Essays on Empirical Asset Pricing

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Contents

List of Abbreviations and Acronyms

AMEX	American Stock Exchange
API	Application Programming Interface
ASIC	Australian Securities and Investments Commission
BBC	British Broadcasting Corporation
CAPM	Capital Asset Pricing Model
CAR	Cumulative Abnormal Return
CMA	Conservative-Minus-Aggressive factor
CRSP	Center for Research in Security Prices
DAPM	Dynamic Asset Pricing Model
DB	Deutsche Börse
DS	Thomson Reuters Datastream
ESMA	European Securities and Markets Authorities
EU	European Union
EUR	Euro
EW	Equally-Weighted
FACSHR	Adjustment Factor for the Number of Shares Outstanding
FCA	Financial Conduct Authority
FENR	Frequency of Extreme Negative Returns
FF3	Fama-French 3-factor model
FF&MOM	Fama-French and Momentum factor model
GBP	Great British Pound
GDP	Gross Domestic Product
GmbH	Gesellschaft mit beschränkter Haftung
HML	High-Minus-Low factor
ICB	Industry Classification Benchmark
IOR	Institutional Ownership Ratio

ISIN	International Securities Identification Number
LLP	Limited Liability Partnership
LOC	Limit-on-Close
LR	Likelihood Ratio
MAPE	Mean Absolute Pricing Error
MktRF	Market Portfolio Minus Risk Free Rate
NASDAQ	National Association of Securities Dealers Automated Quotations
NYSE	New York Stock Exchange
PLC	Public Limited Company
RBS	Royal Bank of Scotland
RMW	Robust-Minus-Weak factor
RSS	Rich Site Summary
S&P	Standard & Poor's
SDF	Stochastic Discount Factor
SMB	Small-Minus-Big factor
STR	Short-Term Reversal factor
TAQ	Trade and Quote
TT	Timothy Tacchi
US	United States
USD	United States Dollar
UK	United Kingdom

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1 General Introduction

1.1 Motivation and Background

This thesis consists of three essays on empirical asset pricing. To situate these three essays within the panorama of the recent literature on empirical asset pricing research, it is useful to consider the "two pillars of asset pricing". They were introduced by Eugene F. Fama in his Nobel Prize lecture delivered on December 8, 2013 at Aula Magna, Stockholm University (Fama, 2014). According to Fama, they are the basis of empirical work in asset pricing.

The first pillar is the research on the efficient market hypothesis, and the second pillar consists of the ongoing work to create more refined asset pricing models. The efficient market hypothesis stipulates that asset prices reflect all information available in the market. The consequence of this hypothesis is that all current information is embedded in the current price and, if the information set does not change, asset prices do not fluctuate. The testable implication thus generated is that currently available information should not be able to predict future returns. In the course of its decades-long development, this theory has been split into three forms according to the information set considered (Fama, 1970). The three forms are (1) weak-form efficiency (2) semi-strong-form efficiency and (3) strong-form efficiency. In the weak-form efficiency, the information set consists of all previous prices, in the semi-strong-form the information set contains all publicly available information, and in the strong-form efficiency the information set additionally comprises all private information.

The asset pricing models considered to constitute the second pillar aim at explaining how asset prices are expected to behave. The underlying assumption in the standard asset pricing literature is that investors are both rational and able to include all available information into prices instantaneously and correctly. In the framework of consumption-based asset pricing, these assumptions lead to the fist-order condition, which defines the price of an asset today as the expected discounted future payoffs of the asset (see, e.g., Cochrane, 2009, for a derivation).[1] The future payoffs of an asset are discounted with the stochastic

[1] $p_t = E(m_{t+1}, X_{t+1})$, where p_t is the price in period t, m_{t+1} is the stochastic discount factor, X_{t+1} is the future payoff, and function E is the expected value.

discount factor which traditionally include macro and micro predictors. A branch of literature has challenged not only the assumptions leading to the equilibrium condition but also the predictors incorporated into the stochastic discount factor (Cochrane, 2011, Adrian, Etula, and Muir, 2014). For example, Malloy, Moskowitz, and Vissing-Jørgensen (2009) and Jagannathan and Wang (2007) find that households do not participate in the stock market actively enough to explain the cross-section of stock returns.

The two pillars of asset pricing cannot be considered in isolation from one another. Specifically, to test the efficient market hypothesis, it is necessary to define an appropriate asset pricing model to determine the way asset prices are expected to behave. So, these two avenues of research in the field of asset pricing converge into the joint hypothesis problem (Fama, 1970), in which any test of the efficient market hypothesis is also jointly a test of the asset pricing model used to assess whether the asset prices reflect all available information.

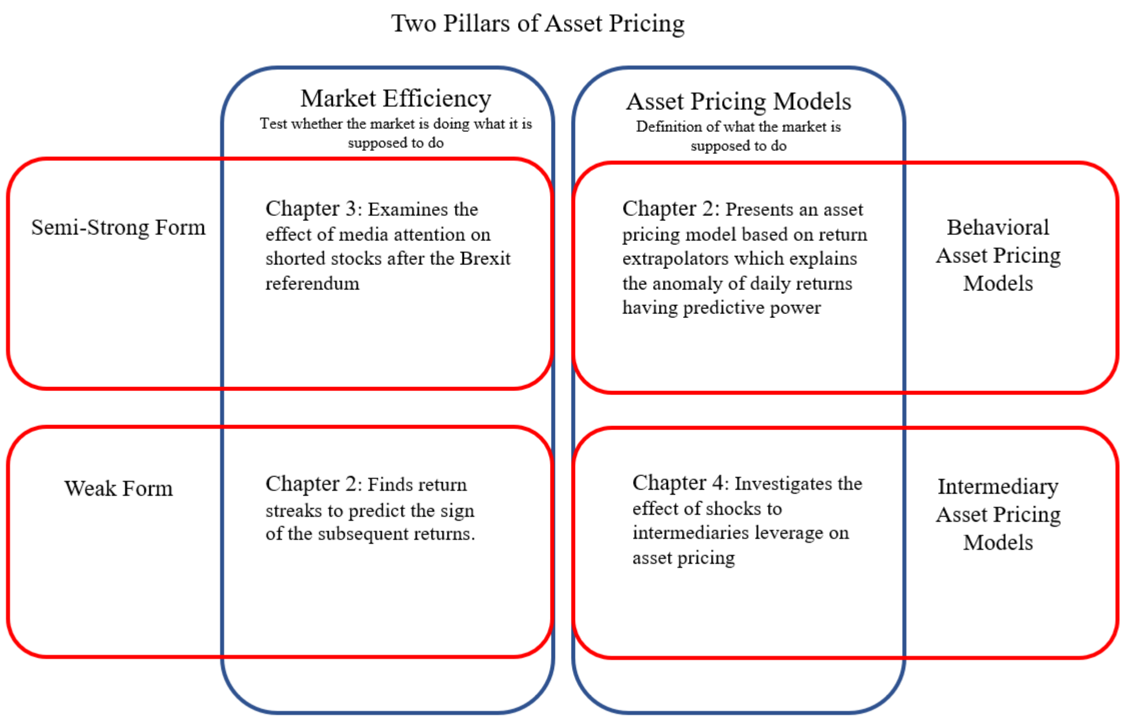

Figure 1: Thesis overview

This figure organizes the chapters of this thesis into the framework of the "two pillars of asset pricing" introduced by Fama (2014) in his Nobel Prize lecture.

The essays presented in this thesis can accordingly be placed into the framework of the two pillars of asset pricing. Figure 1 shows how the essays constituting this thesis can be placed with regard to the two pillars of asset pricing. The first and second essays (Chapters 2 and 3) investigate the weak and semi-strong form of market efficiency, respectively, and thus situate themselves in the field of market efficiency research. The first and third essays (Chapters 2 and 4) examine behavioral asset pricing models and intermediary asset pricing models, respectively, and contribute to the definition of market behavior.

As it can be seen in Figure 1, the first essay (Chapter 2) can be rightfully placed in both fields of asset pricing research. On one hand, it presents a new return anomaly that cannot be explained by the classical market equilibrium models. On the other hand, it applies a behavioral asset pricing model to show how return extrapolation and fundamental traders lead to a market equilibrium that explains the return anomaly. The documented return anomaly challenges the weak-form market efficiency because the theory of market efficiency assumes that all information available on the value of a stock is instantaneously and correctly incorporated into the stock price. However, the high number of return anomalies documented in the literature pose a counter-argument to the efficient market hypothesis (see, e.g., Subrahmanyam, 2010, for an overview). The essay in Chapter 2 adds to this literature and finds that a sequence of trading days with negative or positive returns is followed by significant return reversals. In light of the joint hypothesis problem, the return anomalies observed in the literature do not offer conclusive evidence whether the market efficiency hypothesis is to be rejected or the asset pricing model is not appropriate. An alternative model including both rational agents and return extrapolators, based on Da, Huang, and Jin (2018), is successful in modeling stylized facts on asset returns, in particular momentum, return reversals, volatility, and bubbles (see, e.g., Greenwood and Shleifer, 2014, Barberis, Greenwood, Jin, and Shleifer, 2015, 2018, Da, Huang, and Jin, 2018). So far this model has only been used to explain the return anomalies on a weekly or monthly basis, and we expand its scope to daily return reversals.

The second essay (Chapter 3) is a test for semi-strong market efficiency. Typically, to test the semi-strong market efficiency, the reaction of stock prices to stock specific announcements (see, e.g. Ball, 1978, Watts, 1978, for a discussion) or macro data is examined. After macro or stock-specific events, stock prices are observed to recover after an initial stronger reaction. This suggests that stock prices overreact to news, another well documented behavioral anomaly (see, e.g., DeBondt and Thaler, 1985, 1987, Daniel, Hirshleifer, and Subrahmanyam, 1998). However, it contradicts the semi-strong efficient market hypothesis, which assumes that investors incorporate new information rationally and instantaneously. In accordance with this approach, this essay investigates the post-referendum returns of shorted stocks that received media attention. Overall, this essay confirms that media attention of shorted stocks results in an overreaction of the post-referendum returns.

The last essay of this thesis tests an intermediary asset pricing model in Europe. The joint hypothesis problem postulates that testing market efficiency is also a test of the underlying asset pricing model. In the consumption-based asset pricing model, the average investor considered is the average household. However, Cochrane (2011) maintains that the average household may not be the optimal average investor to consider, arguing that financial intermediaries are actually the ones making the investment decisions for the average household. Therefore, Chapter 4 focuses on the leverage of European financial intermediaries to explain the cross-section of stock returns. Intuitively, due to the leverage constraints of financial intermediaries a devaluation of assets during market downturns forces banks to sell assets contributing to the market downturn. For the US Adrian, Etula, and Muir (2014) find that leverage of financial intermediaries is a more informative marginal value of wealth compared to the marginal value of wealth aggregated over households.

1.2 Outline and Main Results of Thesis Projects

Chapter 2, with the title "*Daily Return Streaks*", finds that consecutive days of positive (negative) returns predict negative (positive) returns on the next day. We call the consecutive days with the same return sign a return streak. A strategy based on return streaks generates significant returns on a value-weighted basis; this degree of return predictability stands out compared to other work in this area (see, e.g., Fama and MacBeth, 1973, Jegadeesh, 1990, Lehmann, 1990, Campbell, Grossman, and Wang, 1993, Llorente, Michaely, Saar, and Wang, 2002, Avramov, Chordia, and Goyal, 2006, Nagel, 2012). The chapter also offers out-of-sample evidence of the return predictability of return streaks by testing the streak strategy both for all US equity as well as on international markets. Furthermore, the empirical finding of this paper is supported by the theoretical return extrapolator model by Da, Huang, and Jin (2018). Our elegantly simple model suggests that consecutive days with a positive (negative) return are a good proxy for days with high (low) extrapolators' sentiment. Furthermore, as the sentiment becomes more extreme, the probability of a return reversal increases. The relationship predicted by the model is confirmed through our empirical analysis.

Chapter 3, titled "*Media Attention and Short Selling around the Brexit Referendum*", investigates the risk of additional media attention on shorted stocks after the Brexit referendum. Not only do disclosed short positions bear the risk of manipulative attacks through other short sellers, but they also increase the risk that unfavorable media attention negatively affects stock returns. For the empirical analysis in this paper, a database is constructed containing the public short positions disclosed under the European short position disclosure regime and data on news articles from the BBC Application Programming Interface (API) called *The Juicer*.[2] In this Chapter, I find that stocks with open short positions do not have more significantly negative returns compared to their matched counterparts; however, if a

[2]Information on the API can be found at http://bbcnewslabs.co.uk/projects/juicer/, last accessed February 26, 2019.

shorted stock receives media attention, it significantly underperforms. From a regulatory point of view, the short position disclosure regime, with consequent publication of information previously not readily available, when coupled with media attention entails the risk of worsening the effect of an adverse market on shorted stocks.

Chapter 4, with the title "*Procyclical Leverage in Europe and its Role in Asset Pricing*", investigates the broker-dealer leverage and its explanatory power for a large cross-section of stock returns in Europe. In the US market, broker-dealer leverage has recently proven to be strongly procyclical, exhibiting explanatory power for a large cross-section of asset returns. In Chapter 4, we can show that European and German broker-dealers actively manage their balance sheets. Moreover, by applying standard Fama-MacBeth regressions as well as dynamic asset pricing models (Adrian, Crump, and Moench, 2015a), we confirm that broker-dealer balance-sheet indicators are procyclical. In particular, leverage shows a procyclical behavior with a positive price of risk.

1.3 Contributions and Acknowledgments

In this subsection the contributors and acknowledgments for the projects of this dissertation are outlined.

Chapter 2 titled "*Daily Return Streaks*" is co-authored with Alexander Klos and Simon Rottke. All authors contributed equally towards the model and empirical sections of the paper. This paper has been accepted for presentation at the 26th Annual Meeting of the German Finance Association (DGF) and the 6th SAFE Asset Pricing Workshop.

Chapter 3, "*Media Attention and Short Selling around the Brexit Referendum*" is my single author paper. I would like to thank Alexander Klos for his helpful comments and ongoing support. Furthermore, I would like to thank the team at BBC Newslab for granting me access to *The Juicer* API.

Chapter 4, with the essay titled "*Procyclical Leverage in Europe and its Role in Asset Pricing*", is the result of a collaboration with Markus Baltzer and Stefan Reitz. Each author contributed equally to each section. This essay is contribution no. 10/2019 in the Bundesbank discussion paper series. I would also like to thank Emanuel Moench, Richard Crump, Ulrich Grosch, and Joachim Keller for their very helpful comments on an earlier draft of the paper. I am very thankful also for the feedback received from the discussant Francisco Ilbaca and the participants of the Kiel workshop in Financial Econometrics and Empirical Modeling of Financial Markets. This essay has been accepted for presentation at the 2019 annual meeting of the German Economic Association (Verein für Socialpolitik).

2 Daily Return Streaks

Coauthored by: Alexander Klos and Simon Rottke

2.1 Introduction

Theories about return extrapolation have recently received growing attention in the finance literature (Greenwood and Shleifer, 2014, Barberis, Greenwood, Jin, and Shleifer, 2015, 2018, Da, Huang, and Jin, 2018). Consistent with the literature on return extrapolation in other fields of economics (see, e.g., Coibion and Gorodnichenko, 2015, Mankiw and Reis, 2002), the time frame over which return extrapolation is analyzed empirically is often just one quarter (Barberis, Greenwood, Jin, and Shleifer, 2018). Recent research has looked at even shorter horizons. Da, Huang, and Jin (2018) analyze weekly data and find evidence for short-term return extrapolation. We pursue this avenue of investigation and explore the idea that return extrapolation also plays a role in forming daily expectations.

We start by clarifying the form of return predictability that could arise from daily return extrapolation. Intuitively, one would expect extreme sentiment among extrapolators after a series of positive or negative daily returns. Extreme sentiment finds its way into equilibrium prices if fundamental traders do not eliminate all mispricing caused by extrapolators. The resulting temporary over- or underpricing tends to reverse on the following trading day. We use a simplified version of the model by Da, Huang, and Jin (2018) to show that streaks in daily returns are a useful proxy to identify stocks with high or low sentiment among extrapolators. In our definition, a streak in daily returns of length n occurs when an asset has outperformed or underperformed the market over n consecutive days.

