expensive implementation that suffers entirely under market impact but not under the costs of waiting to trade towards the desired position. Second, opposing the market impact model, we implement a perfectly passive opportunity cost model. This approach assumably induces zero market impact but slowly trades towards its goal with a low participation rate of 15% per trading day. With daily participation of 15%, a cost-mitigation strategy of limiting trades to 300% of the observed liquidity, on average, takes the entire month to rebalance. Our results are robust concerning participation rates ranging from 5 to 20% per trading day. Rates below 5% are too low to rebalance a factor-based strategy in time, given the illiquid structure of the emerging markets. On the other hand, participation rates above 20% do not suffice the assumption of zero market impact as such participation might induce considerable adverse price movements. To demonstrate the benefits of ML-based stock liquidity predictions against the naïve measure of observed liquidity for the implicit cost control, we provide empirical evidence concerning a broad range of sensitivity analyses. These include the two cost models and their parameters. The total costs applied in both liquidity-driven approaches are split into three components. Execution fees and the half bid-ask spread form the basis of this decomposition. The third component is defined by the cost model.

4.3.3.1 Aggressive Cost Model

This cost model is drawn on the findings of Grinold and Kahn (1999) and Frazzini et al. (2018). The market impact embodies the third cost component of this model and reflects the implementation hurdle of the illiquid emerging markets. We model the *market impact* costs with a one-dimensional square root functionality drawing on Grinold and Kahn (1999):

$$market\ impact_{T,i} := cost\ parameter \cdot \sqrt{\%ADV_{T,i}} \quad \forall i \in Trading\ Basket_T \tag{19}$$

Where T indicates the rebalancing steps of the portfolio construction ranging from 2004-12-31 to 2019-11-30. Further, ADV denotes the linearly weighted[36] liquidity average over the next business month to calculate the realized market impact of a portfolio decision. This observed average liquidity is calculated across primary and secondary stock exchanges. $\%ADV$ finally denotes the stock-wise order size relative to the empirical ADV during trade execution. The empirical ADV during the trading process is unknown at the rebalancing and therefore has to be estimated in portfolio decisions. With this market impact model, we analyze the impact of three exemplary cost levels of market impact specified by the *cost parameter* (displayed in Figure 4-2). These levels reflect an efficient trade timing by an institutional practitioner with a local EM-based trading desk, followed by a proxy for average trading results. Finally, expensive trading costs are embodied by the idea of incorporating issues with EM brokers and a potential time lag. Eventually, we define the aggressive transaction costs model as the sum of fees (which we conservatively fix at 10bps), the empirical half bid-ask spread as explicit costs[37] and the liquidity-driven market impact as follows:

[36]We weigh the future near-term liquidity for the realized market impact calculation in a linearly decreasing fashion. Here, we follow the idea that the most extensive parts of a rebalancing are traded as quickly as possible.

[37]Execution and commission fees are negotiable and equal to over 7bps in emerging markets. These

$$TCost_{T,i} := fees + \frac{1}{2} spread_{T,i} + market\ impact_{T,i} \quad \forall i \in Trading\ Basket_T \tag{20}$$

More complex market impact models were also researched with respect to incorporating stock volatility but did not distort the results presented in this study. We apply the one-dimensional market impact model concerning simplicity.

4.3.3.2 Passive Cost Model

The cost of waiting expresses the third cost component of the opportunity cost model. The idea and assumption behind this passive implementation are that the daily participation rate (PR) of 15% of available liquidity (DV) might not induce the implicit costs of market impact. Purposely delaying an order execution might save the market impact but will postpone the execution for several days concerning trade size and liquidity demand. This delay also occurs when liquidity is overestimated at the rebalancing. When prices rise as expected, the induced cost of waiting arises by not fully holding the desired position. Therefore, the opportunity costs of a portfolio decision are calculated on a weighted[38] aggregation concerning daily stock returns (ret) and daily empirical liquidity (DV) during the trade execution:

$$opportunity\ costs_{T,i} := exp(\sum_{t=1}^{N_T} ln(ret_{t,T,i})\,(\frac{order\ size_{T,i} - \sum_{\tau=1}^{t} DV_{\tau,T,i}\ pr}{order\ size_{T,i}})) \quad \forall i \in Trading\ Basket_T \tag{21}$$

Where T indicates the rebalancing steps of the portfolio construction ranging from 2004-12-31 to 2019-11-30. Further, N_T indicates the number of trading days in the underlying business month of trade execution. Eventually, the total costs of this passive approach sum to:

fees cover all legal middle office activities of the sell-side and ensure the backup of all trade documentation through a global custodian. These electronic backups are by law completed by carbon copies in case of emergency.

[38]This weighting reflects the differences in desired and already executed parts of each portfolio decision and therefore missed returns induced by trading slowly. In the case of negative return, the cost of waiting is also negative and therefore benefits the portfolio. This weighting is applied to the waiting cost and the empirical half bid-ask spread.

$$TCost_{T,i} := fees + \frac{1}{2} weighted\ spread_{T,i} + opportunity\ costs_{T,i} \quad \forall i \in Trading\ Basket_T \tag{22}$$

We also combined both trading patterns as another robustness check and could not find a deviation from the empirical results in the next section.

4.4 Empirical results

In this section, we utilize an improved liquidity forecast in portfolio constructions and analyze its benefits. At first, we display its advantage by comparing several error metrics between the one-step estimate and ML-based liquidity forecast. Further, this forecast is implemented in ex-ante cost control of limiting order sizes relative to their underlying stocks' liquidity expectations. This implicit approach is a possible cost-mitigation and is beneficial in the cross-section of EM factor investing[39]. The more accurate the liquidity forecast, the more efficiently this strategy controls trading costs. We researched that this strategy has a sweet-spot parameter in the return-to-cost trade-off concerning the invested portfolio size. Implementing factor investing without such an implicit cost control results in illiquid decisions that do not pay off on average. To demonstrate this in combination with improved liquidity estimates, we compare the strict (100%ADV) and less strict (300%ADV) cost-mitigation parameters. Both implementations are analyzed concerning the presented trading cost models and various portfolio sizes to reflect the institutional investors' size.