Our first empirical test of this theoretical result uses daily US stock returns from 1997 to 2017. We find that stocks with streaks in daily returns up to day $t-1$ exhibit significant reversals on day t, consistent with the theoretical prediction. Value-weighted, long-short portfolios that long stocks with negative streaks in returns and short stocks with positive streaks in returns earn economically sizeable returns over the next trading day. Returns of long-short portfolios increase monotonically with streak length. Abnormal daily returns of streak strategies are substantially higher for equally-weighted portfolios, consistent with the idea that mispricing is more pronounced among smaller stocks.

We then move to international data and find qualitatively similar evidence in equity markets around the globe. The time series of local streak strategy returns exhibit only modest correlations among each other. Building a global diversified streak strategy portfolio increases the Sharpe ratio further.

Subsequently we revisit the US evidence, where data availability allows to gather further empirical evidence. Returns from streak strategies are higher on earnings announcement days and if the holding day coincides with high trading volume. We further show that streaks are distinct from classic short-term reversal strategies and bid-ask bounces. Excess returns calculated based on mid-quote prices still earn 11.6 bps per day in the US. After bid-ask spreads have fallen dramatically in the early 2000's, a streak strategy with trading-cost mitigation enhancements outperforms the market after transaction costs. The value-weighted streak strategies considered here are conceptually different from return-weighted reversal strategies designed to capture compensation for liquidity provision (Nagel, 2012). Streak strategy returns cannot be explained by the five Fama-French factors and the short-term reversal factor. We additionally match stocks in streak portfolios with control stocks that have similar returns on day $t-1$ but no streak in returns. A value-weighted portfolio of stocks with streaks outperforms a value-weighted portfolio of control stocks on day t and the outperformance increases with streak length. We also regress daily returns on streak dummies, previous day, and cumulative previous n-days excess returns in market value-weighted Fama-MacBeth regressions (Fama and MacBeth, 1973, Green, Hand, and Zhang, 2017). Streak dummies remain statistically significant and economically sizable.

To investigate the role of institutional ownership, we sort all stocks by institutional ownership (IOR) and implement the streak strategy on stocks with high IOR and low IOR. We find that, for equally-weighted portfolios, returns from streak strategies of low IOR firms contribute more to the empirical success of streak strategies. Surprisingly, excess returns of value-weighted streak strategies do not follow this pattern in the sense that value-weighted strategies for high IOR firms do not underperform value-weighted strategies for medium IOR firms. We consider this result to be remarkable for two reasons. First, it helps explain why the value-weighted streak strategies exhibit high Sharpe ratios, as there is a sizeable effect among a subgroup of large firms. Second, to the extent that institutional ownership proxies for the fraction of fundamental traders in the population, this result is inconsistent with the extrapolation model laid out in Section 2.2. A larger effect among firms with high IOR compared to firms with medium IOR is also inconsistent with alternative explanations that interpret returns from streak strategies as compensation for liquidity provision.

2.2 Inferring a New Testable Implication from Behavioral Models on Return Extrapolation

We explore the model of Da, Huang, and Jin (2018) to develop previously unstated implications of recent theories on return extrapolation. In Da, Huang, and Jin (2018), agents trade a risk-free asset with a zero interest rate and multiple risky assets. Each asset i has a time-invariant supply of shares Q_i and pays a terminal dividend $D_{i,T} = D_{i,0} + \epsilon_{i,1} + ... + \epsilon_{i,T}$ at time T. The dividend innovations $\epsilon_{i,t}$ are observed by all traders at time t. Da, Huang, and Jin (2018) assume that the dividend innovations consist of a firm-specific and a market-wide component. We simplify their setting by assuming that all dividend innovations for all assets i come from a normal distribution with mean zero and variance σ^2. The dividend innovations, therefore, have only a firm-specific component and are identically and independently distributed over assets and time. If N is the number of risky assets in the economy, we can think of these risky assets as N time-series realizations of the same data-generating process. We drop the asset index i in the following for the sake of brevity.

Two types of agents with constant absolute risk aversion γ exist in the model: extrapolators and fundamental traders. The extrapolators' belief about the next price change of an asset in period t is given by:

$$\mathbb{E}_t^E[P_{t+1} - P_t] = \lambda_0 + \lambda_1 S_t. \tag{2.1}$$

The expected price change in the next period is a linear function of this period's sentiment, which is defined as

$$S_t = (1-\lambda_2)\sum_{k=0}^{t-1} \lambda_2^k \left(P_{t-k} - P_{t-k-1}\right) + \lambda_2^t S_0. \tag{2.2}$$

Sentiment is a weighted average of past price changes and a starting value S_0. The parameter $0 < \lambda_2 < 1$ governs how strongly the extrapolator is influenced by recent price changes relative to more distant ones. Fundamental traders form the second group of traders. They maximize their expected utility of wealth next period and assume that any mispricing will be corrected next period. The population of traders can be split into a fraction μ^E of extrapolators and a fraction $\mu^F = 1 - \mu^E$ of fundamental traders.

Defining $\alpha_t = \gamma\sigma^2 Q\left(T - t - 1 + \frac{1}{\mu^F}\right)$, Da, Huang, and Jin (2018) derive a closed-form solution for the equilibrium price of all assets in this economy. The price change of an asset is the difference between two adjoining prices and, in our setting, given by

$$\begin{aligned}
&P_t - P_{t-1} = \\
&\frac{D_t + (\mu^F)^{-1}\mu^E[\lambda_0 + \lambda_1\left[(1-\lambda_2)\sum_{k=1}^{t-1}\lambda_2^k\left(P_{t-k} - P_{t-k-1}\right) + \lambda_2^t S_0\right] - \lambda_1(1-\lambda_2)P_{t-1}] - \alpha_t}{1 - (\mu^E/\mu^F)\lambda_1(1-\lambda_2)} \\
-&\frac{D_{t-1} + (\mu^F)^{-1}\mu^E[\lambda_0 + \lambda_1\left[(1-\lambda_2)\sum_{k=1}^{t-2}\lambda_2^k\left(P_{t-k-1} - P_{t-k-2}\right) + \lambda_2^{t-1} S_0\right] - \lambda_1(1-\lambda_2)P_{t-2}] - \alpha_{t-1}}{1 - (\mu^E/\mu^F)\lambda_1(1-\lambda_2)} \\
&= \frac{1}{1 - (\mu^E/\mu^F)\lambda_1(1-\lambda_2)}\left[\epsilon_t + \gamma\sigma^2 Q\right] \\
&- \frac{(\mu^F)^{-1}\mu^E\lambda_1(1-\lambda_2)}{1 - (\mu^E/\mu^F)\lambda_1(1-\lambda_2)}\left[\sum_{k=1}^{t-1}(\lambda_2^{k-1} - \lambda_2^k)(P_{t-k} - P_{t-k-1})\right] \\
&- \frac{(\mu^F)^{-1}\mu^E\lambda_1}{1 - (\mu^E/\mu^F)\lambda_1(1-\lambda_2)}\left[((\lambda_2)^{t-1} - (\lambda_2)^t)S_0\right].
\end{aligned} \tag{2.3}$$

The price change is a weighted sum of (i) the most recent dividend innovation ϵ_t and the market risk premium $\gamma\sigma^2 Q$, (ii) the past price changes, and (iii) the starting sentiment S_0. The weights depend on the degree of return extrapolation (captured by the parameters λ_1 and λ_2) and the fraction of extrapolators μ^E in the economy.[3]

Equation (2.3) suggests that price changes in period t are just a function of previous dividend innovations and the starting sentiment S_0. The following proposition states an exact formula for our setting. Appendix 2.7.1 contains the proof.

Proposition 1 (Price changes as a function of past epsilon shocks for $t \geq 2$)**.** For $S_0 = \gamma\sigma^2 Q$,

$$P_t - P_{t-1} = \left(\frac{1}{1-A}\right)\epsilon_t - \frac{A(1-\lambda_2)}{(1-A)^2}\sum_{j=1}^{t-1}\epsilon_j\left(\frac{\lambda_2 - A}{1-A}\right)^{t-1-j} + \gamma\sigma^2 Q, \tag{2.4}$$

$$\text{with } A = (\mu^E/\mu^F)\lambda_1(1-\lambda_2).$$

In Proposition 1 we assume $S_0 = \gamma\sigma^2 Q$.[4] This assumption implies that extrapolators' belief about the mean of the first price change in the economy is a linear function of the market risk premium. For $\lambda_0 = 0$ and $\lambda_1 = 1$, the beliefs of all agents about the first price change coincide and are equal to the market risk premium.

An interesting special case is the parameterization $\lambda_2 = A$. Equation (2.4) in Proposition 1 becomes

$$P_t - P_{t-1} = \frac{1}{1-\lambda_2}\epsilon_t - \frac{\lambda_2}{1-\lambda_2}\epsilon_{t-1} + \gamma\sigma^2 Q. \tag{2.5}$$

We consider $\lambda_2 = A$ to be an attractive parameter choice for an application to daily data for two reasons. First, equation (2.5) implies that dividend innovations from the day before yesterday have no predictive power for price changes today, consistent with the idea that several days old information is hardly of value for predicting price changes. Second, equation (2.5) further implies that this period's price change is normally distributed with mean $\gamma\sigma^2 Q - \frac{\lambda_2}{1-\lambda_2}\epsilon_{t-1}$ and variance $\frac{1}{(1-\lambda_2)^2}\sigma^2$. The mean of this period's price change is

[3]Note that equation (2.3) holds for all assets in the economy. Differences in prices across assets are only caused by differences in dividend innovations.

[4]Equation (2.23) in Appendix 2.7.1 states the more involved formula for an arbitrary S_0.

larger (smaller) than the market risk premium if the previous period's dividend innovation was negative (positive), consistent with the evidence on negative autocorrelations of daily returns. We therefore work with the assumption $\lambda_2 = A$, although the derivation of our empirical implications is also valid for other parameterizations.

Equations (2.4) and (2.5) show that this period's dividend innovation ϵ_t has predictive power for the next price change $P_{t+1} - P_t$. A classic problem in financial economics is that researchers cannot directly observe dividend innovations. Even for salient information, it is often hard to pin down the exact day the information hits the market (see, for example, the discussion in MacKinlay, 2017, among others), let alone the more difficult task of extracting the exact piece of information that agents trade on for each asset on each single day.

However, in our setting it is possible to use past prices to make inferences about the most recent dividend innovation. Solving equation (2.5) for ϵ_t gives

$$\epsilon_t = (1 - \lambda_2)(P_t - P_{t-1}) + \lambda_2 \epsilon_{t-1} - (1 - \lambda_2)\gamma\sigma^2 Q. \tag{2.6}$$

It further holds for the dividend innovation in the previous period ϵ_{t-1},

$$\epsilon_{t-1} = (1 - \lambda_2)(P_{t-1} - P_{t-2}) + \lambda_2 \epsilon_{t-2} - (1 - \lambda_2)\gamma\sigma^2 Q. \tag{2.7}$$

In equation (2.6) we can substitute ϵ_{t-1} with its expression from equation (2.7). Iterating this procedure for n periods, the formula for this period's dividend innovation becomes

$$\epsilon_t = \lambda_2^n \epsilon_{t-n} + (1 - \lambda_2) \sum_{i=t-n+1}^{t} \lambda_2^{t-i} \left[(P_i - P_{i-1}) - \gamma\sigma^2 Q \right]. \tag{2.8}$$

An econometrician who observes an asset from the start of the economy is able to deduct all dividend innovations if the market risk premium ($\gamma\sigma^2 Q$) and the degree of return extrapolation (λ_2) are known and constant over time. However, time-constant parameters are unlikely, given the ample evidence on time-varying risk aversion (Campbell and Cochrane, 1999), volatility jumps (Merton, 1976, Duffie, Pan, and Singleton, 2000), and time-variation in investor sentiment (Baker and Wurgler, 2006).

A more realistic assumption is that the market risk premium and the degree of return extrapolation are approximately constant for a sufficiently short time period. Under this assumption, equation (2.8) suggests that past price changes from n previous periods can serve as a proxy for today's dividend innovation. Even without exact knowledge of γ, σ^2, and λ_2, assets that outperformed the market several times in a row ($(P_i - P_{i-1}) > \gamma\sigma^2 Q$ over the previous n periods) tend to have a higher dividend innovation ϵ_t in this period. Assets that have underperformed over the previous n periods tend to have a smaller dividend innovation ϵ_t. We call a situation where an asset has outperformed (underperformed) the market over n previous periods without an exception a positive (negative) streak of length n. We are now ready to formulate the main empirical predictions that we test in this paper.

Main Empirical Predictions: First, assets that have experienced a negative (positive) streak in returns over the previous periods are expected to outperform (underperform) the market going one period forward. Second, these abnormal returns tend to increase in absolute terms the longer the streak length becomes.

2.3 Data

Theory provides little guidance on how long the empirical equivalent of one model period should be. As discussed in more detail in Da, Huang, and Jin (2018), the behavioral assumptions of the model imply quick reversals of sentiment and prices and therefore seem more suitable for short-term data. We have argued in Section 2.2 that the implications of the model are broadly consistent with existing empirical evidence collected on daily data. Our main analysis is therefore conducted with daily US data. The fact that our empirical implications can be tested using only past prices as data inputs allows us to examine international markets as well.

2.3.1 US Data

For the US, we use daily stock data from the Center for Research in Security Prices (CRSP). The data of stocks listed on the NYSE, AMEX, or NASDAQ are collected over the period from January 1, 1997 to October 29, 2017.[5] We consider common stocks (share code 10 or 11) and exclude stocks quoted below $1 at the end of the previous month. Returns are calculated on the basis of closing prices and dividends. On delisting days, we adjust the returns using the delisting returns provided by CRSP. Turnover is calculated as number of shares traded on a given day divided by number of shares outstanding.

In order to test whether our results are driven by bid-ask bounces, we also calculate portfolio returns on the basis of mid-quotes, using end-of-day bid and ask prices as well as dividends. We control for possible data inconsistencies by removing any observation where the bid to midpoint ratio is smaller than 50%, and the percentage point difference between midpoint return and closing price return is larger than 100% or smaller than -50%. This filter follows Nagel (2012).

Streaks in returns can be identified with market-adjusted returns of the past few trading days. The market-adjusted return is the raw stock return minus the market return, which is the value-weighted portfolio of all stocks in the sample. A streak in returns of length n has market-adjusted returns of the same sign on each day between $t-1$ and $t-n$, where n is in the set {2,...,5}.

Quarterly earnings announcements are collected from Compustat and matched to the stocks in our sample. There are 371,351 successfully matched earnings announcements. The dates of the earnings announcements are defined as the day with a trading volume reaction. This allows especially earnings announcements that are published during non-trading hours to be matched to the date of the first possible day a trading reaction could occur.

[5]We exclude data before 1997 to concentrate on a period with lower transaction costs and lower bid-ask spreads (Barclay, Christie, Harris, Kandel, and Schultz, 1999). As noted by Nagel (2012), these are all factors that could influence the serial autocorrelation and lead to regime switches within the sample.

We compute institutional ownership based on 13-F filings provided by Thomson-Reuters. The institutional ownership ratio (IOR) is the number of shares held by institutional owners divided by the number of shares outstanding reported in CRSP. As in Nagel (2005), the IOR of stocks without reported institutional holdings is set to zero. Institutional ownership is only reported on a quarterly basis: therefore, the filings at the beginning of a quarter are used for all days in the following quarter. Data corrections are implemented as in Daniel, Klos, and Rottke (2018).

To test the relationship between streak strategy returns and trading volume on the holding day, we compute the detrended trading turnover. For this computation, we calculate turnover as the number of shares traded divided by the number of shares outstanding. The detrended turnover variable is the trading turnover minus the average turnover of the past 200 days; this value is positive or negative when turnover in t is respectively larger or smaller than the average turnover of the past 200 days.

2.3.2 International Data

In an out-of-sample test, we compare our empirical implications with data from the regions Japan, Asia Pacific, Europe and Canada. The regions investigated are based on Fama and French (2012), with the exception that we investigate Canada separately from the US. We collect daily market values and return data from Datastream from January 1, 1997 to October 29, 2017 for all stocks that are primarily quoted in the regions Japan, Asia Pacific, Europe and Canada. In order to correct for data mistakes, we filter the data following Ince and Porter (2006) and Schmidt, von Arx, Schrimpf, Wagner, and Ziegler (2017). Furthermore, we expand the word searches from Ince and Porter (2006) by the country specific screens reported in Griffin, Kelly, and Nardari (2010). We adjust the monthly dynamic filters implemented by Ince and Porter (2006) for daily data along the lines of Jacobs (2016), so that returns higher than 300% are set to "missing," as well as returns for which Ret_t and Ret_{t-1} are larger than 100% and $(1+Ret_t)(1+Ret_{t-1})-1$ is smaller than 50% (Ince and Porter, 2006).

Furthermore, companies that account for more than 90% of the entire market capitalization of the country are eliminated. Micro-cap stocks, i.e. stocks with an end of month unadjusted price below the 5% percentile of the domestic price distribution, are removed from the dataset. All observations are expressed in USD, and the market values and returns reported in other currencies are converted to USD using exchange rates from Datastream. During the considered time period, on January 2, 2002, many EU countries have switched to the Euro. In Datastream, all stocks delisted before the switch in 2002 still have their values reported in the original currency, whereas stocks that have delisting dates following the currency change or are still active are reported in Euro.

Streaks in daily returns are identified in the same manner as those on the US market. The market-adjusted return is the raw return of the stock minus the market return of the country in which the stock is listed. The market return for each country is calculated as the value-weighted portfolio of all the stocks primarily listed in that country.

2.4 Main Results

In this section, we report our main tests of the empirical implications derived in Section 2.2. The model suggests that streaks in daily returns have predictive power for the stock return of the following day.

2.4.1 US Evidence

In a first approach, we examine the return predictability of streaks using an event study. Table 2.1 reports equally-weighted holding day returns and average turnover during and after streaks. Returns behave in the manner predicted by the model: after positive streaks, we see negative returns on the holding day t. Negative streaks are followed by positive daily returns. This suggests that streaks in returns are an empirical proxy to identify the days in which a stock is more likely to over- or underperform.[6]

[6]To some readers, the average absolute returns in Table 2.1 during a streak might seem to be high, with about 2% during a positive streak and about -2% during a negative streak. However, note that these values

Table 2.1 shows further that holding day returns after negative streaks tend to be larger in absolute terms than holding day returns after positive streaks. This result is consistent with the idea that negative returns influence extrapolators' beliefs more strongly than positive returns (see Cassella and Gulen, 2018, and Da, Huang, and Jin, 2018, for direct empirical evidence). It also suggest that returns are not driven entirely by market frictions, as short selling stocks after positive streaks is less profitable than buying stocks after negative streaks, although we do not control for short selling costs.

We continue by forming 10 portfolios based on the sign of past daily market-adjusted returns and assume that stocks are bought at the day's closing price.[7] In what follows, we focus on value-weighted portfolios because previous explanations of short-term autocorrelations, like non-trading periods or non-synchronous trading (see, e.g., Boudoukh, Richardson, and Whitelaw, 1994), are less likely to apply for larger and more actively traded stocks. Furthermore, classic short-term reversal returns tend to be substantially weaker for value-weighted portfolios, making value-weighted portfolios a more challenging ex-ante testing ground. In addition, trading costs, particularly market impact costs, tend to be smaller for larger stocks. For the sake of completeness, we also report results for equally-weighted portfolios.

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are conditional average returns, where we take averages only over positive or only over negative daily returns. A simple simulation in Appendix 2.7.2 shows that the reported magnitudes are well expected.

[7]A difficulty is that we need to know the closing price at the end of a day in order to determine whether or not a streak in returns is intact. At the same time, though, a straightforward testing procedure would assume that a stock can be bought at the closing price. This constitutes a timing problem, which can be dealt with in at least two ways. First, one can construct a portfolio shortly before the closing auction, including only those stocks that have extreme returns today and are unlikely to break streaks during the closing auction. From a theoretical point of view, such stocks are also those with the highest expected return in absolute terms over the holding period. Second, the strategy can be implemented by placing limit-on-close (LOC) orders for stocks whose streaks have a substantial probability to break in the closing auction. For example, let's assume that a stock has had a four-day negative streak in returns and has closed at \$100.01 on the previous day. Shortly before bids for the closing auction must be submitted, the stock is trading at \$99.99 and the market is expected to earn a zero return today. Assuming that the market return is indeed zero, the streak will be intact if the closing price is smaller than or equal to \$100. A LOC order with a buying limit of \$100 ensures that the stock will only be bought if the streak in daily returns continues. A recent academic paper that discusses order types in closing auctions at the US stock exchanges in detail is Comerton-Forde and Putniņš (2011).

Table 2.1: Event study around streaks in returns

This table reports the equally-weighted average stock returns and turnover in an event study. A streak in returns of length n has market-adjusted returns of the same sign on each day between $t-1$ and $t-n$, where n is in the set $\{2, ..., 5\}$. The variable n measures the streak length in days. Day t is the holding day of the streak strategy and day $t+1$ to $t+20$ are the days following it. Return and turnover are expressed as percentages. The return reported is the market-adjusted return.

	Positive streak returns		Negative streak returns	
	Portfolio with 5-day streak length			
Day	Return	Turnover	Return	Turnover
t-20	0.017	0.757	0.009	0.861
t-5	2.076	0.808	-2.047	0.780
t-4	2.121	0.860	-2.031	0.783
t-3	2.187	0.921	-2.069	0.813
t-2	2.261	0.988	-2.158	0.857
t-1	2.317	1.058	-2.316	0.920
t	**-0.117**	**0.977**	**0.289**	**0.949**
t+1	-0.100	0.907	0.189	0.932
t+2	-0.071	0.876	0.141	0.912
t+3	-0.042	0.855	0.107	0.899
t+4	-0.038	0.847	0.078	0.885
t+5	-0.013	0.837	0.046	0.879
t+20	0.031	0.758	0.007	0.850
	Portfolio with 4-day streak length			
Day	Return	Turnover	Return	Turnover
t-20	0.018	0.785	0.010	0.828
t-5	-0.191	0.770	0.324	0.836
t-4	2.144	0.806	-2.066	0.764
t-3	2.198	0.866	-2.046	0.768
t-2	2.283	0.935	-2.106	0.802
t-1	2.343	1.013	-2.263	0.859
t	**-0.122**	**0.934**	**0.270**	**0.886**
t+1	-0.070	0.871	0.149	0.875
t+2	-0.053	0.844	0.119	0.862
t+3	-0.040	0.829	0.088	0.854
t+4	-0.030	0.820	0.074	0.847
t+5	-0.025	0.813	0.055	0.839
t+20	0.032	0.750	0.010	0.840
	Portfolio with 3-day streak length			
Day	Return	Turnover	Return	Turnover
t-20	0.016	0.766	0.017	0.808
t-5	-0.044	0.751	0.113	0.806
t-4	-0.217	0.758	0.330	0.809
t-3	2.216	0.799	-2.086	0.741
t-2	2.282	0.868	-2.082	0.748
t-1	2.366	0.946	-2.211	0.794
t	**-0.137**	**0.879**	**0.255**	**0.822**

Continued on next page

Table 2.1 – (continued from previous page)

	Positive streak returns		Negative streak returns	
t+1	-0.050	0.827	0.108	0.819
t+2	-0.035	0.806	0.092	0.813
t+3	-0.026	0.796	0.075	0.810
t+4	-0.026	0.792	0.065	0.806
t+5	-0.015	0.785	0.052	0.803
t+20	0.027	0.741	0.019	0.800
	Portfolio with 2-day streak length			
Day	Return	Turnover	Return	Turnover
t-20	0.021	0.776	0.026	0.731
t-5	-0.006	0.737	0.059	0.775
t-4	-0.038	0.736	0.096	0.776
t-3	-0.239	0.742	0.317	0.777
t-2	2.304	0.787	-2.124	0.715
t-1	2.377	0.864	-2.191	0.733
t	**-0.153**	**0.815**	**0.236**	**0.764**
t+1	-0.031	0.781	0.079	0.770
t+2	-0.018	0.767	0.065	0.770
t+3	-0.010	0.76	0.056	0.770
t+4	-0.013	0.759	0.053	0.769
t+5	-0.010	0.757	0.045	0.769
t+20	0.024	0.771	0.018	0.745

Table 2.2, Panel A, reports the value-weighted returns of portfolios formed on different streak lengths. After negative streaks in returns, portfolio returns increase with streak length; analogously, a longer positive streak is associated with lower returns.[8] For example, if we build a value-weighted portfolio with stocks that have lost value relative to the market on all the five previous trading days, the average market-adjusted return of this portfolio over the next trading day is 13.1 basis points, with a t-stat of 8.408.[9] Controlling for bid-ask bounces by using mid-quote returns does not eliminate the effect: see Panel B of Table 2.2. This result is not surprising, since we are building value-weighted portfolios, and spreads tend to be small for large stocks (Amihud, 2002).[10]

[8]These portfolio returns are qualitatively similar to the price changes that we observe in simulated data using the model from Section 2.2, see Appendix 2.7.3, Table 2.20.

[9]Table 2.21 in Appendix 2.7.4 reports the Fama-French three-factor model (FF3) alphas of the value-weighted streak portfolios. The portfolio with stocks that have lost value during all previous 5 trading days yields a Fama-French three-factor alpha of 12.5 basis points with a t-stat of 6.985.

[10]Our results also contrast Cox and Peterson (1994), who investigate the returns following large price declines. They find that, when accounting for size and bid-ask bounce, there is no daily reversal effect after October 1987. We find that bid-ask bounces do not account for our streak strategy returns.

Table 2.2: Value- and equally-weighted market-adjusted returns of streak portfolios

For streak portfolios with different streak lengths, this table reports average market-adjusted portfolio returns, standard deviations, t-stats, and average number of stocks in the portfolio. The length of a streak is measured in number of days ranging from 1 to 5. The values reported are those recorded on the day following the streak. Portfolio returns are based on closing prices in Panels A and C, and on mid-quote prices in Panels B and D. *No. of stocks* reports the average number of firms in each portfolio per day. For each portfolio and day, we compute the value-weighted and the equally-weighted average of the quoted half-spreads. Panel A (C) reports the time series of the value-weighted (equally-weighted) quoted half-spreads. Portfolio returns, their standard deviation, and quoted half-spreads are reported in percentages. Panels A and B report the portfolio returns weighted on the basis of the market value of the previous day. Panels C and D report the returns of an equally-weighted portfolio. The t-statistics are Newey-West t-statistics corrected for serial correlation and heteroskedasticity in the error term.

	Length of streak (days)				
	1	2	3	4	5
Panel A: Value-weighted portfolio returns (in %)					
After negative streaks	0.009	0.046	0.069	0.107	0.131
Std. dev.	0.333	0.517	0.689	0.864	1.081
t-stat	2.318	7.120	7.632	7.914	8.408
No. of stocks	2,400	1,187	579	282	138
VW quoted half-spread	0.151	0.153	0.156	0.161	0.170
After positive streaks	−0.009	−0.037	−0.052	−0.061	−0.085
Std. dev.	0.311	0.462	0.582	0.714	0.858
t-stat	−2.412	−5.596	−5.678	−5.798	−6.543
No. of stocks	2,250	1,037	476	220	103
VW quoted half-spread	0.148	0.146	0.146	0.147	0.149
Panel B: Value-weighted portfolio returns with midquotes (in %)					
After negative streaks	−0.004	0.033	0.054	0.091	0.118
Std. dev.	0.346	0.536	0.708	0.892	1.113
t-stat	−0.880	4.926	5.742	7.044	7.271
No. of stocks	2,348	1,160	566	276	135
After positive streaks	0.006	−0.021	−0.038	−0.044	−0.068
Std. dev.	0.325	0.474	0.595	0.737	0.886
t-stat	1.465	−3.442	−4.051	−4.180	−5.291
No. of stocks	2,201	1,013	466	215	100
Panel C: Equally-weighted portfolio returns (in %)					
After negative streaks	0.141	0.194	0.211	0.227	0.240
Std. dev.	0.294	0.462	0.596	0.720	0.873
t-stat	16.760	18.804	20.134	20.207	17.970
No. of stocks	2,400	1,187	579	282	138
EW quoted half-spread	0.777	0.740	0.697	0.660	0.630
After positive streaks	−0.145	−0.149	−0.125	−0.107	−0.098
Std. dev.	0.290	0.407	0.485	0.559	0.675
t-stat	−16.543	−16.225	−14.161	−11.663	−9.582
No. of stocks	2,250	1,037	476	220	103
EW quoted half-spread	0.750	0.677	0.603	0.540	0.492
Panel D: Equally-weighted portfolio returns with mid-quotes (in %)					
After negative streaks	−0.049	−0.015	0.012	0.045	0.076
Std. dev.	0.278	0.440	0.570	0.692	0.843
t-stat	−7.936	−2.364	1.609	5.445	7.537
No. of stocks	2,348	1,160	566	276	135
After positive streaks	0.034	0.037	0.037	0.029	0.015
Std. dev.	0.294	0.404	0.488	0.560	0.677
t-stat	5.405	5.114	4.650	3.502	1.606
No. of stocks	2,201	1,013	466	215	100

Panel A also reports the time-series average of the value-weighted, quoted half-spread on the holding day. We follow the market microstructure literature and compute the quoted half-spread of a stock as the difference between the quoted bid and the quoted ask prices divided by two times the mid-price (see, e.g. Bessembinder and Venkataraman, 2010). If trades are executed at the quoted ask and bid prices, quoted half-spreads can be viewed as a proxy for the one-way transaction costs of a trade. CRSP quoted spreads closely approximate TAQ effective spreads, especially in recent years (Chung and Zhang, 2014, Abdi and Ranaldo, 2017). On average, spreads are higher than portfolio returns. However, the comparison of averages masks considerable time-variations in portfolio returns and quoted half-spreads, which we will be discussed shortly.

Panel C shows that market-adjusted returns tend to be higher in equally-weighted portfolios than in value-weighted portfolios.[11] However, market-adjusted returns are not monotonic in the length of streaks after a positive streaks in daily returns. Returns are much more affected by using mid-quote prices instead of end-of-day prices (see Panel D). Market-adjusted returns after positive streaks are even positive. Perhaps surprisingly, if we compute portfolio returns based on mid-quotes, value-weighted portfolio returns are more extreme than equally-weighted portfolio returns. These results suggests that, while equally-weighted returns from streak strategies are largely caused by bid-ask bounces, value-weighted returns cannot solely be explained by large bid-ask spreads.

Overall, portfolios formed on the basis of streaks in daily returns strongly support the main empirical predictions of the theoretical model. The return of the trading strategy increase monotonically with streak length. This holds especially for the value-weighted portfolios.[12]

[11]In Nagel's (2012) computation of liquidity provision returns, he uses the stock returns for the portfolio weighting, resulting in large weights for small stocks, even compared to equally-weighting. In Appendix 2.7.5, we apply a similar weighting scheme to our streak portfolios. In this specification, we use the absolute sums of daily returns during the streaks as weights to construct the portfolios.

[12]The results of a market-value-weighted Fama-MacBeth regression in Appendix 2.7.6 confirm that the streak strategy returns increase with streak length.

Table 2.3: Summary of the dollar-neutral long-short strategy

The long leg consists of an equally-weighted portfolio including the four value-weighted streak portfolios based on negative streaks stretching over 2 to 5 days. The short leg consists of an equally-weighted portfolio of the four value-weighted portfolios based on positive streaks stretching over 2 to 5 days. The reported daily returns of the strategy are based on end-of-day prices in column 1 and on mid-quote prices in column 2. Portfolio returns and standard deviations are reported in percentages. The Sharpe ratio of the long-short portfolio is annualized. The t-statistics are Newey-West t-statistics corrected for serial correlation and heteroskedasticity in the error term. The strategy beta is the coefficient of the full sample time-series regression of the trading strategy on the CRSP value-weighted market.