4.4.1 Naïve versus boosted liquidity prediction performance

We apply the machine learning method described in the previous section to predict the (linearly-) weighted liquidity changes over the next business month and retransform them to liquidity in USD for an error overview. We compare the naïve estimate of equal-weighted average liquidity over the

[39] The cost-mitigation can be understood as a liquidity tilt concerning the trade-off between illiquidity premia and implementation costs. Interestingly, its net performance increase does not solely rely on lowered trading costs. This liquidity constraint is quasi-periodically not much of a constraint at all. While illiquidity premia are well understood in the long run, they underlie inevitable short-term cyclicality. Eventually, the efficacy of this cost-mitigation strategy is borne by mitigated implementation costs and recurring liquidity premia. The empirical analysis finds its optimal parameter and largely depends on invested portfolio size.

past 20 trading days with the boosted liquidity predictions concerning several error metrics. Table 4-1 summarizes this comparison over the whole universe of emerging markets from 2004-12-31 to 2019-11-30, excluding the training set. The boosted forecast outperforms concerning its abilities to map non-linearities and is tuned with an asymmetric and weighted loss function. The machine learning forecast keeps the overall error and underestimates stable without any induced size bias, while harmful overestimate errors are vastly reduced. We remark that the GBM detects reversal effects in liquidity changes and the seasonality as displayed in Figure 4-3. The one-step estimate cannot capture this and these effects are why the boosted forecast highly outperforms the naïve expectation. Previous studies on ML-based predictions for monthly excess returns report that past return-based predictors were deemed most important. In our case, we can translate this into the importance of liquidity-based predictors and confirm this as displayed in Figure 4-1. In this chart, the time-averaged percentage variable importances are reported. Liquidity changes over various time windows and their lags are preferably selected for the splits of the predictor space.

We can also translate another finding of previous examinations on predicting returns. While the general importance of predictors depends on the ML method used, (short-term) reversal effects are the most relevant features for predicting short-term liquidity changes. These features are followed by further past liquidity-based (return-based in the previous examinations) characteristics. The ensemble method of the GBM can fit non-linear effects. Similar to the effect of estimated regression betas from an OLS regression, the PDPs explain the effect of the single variables on future liquidity. Besides reversal effects on liquidity changes, we emphasize the seasonality effect of the past business year's market return. The general tenor of the articles on predicting subsequent cross-sectional stock returns is that ML models are superior to traditional linear factor models. We confirm the superiority of ML-based stock liquidity prediction compared to the best naïve estimate[40] of observed average liquidity. While, in general, one-step estimates embody a strong forecast for liquidity measured in USD, ML-based methods outstand concerning the implementation of investment strategies. The main reason is the incapability of one-step estimates to capture reversal effects. Despite our expectations, a set of promising features was not highly important for predicting stock liquidity changes with the GBM.

[40]We find that the observed stock liquidity over the past 20 business days is the most robust forecast for the future stock liquidity over the following 20 business days. Various error metrics can confirm this. Therefore, stock liquidity in EM equities is less determined by a mid- or long-term trend but its cross-sectional first-order autocorrelation (monthly data) lies above 80%. Unfortunately, this already robust and naïve estimate can not capture liquidity reversal effects. This is where ML-based methods come into play and eventually outperform.

Media coverage and news sentiment indicators are no relevant predictors. We further investigated the count of holidays or trade-free days in the upcoming business month. This feature is also not relevant on a monthly view since investors seem to compensate for the trade-free days with increased trading activity around these days. We also could not find relevance in hot-encoded features based on the country, month, sector, or combinations of these. The importance of market and firm-specific volatility is only of second order. Eventually, the ML-based forecast is undoubtedly more robust from a raw statistical perspective. Therefore it is indispensable concerning its ability to be tuned to reduce harmful liquidity overestimates (liquidity traps). It is yet unclear if this advantage also materializes in cost-efficient portfolio constructions. To answer this, we implement the boosted liquidity estimate into portfolio decisions with respect to the outlined cost-mitigation approach and investigate its supposed benefits.

4.4.2 Sensitivity analysis on portfolio decisions

In the previous subsection, we find that a boosted stock liquidity prediction is highly beneficial over the whole universe concerning the reduction of costly liquidity overestimates. Therefore, we now compare both liquidity estimates in multiple sensitivity analyses to assess the effect of the supposedly superior machine learning forecast. Further, these analyses are fully robustness-checked concerning time by implementing a stationary block-bootstrapping with random block length[41] to assess statistical significance. We conduct sensitivity analyses with respect to both trade execution patterns, two proven cost-mitigation parameters and six representative initial portfolio sizes. Successful implementation of the boosted forecast is considered to either outperform its baseline portfolio with respect to significant risk-adjusted net performance or at least significant excess return. Table 4-2 to Table 4-4 report the performance statistics of all portfolio constructions in terms of the three-dimensional sensitivity analysis. Without any additional turnover constraint, all reported portfolio tiltings result in around 250% two-sided turnover per annum. As an additional robustness check, we researched the effect of different meaningful turnover levels, which resulted in similar findings. Here, we research all combinations of the six ascending portfolio sizes (250 million, 500 million, 1 billion, 2.5 billion, 5 billion and 10 billion USD), strict and less strict cost-mitigation parameters ($100\%ADV$ and $300\%ADV$) as well as both opposing cost models. All portfolio tiltings investigate the empirical evidence for the boosted liquidity forecasts concerning the investment period from 2004-12-31 to 2019-12-31. The smallest initial

[41] Detailed description in Appendix D.

portfolio, 250 million USD invested in EM equities at 2004-12-31, reflects a small-scale institutional investor's potential wealth and is too small to have problems with order implementation. Therefore, neither boosted liquidity forecasts nor cost-mitigation approaches, in general, are necessary and do not pay off either. Just the second smallest initial portfolio size of 500 million USD invested at 2004-12-31 is large enough to benefit from the cost-mitigation strategy and also boosted liquidity forecast. The extent to which their performance increases compared to the base strategy is empirically proven to be scaling with portfolio size and cost level. At 1 billion USD initially invested, cost-mitigations start to be indispensable just when the base strategy alone does not secure a significant outperformance relative to the market (9.49% p.a.) anymore[42]. At the same time, the 300%ADV implementation[43] is enough to secure significant outperformance (.39% p.a.) relative to the market. With 1 billion USD or more initially invested, 100%ADV is necessary to generate significant alpha. At 2.5 billion USD, the 100%ADV constraint on the base strategy still results in 9.88% net performance per annum. While the ML-based liquidity forecast is never the crucial extension that saves the outperformance relative to the market, after 500 million USD, it solidly generates significant alpha from 2 to 26bps p.a. This performance increase also consistently materializes in increased Sharpe ratios. Between 1 billion and 5 billion USD invested, a small positive gross effect is induced by the liquidity constraint. This positive effect of the aggressive trade execution is fully offset by increased implementation costs of trading larger order volumes. Further, at 5 billion USD, the base strategy also loses its significant risk-adjusted outperformance measured in the Sharpe ratio. At the largest initial portfolio size of 10 billion USD, the aggressively executed but cost-mitigated base strategy with boosted liquidity estimates still secures roughly 1.5% alpha (15bps larger Sharpe ratio) relative to the market p.a. While the delayed trade implementation generally preserves significant amounts of outperformance relative to the market, after 10 billion USD this pattern is not applicable anymore in this context. On a monthly rebalancing level, the average trade duration exceeds the number of available trading days and large cash positions distort the factor investing strategy. Another minor limitation of this cost-mitigation approach is an inevitable but small size tilt towards mid- and small caps. As the strategy operates as a redistribution of liquidity demand, larger positions of liquid mid- and small caps are held with respect to ascending portfolio size. Unfortunately, this negatively impacts the average bid-ask spread, which

[42]The uncapped base implementation of factor investing reaches its so-called equilibrium size at 1 billion USD invested on 2004-12-31 with only a medium cost level of an aggressive trade execution applied.

[43]The 300%ADV constraint serves as ex-ante cost control. No order larger than 300% of the observed (forecasted) stock liquidity is permitted at any rebalancing step.

is part of the transaction costs. However, for both trade patterns, this negative effect is more than offset by the reduced market impact or cost of waiting. Another minor downside of this approach is giving up small parts of excess return expectation from the multi-factor mix. Fortunately, on average, this does not dematerialize in the gross performance of the portfolio tiltings but is further offset by lowered portfolio volatility. The lowered portfolio volatility is achieved by a highly reduced exposure to peaks in stock liquidity demand which are regularly induced by momentum stocks.

In general, we see that the success of factor investing relies on a cost-efficient implementation. If an institutional investor is not blessed with a local trading desk, ex-ante cost control is indispensable for cost-efficient factor investing. Further, boosted liquidity expectations provide a statistical advantage and materialize in additional value. This increase in wealth is empirically shown to be robust with respect to time and increasing with invested portfolio size or cost level. In Appendix D the hypothesis testing methodology is described to determine statistically significant differences in returns, costs and Sharpe ratios concerning auto-correlated return series. Further, we see that even the most negligible differences can be statistically significant due to the naturally high serial correlations between the portfolio returns. This testing serves as the robustness check and empirically proves that the reported statistical significances do not rely on certain sub-periods but are stable over time.

4.5 Conclusion

In this study, we investigated the success of factor investing in emerging markets concerning trading costs and researched the impact of liquidity expectations on equity allocations. The simplest way to successfully implement factor investing strategies lies in the cost-efficiency found at a low cost level. Unfortunately, many reasons might inhibit investors from achieving a sufficiently small cost level in the stock execution at EM exchanges. Therefore, alternative methods are required to control the implementation costs. From our analysis, we can draw several conclusions. First, we successfully implement a sophisticated machine learning prediction of stock liquidity as additional cost-mitigation. Second, we better understand the impact of several stock and market characteristics on stock liquidity changes. Further, this knowledge is utilized to tune the model to run less often into costly liquidity traps. Third, we achieve that the GBM outperforms the best naïve liquidity estimate and other ML-based models in forecasting the liquidity concerning crucial error metrics. Finally, the boosted liquidity forecast does also add significant value in cost-efficient implementations of factor investing in emerging equity markets across various sizes of investors. With this examination, we close a gap in literature by delivering a cross-sectional model for stock liquidity prediction in emerging equity markets based on machine learning. Further, we extend the existing research by utilizing this model to increase the net performance of factor investing approaches. The main limitation of our study is induced by a sufficiently large trading database covering emerging equity markets. All investigation was carried out with respect to sensitivity analyses. This limitation opens an exciting avenue for further research. Given such a trading database over any specific factor-based strategy, all results presented in this study can be checked for robustness by accurately fitted cost models. Further research can be conducted with respect to rebalancing higher frequency strategies and liquidity predictions or more long-term liquidity predictions as additional portfolio constraint.

4.6 List of Charts and Tables

Figure 4-1: Time-averaged percentage variable importances.
This chart visualizes the normalized feature importances of the GBM on predicting stock liquidity changes over the following month. The feature importances displayed are equal-weighted over all estimation steps of the expanding window application.

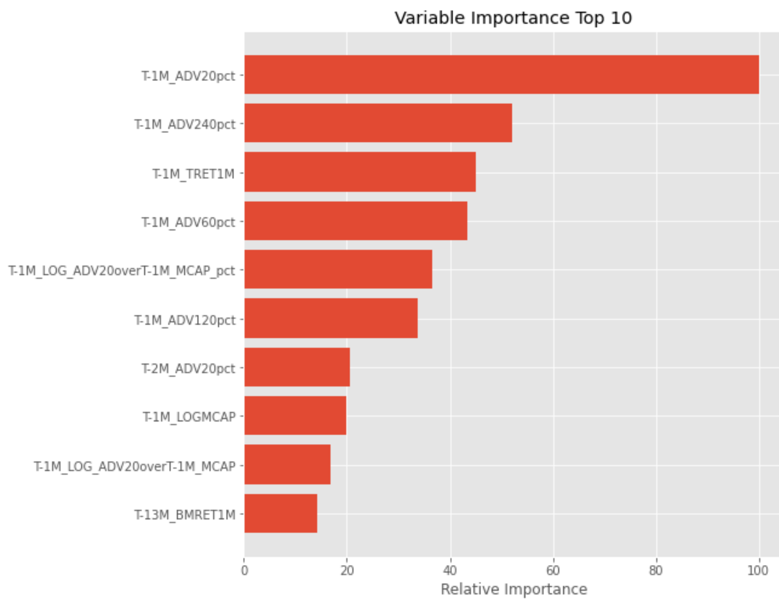


Figure 4-2: Aggressive cost parameters.
This chart displays three cost levels of market impact applied in this paper. The three parameters are scaling factors for the square root functionality of order sizes relative to liquidity on market impact.