	End-of-day returns	Mid-quote returns
Ret (in %)	0.147	0.116
Std. dev. (in %)	1.118	1.135
t-stat	8.422	6.758
Annualized Sharpe ratio	2.086	1.629
Beta	0.227	0.233

The value-weighted portfolios based on a streak length of 2 to 5 days in Table 2.2 are used to create a dollar-neutral long-short portfolio. The short leg consists of the four portfolios with a positive return streaks of 2 to 5 days; the long leg consists of the portfolios with negative return streaks of 2 to 5 days. In the long and the short leg, each streak-length portfolio receives the weight of $\frac{1}{4}$. Within each streak-length portfolio, stocks are still value-weighted. Descriptive statistics of the dollar-neutral long-short portfolio are reported in Table 2.3. We calculate returns based on transaction prices and based on mid-quotes. The value-weighted portfolios earn 14.7 (t-stat: 8.422) and 11.6 (t-stat: 6.758) basis points on average, respectively. Based on transaction prices, the strategy has an annualized Sharpe ratio of 2.086. Using mid-quotes reduces the annualized Sharpe ratio to 1.629.[13] To put these numbers into perspective, Nagel's (2012) value-weighted industry reversal strategy, calculated on the basis of transactions prices, earns 2 bps per day and has an annualized Sharpe ratio of 0.56.

[13]Figure 2.4 in Appendix 2.7.7 reports the betas of the long-short streak strategy over time.

Figure 2.1 contains four panels that show the development of streak-returns and several short-term reversal strategies over time. These panels highlight differences and similarities among them.

Panel A shows the six-month moving average of streak returns and quoted half-spreads. Half-spreads, which are expressed as percentages of mid-prices and are weighted in exactly the same way as returns, are high in the late 90's. In the early 2000's, spreads significantly decline as a result of the decimalization of quotes (Bessembinder, 2003) and the rise of algorithmic trading (Hendershott, Jones, and Menkveld, 2011). Afterwards, they continue to decrease at low levels with a temporary rise after the market decline during the financial crisis (Hameed, Kang, and Viswanathan, 2010). Starting in mid 2002, value-weighted quoted half-spreads roughly equal portfolio returns. In the following years, returns seem to be slightly higher than spreads. This pattern is consistent with a *limits of arbitrage* story. To the extent that streak returns constitute mispricing, arbitraging the mispricing away was impossible in the late 90's. After spreads have fallen in the 2000's, streak returns have decreased as well. However, they have decreased in such a way that one can earn slightly more than the transaction costs implied by quoted spreads (see Section 2.5 for further details). Recognizing that there are other transaction costs than bid-ask spreads, the strategy earns most likely just its costs for a small arbitrageur that does not move prices much.

Panel B of Figure 2.1 plots the development of $1 invested in the long-short streak portfolio, calculated either on the basis of end-of-day prices or mid-quotes. The figure further compares our long-short streak strategy to the market portfolio, a value-weighted long-short portfolio that goes long on all previous day's losers and short on all previous day's winners, and the short-term reversal (STR) strategy from Kenneth French's data library. Panel C compares these four strategies in terms of their six-month moving average.

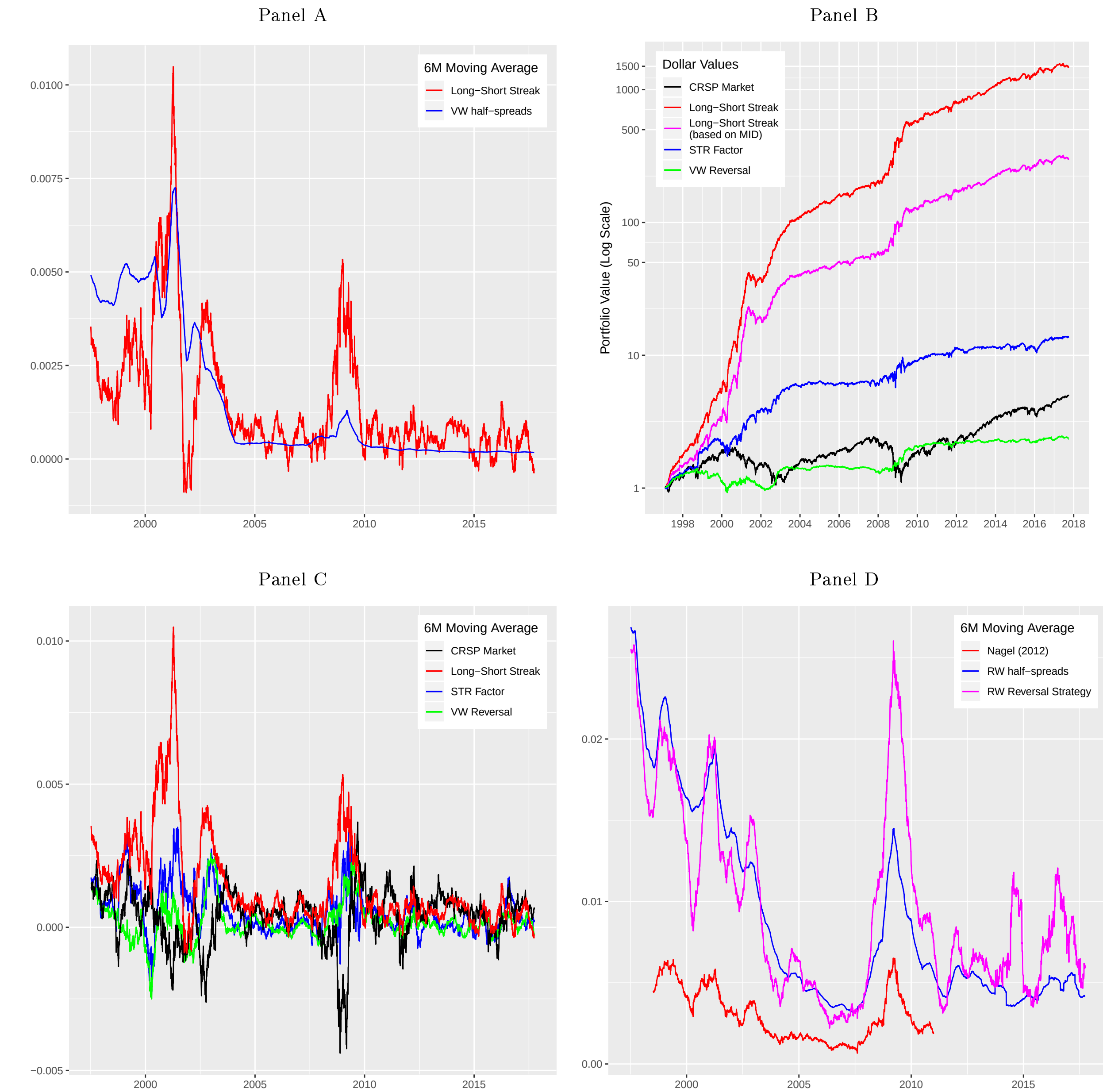

Figure 2.1: Returns and spreads over time

Panel A reports the six-month moving average of daily returns and the average value-weighted quoted half-spreads of the long-short streak portfolio. The average value-weighted quoted half-spreads are computed as simple average of the ten value-weighted quoted half-spreads of all portfolios that were combined to long-short streak strategy as in Table 2.3. The weighting schemes of returns and spreads in Panel A are identical. Panel B plots how a dollar invested in each of the four strategies at the beginning of 1997 would have developed over time before costs. The long-short streak strategy is plotted based on end-of-day returns and on mid-quote returns. The graph also shows the development for the value-weighted market and the short-term reversal factor. Panel C reports the six-month moving average of daily streak returns (as in Panel A) but adds the market portfolio, the STR factor, and a value-weighted portfolio that longs (shorts) all stocks that have underperformed (outperformed) the market over the previous days. Panel D shows the six-month moving averages of Nagel's (2012) reversal strategy (Data source: https://voices.uchicago.edu/stefannagel/code-and-data/, last accessed: April 2019) and of the return-weighted average of quoted half-spreads. The RW reversal strategy forms a portfolio that long (short) the stocks that have underperformed (outperformed) the market over the previous day, and weights each stock with the absolute value of the market-adjusted return from the previous day. The weighting schemes of *RW Reversal Strategy* and *RW half-spreads* in Panel D are identical.

On a value-weighted basis, our streak strategy outperforms the well-known Fama-French short-term reversal factor by a wide margin. This is a fair comparison, as the STR factor, like our long-short portfolio, is a combination of value-weighted portfolios. Note that the outperformance of the streak portfolio is not achieved by overweighting small stocks; on the contrary, our long-short portfolio invests in larger firms than the STR factor. The stocks in streak portfolios have an average market capitalization of \$3,714.6 millions and a value-weighted average market capitalization of \$80,987.24 millions. The corresponding numbers for the STR factor are \$2,885.1 millions and \$75,480.17 millions, respectively. Both differences are highly statistically significant (t-stats > 10) and based on our replication of the STR factor.

Panel D shows the six-month moving average of a return-weighted reversal strategy. This strategy overweights small stocks and is therefore conceptually different from the strategies that partly or completely follow value-weighted approaches. Not surprisingly, returns and spreads for these smaller stocks are much higher. We also plot Nagel's (2012) reversal strategy, which is an equally-weighted combination of ten return-weighted reversal portfolios. Return-weighted strategies are highly correlated with return-weighted quoted half-spreads over the entire sample, while returns from streak strategies are substantially smaller than spreads in the late 90's and during several months of the bear market in the early 2000's. This observation is consistent with the idea that return-weighted strategies solely capture returns from liquidity provisions, while streak strategies do not. We further see that a simple value-weighted reversal strategy underperforms the market (Panel B). Value-weighted strategies tend to perform well when the market does poorly (Panels B and C).

We want to make sure that our strategy is conceptually and economically different from established short-term reversal strategies, beyond the qualitative discussion of the patterns visualized in Figure 2.1. Therefore, we conduct four empirical tests.

Table 2.4: Alphas of streak portfolios controlled for the Fama-French five-factors and the short-term reversal factor

This table reports the regression of the value-weighted (Panel A) and equally-weighted (Panel B) streak portfolios on the five Fama-French factors, the Fama-French three-factors, and the short-term reversal factor. The t-statistics are reported in brackets below the estimates. The factors are taken from Kenneth French's website: *MktRF* is the market portfolio minus the risk free rate; *SMB* is the small-minus-big factor; *HML* is the high-minus-low factor; *RMW* is the factor robust-minus-weak, and *CMA* is the conservative-minus-aggressive factor. More detail on the factors can be found in Fama and French (1993, 2015). *STR* is the short-term reversal factor from Kenneth French's data library. The t-statistics are Newey-West t-statistics corrected for serial correlation and heteroskedasticity in the error term. The streak portfolios are based on daily data of stocks listed on NYSE, AMEX, or NASDAQ and collected from CRSP for the sample period from January 1, 1997 to October 31, 2017.

Panel A: Value-weighted streak portfolio					Panel B: Equally-weighted streak portfolio				
Constant	0.124***	0.117***	0.142***	0.116***	Constant	0.312***	0.308***	0.331***	0.308***
	(6.643)	(6.429)	(6.303)	(7.511)		(20.195)	(17.923)	(15.643)	(16.749)
MktRF	0.039	0.086***	0.225***		MktRF	0.088***	0.109***	0.235***	
	(1.490)	(3.010)	(7.163)			(3.626)	(4.812)	(9.044)	
SMB	−0.040	−0.015	−0.017		SMB	0.008	0.040	0.039	
	(−1.107)	(−0.399)	(−0.461)			(0.240)	(1.047)	(0.749)	
HML	0.022	−0.070	−0.139*		HML	−0.063	−0.077*	−0.139***	
	(0.386)	(−1.191)	(−1.806)			(−1.169)	(−1.660)	(−2.698)	
RMW	−0.129**				RMW	−0.128**			
	(−2.262)					(−2.575)			
CMA	−0.266***				CMA	−0.016			
	(−2.970)					(−0.223)			
STR	0.499***	0.525***		0.571***	STR	0.464***	0.472***		0.530***
	(10.841)	(10.184)		(11.076)		(12.447)	(12.656)		(12.651)
Adj. R^2	0.238	0.227	0.067	0.218	Adj. R^2	0.259	0.256	0.092	0.239

First, our long-short streak portfolio generates a daily alpha of 12.4 basis points after controlling for the five Fama-French factors and the short-term reversal factor (see Table 2.4). If our strategy is just a different way of calculating the well-known reversal-factor portfolio, we would observe an alpha of zero.

Second, we investigate if our streak strategy does solely capture that stocks with extreme $t-1$ returns have more extreme reversal returns on the following day. We match streak stocks to stocks without streaks on size and return in $t-1$. As in Barber and Lyon (1997), we first find all stocks with a market value between 70% and 130% of the market value of the streak stock, choosing then from this group of possible control stocks those with the returns on day $t-1$ closest to the streak stocks. If the streak strategy is only capturing the reversal of a stock with very high return in $t-1$, then portfolios of the streak stocks and their matched control stocks would not have significantly different returns.

In Panel A of Table 2.5, we report the daily value-weighted portfolio return on the holding day for streak stocks and control stocks. We report the value-weighted returns after negative and positive streaks in returns. Streak length varies from 2 to 5 days. For example, if a stock has a 5-day negative streak in returns, then the market-adjusted returns on all 5 days prior to t are negative; however, the matched control stock has a negative market-adjusted return only on day $t-1$, but a positive one on day $t-2$. We report the difference in returns between the streak stock portfolio and control stock portfolio in the last column of Table 2.5.

On holding day t, returns of streak portfolios are consistently more extreme than returns of portfolios built on control stocks. All differences are highly statistically significant. The Newey-West t-statistics are reported underneath the values in brackets. We further observe that, for both negative and positive streaks, differences in the absolute value-weighted portfolio returns increase with streak length.

Table 2.5: Holding day returns of streak stocks vs. control stocks

This table reports the holding day returns of stocks with streaks in returns and those of the matched control stocks. To find matching controls for size and the most recent daily return, the following two step procedure is used. First, the universe of possible control stocks is defined as all firms where (i) the market-adjusted return on the day before yesterday has the opposite sign of yesterday's market-adjusted return and (ii) the market capitalization lies between 70% and 130% of the market capitalization of the streak stock. Second, stocks with streaks in returns are matched to potential control stocks based on the most recent daily return. The table reports the average value- and equally-weighted holding day return for a portfolio of streak stocks and a portfolio of matched control stocks in Panel A and B, respectively. The length of a streak is measured in number of days, ranging from 2 to 5. The sign of the streak return is reported in the second column. The values reported are those recorded on the day after the streak. Portfolio returns are based on returns of closing prices. The last column reports the difference in holding day returns of the streak stocks and the control stocks. Returns are expressed as percentages. T-statistics are reported in brackets below the average returns. The t-statistics are Newey-West t-statistics corrected for serial correlation and heteroskedasticity in the error term.

Panel A: Value-weighted portfolios					Panel B: Equally-weighted portfolios				
Streak length	Return streak sign	Streak stocks	Control stocks	Difference	Streak length	Return streak sign	Streak stocks	Control stocks	Difference
5	-	0.170	0.063	0.107	5	-	0.301	0.122	0.179
		(7.600)	(3.603)	(5.836)			(12.221)	(6.583)	(11.789)
4	-	0.146	0.058	0.088	4	-	0.287	0.116	0.171
		(7.128)	(3.519)	(5.706)			(12.352)	(6.502)	(13.288)
3	-	0.108	0.059	0.049	3	-	0.271	0.114	0.157
		(6.101)	(3.990)	(4.142)			(12.298)	(6.578)	(14.124)
2	-	0.085	0.056	0.029	2	-	0.255	0.116	0.139
		(5.272)	(3.696)	(3.121)			(12.471)	(6.798)	(14.672)
5	+	-0.047	0.114	-0.160	5	+	-0.036	-0.012	-0.024
		(-2.522)	(5.698)	(-8.344)			(-1.753)	(-0.59)	(-1.988)
4	+	-0.022	0.100	-0.122	4	+	-0.045	-0.016	-0.029
		(-1.192)	(5.456)	(-8.125)			(-2.139)	(-0.830)	(-2.954)
3	+	-0.013	0.104	-0.117	3	+	-0.064	-0.023	-0.042
		(-0.773)	(5.850)	(-7.964)			(-2.868)	(-1.167)	(-4.916)
2	+	0.002	0.097	-0.095	2	+	-0.088	-0.035	-0.053
		(0.125)	(5.635)	(-7.546)			(-3.900)	(-1.776)	(-7.429)

We also report equally-weighted returns in Panel B of Table 2.5. This approach is equivalent to comparing the simple average of all streak stocks to that of all matched stocks. Panel B shows that, as with the value-weighted portfolios, absolute returns of streak stocks are larger compared to returns of control stocks. However, the differences in the equally-weighted portfolios do not show a monotonic increase in streak length after positive streaks in returns.

Our third test deals with the possibility that streak strategies are just picking up large liquidity shocks among highly illiquid stocks. The premise would then be that those shocks need more than a day to find their way into prices. We consider this possibility to be ex-ante unlikely, given the excess returns that we have already reported for value-weighted portfolios. In a value-weighted portfolio, the stocks with the highest weights tend not to be illiquid.

To address the argument formally, we run Fama-MacBeth regressions weighted on market value. Streak dummies always remain significant, no matter if we include just the market-adjusted return of the previous day or additionally the previous n-day market-adjusted returns (see Panels C and D in Table 2.24, Appendix 2.7.8).[14]

In our fourth and final test, we first sort the cross-section of returns by its $t-1$ market-adjusted return each day. Then we divide the stocks into four equally sized quartiles based on their previous day's returns. Afterwards, we calculate streak strategies within these quartiles. Table 2.6 reports the value-weighted market-adjusted returns on the holding day. We find that value-weighted portfolios in the upper and lower $t-1$ return quartile still have significant holding day returns after streaks. This provides further evidence that streaks in returns do not simply identify stocks with high $t-1$ returns.

[14]It is interesting to note that some streak dummies switch signs in standard Fama-MacBeth regressions after adding previous n-day market-adjusted returns as additional control variables (see Panels A and B in Table 2.24). Earlier forms of daily return predictability tend to vanish with firm size. In contrast, the empirical importance of streaks in daily returns seems to be even more robust among large stocks.

Table 2.6: Sorts on t-1 returns within each streak portfolio

On each day, the cross-section of stocks is ranked based on their market-adjusted return yesterday ($t-1$) and assigned to one of four buckets. For the assignment of the stocks, the 25%, 50%, and 75% quantiles of yesterday's returns are used as breakpoints. In each bucket, the streak portfolios are constructed for a streak length of 1 to 5 days, and the resulting portfolios are value-weighted. The returns are market-adjusted and the t-statistics are Newey-West t-statistics corrected for serial correlation and heteroskedasticity in the error term. *No. of stocks* reports the average number of stocks in the portfolio for all days for which the portfolio is not empty. The 75% quantile breakpoint is negative on 8 different dates due to a skewed return distribution on these days: August 9, 1997, September 29, 1999, March 22, 2000, April 4, 2000, May 25, 2000, May 5, 2002, and October 2, 2002. The portfolios with negative streaks in returns and a $t-1$ return above the 75% quantile are not reported because of their limited size. The 25% quantile breakpoint is positive on two occasions – August 34, 2015 and September 30, 2017 – and the portfolio returns of stocks with a positive streak and a $t-1$ return in the lower 25% quantile are also not reported due to the small sample.

	Length of streak (days)				
	1	2	3	4	5
Market-adjusted returns above the 75% quantile on day $t-1$					
Value-weighted portfolio returns after positive streaks	-0.017	-0.046	-0.070	-0.094	-0.128
Std. dev.	0.581	0.706	0.848	1.019	1.241
t-stat	-2.212	-4.621	-4.965	-6.564	-6.834
No. of stocks	1,171	526	241	111	52
Market returns above the 50% and below the 75% quantile on day $t-1$					
Value-weighted portfolio returns after positive streaks	-0.006	-0.030	-0.044	-0.050	-0.056
Std. dev.	0.319	0.474	0.617	0.775	0.965
t-stat	-1.404	-5.178	-5.345	-4.536	-4.199
No. of stocks	965	454	209	97	45
Value-weighted portfolio returns after negative streaks	0.005	0.029	0.021	0.061	0.099
Std. dev.	0.454	0.598	0.863	1.068	1.581
t-stat	0.542	2.527	1.379	3.232	3.401
No. of stocks	464	244	118	55	27
Market returns above the 25% and below the 50% quantile on day $t-1$					
Value-weighted portfolio returns after positive streaks	-0.016	-0.021	-0.054	-0.060	-0.043
Std. dev.	0.632	0.777	1.006	1.152	1.403
t-stat	-1.242	-1.233	-2.434	-2.377	-1.397
No. of stocks	280	140	66	31	15
Value-weighted portfolio returns after negative streaks	0.002	0.030	0.044	0.076	0.086
Std. dev.	0.309	0.465	0.672	0.819	1.056
t-stat	0.446	4.829	4.837	6.081	5.816
No. of stocks	974	489	239	116	57
Market returns below the 25% quantile on day $t-1$					
Value-weighted portfolio returns after negative streaks	0.031	0.083	0.119	0.179	0.230
Std. dev.	0.737	0.927	1.116	1.335	1.583
t-stat	3.334	7.245	8.177	9.349	10.284
No. of stocks	1,168	561	274	135	67

2.4.2 International Evidence

The theory-driven trading strategy based on streaks in returns exhibits significant daily abnormal returns when applied to US stocks. In the following, we replicate these results on international stock markets for two reasons. First, going outside the US provides out-of-sample evidence (see, e.g., the discussion in Asness, Moskowitz, and Pedersen, 2013). Second, a larger stock universe would allow us to develop a streak strategy that achieves a higher level of diversification.

We analyze four additional international regions: Japan, Europe, Asia Pacific, and Canada, which we have chosen following Fama and French (2012). Unlike their work, we do not include the US stock market in the same region as Canada, because we have already given a detailed summary of the streak strategy in the US stock market.

Table 2.7: International streak portfolios by region

This table presents the value-weighted streak portfolio returns for different streak lengths for 4 regions: Japan, Canada, Europe, and Asia Pacific. For each streak portfolio with different streak lengths of positive and negative returns, this table reports portfolio market-adjusted returns, standard deviations, and t-statistics. The length of a streak is measured in number of days, ranging from 1 to 5. The values reported are those recorded on the day following the streak. *No. of stocks* is the average number of stocks in each portfolio on each day. Portfolio returns and their standard deviations are expressed as percentages. The t-statistics are Newey-West t-statistics corrected for serial correlation and heteroskedasticity in the error term.

	Length of streak (days)				
	1	2	3	4	5
Japan					
Value-weighted portfolio returns after negative streaks	-0.011	0.026	0.065	0.094	0.108
Std. dev.	0.332	0.511	0.669	0.824	1.006
t-stat	-2.058	3.777	7.334	8.241	7.187
No. of stocks	1,263	667	351	183	94
Value-weighted portfolio returns after positive streaks	0.016	-0.017	-0.044	-0.070	-0.082
Std. dev.	0.416	0.617	0.831	1.040	1.308
t-stat	2.214	-1.846	-3.514	-4.601	-4.431
No. of stocks	1,112	511	232	104	46
Europe					

Continued on next page

Table 2.7 – (continued from previous page)

	Length of streak (days)				
	1	2	3	4	5
Value-weighted portfolio returns after negative streaks	-0.008	0.024	0.041	0.056	0.066
Std. dev.	0.271	0.396	0.518	0.651	0.788
t-stat	-1.890	5.071	6.842	6.538	6.183
No. of stocks	2,731	1,423	737	384	201
Value-weighted portfolio returns after positive streaks	0.008	-0.018	-0.044	-0.059	-0.068
Std. dev.	0.266	0.385	0.496	0.640	0.812
t-stat	1.986	-3.581	-6.539	-7.686	-6.723
No. of stocks	2,424	1,118	513	234	109
Asia Pacific					
Value-weighted portfolio returns after negative streaks	-0.027	0.019	0.048	0.078	0.105
Std. dev.	0.280	0.442	0.592	0.783	0.955
t-stat	-6.250	3.255	6.376	7.658	8.034
No. of stocks	1,472	780	408	213	111
Value-weighted portfolio returns after positive streaks	0.027	-0.011	-0.034	-0.062	-0.064
Std. dev.	0.286	0.443	0.612	0.792	1.046
t-stat	5.890	-1.872	-4.314	-6.175	-4.759
No. of stocks	1,223	531	228	97	42
Canada					
Value-weighted portfolio returns after negative streaks	-0.017	0.026	0.044	0.058	0.083
Std. dev.	0.529	0.740	0.926	1.203	1.580
t-stat	-2.212	2.466	3.174	3.167	3.469
No. of stocks	444	221	108	52	25
Value-weighted portfolio returns after positive streaks	0.013	-0.021	-0.019	-0.034	-0.032
Std. dev.	0.512	0.696	0.924	1.180	1.664
t-stat	1.795	-2.086	-1.413	-2.000	-1.299
No. of stocks	401	178	78	35	15

In all regions, similar return predictability after streaks in daily returns can be observed. Table 2.7 reports the value-weighted market-adjusted returns after 1- to 5-day streaks. In all regions, we see sizeable returns. Absolute portfolio returns on the holding day increase with streak length in the predicted direction.[15] In terms of magnitude, absolute returns in international markets tend to be slightly smaller than in the US. This result is broadly consistent with Jacobs (2016) and Jacobs and Müller (2019), who report that stock market anomalies are often of comparable magnitude and sometimes even less pronounced in international markets.

Table 2.8: Correlation of streak strategy in different regions

Correlation matrix of the long-short streak portfolios of different regions. For the regions Japan, Canada, Europe, Asia Pacific and US, the long-short streak portfolio is computed. In each region, the long leg consists of the four portfolios with streaks of 2 to 5 days in negative returns; the short leg consists of the portfolios with streaks of 2 to 5 days in positive returns.

	Japan	Canada	Europe	US	Asia Pacific
Japan	1	0.072	0.134	0.043	0.214
Canada	0.072	1	0.267	0.424	0.098
Europe	0.134	0.267	1	0.358	0.181
US	0.043	0.424	0.358	1	0.058
Asia Pacific	0.214	0.098	0.181	0.058	1

The US and international streak portfolios do not exhibit highly correlated returns, as reported in Table 2.8. This suggests further benefits from diversifying internationally. Indeed, a diversified streak strategy that puts the same weight on the regions Japan, US, Canada, Europe and Asia Pacific increases the annualized Sharpe ratio to 2.696. A strategy based solely on US stocks has an annualized Sharpe ratio of 2.086.

[15] In Appendix 2.7.9, Table 2.25 and Table 2.26 report the streak portfolio returns for each country separately.

2.5 Further Empirical Evidence

In this section, we gather further empirical evidence on the US streak strategy. First, we estimate the model parameter λ_2 empirically and show that stocks which are subject to a higher degree of return extrapolation earn higher streak returns. Second, we test whether the streak strategy has significant returns after accounting for trading costs. This is especially important for a trading strategy that is rebalanced daily. Third, we look at streak strategy returns on earnings announcement days. Fourth, we investigate the relationship between trading volume on the holding day and streak strategy returns. Last, we test the streak strategy on stocks with different level of institutional ownership.

Estimating the level of extrapolation λ_2

The model suggests that the holding day returns after streaks in daily returns should be higher for stocks with a higher λ_2 parameter. Let's recall that the parameter λ_2 determines the weight extrapolators put on more recent price changes compared to price changes that are further back in the past. To test whether stocks with a higher λ_2 have higher holding day returns after streaks, we estimate an empirical λ_2 for each stock in our sample.

We go back to the model and rearrange equation (2.8) to write $P_t - P_{t-1}$ as a function of the last 5 price changes, so that n = 6. This leads to the following specification of $P_t - P_{t-1}$:

$$\begin{aligned} P_t - P_{t-1} = Q\gamma\sigma^2 &- \lambda_2^5 \left(P_{t-5} - P_{t-6} - Q\gamma\sigma^2\right) - \lambda_2^4 \left(P_{t-4} - P_{t-5} - Q\gamma\sigma^2\right) \\ &- \lambda_2^3 \left(P_{t-3} - P_{t-4} - Q\gamma\sigma^2\right) - \lambda_2^2 \left(P_{t-2} - P_{t-3} - Q\gamma\sigma^2\right) \\ &- \lambda_2 \left(P_{t-1} - P_{t-2} - Q\gamma\sigma^2\right) + \frac{\epsilon_t - \lambda_2^6 \epsilon_{t-6}}{1 - \lambda_2}. \end{aligned} \tag{2.9}$$

A time-series regression is run separately for each stock in the sample:

$$\begin{aligned} AdjRet_{i,t} = \alpha_i + \beta_{i,1} AdjRet_{i,t-1} + \beta_{i,2} AdjRet_{i,t-2} + \beta_{i,3} AdjRet_{i,t-3} \\ + \beta_{i,4} AdjRet_{i,t-4} + \beta_{i,5} AdjRet_{i,t-5} + u_i, \end{aligned} \tag{2.10}$$

where $AdjRet_{i,t}$ is the market-adjusted return of stock i in period t. Equations (2.9) and (2.10) allow to set up the following minimization problem to estimate the $\hat{\lambda}_{i,2}$ of stock i given the estimated $\hat{\beta}_i$'s from equation (2.10):

$$\hat{\lambda}_{i,2} = \arg\min_{\lambda_{i,2}} \ (\hat{\beta}_{i,1} + \lambda_{i,2})^2 + (\hat{\beta}_{i,2} + \lambda_{i,2}^2)^2 + (\hat{\beta}_{i,3} + \lambda_{i,2}^3)^2 + (\hat{\beta}_{i,4} + \lambda_{i,2}^4)^2 + (\hat{\beta}_{i,5} + \lambda_{i,2}^5)^2. \tag{2.11}$$

Using the estimated $\hat{\lambda}_2$ values, we compute the 25%, 50%, and 75% quantile breakpoints and use them to separate the stocks into quartiles. We compute the streak strategy returns within each of the four quartiles. Table 2.9 reports the value- and equally-weighted returns. Consistent with the theory, we observe that streak strategy returns are monotonically increasing in $\hat{\lambda}_2$.

Note that an implicit assumption in this empirical exercise is that each stock in the sample has a time-constant λ_2, while our main tests in Section 2.4 rely on the weaker assumption that λ_2 is constant over a few days.

Table 2.9: Relationship between streak strategy returns and estimated $\hat{\lambda}_2$

For the cross-section of US equity, the estimated $\hat{\lambda}_2$ values are used to compute the 25%, 50%, and 75% quantile breakpoints. The breakpoints are used to separate the streak portfolios into four quartiles. In each of the buckets, the 5 positive and negative streak portfolios are computed. Panel A reports the value-weighted portfolio returns and Panel B the equally-weighted portfolio returns. The *High-Low* column computes the difference in return of the portfolios with an estimated $\hat{\lambda}_2$ over the 75% quantile breakpoint and the portfolios with an estimated $\hat{\lambda}_2$ below the 25% quantile breakpoint. The Newey-West statistics corrected for serial correlation and heteroskedasticity in the error term are reported in brackets next to the *High-Low* value. The returns are expressed as percentages.

		Panel A: Value-weighted portfolios					Panel B: Equally-weighted portfolios				
Streak length	Return streak sign	Estimated $\hat{\lambda}_2$ High			Low	High-Low	Estimated $\hat{\lambda}_2$ High			Low	High-Low
1 day	+	-0.189	-0.059	-0.011	0.019	-0.207 (-11.712)	-0.455	-0.131	-0.013	0.081	-0.536 (-16.731)
2 days	+	-0.244	-0.087	-0.036	-0.009	-0.235 (-13.883)	-0.526	-0.132	-0.014	0.083	-0.609 (-16.246)
3 days	+	-0.241	-0.092	-0.051	-0.03	-0.211 (-11.919)	-0.480	-0.115	-0.016	0.079	-0.558 (-15.446)
4 days	+	-0.244	-0.092	-0.072	-0.037	-0.207 (-9.216)	-0.397	-0.108	-0.025	0.066	-0.463 (-15.457)
5 days	+	-0.235	-0.092	-0.089	-0.06	-0.175 (-6.819)	-0.333	-0.098	-0.044	0.062	-0.396 (-12.711)
1 day	-	0.175	0.066	0.021	-0.027	0.203 (14.162)	0.509	0.162	0.06	-0.044	0.553 (17.716)
2 days	-	0.253	0.103	0.067	0.001	0.252 (13.692)	0.659	0.219	0.102	-0.012	0.671 (17.339)
3 days	-	0.290	0.121	0.09	0.023	0.267 (12.595)	0.710	0.253	0.127	0.007	0.703 (16.402)
4 days	-	0.320	0.170	0.141	0.050	0.270 (11.27)	0.735	0.287	0.158	0.042	0.693 (15.752)
5 days	-	0.370	0.201	0.154	0.064	0.305 (9.136)	0.737	0.326	0.199	0.064	0.672 (13.723)

Streak Strategy and Trading Costs

Implementing the streak trading strategy entails a large amount of daily trading. For example, the 5-day streak portfolio requires, on average, 102 sales and 138 buys per day with a holding period of only one day. A growing number of recent studies investigates the trading costs faced by institutional investors (see, e.g., Keim and Madhavan, 1997, Korajczyk and Sadka, 2004, Lesmond, Schill, and Zhou, 2004, Frazzini, Israel, and Moskowitz, 2012, Engle, Ferstenberg, and Russell, 2012, Groot, Huij, and Zhou, 2012, Novy-Marx and Velikov, 2016, Frazzini, Israel, and Moskowitz, 2018).