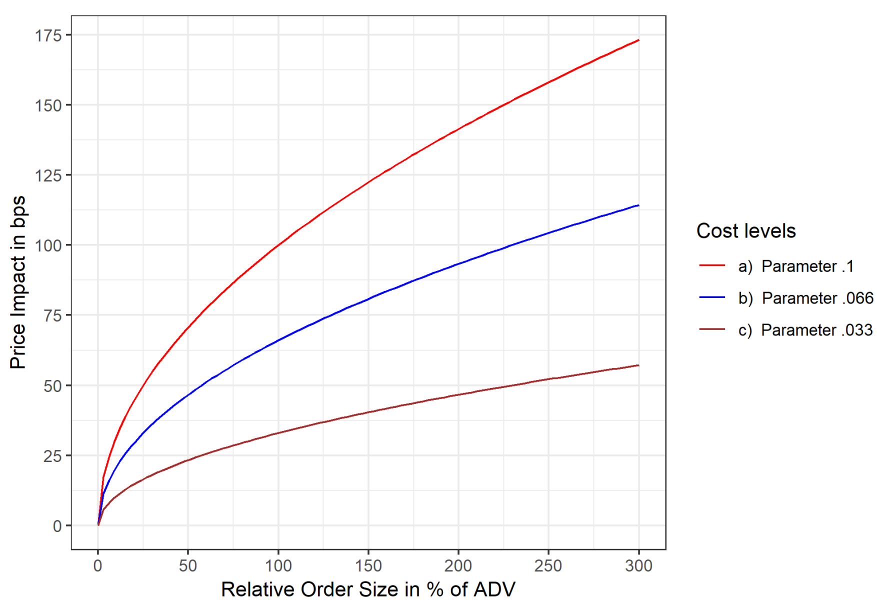


Figure 4-3: Partial dependence plots.
These charts visualize the features' partial dependencies learned by the GBM on predicting stock liquidity changes over the following month. Reversal effects of liquidity-based features dominate with respect to the feature importances.

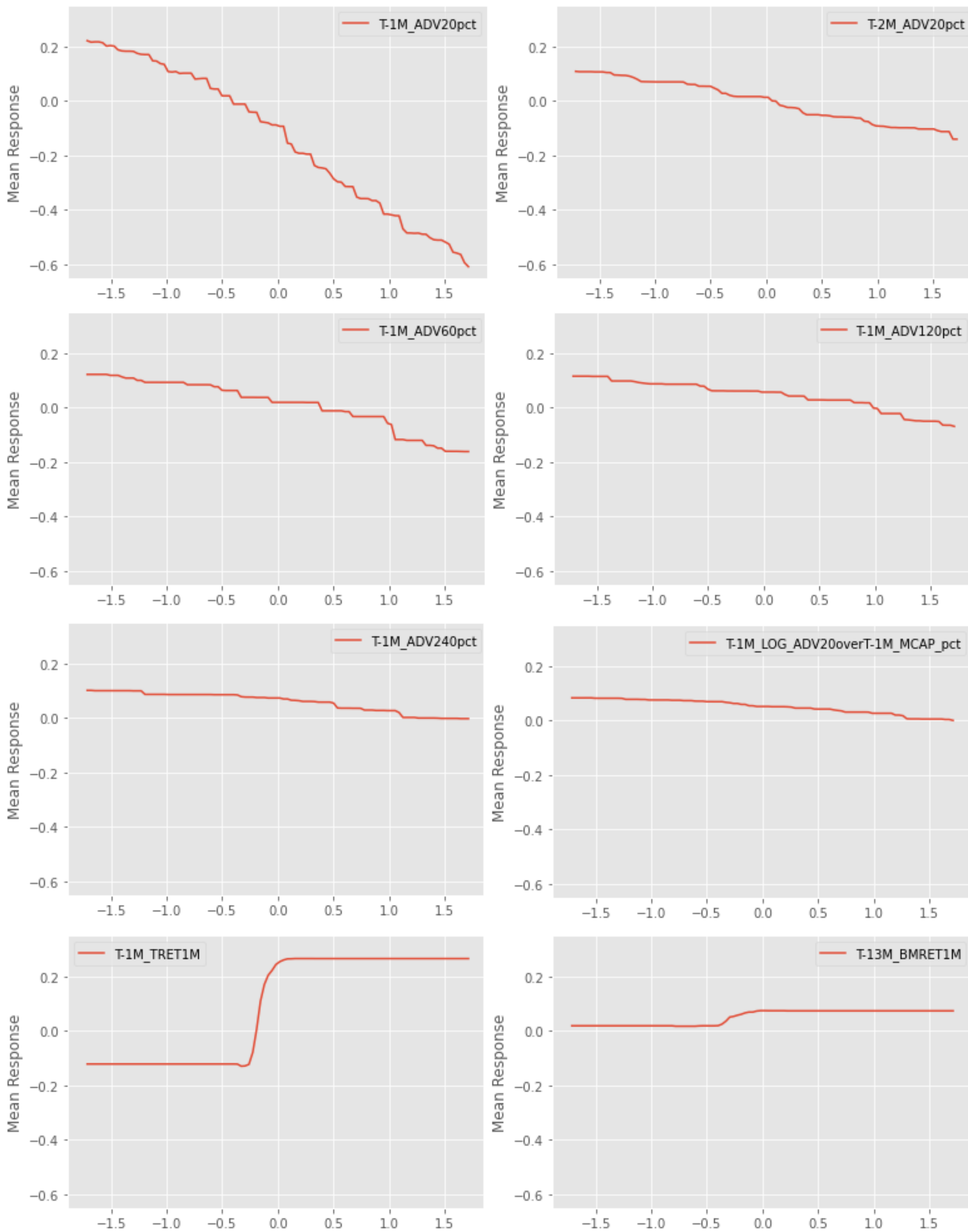


Figure 4-4: Overview of factor-based portfolio tilting.
This graphic visualizes the combination of multiple risk premia to a multi-factor mix for the portfolio tiling scheme to obtain desired portfolio positions.