A full analysis of the question whether daily return predictability could be economically exploited is beyond the scope of the paper. However, we aim to get a rough idea on how close to tradeability the strategy might be. We start approaching this question by looking at quoted half-spreads. Assuming that trades occur at quoted bids and asks, quoted spreads equal the trading costs of a round-trip, and half-spreads equal the costs of a single trade. We look at an equally-weighted average of the two value-weighted long portfolios consisting of stocks that have experienced a negative streak in daily returns of length 4 and 5 days, respectively (long 4/5 strategy). Table 2.2 shows that these portfolios are the two best performing ones in the entire sample. Furthermore, long portfolios avoid concerns regarding short-sale costs.

Panel A of Figure 2.2 plots the six months moving averages of portfolio returns based on transaction prices and value-weighted quoted half-spreads. The overall pattern is similar to the one for the long-short streak portfolio shown in Panel A of Figure 2.1.

To get an idea whether the performance after costs could be higher than the performance of the market, we perform the following calculation:

$$r_t^{AC} = \sum_{i=1}^{N_t} w_{i,t} r_{i,t} - \sum_{i=1}^{N_t \cup N_{t-1}} |w_{i,t} - w_{i,t-1}| q_{i,t}, \tag{2.12}$$

where r_t^{AC} is the portfolio return after transaction costs on day t, N_t is the number of stocks in the portfolio at time t, $w_{i,t}$ is the portfolio weight of stock i at time t, $r_{i,t}$ is the raw return, and $q_{i,t}$ is the quoted half-spread. Stocks that get delisted on day $t-1$ do not have a valid quoted-half spread on day t, and we assume that these stocks earn the delisting return without further transaction costs. If a stock has a valid quoted half-spread on day $t-1$ but not on day t, we take the quoted half-spread from day $t-1$ to approximate the trading costs. This procedure is necessary if a stock no longer belongs to the tradeable universe according to our filters. We then close the position assuming that the spread of the previous day equals the spread today. The union in the second summand ensures that trading costs are also paid if a position is entirely sold.[16]

[16]An alternative way of calculating returns after paying the bid-ask spread would be to start with \$1m on January 1, 2004. We then determine the number of shares that we want to hold based on mid-prices. We truncate the number of shares to the next smaller integer and buy this number of shares at the ask price. Cash holding on the first day is the difference between \$1m and the cash we need to build the portfolio and is due to imperfect divisibility. We assume that neither positive nor negative cash holdings yield any interest. After the first day, we value our portfolio at closing mid-prices. The current value of the strategy is now the

To reduce trading costs, we apply a straightforward trading-cost mitigation strategy. On each day, we only consider stocks in the low cost universe. Following Novy-Marx and Velikov (2016), we restrict our strategy to those stocks that lie within the tercile with lowest bid-ask spreads at the time of portfolio formation. Novy-Marx and Velikov (2016) perform a double sort on size and spreads "to avoid a large cap bias" (page 138). The goal of our exercise here is to implement a strategy among the most liquid stocks, irrespective of size. We therefore just do a single sort each day.

Panel B of Figure 2.2 reports on the development of the value of the trading cost minimized long 4/5 strategy. The strategy starts with an investment amount of \$1m on January 1, 2004. The starting date is chosen after inspection of the plots in Panel A. With the beginning of the year 2004, spreads have fallen to a level where profitability after costs seems feasible. We include the value of a strategy that invests in the market. The investment in the market is before costs and simply tracks the value-weighted return of all stocks listed in CRSP. Between 2004 and the financial crisis the long 4/5 strategy performs slightly better than the market. In this time period, excess returns are approximately eaten up by the transaction costs implied by quoted bid-ask spreads. Given that the long 4/5 strategy has a beta sightly above 1 (see Panel D), the graph suggests a near zero alpha. Spreads and returns before costs increase dramatically during the financial crisis, but the overall picture of excess returns being roughly equal to transaction costs remains unchanged.

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portfolio value at closing mid-prices plus the cash holding. We rebalance the portfolio by determining the numbers of shares that we want to hold based on mid-prices, truncate these numbers to the next integer, and buy at asks as well as sell at bids. If a share is delisted, we assume that the money invested in the stock earns the delisting return. If necessary, the number of shares is adjusted using CRSP's adjustment factor for the number of shares outstanding (FACSHR). The updated cash position is the cash position from the previous day plus capital inflows from selling shares and delistings minus capital outflows from buying shares. Typical transactions are the selling of shares after a streak is broken and the increase of positions if a streak continues. We have excluded Berkshire Hathaway and Kerr-McGee Corp in May 2005 from the sample. Berkshire's high stock price yields high cash holdings as we truncate the number of shares to next smaller integer. Kerr-McGee bought back shares in a Dutch auction above the market price in May 2005. We were unable to construct the details of this event. The time-series correlation of the daily returns calculated using equation (2.12) and the more detailed method described in this footnote is 0.998.

However, the situation changes significantly after the financial crisis. Spreads come down to levels below the spreads we have seen in the years preceding the financial crisis and continue to fall at low levels (see Panel C). At the end of the sample, the average of the value-weighted quoted half-spreads of the 4- and 5-day portfolios is roughly 1 basis point. At the same time, returns do not fall as much as spreads, making positive excess returns possible. After costs, the alpha of the strategy with respect to the five Fama-French factors is 3.05 bps with a Newey and West (1987) adjusted t-statistic of 3.0338 in the time period from January 1, 2004 until the end of the sample in September 2017.

The main takeaway of the empirical exercise shown in Figure 2.2 is that the dramatic increase in liquidity since the early 2000's opens the door to the possibility that a value-weighted portfolio strategy with daily rebalancing can be profitable after costs, in contrast to the situation in the twentieth century.[17] There are certainly further ways to increase profitability after transaction costs (Novy-Marx and Velikov, 2016). However, even if a short-term strategy is not profitable after trading costs, it is still possible that the reported return predictability provides useful information for optimizing already existing trading and/or transaction-costs minimization strategies.[18]

[17]The main open question is the potential price impact of trades. There is reason to believe that streak strategies have much smaller price impact costs than most other daily strategies. First, our main results are based on value-weighted portfolios, and most trading takes place in liquid stocks. Second, our strategy buys on days with falling prices and sells on days with rising prices, suggesting that a financial institution which implements the strategy is rather liquidity provider than demander. However, the reliable estimation of the strategies' capacity is not possible due to the lack of the necessary data.

[18]Our results seem to be at odds with recent evidence reported by Chen and Velikov (2019). They show that many anomalies face high trading costs post-publication, that is, in recent years. The reason for this qualitative difference is that the long 4/5 strategy trades only the most liquid and largest stocks, while the anomalies analyzed by Chen and Velikov (2019) often form equally-weighted portfolios over the entire CRSP universe, leading to portfolios with much higher average spreads.

Figure 2.2: Streak strategies and transaction costs implied by quoted half-spreads

The figure considers an equally-weighted portfolio of the two value-weighted portfolios built based on negative streaks with length 4 and 5, respectively. The red line in Panel A shows the six-month moving average of daily returns based on transaction prices. The green line shows the six-month moving average of the simple average of the two value-weighted quoted half-spreads. Panel B reports on the development of a \$1m investment amount in the trading cost-minimized long 4/5 strategy as outlined in the text. Panel C shows the six-month moving average of the number of stocks in the portfolio and the value-weighted average of the quoted half-spreads. To calculate the value-weighted average of quoted half-spreads, we use exactly the same weights as for weighting the portfolio returns in Panel B. Panel D shows the six-month average of the strategies' market beta. Each day, market beta is calculated by estimating the beta with daily data from the previous six month. The graphs in Panels A and D refer to the strategy without trading costs minimization, while the graphs in Panels B and C rely on a version of the strategy that trades only in the low cost universe.

Earnings Announcements

Recent evidence suggests that behavioral agents trade more aggressively during the days preceding an earnings announcement. Prior to an earnings announcement, retail demand for lottery-stocks (Liu, Wang, Yu, and Zhao, 2019) and for stocks with recent previous earnings surprises (Frieder, 2008, Shanthikumar, 2012, Ertan, Karolyi, Kelly, and Stoumbos, 2019) increases. The increased demand is associated with abnormal price increases before earnings announcements and reversals afterwards (Liu, Wang, Yu, and Zhao, 2019, Ertan, Karolyi, Kelly, and Stoumbos, 2019).[19] To the extent that these results carry over to return extrapolation, we would expect returns from streak strategies to be higher if the holding day coincides with an earnings announcement day. Initial evidence consistent with this prediction comes from So and Wang (2014), who document that an equally-weighted short-term reversal strategy based on cumulative three-day returns is more profitable around earnings announcements.[20]

Table 2.10 reports the value-weighted returns on holding days with an earnings announcement. The returns are substantially higher than the returns of the portfolios reported in our baseline specification (see Table 2.2, Panel A). Since an earnings announcement and a streak in daily returns on the same day are a rarer event than a streak in daily returns alone, streak portfolios do not contain at least a firm every day, unlike the baseline portfolios. Table 2.10 shows the percentage of holding days with earnings announcements in the baseline streak portfolios. For example, 56% of the holding days in the 5-day negative streak portfolio are also included in the portfolio that additionally requires an earnings announcement day. Due to the discrepancy in holding days, we run additional Fama-MacBeth regressions to test for a difference in holding day returns on announcement days and non-announcement days.

[19] Going beyond short-term horizons, several authors have investigated patterns in earning surprises (see, e.g., Barth, Elliott, and Finn, 1999), including streaks (Loh and Warachka, 2012) and their implications for longer term returns.

[20] So and Wang (2014) interpret their empirical result as an increased compensation for liquidity provision prior to uncertain information events. Our alternative interpretation, mutually non-exclusive with theirs, is that extrapolators cause more mispricing prior to earnings announcements, and that this mispricing gets eliminated afterwards.

Table 2.11 reports the results. The dependent variable in the Fama-MacBeth regression is the daily stock return minus the risk-free rate. With the use of dummy variables, we indicate the length and sign of the preceding streak in returns. The dummies take on the value one for the maximal streak length only, and not for each of the shorter streaks, in order to facilitate the interpretation of the coefficients. In this case, the coefficient of each dummy indicates the size of the holding day return associated with the streak length instead of just the marginal change.

The coefficients of the interaction term between the streak dummies and the earnings announcement dummy show an increase of absolute holding day returns after streaks in returns when the holding day coincides with the earnings announcement. For positive streak dummies, the returns on the holding day are significantly smaller if there is an earnings announcement on that day. For negative streak dummies, the coefficients of interaction terms are significantly positive. The only exception in regressions weighted on market value is the 2-day negative streak with an estimated coefficient of -0.005. The results are broadly consistent with the idea that earnings announcements reduce mispricing caused by disagreement among market participants (Berkman, Dimitrov, Jain, Koch, and Tice, 2009, Engelberg, Reed, and Ringgenberg, 2018, Daniel, Klos, and Rottke, 2018).

Table 2.10: Streak portfolio returns and earning announcements

For both positive and negative streaks in returns, this table reports the value-weighted streak portfolio returns for different streak lengths with an earnings announcement on the holding day. Returns are end-of-day returns are expressed as percentages. The t-statistics are Newey-West statistics corrected for serial correlation and heteroskedasticity in the error term. *No. of stocks* reports the number of stocks in each portfolio on the days the portfolio can be constructed. *Share of announcements holding days in streak portfolios* reports the percentage of holding days in the overall streak portfolios that are also in the streak portfolio conditioned on earnings announcements.

	1	2	3	4	5
Value-weighted portfolio with earning announcement on holding day					
After negative streak	0.269	0.348	0.415	0.472	0.703
Std. dev.	2.891	3.451	4.385	5.372	6.848
t-stat	4.109	4.401	4.089	3.867	4.632
No. of stocks	69	34	16	8	4
Share of announcements holding days in streak portfolio	0.974	0.934	0.819	0.723	0.561
After positive streak	-0.071	-0.145	-0.166	-0.298	-0.259
Std. dev.	2.896	3.268	3.913	4.955	6.678
t-stat	-1.091	-2.011	-1.990	-2.676	-1.682
No. of stocks	69	32	15	7	3
Share of announcements holding days in streak portfolio	0.975	0.933	0.848	0.704	0.536

Table 2.11: Fama-MacBeth regression on streak portfolio returns, earning announcements, and institutional ownership ratio

Results of Fama-MacBeth regressions with stock returns on day t as dependent variable (R_t). Each regression is conducted once weighted by market value of the previous day (t-1) and once without any weighting. The streak dummy variables indicate whether there has been a positive or negative streak in returns of length 5, 4, 3, or 2 days. The dummies take on value 1 if there was a streak between t-1 and t-5. The dummies take on the value 1 for the maximal streak length only, and not for each of the shorter streaks. In column (1) and (2) the variable ea_t is a dummy variable indicating whether there was an earnings announcement or not. In column (3) and (4) the variable IOR_{low} (IOR_{high}) is a dummy variable indicating whether the institutional ownership ratio is below (above) the 33% (66%) quantile of the IOR. The coefficients are expressed as percentages and all coefficients are significant at the 1% level.

	(1) Weighted	(2) Not weighted	(3) Weighted	(4) Not weighted
Intercept	0.034	0.033	0.033	0.034
$Streak_5^+$	-0.076	-0.065	-0.073	-0.041
$Streak_4^+$	-0.034	-0.089	-0.039	-0.051
$Streak_3^+$	-0.039	-0.115	-0.036	-0.059
$Streak_2^+$	-0.014	-0.145	-0.015	-0.083
$Streak_5^-$	0.130	0.266	0.117	0.205
$Streak_4^-$	0.079	0.242	0.070	0.175
$Streak_3^-$	0.041	0.222	0.016	0.152
$Streak_2^-$	0.030	0.207	0.020	0.139
$Streak_5^+ * ea_t$	-0.359	-0.465		
$Streak_4^+ * ea_t$	-0.087	-0.135		
$Streak_3^+ * ea_t$	-0.316	-0.257		
$Streak_2^+ * ea_t$	-0.134	-0.020		
$Streak_5^- * ea_t$	0.373	0.178		
$Streak_4^- * ea_t$	0.123	-0.043		
$Streak_3^- * ea_t$	0.209	0.064		
$Streak_2^- * ea_t$	-0.005	0.008		
ea_t	0.119	0.164		
$Streak_5^+ * IOR_{low}$			0.058	-0.117
$Streak_4^+ * IOR_{low}$			-0.038	-0.257
$Streak_3^+ * IOR_{low}$			-0.022	-0.314
$Streak_2^+ * IOR_{low}$			-0.062	-0.355
$Streak_5^- * IOR_{low}$			0.127	0.401
$Streak_4^- * IOR_{low}$			0.109	0.372
$Streak_3^- * IOR_{low}$			0.116	0.375
$Streak_2^- * IOR_{low}$			0.069	0.340
$Streak_5^+ * IOR_{high}$			-0.009	0.007
$Streak_4^+ * IOR_{high}$			0.049	0.049
$Streak_3^+ * IOR_{high}$			-0.010	0.061
$Streak_2^+ * IOR_{high}$			0.004	0.097
$Streak_5^- * IOR_{high}$			0.036	-0.077
$Streak_4^- * IOR_{high}$			0.024	-0.074
$Streak_3^- * IOR_{high}$			0.057	-0.078
$Streak_2^- * IOR_{high}$			0.026	-0.068

Trading Volume and Streaks in Daily Returns

The model predicts that, when mispricing caused by extrapolators is corrected, trading activity is higher in these stocks. We therefore consider stocks where the market-adjusted return on the holding day has the opposite sign of the streak in daily returns. Table 2.12 reports value-weighted returns of portfolios consisting of such stocks. We further sort firms based on the trading volume on the holding day. Consistent with the model, we observe that larger absolute returns are reported for stocks with higher trading activity on the holding day. In the model, extrapolators' sentiment changes significantly when a streak is broken and, as a result, extrapolators trade extensively with fundamental traders.