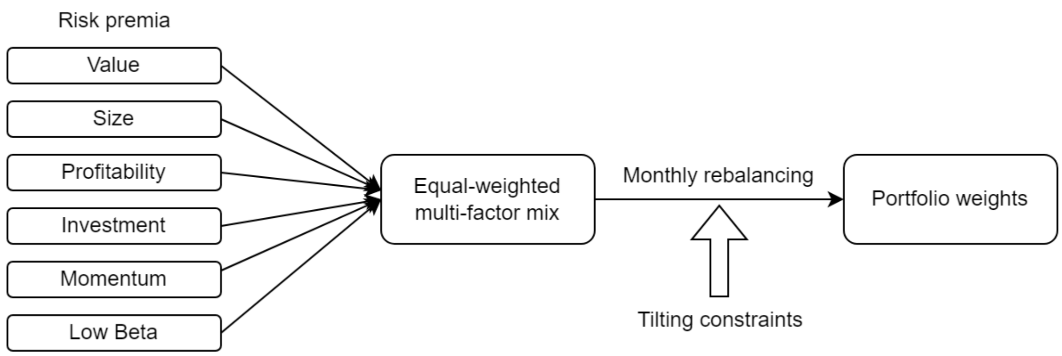


Figure 4-5: Overview of the trading process.
This graphic visualizes the approximation of trading under market friction after a portfolio rebalancing.

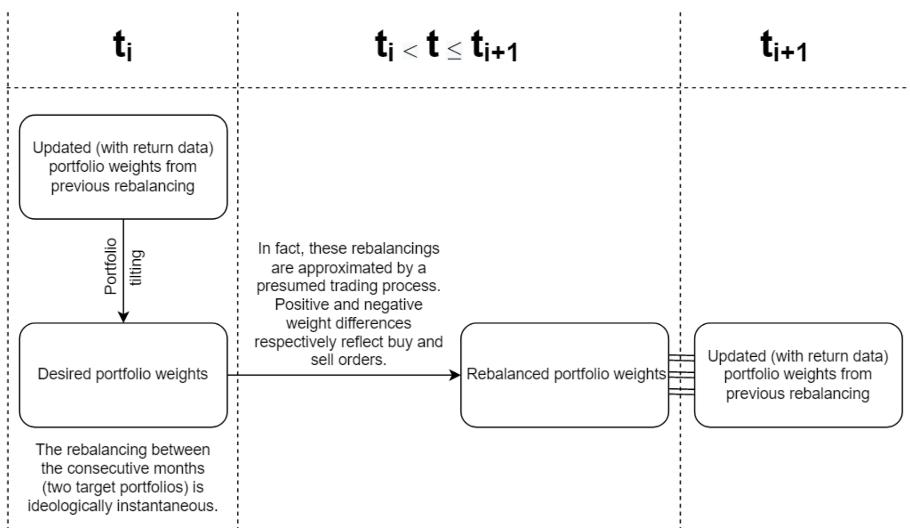


Table 4-1: Overview of the statistical error metrics in the liquidity prediction problem from 2004-12-31 to 2019-12-31. Absolute metrics are reported in million USD. The predictions based on the equal-weighted future daily volumes (for the passive trade execution) perform analogously.

	One-step ADV20d forecast	linearly-weighted boosted forecast
RMSE	14.255	11.135
RMSE (Mcap-weighted)	51.982	51.395
RMSE (weighted by inverted ranks of observed liquidity)	5.434	4.293
RMSE on overestimates	13.771	6.081
RMSE on overestimates (Mcap-weighted)	40.106	22.550
RMSE on overestimates (...)	3.675	1.455
RMSE on underestimates	14.799	13.085
RMSE on underestimates (Mcap-weighted)	60.141	57.440
RMSE on underestimates (...)	6.820	5.234
Symmetric MAPE	41.587%	37.534%
Symmetric MAPE (Mcap-weighted)	35.076%	36.371%
Symmetric MAPE (...)	44.618%	41.408%
MAD	4.238	3.067
MAD (Mcap-weighted)	26.688	25.624
MAD (...)	1.439	1.076
MASE	100%	72.412%
MASE (Mcap-weighted)	100%	96.047%
MASE (...)	100%	74.832%

Table 4-2: **One-sided outperformance significance (* for p < 0.05, ** for p < 0.01 and *** for p < 0.001) against the market for the base strategy, against the base strategy for the one-step estimates and against the one-step estimates for the boosted implementation.** Two initial portfolio sizes, as well as both trade execution patterns, are displayed. The aggressive trading is applied at a medium cost level (Figure 4-2) and passive trading results are displayed in (parentheses).
We report an annualized market return of 9.49% and Sharpe ratio of 0.57.

	Strategy	Net Return (% p.a.)	Trading Costs (% p.a.)	Sharpe Ratio
2004-12-31 to 2019-12-31 250 million USD	Base	10.74*** (11.37***)	1.51 (.88)	.76*** (.81***)
	TradeCap300_Onestep	10.56*** (11.05)	1.26*** (.77***)	.75 (.78)
	TradeCap300_Boosted	10.53 (11.03)	1.25* (.76**)	.74 (.78)
	TradeCap100_Onestep	10.49 (10.97)	1.23*** (.75***)	.74 (.78)
	TradeCap100_Boosted	10.47 (10.96)	1.23* (.74**)	.74 (.78)
2004-12-31 to 2019-12-31 500 million USD	Base	10.29* (11.27***)	1.90 (.93)	.72*** (.80***)
	TradeCap300_Onestep	10.23 (10.97)	1.54*** (.80***)	.72 (.78)
	TradeCap300_Boosted	10.22 (10.97)	1.53 (.79)	.72 (.78**)
	TradeCap100_Onestep	10.25 (10.98)	1.50*** (.77***)	.72 (.78)
	TradeCap100_Boosted	10.30** (11.02**)	1.49*** (.76*)	.72* (.78)

Table 4-3: **One-sided outperformance significance (* for $p < 0.05$, ** for $p < 0.01$ and *** for $p < 0.001$) against the market for the base strategy, against the base strategy for the one-step estimates and against the one-step estimates for the boosted implementation.** Two initial portfolio sizes, as well as both trade execution patterns, are displayed. The aggressive trading is applied at a medium cost level (Figure 4-2) and passive trading results are displayed in (parentheses).
We report an annualized market return of 9.49% and Sharpe ratio of 0.57.

	Strategy	Net Return (% p.a.)	Trading Costs (% p.a.)	Sharpe Ratio
	Base	9.73 (11.18***)	2.46 (1.01)	.67*** (.79***)
2004-12-31 to 2019-12-31 1 billion USD	TradeCap300_Onestep	9.88* (11.01)	2.01*** (.88***)	.69* (.78)
	TradeCap300_Boosted	9.89 (11.02**)	2.01 (.87*)	.69 (.78)
	TradeCap100_Onestep	10.11*** (11.15)	1.87*** (.83***)	.71*** (.79)
	TradeCap100_Boosted	10.16** (11.16)	1.76** (.79***)	.72*** (.79**)
	Base	8.71 (10.96***)	3.50 (1.24)	.59* (.78***)
2004-12-31 to 2019-12-31 2.5 billion USD	TradeCap300_Onestep	9.20*** (11.08***)	2.97*** (1.09***)	.63*** (.78***)
	TradeCap300_Boosted	9.32*** (11.15***)	2.85* (1.05*)	.64*** (.79***)
	TradeCap100_Onestep	9.88*** (11.33***)	2.31*** (.85***)	.70*** (.82***)
	TradeCap100_Boosted	10.14*** (11.41***)	2.06** (.79***)	.72*** (.82***)

Table 4-4: **One-sided outperformance significance (* for p < 0.05, ** for p < 0.01 and *** for p < 0.001) against the market for the base strategy, against the base strategy for the one-step estimates and against the one-step estimates for the boosted implementation.** Two initial portfolio sizes, as well as both trade execution patterns, are displayed. The aggressive trading is applied at a medium cost level (Figure 4-2) and passive trading results are displayed in (parentheses).
We report an annualized market return of 9.49% and Sharpe ratio of 0.57.

	Strategy	Net Return (% p.a.)	Trading Costs (% p.a.)	Sharpe Ratio
2004-12-31 to 2019-12-31 5 billion USD	Base	7.58 (10.62^{**})	4.66 (1.62)	$.49$ ($.75^{***}$)
	TradeCap300_Onestep	8.58^{***} (10.94^{***})	3.55^{***} (1.26^{**})	$.58^{*}$ ($.78^{***}$)
	TradeCap300_Boosted	8.94^{***} (11.12^{***})	3.38^{*} (1.17)	$.61^{**}$ ($.80^{***}$)
	TradeCap100_Onestep	9.95^{***} (11.22^{***})	2.17^{***} ($.80^{***}$)	$.71^{***}$ ($.82^{***}$)
	TradeCap100_Boosted	10.01^{***} (11.32^{**})	1.93^{***} ($.71^{*}$)	$.72^{***}$ ($.82$)
2004-12-31 to 2019-12-31 10 billion USD	Base	5.98 (9.86^{ast})	6.19 (2.32)	$.37$ ($.70^{***}$)
	TradeCap300_Onestep	8.54^{***} (10.87^{***})	3.79^{***} (1.39^{***})	$.59^{***}$ ($.79^{***}$)
	TradeCap300_Boosted	8.92^{***} (11.09^{***})	3.40 (1.23)	$.62^{***}$ ($.80^{**}$)
	TradeCap100_Onestep	9.82^{***} (10.98^{***})	2.22^{***} ($.89^{***}$)	$.71^{***}$ ($.80^{***}$)
	TradeCap100_Boosted	10.04^{**} (11.00^{**})	2.01^{*} ($.78^{*}$)	$.73^{***}$ ($.81^{**}$)

4.7 Appendix

4.7.1 Appendix A

4.7.1.1 Descriptions of factors

Factor	
Momentum	Logarithmic price momentum is calculated as the sentiment of the stock price 12 months ago up to the previous month's end price based on Jegadeesh and Titman (1994). The so-called $12X1$ momentum omits the last month concerning the reversal effect for long-term investments. It is the supreme example of a generic market factor and a superior long-term alpha driver in the cross-section of sectors and regions. The persistence of this factor can be reasoned by the behavioral traits of investors that follow strong-performing stocks. These investors' attention leads to a crowding effect that fosters the price sentiment until a macroeconomic event, earnings miss, or other incident stops the trend. In this paper, the price momentum is determined as $$Mom12X1_t := log(\frac{pClose_{t-12}}{pClose_{t-1}}) \qquad (23)$$

Factor	
Value	The value factor as researched in Rosenberg et al. (1985) denotes a common book-to-price multiple that compares an asset's book value relative to the actual market price. An immense book-to-price value represents a cheap stock and therefore assigns a buy signal concerning factor investing approaches. The origin of this fundamental risk premium dates back to the investigations of Benjamin Graham and David L. Dodd and has behavioral-based characteristics beneath its systematic and fundamental nature. A possible explanation of the persistence of this systematic risk premium lies in the investors' optimism about bargains and pessimistic overreactions, often resulting in bargains when poor financials are reported.
Beta	The low beta factor investigated by Ang et al. (2006) and Frazzini and Pedersen (2014) describes how stock returns co-vary with market returns. Empirical research proves that low beta stocks explain cross-sectional premia in the long run and, by construction, serve as a cushion in drawdowns. In this study, $$Beta := \frac{cov(r_i, r_{uni})}{\sigma^2(r_{uni})} \tag{24}$$ is calculated with weekly data over the last 250 business days and the $cov()$ is exponentially weighted with a 125 business days half-life.

Factor	
Size	The size factor researched in Banz (1981) shows that smaller stocks in market capitalization explain cross-sectional excess return as an investor's compensation for taking additional risk. The efficacy of the size factor can be economically explained as a systematic risk premium based on the volatile nature and higher risk of bankruptcy of small caps. This examination calculates the size factor as the logarithmic free-floating market capitalization.
Operating Profit (Profitability)	Operating profit (commonly known as EBIT) denotes the profitability of the company's business before interest and taxes and is widely applied as another quality factor. The operating expenses are subtracted from the gross profit to determine operating profit. Haugen and Baker (1996) and Novy-Marx (2013) find an additional risk premium with this factor. Financially healthy companies tend to continue their good business in the future, which economically justifies this risk factor.
Total Assets Growth (Investment)	This risk factor measures the growth of the total assets to forecast future excess return as a second quality factor. Titman et al. (2004), Cooper et al. (2008) and Watanabe et al. (2013) find that stocks with lower recent total assets growth tend to outperform the market. In this paper, we compute the growth of the total assets over the last 500 business days.