However, there is one empirical pattern regarding turnover that is inconsistent with the model. Table 2.1 shows that turnover increases during the formation of a streak in daily returns. Theoretically, turnover is generated by trading between extrapolators and fundamental traders. If expectations of extrapolators are reinforced through dividend innovations, there is not much incentive to trade. We would therefore expect low levels of trading volume during the formation of a streak. This inconsistency between model and empirical results mirrors the inability of classic long-term extrapolation models to account for high trading volume during the formation of an asset price bubble (see Barberis, Greenwood, Jin, and Shleifer, 2018, DeFusco, Nathanson, and Zwick, 2018, Liao and Peng, 2019, for recently proposed models that address this issue).

Table 2.12: Relationship between streak portfolio returns and trading volume

In each streak portfolio where a significant holding day return is actually observed, stocks are sorted on the basis of their demeaned trading turnover on the holding day, i.e. the day the stocks are held. The stocks in the portfolios with high value have a demeaned turnover larger than the 75% quantile, and in the low value portfolios the stocks' demeaned turnover is below the 25% quantile. In each of the 40 portfolios, the returns are value-weighted and expressed as percentages. The demeaned turnover is the trading turnover in t minus the mean turnover of the previous 200 days.

		Turnover on holding day			
Streak length	Return streak sign	High			Low
1 day	+	-2.030	-1.094	-1.079	-1.341
2 day	+	-2.008	-1.136	-1.128	-1.361
3 day	+	-1.995	-1.186	-1.167	-1.379
4 day	+	-2.020	-1.264	-1.227	-1.418
5 day	+	-2.088	-1.369	-1.324	-1.505
1 day	-	2.198	1.189	1.130	1.354
2 day	-	2.208	1.247	1.196	1.415
3 day	-	2.252	1.323	1.271	1.477
4 day	-	2.327	1.445	1.368	1.581
5 day	-	2.466	1.603	1.523	1.689

Institutional Ownership in Streak Stocks

Da, Huang, and Jin (2018) use IOR as a proxy to determine the share of extrapolators involved in a stock. More precisely, low IOR would indicate a higher share of extrapolators and vice versa. Based on the literature, we expect the holding day returns after streaks to be extremer when the ratio of stocks held by institutions is lower, because the mispricing is assumed to be higher with a lower level of non-institutional owners (Nagel, 2005).

Table 2.13 reports both the value-weighted (Panel A) and equally-weighted (Panel B) streak portfolio returns sorted by the institutional ownership ratio (IOR). For the equally-weighted portfolios, we observe a monotonic increase in absolute portfolio returns with decreasing IOR. This result is also reflected in the Fama-MacBeth regression in Table 2.11. Column (4) reports the coefficients of a standard Fama-MacBeth regression testing the relationship between streak returns and IOR. The coefficients show that streak returns among high IOR stocks are smaller in absolute terms than streak returns of stocks with lower IOR. Therefore, consistent with the model in Section 2.2, the mispricing due to return extrapolators is inversely proportional to the share of institutional ownership of the stock.

The value-weighted portfolio sorts in Table 2.13, Panel A, draw a different picture. The differences between portfolios with high IOR stocks and portfolios with low IOR stocks tend to be less pronounced and are sometimes insignificant. Furthermore, a comparison of streak portfolio returns shows that value-weighted portfolios with high IOR stocks tend to have a slightly higher absolute return than equally-weighted portfolios with high IOR stocks.

We continue along the lines of Da, Huang, and Jin (2018) and test the relationship between streak portfolio returns and institutional ownership by testing the difference in performance of the long-short streak strategy based on stocks with an IOR level in the top third and an IOR level in the bottom third. The results are reported in Table 2.14. Consistent with the results presented in Table 2.13, the equally-weighted portfolio returns are monotonically decreasing with the IOR. However, for the value-weighted portfolios, the streak returns are smallest for a portfolio of medium IOR stocks and not for a portfolio of high IOR stocks. A market value-weighted Fama-MacBeth regression reported in Table 2.11 indicates significantly higher returns after negative streaks in daily returns for high IOR stocks compared to medium IOR stocks (see column (3)). These results suggest that the reason for the sizeable value-weighted returns documented in our baseline specification is the presence of a considerable effect among large stocks, even for those with high IOR.

This empirical observation is inconsistent with the theory laid out in Section 2.2, as long as IOR is assumed to be a good proxy for the share of extrapolators in the population. It is also inconsistent with alternative explanations that interpret returns from streak strategies as a compensation of liquidity provision.

Table 2.13: Relationship between streak portfolio returns and institutional ownership ratio

For the cross-section of US equity, the 25%, 50%, and 75% quantile breakpoints based on the institutional ownership ratio are computed. Each day the stocks are separated into four equally sized institutional ownership buckets. In each of the buckets, the 5 positive and negative streak portfolios are computed. Panel A reports the value-weighted portfolio returns, and Panel B the equally-weighted portfolio returns. The *Overall* row shows the equally-weighted portfolios of all streak portfolios within an IOR bucket. The *High - Low* column computes the difference in return of the portfolios with an IOR over the 75% quantile breakpoint and the portfolios with an IOR below the 25% quantile breakpoint. The Newey-West statistics corrected for serial correlation and heteroskedasticity in the error term are reported in brackets beside the *High-Low* value. The returns are expressed as percentages.

		Panel A: Value-weighted					Panel B: Equally-weighted				
Streak length	Return sign in streak	Institutional ownership ratio High			Low	High-Low	Institutional ownership ratio High			Low	High-Low
1 day	+	-0.004	-0.013	-0.015	-0.041	0.037 (3.195)	0.017	-0.027	-0.123	-0.365	0.382 (18.739)
2 days	+	-0.038	-0.035	-0.038	-0.048	0.009 (0.668)	0.000	-0.031	-0.115	-0.386	0.386 (17.886)
3 days	+	-0.060	-0.054	-0.037	-0.029	-0.031 (-1.626)	-0.012	-0.025	-0.087	-0.316	0.304 (15.17)
4 days	+	-0.065	-0.055	-0.076	-0.037	-0.028 (-1.017)	-0.021	-0.028	-0.071	-0.241	0.22 (10.024)
5 days	+	-0.087	-0.063	-0.085	-0.019	-0.067 (-1.875)	-0.038	-0.035	-0.047	-0.161	0.124 (4.416)
Overall	+	-0.051	-0.044	-0.05	-0.035	-0.016 (-0.910)	-0.026	-0.009	-0.082	-0.31	0.284 (14.334)
1 day	-	0.032	0.005	-0.028	0.047	-0.015 (-1.321)	0.050	0.068	0.150	0.387	-0.337 (-16.984)
2 days	-	0.068	0.040	0.005	0.094	-0.026 (-1.799)	0.077	0.100	0.200	0.501	-0.423 (-16.766)
3 days	-	0.092	0.062	0.016	0.122	-0.029 (-1.607)	0.090	0.115	0.219	0.539	-0.449 (-17.014)
4 days	-	0.122	0.104	0.065	0.177	-0.055 (-2.213)	0.115	0.133	0.244	0.564	-0.450 (-17.128)
5 days	-	0.147	0.115	0.111	0.240	-0.094 (-3.229)	0.123	0.147	0.27	0.606	-0.483 (-15.585)
Overall	-	0.092	0.065	0.034	0.136	-0.044 (-2.642)	0.082	0.093	0.227	0.574	-0.491 (-17.873)

Table 2.14: Long-short streak strategy for high and low IOR

First, the universe of US stocks is sorted based on the level of IOR. The sorted stocks are then separated into 3 buckets: the first bucket consists of all stocks with low IOR (below the 33% quantile), the second bucket contains all stocks with medium IOR level (above the 33% and below the 66% quantile), and the third bucket all stocks with high IOR (above the 66% quantile). Within each of these buckets, the long-short streak portfolios are computed and the return is reported. The column *Low-High* tests the difference in returns of the streak strategy based on low IOR stocks minus high IOR stocks. To offer a comparison, the market return and the return of the one-day reversal strategy are reported as well. In Panel A, all the portfolio returns are equally-weighted, Panel B reports value-weighted returns. The market return is based on all stocks reported in CRSP. The one-day reversal strategy buys (sells) all stocks in t with a negative (positive) return in $t-1$. Each return is expressed as percentages and use t-statistics Newey-West standard errors corrected for serial correlation and heteroskedasticity.

Panel A: Equally-weighted portfolios

	Long-short streak portfolios					
	Low IOR	Medium IOR	High IOR	Low-High	Market	One-day reversal
Return	0.769	0.194	0.119	0.649	0.061	0.285
t-stat	16.246	11.516	8.911	15.027	3.415	16.661

Panel B: Value-weighted portfolios

	Long-short streak portfolios					
	Low IOR	Medium IOR	High IOR	Low-High	Market	One-day reversal
Return	0.309	0.088	0.149	0.161	0.039	0.018
t-stat	11.148	6.115	8.097	6.484	2.694	2.317

2.6 Conclusion

A simplified version of the extrapolation model by Da, Huang, and Jin (2018) implies that streaks in returns have predictive power for future returns. Consistent with the theoretical predictions, we find that value-weighted long-short portfolios based on streaks in daily returns earn sizable returns on the US and other international markets. Diversifying internationally and across different streak lengths yields an annualized Sharpe ratio before costs of 2.696. Several additional tests in the US show that the form of return predictability documented in this paper is economically different from previously reported forms of daily return predictability.

Excess returns from streak strategies vary systematically with institutional ownership. In our simplest test, we subdivide the cross-section of stocks on each day into stocks with high, medium, and low IOR. For equally-weighted portfolios, excess returns decrease monotonically with institutional ownership. However, for value-weighted portfolios, we do not see such a monotonic decline. This result raises the question of why large stocks with high IOR show such strong daily return predictability. Neither theories of liquidity provision nor extrapolation models with IOR as a proxy for the importance of fundamental traders are able to explain this finding.

2.7 Appendix

2.7.1 Proof

Proof of Proposition 1. To derive the corresponding formula, it is useful to take a closer look at the early price changes in an economy that sees its first dividend innovation ϵ_1 in period 1. Da, Huang, and Jin (2018) call $\frac{1}{1-(\mu^E/\mu^F)\lambda_1(1-\lambda_2)}$ the amplification factor. For the sake of brevity, we set $A = (\mu^E/\mu^F)\lambda_1(1-\lambda_2)$ and therefore $\frac{1}{1-A} = \frac{1}{1-(\mu^E/\mu^F)\lambda_1(1-\lambda_2)}$. For the first price change, we have:

$$P_1 - P_0 = \frac{1}{1-A}\left[\epsilon_1 + \gamma\sigma^2 Q\right] - \frac{A}{(1-A)(1-\lambda_2)}(1-\lambda_2)S_0, \tag{2.13}$$

(we deliberately do not cancel the $(1-\lambda_2)$ in the second term). The second price change can be written as

$$\begin{aligned} P_2 - P_1 &= \frac{1}{1-A}\left[\epsilon_2 + \gamma\sigma^2 Q\right] - \frac{A}{(1-A)(1-\lambda_2)}(\lambda_2 - \lambda_2^2)S_0 \\ &- \frac{A}{(1-A)}\left[(1-\lambda_2)\left[\frac{1}{1-A}\left[\epsilon_1 + \gamma\sigma^2 Q\right] - \frac{A}{(1-A)(1-\lambda_2)}(1-\lambda_2)S_0\right]\right] \\ &= \frac{1}{1-A}\left[\epsilon_2 + \gamma\sigma^2 Q\right] - \frac{A}{(1-A)^2}(1-\lambda_2)\left[\epsilon_1 + \gamma\sigma^2 Q\right] \\ &- \frac{A}{(1-A)(1-\lambda_2)}(\lambda_2 - \lambda_2^2)S_0 + \frac{A^2}{(1-A)^2(1-\lambda_2)}(1-\lambda_2)^2 S_0. \end{aligned} \tag{2.14}$$

Now consider the coefficients of the summands who contain the dividend innovation ϵ_1. In $P_2 - P_1$, ϵ_1 appears in just one summand with coefficient $-\frac{A}{(1-A)^2}(1-\lambda_2)$. ϵ_1 appears once in $P_2 - P_1$, because $P_1 - P_0$ enters $P_2 - P_1$ once with coefficient $-\frac{A}{(1-A)}(1-\lambda_2)$ and ϵ_1 enters $P_1 - P_0$ once with coefficient $\frac{1}{1-A}$.

The third price change can be written as

$$
\begin{aligned}
P_3 - P_2 = & \frac{1}{1-A}\left[\epsilon_3 + \gamma\sigma^2 Q\right] - \frac{A}{(1-A)(1-\lambda_2)}(\lambda_2^2 - \lambda_2^3)S_0 \\
& - \frac{A}{(1-A)}\left[(1-\lambda_2)(P_2 - P_1) + (\lambda_2 - \lambda_2^2)(P_1 - P_0)\right] \\
= & \frac{1}{1-A}\left[\epsilon_3 + \gamma\sigma^2 Q\right] - \frac{A}{(1-A)^2}(1-\lambda_2)\left[\epsilon_2 + \gamma\sigma^2 Q\right] \\
& + \frac{A^2}{(1-A)^3}(1-\lambda_2)^2\left[\epsilon_1 + \gamma\sigma^2 Q\right] - \frac{A}{(1-A)^2}(\lambda_2 - \lambda_2^2)\left[\epsilon_1 + \gamma\sigma^2 Q\right] \\
& - \frac{A}{(1-A)(1-\lambda_2)}(\lambda_2^2 - \lambda_2^3)S_0 \\
& + \frac{A^2}{(1-A)^2(1-\lambda_2)}(1-\lambda_2)(\lambda_2 - \lambda_2^2)S_0 - \frac{A^3}{(1-A)^3(1-\lambda_2)}(1-\lambda_2)^3 S_0 \\
& + \frac{A^2}{(1-A^2)(1-\lambda_2)}(1-\lambda_2)(\lambda_2 - \lambda_2^2)S_0. \qquad (2.15)
\end{aligned}
$$

In $P_3 - P_2$, ϵ_1 now appears in two summands with coefficients $\frac{A^2}{(1-A)^3}(1-\lambda_2)^2$ and $-\frac{A}{(1-A)^2}(\lambda_2 - \lambda_2^2)$.

1. The coefficient of the first summand with factor $(\epsilon_1 + \gamma\sigma^2 Q)$ comes from the fact that ϵ_1 enters $P_2 - P_1$ once with coefficient $-\frac{A}{(1-A)^2}(1-\lambda_2)$. $P_2 - P_1$ has now coefficient $-\frac{A}{(1-A)}(1-\lambda_2)$ in $P_3 - P_2$. The overall coefficient of the first appearance of ϵ_1 must therefore be $\frac{A^2}{(1-A)^3}(1-\lambda_2)^2$.

2. The coefficient of the second summand with factor $(\epsilon_1+\gamma\sigma^2 Q)$ comes from the fact that ϵ_1 enters $P_1 - P_0$ once with coefficient $-\frac{1}{(1-A)}$. $P_1 - P_0$ has coefficient $-\frac{A}{(1-A)}(\lambda_2 - \lambda_2^2)$ in $P_3 - P_2$. The overall coefficient of the second appearance of ϵ_1 must therefore be $\frac{A}{(1-A)^2}(\lambda_2 - \lambda_2^2)$.

There are two helpful ways to think about these two changes that have happened to the original coefficient of ϵ_1 in $P_2 - P_1$ as we build $P_3 - P_2$.

1. Reproduction: The ϵ_1-term with the old coefficient $-\frac{A}{(1-A)^2}(1-\lambda_2)$ already incorporated in P_2-P_1 reproduces itself, as this coefficient is also part of P_3-P_2. The new coefficient is the old coefficient $-\frac{A}{(1-A)^2}(1-\lambda_2)$ times $-\frac{A}{(1-A)}(1-\lambda_2)$.