4.7.2 Appendix B

4.7.2.1 Multi-factor tilting construction methodology

Concerning single factor cyclicality, we seek to diversify the excess return expectation to maintain more persistent premia. With the six Z-scored factors depicted in Appendix A, we build an equal-weighted Z-score. The stock positions in the initial portfolio (at t_0) as well as all the following rebalancing weights (at $t > t_0$) are constructed by screening the positive Z-scores ($Z\text{-}score_i > 0$) from the multi-factor mix. To calculate portfolio weights for each stock i, the universe weights $weight_{universe,i}$ are tilted under several constraints as follows:

$$weight_{tilt,i} := \begin{cases} weight_{universe,i} \cdot Z\text{-}score_i, & \forall i \in \{EM : Z\text{-}score_i > 0\} \\ 0, & \text{else} \end{cases} \tag{25}$$

Where the market weights $weight_{universe,i}$ are determined by free-floating market capitalization. In every monthly rebalancing, each stock i is assigned its return expectation $Z\text{-}score_i$. After each rebalancing, the portfolio weights $weight_{tilt,i}$ are updated with empirical return indices[44] to the next rebalancing until this loop terminates.

[44]Thompson Reuters Datastream return indices for emerging equity represent the empirical stock returns as done by the Center for Research in Security Prices (CRSP) concerning dividend payments and stock splits.

4.7.2.2 Descriptions of rebalancing and tilting constraints (applied values in parentheses)

Constraint	Description
Relative Maximum Order Size Cap (300% / 100% of ADV)	This parameter distinguishes cost-mitigated portfolios from their base case. This sets a limit for the relative order sizes in the rebalancing steps.
Initial Threshold (Top 50%)	This threshold determines the lower bound for the mixed factor exposure at portfolio initialization. It controls the number of titles in the initial portfolio. This constraint represents the banding constraint from Novy-Marx and Velikov (2018).
Rebalancing Threshold (Top 50%)	Alike the initial threshold constraint, a lower bound for the factor exposures is set for each rebalancing step. This banding constraint controls turnover and guides the number of holdings in the portfolio concerning the trade-off of diversification and return expectation.
Relative Minimum Order Size (10%)	This constraint manages the minimum size of position changes of already held assets in the rebalancing. It can be utilized to control turnover.
Absolute Minimum Order Size (1 basis point of portfolio size)	Alike the relative minimum order size in absolute terms. This constraint prohibits the factor-tilt from generating economically insignificant orders that would artificially raise the average holdings.
Absolute Minimum Holding Size (5 basis points of portfolio size)	Declares the smallest permitted size of weight in the constructed portfolio that a position might have.

Constraint	Description
Absolute Maximum Holding Size (2% of portfolio size)	With respect to implementability and diversification, a maximum holding constraint limits portfolio weights to a certain fraction of the whole portfolio size. Each asset's total market capitalization is additionally considered in this constraint.

4.7.3 Appendix C

4.7.3.1 Overview of features applied in machine learning modeling

Feature	Origin	Description
ADV 20d change	liquidity-based	previous 20d liquidity change + 12 lags
ADV 60d change	liquidity-based	previous 60d liquidity change
ADV 126d change	liquidity-based	previous 126d liquidity change
ADV 252d change	liquidity-based	previous 252d liquidity change
ADV 20d to Mcap	liquidity-based	previous 20d liquidity relative to market capitalization + 12 lags
ADV 20d to Mcap change	liquidity-based	change of previous 20d liquidity relative to market capitalization + 12 lags
TRET20d	return-based	previous 20d total return + 12 lags
TRET60d	return-based	previous 60d total return
TRET126d	return-based	previous 126d total return
TRET252d	return-based	previous 256d total return
12X1 momentum factor	Jegadeesh and Titman (1994)	price momentum
historical vola 20d	volatility-based	previous 20d volatility (daily data) + 12 lags
historical vola 20d change	volatility-based	change of previous 20d volatility (daily data) + 12 lags
historical vola 60d	volatility-based	previous 60d volatility (daily data)
historical vola 60d change	volatility-based	change of previous 60d volatility (daily data)
historical vola 126d	volatility-based	previous 126d volatility (daily data)

Feature	Origin	Description
historical vola 126d change	volatility-based	change of previous 126d volatility (daily data)
historical vola 252d	volatility-based	previous 252d volatility (daily data)
historical vola 252d change	volatility-based	change of previous 252d volatility (daily data)
BMRET20d	return-based	previous 20d market return (Mcap-weighted) + 12 lags
BMRET60d	return-based	previous 60d market return (Mcap-weighted)
BMRET126d	return-based	previous 126d market return (Mcap-weighted)
BMRET252d	return-based	previous 252d market return (Mcap-weighted)
historical vola 20d	volatility-based	previous 20d volatility (daily data) + 12 lags
hist. market vola 20d change	volatility-based	change of previous 20d market volatility (daily data) + 12 lags
hist. market vola 60d	volatility-based	previous 60d market volatility (daily data)
hist. market vola 60d change	volatility-based	change of previous 60d market volatility (daily data)
hist. market vola 126d	volatility-based	previous 126d market volatility (daily data)
hist. market vola 126d change	volatility-based	change of previous 126d market volatility (daily data)
hist. market vola 252d	volatility-based	previous 252d volatility (daily data)
hist. market vola 252d change	volatility-based	change of previous 252d market volatility (daily data)

Feature	Origin	Description
market liquidity dispersion 20d	liquidity-based	variation coefficient of 20d average liquidity in currency (USD) + 12 lags
market liquidity dispersion 20d change	liquidity-based	change of variation coefficient of 20d average liquidity in currency (USD) + 12 lags
market liquidity 20d change	liquidity-based	change of previous 20d market liquidity (Mcap-weighted) + 12 lags
market liquidity 60d change	liquidity-based	change of previous 60d market liquidity (Mcap-weighted)
market liquidity 126d change	liquidity-based	change of previous 126d market liquidity (Mcap-weighted)
market liquidity 252d change	liquidity-based	change of previous 252d market liquidity (Mcap-weighted)
media coverage	news-based	linearly-weighted count of media references until the end of the business month (logged)
news sentiment score	news-based	news sentiment relative to the average market level
upcoming holidays	calendar-based	(linearly-weighted) count of occurrences of closed stock exchanges
country	hot-encoded	factorial feature
sector	hot-encoded	factorial feature
month	hot-encoded	factorial feature
country_sector	hot-encoded	factorial feature
country_month	hot-encoded	factorial feature
sector_month	hot-encoded	factorial feature

All referenced change rates are calculated monthly. The upcoming holidays feature is implemented linearly-weighted for the aggressive trade model and equal-weighted for the opportunity cost model.

4.7.4 Appendix D

4.7.4.1 Pairwise portfolio significance testing for differences in annualized (excess) returns, trading costs and Sharpe ratios

Due to serial correlations between portfolios and auto-correlation in the tiltings and a stochastic dependency in the portfolios, an ordinary t-test can not be applied. To test the statistical significance of our presented evidence, we apply the following test statistic Z_μ as a one-sided t-test on the return differences for stochastically dependent, identically distributed portfolios:

$$Z_\mu = \frac{\sqrt{N}(\hat{\mu_1} - \hat{\mu_2})}{\sqrt{\hat{\sigma_1}^2 - 2\hat{\rho_{1,2}}\hat{\sigma_1}\hat{\sigma_2} + \hat{\sigma_2}^2}} \tag{26}$$

With N degrees of freedom ($\#rebalancing\ months - 2$; because portfolio initialization is cost-mitigation independent) and μ_i, σ_i assigning the estimated annualized means and standard deviations of both observations.

We also report the statistical significance of the Sharpe Ratio (SR) difference between two stochastically dependent portfolios with the following test statistic from Ledoit and Wolf (2008):

$$Z_{SR} = \frac{\sqrt{N}(\hat{SR}_1 - \hat{SR}_2)}{\sqrt{2 - 2\hat{\rho_{1,2}} + \frac{1}{2}[\hat{SR}_1^2 + \hat{SR}_2^2 - 2\hat{SR}_1\hat{SR}_2\hat{\rho_{1,2}}^2]}} \tag{27}$$

Based on these test statistics, all hypothesis tests check the alternatives: $H_0 : \mu_1 = \mu_2 \quad (SR_1 = SR_2)$, $H_1 : \mu_1 \neq \mu_2 \quad (SR_1 \neq SR_2)$ and report the p-value to the error levels $p < 0.05$, $p < 0.01$ and $p < 0.001$.

To additionally account for and correct the auto-correlation of the tiltings, we do not just report the results of the above hypothesis tests but perform a bootstrap explained as follows.

4.7.4.2 Stationary Circular Block-Bootstrapping

The hypothesis tests above are robustness-checked with a block-bootstrap to correct for auto-correlation as researched in Efron and Tibshirani (1993). Politis and Romano (1992) proved that randomization of the block length in the circular block-bootstrapping maintains the stationarity of the observations in the bootstrapped samples. Therefore the reported p-values are finally calculated as follows:

- Calculate the Z-statistic as Z once for return- or Sharpe ratio testing
- To apply the stationary circular block-bootstrap to test H_0, transform the data so that H_0 is true.
    - For return testing this transformation is given by $\tilde{X}_i := X_i - \hat{\mu_i} + \hat{\mu}_{combinedsample}$ for both time series.
    - For Sharpe ratio testing it is: $\tilde{X}_i := [\frac{X_i - \hat{\mu_i}}{\hat{\sigma_i}} \hat{\sigma}_{combinedsample}] + \hat{\mu}_{combinedsample}$ for both time series.
- The robustness-checked hypothesis test works by simulating the distribution of the Z-statistic with block-bootstrapping under a true H_0. We do that by generating $M = 10000$ block-bootstrap samples for both time series of forced length N (circular) with uniformly randomized block-length $b \in \{1, 2, ..., \lfloor \frac{N}{2} \rfloor\}$ to maintain stationarity. The Z-statistic is calculated for each of the M bootstrap samples as $\tilde{Z}_i$.
- Now we sum $\frac{\sum_{i=1}^{M=10000} I(|\tilde{Z}_i| \geq |Z|)}{M} =: p$ where $I()$ denotes the indicator function (that equals 1 if its argument is true and 0 otherwise) to get the p-value of our hypothesis test given H_0 is true. This p-value is the reported statistic for each hypothesis test in the results section.

5 GENERAL CONCLUSION

In general, many aspects of factor investing are thoroughly examined. This dissertation focuses on its implementability in the context of illiquid emerging equity markets and extends the research by presenting a set of novel improvements regarding its cost-efficiency. It contributes to the gaps in literature as follows. At first, this dissertation ties on the existing research and combines the often separately investigated fields of return and liquidity prediction relative to simple cost models to understand better the trade-off between portfolio return and implementation costs in emerging equity markets. Second, a simple cost-mitigation technique is examined concerning cost level and invested portfolio size. Third, one of the most exciting findings of this dissertation is the demonstration of factor timing in emerging equity markets. I again emphasize that the entanglement of developed and emerging markets can be utilized by machine learning in portfolio construction. When examining developed markets alone, there is less variety and interaction in macroeconomic data and factor timing remains controversial. Fourth, the prediction of stock liquidity changes is another prime example of machine learning applications that can be utilized to increase portfolio cost-efficiency. This dissertation has a few limitations. Recent trends of quantitative easing and factor crowding seem to harm the performance of risk factors in the cross-section. Literature on breaches of risk factors is emerged but is not in consensus on whether these strategies persist in the future. Also, all empirical analyses are carried out by strict assumptions on the cost models and their sensitivity analyses. An extensive trading database of a unique live strategy might be the most exciting extension of this dissertation. Lastly and overall concluding, this dissertation repetitively emphasizes the importance of trading costs to implement factor investing in emerging equity markets successfully. While long-term risk premia are well-examined, a thoughtful execution or cost-mitigation approach decides the underlying strategy's success. Today, this might be the only skill a manager that beats her peers possesses. Therefore, the increasing investors' attention to emerging equity markets can be justified under the assumption of a possible low cost level. However, while finding a novel source of alpha is increasingly difficult, there is another path to increase the net of cost performance of factor investing. The investigations carried out in this dissertation do not provide an additional source of alpha but show how on-paper returns can often be largely preserved by implicitly controlling the cost component. So, if one does not implement a factor strategy mindlessly, what you see might be close to what you get.

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DECLARATION OF HONOR

I declare upon my word of honor that the dissertation submitted herewith is my own work. All sources and aids used have been listed. All references or quotations in any form and their use have been clearly identified. The dissertation has not been submitted for examination purposes to any institution before.

Ich erkläre hiermit ehrenwörtlich, dass ich die vorliegende Arbeit selbstständig angefertigt habe. Sämtliche aus fremden Quellen direkt und indirekt übernommene Gedanken sind als solche kenntlich gemacht. Die Dissertation wurde bisher keiner anderen Prüfungsbehörde vorgelegt und noch nicht veröffentlicht.

Kay Stankov

2022