2. Aging: The ϵ_1-term with the old coefficient $-\frac{A}{(1-A)^2}(1-\lambda_2)$ already incorporated in P_2-P_1 is also still part of P_3-P_2, as P_3-P_2 is a function of P_2-P_1. However, the coefficient becomes "older" in the sense that it receives weight $(\lambda_2-\lambda_2^2)$ instead of $(1-\lambda_2)$, thereby "transforming" $-\frac{A}{(1-A)^2}(1-\lambda_2)$ into $-\frac{A}{(1-A)^2}(\lambda_2-\lambda_2^2)$.

"Reproduction" and "Aging" happens to all coefficients when we go one price change in the future, i.e. from P_t-P_{t-1} to $P_{t+1}-P_t$. Note that any "Reproduction" comes along with a sign flip of the coefficient. Figure 2.3 illustrates this process for summands with the term $(\epsilon_1+\gamma\sigma^2 Q)$ for the first four price changes.

Generalizing this reasoning, we can write all summands that include the factor $(\epsilon_1+\gamma\sigma^2 Q)$ in price difference P_t-P_{t-1} as

$$\frac{A}{(1-A)^2}\left[\sum_{i=0}^{t-2}\binom{t-2}{i}\left(\frac{A}{1-A}\right)^i(1-\lambda_2)^i(-1)^{i+1}\left(\lambda_2^{t-2-i}-\lambda_2^{t-1-i}\right)\right](\epsilon_1+\gamma\sigma^2 Q). \quad (2.16)$$

The summands that include the factor $(\epsilon_2+\gamma\sigma^2 Q)$ in price difference P_t-P_{t-1} evolve exactly in the same way, except that the dividend innovation ϵ_2 starts one period later than ϵ_1. We can write all summands as

$$\frac{A}{(1-A)^2}\left[\sum_{i=0}^{t-3}\binom{t-3}{i}\left(\frac{A}{1-A}\right)^i(1-\lambda_2)^i(-1)^{i+1}\left(\lambda_2^{t-3-i}-\lambda_2^{t-2-i}\right)\right](\epsilon_2+\gamma\sigma^2 Q). \quad (2.17)$$

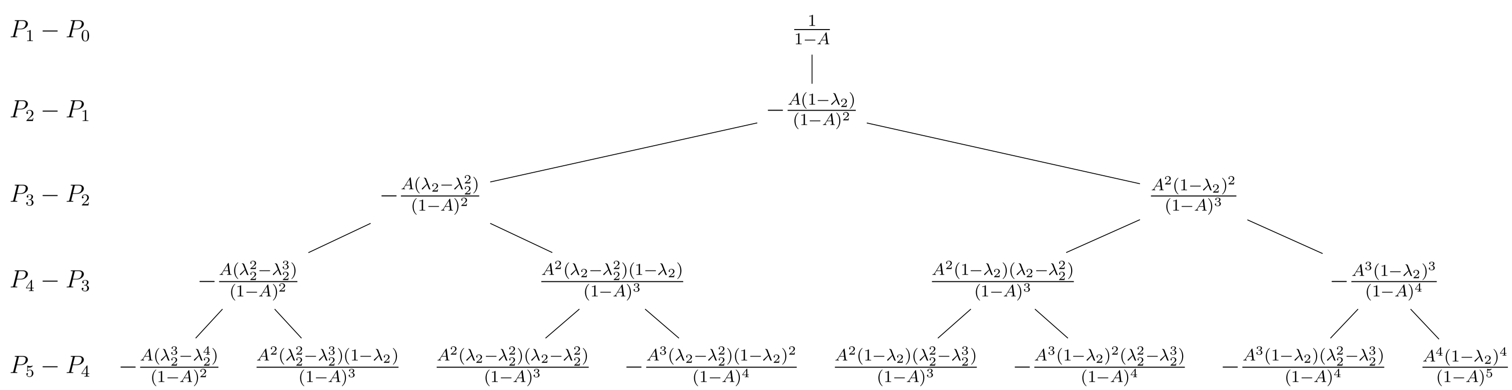

Figure 2.3: Coefficients of summands including the factor $(\epsilon_1 + \gamma\sigma^2 Q)$ in the first four price differences

Applying this logic to all t dividend innovations that determine $P_t - P_{t-1}$ yields a formula for all summands in price difference $P_t - P_{t-1}$ that include a dividend innovation:

$$\left(\frac{1}{1-A}\right)(\epsilon_t + \gamma\sigma^2 Q) + \sum_{j=1}^{t-1}(\epsilon_j + \gamma\sigma^2 Q)\left[\frac{A}{(1-A)^2}\sum_{i=0}^{t-1-j}\binom{t-1-j}{i}\left(\frac{A}{1-A}\right)^i (1-\lambda_2)^i(-1)^{i+1}\left(\lambda_2^{t-1-j-i} - \lambda_2^{t-j-i}\right)\right]. \tag{2.18}$$

Note that $(-1)^x = (-1)^{-x}\ \forall x \in \mathbb{Z}$. We can write equation (2.18) as

$$\begin{aligned}&\left(\frac{1}{1-A}\right)(\epsilon_t + \gamma\sigma^2 Q) + \\ &\sum_{j=1}^{t-1}(\epsilon_j + \gamma\sigma^2 Q)\left[\frac{A}{(1-A)^2}\sum_{i=0}^{t-1-j}\binom{t-1-j}{i}\left(\frac{A}{1-A}(1-\lambda_2)\right)^i(-1)^{t-j}(-\lambda_2)^{t-1-j-i}\right. \\ &\left. - \frac{A\lambda_2}{(1-A)^2}\sum_{i=0}^{t-1-j}\binom{t-1-j}{i}\left(\frac{A}{1-A}(1-\lambda_2)\right)^i(-1)^{t-j}(-\lambda_2)^{t-1-j-i}\right].\end{aligned} \tag{2.19}$$

The general binomial theorem allows us to simplify to

$$\begin{aligned}&\left(\frac{1}{1-A}\right)(\epsilon_t + \gamma\sigma^2 Q) + \\ &\sum_{j=1}^{t-1}(\epsilon_j + \gamma\sigma^2 Q)\left[\left(\frac{A}{(1-A)^2} - \frac{A\lambda_2}{(1-A)^2}\right)\left(\frac{A}{1-A}(1-\lambda_2) - \lambda_2\right)^{t-1-j}(-1)^{t-j}\right]\end{aligned} \tag{2.20}$$

and finally

$$\left(\frac{1}{1-A}\right)(\epsilon_t + \gamma\sigma^2 Q) + \frac{A}{(1-A)^2}(1-\lambda_2)\sum_{j=1}^{t-1}(\epsilon_j + \gamma\sigma^2 Q)\left(\frac{A}{1-A}(1-\lambda_2) - \lambda_2\right)^{t-1-j}(-1)^{t-j}. \tag{2.21}$$

We can make a similar argument with regard to the coefficients of all terms that share S_0 as a factor. All terms including S_0 as a factor can be written as

$$-\frac{A}{(1-A)(1-\lambda_2)}(\lambda_2^{t-1}-\lambda_2^{t})S_0-\left(\frac{A}{1-A}\right)^2 S_0\sum_{j=1}^{t-1}(\lambda_2^{j-1}-\lambda_2^{j})\left(\frac{A}{1-A}(1-\lambda_2)-\lambda_2\right)^{t-1-j}(-1)^{t-j}. \tag{2.22}$$

Combining the terms from equations (2.21) and (2.22), we get

$$\begin{aligned}
&P_t - P_{t-1} = \\
&\left(\frac{1}{1-A}\right)(\epsilon_t+\gamma\sigma^2 Q)+\frac{A}{(1-A)^2}(1-\lambda_2)\sum_{j=1}^{t-1}(\epsilon_j+\gamma\sigma^2 Q)(-1)^{t-j}\left(\frac{A}{1-A}(1-\lambda_2)-\lambda_2\right)^{t-1-j} \\
&-\frac{A}{1-A}\lambda_2^{t-1}S_0-\left(\frac{A}{1-A}\right)^2 S_0\sum_{j=1}^{t-1}\lambda_2^{j-1}(1-\lambda_2)(-1)^{t-j}\left(\frac{A}{1-A}(1-\lambda_2)-\lambda_2\right)^{t-1-j}.
\end{aligned} \tag{2.23}$$

We now assume that extrapolators are unbiased at $t=0$, in the sense that their expectation of the first price change is equal to the market risk premium if sentiment directly determines demand ($\lambda_0 = 0$ and $\lambda_1 = 1$). This assumption implies $S_0 = \gamma\sigma^2 Q$.[21] All terms with the market risk premium $\gamma\sigma^2 Q$ are given by

$$\begin{aligned}
&\left(\frac{1}{1-A}\right)\gamma\sigma^2 Q-\frac{A}{(1-A)^2}(1-\lambda_2)\gamma\sigma^2 Q\sum_{j=1}^{t-1}\left(\lambda_2-\frac{A}{1-A}(1-\lambda_2)\right)^{t-1-j} \\
&-\frac{A}{1-A}\lambda_2^{t-1}\gamma\sigma^2 Q+\left(\frac{A}{1-A}\right)^2(1-\lambda_2)\gamma\sigma^2 Q\sum_{j=1}^{t-1}\lambda_2^{j-1}\left(\lambda_2-\frac{A}{1-A}(1-\lambda_2)\right)^{t-1-j}.
\end{aligned} \tag{2.24}$$

Equation (2.24) contains the sums of two finite geometric series.
Note that $\sum_{j=1}^{t-1} x^{t-1-j} = x^{t-1}\left[\sum_{j=0}^{t-1} x^{-j} - 1\right] = \frac{x^{t-1}-1}{x-1}$ and
$\sum_{j=1}^{t-1}\lambda_2^{j-1}x^{t-1-j} = \frac{x^{t-1}}{\lambda_2}\left[\sum_{j=0}^{t-1}\left(\frac{\lambda_2}{x}\right)^j - 1\right] = \frac{x^{t-1}\lambda_2-\lambda_2^t}{\lambda_2(x-\lambda_2)}$ with $x = \lambda_2 - \frac{A}{1-A}(1-\lambda_2) = \frac{\lambda_2 - A}{1-A}$.

[21] Barberis, Greenwood, Jin, and Shleifer (2018) use the same assumption for initial sentiment.

Using these observations to rewrite equation (2.24) yields

$$
\begin{aligned}
&\left(\frac{1}{1-A}\right)\gamma\sigma^2 Q-\frac{A}{(1-A)^2}(1-\lambda_2)\gamma\sigma^2 Q\frac{\left(\frac{\lambda_2-A}{1-A}\right)^{t-1}-1}{\frac{\lambda_2-A}{1-A}-1}\\
&-\frac{A}{1-A}\lambda_2^{t-1}\gamma\sigma^2 Q+\left(\frac{A}{1-A}\right)^2(1-\lambda_2)\gamma\sigma^2 Q\frac{\left(\frac{\lambda_2-A}{1-A}\right)^{t-1}\lambda_2-\lambda_2^t}{\lambda_2\left(\frac{\lambda_2-A}{1-A}-\lambda_2\right)}.
\end{aligned}
\tag{2.25}
$$

After some tedious rearrangements, equation (2.25) evaluates to just $\gamma\sigma^2 Q$. Using this insight together with equation (2.23) gives the formula in the proposition.

□

2.7.2 Plausibility of Average Conditional Returns

In the event study in Table 2.1, we report the average returns during streaks in returns and in the days after the streaks. The returns during streaks, with an average of around 2.1%, may seem to be high. To test if these values are plausible, we repeat the empirical exercise for simulated returns. We draw realizations from a normal distribution with a mean of 0.0212% and a standard deviation of 4.17%. These values are simply the unconditional mean and standard deviation of all daily stock returns in our sample. For 10,000 hypothetical firms, we draw 10,000 daily realizations from the normal distribution. We then report the same event study as in Table 2.1 with the simulated returns for a streak length of 5. We observe that average returns are large for $t-5$ to $t-1$. Here, we just look at streak stocks, which by definition have only positive or only negative values for the periods from $t-5$ to $t-1$. In the rows t to $t+5$, we see averages close to the mean of the normal distribution, consistent with the fact that simulated returns are not predictable by construction. This simple exercise shows that, during a streaks in returns, conditional daily absolute returns in excess of 2% per day are not surprisingly high and should rather be well expected.

Table 2.15: Simulated positive and negative streaks with mean = 0.0212% and sd = 4.174%

A random variable is generated by drawing 10,000 observations, one for each of the 10,000 days in the sample. The independent random variables are drawn from a normal distribution with a mean of 0.0212% and a standard deviation of 4.17%. In this table, we report the average of the random variable when the variable is conditioned to be higher than 0 (positive streak) and lower than zero (negative streak) on the days t 5 to t 1. The means on the days t to t + 5 are simple means, not being conditioned to be larger or smaller than zero. The values are reported in percentage.

	Positive streak	Negative streak
t-5	3.335	-3.322
t-4	3.339	-3.322
t-3	3.333	-3.323
t-2	3.334	-3.323
t-1	3.338	-3.327
t	0.022	0.021
t+1	0.023	0.024
t+2	0.019	0.02
t+3	0.026	0.018
t+4	0.023	0.025
t+5	0.024	0.023

2.7.3 Simulation of Cross-Sectional Extrapolation Model

We simulate asset prices for a market with 1,000 assets and 100 time periods in order to illustrate the theoretical results and economic intuitions of the model. We allow each firm i to have a different pair of extrapolation parameters, $\lambda_{i,1}$ and $\lambda_{i,2}$. To emphasize this fact, we will keep the index i, in contrast to large parts of the main text.

We set $\gamma = 0.01$, $\mu^E = 0.5$, $Q = 1$, and $\sigma^2 = 1$. $\lambda_{i,1}$ is sampled from a normal distribution with mean 1 and standard deviation 1. We truncate the realization of $\lambda_{i,1}$ in the sense that the realization cannot be smaller than 0.5 or larger than 5. Furthermore, $\lambda_{i,2}$ is sampled from a normal distribution with mean 0.7 and standard deviation 0.2 and required to be larger than 0 and smaller than 1. If $(\mu^E/\mu^F)\lambda_{i,1}(1-\lambda_{i,2}) > 1$, we throw away the observation and draw another $\lambda_{i,1}$ and $\lambda_{i,2}$ observation.

In Table 2.16, Fama and MacBeth (1973) regressions show the relationship between extrapolators' current sentiment and next period price changes. Consistent with the theoretical predictions of the model, the coefficient of this period sentiment is negative, showing that the next period price changes will be lower if the sentiment today is more positive and vice versa.

Table 2.16: Relationship between sentiment and next-day price change

Fama-Macbeth regression reporting the relationship between price change in t and sentiment in t-1. Price changes and sentiment are calculated based on Da, Huang, and Jin (2018).

	$Price\ Change_t$
$Sentiment_{t-1}$	-0.242^{***}
	(-34.596)
$Constant$	0.398^{***}
	(32.790)

Our goal is to apply this insight to the entire cross-section of equity returns. The fundamental problem is that sentiment S_{it} is not directly observable and, as shown by equation (2.2), depends not only on past price changes, but also on the stock-specific, unobservable, and potentially time-varying parameter $\lambda_{i,2}$, not to mention the fact that further determinants of extrapolators' demands, $\lambda_{i,0}$ and $\lambda_{i,1}$, are not directly observable either, and their time-series properties are unknown.

To circumvent these problems, we look for empirical proxies that are easy to use and correlate with sentiment $S_{i,t}$ in a reliable way. We start with equation (2.2), which defines $S_{i,t}$. Sentiment for stock i in period t is a non-linear function of recent price changes. If past price changes have opposite signs and $\lambda_{i,2}$ is not known, it is almost always hard for econometricians to determine if sentiment on any given day is positive or negative. However, if all the most recent price changes have the same sign, sentiment today has this sign too, as long as $\lambda_{i,2}$ and the absolute values of past price changes before the streak are not implausibly high in absolute terms. We therefore hypothesize that past-price change streaks, i.e., several days of price changes of the same sign, are a simple and powerful predictor of the next day's price change. Section 2.2 in the main text develops this intuition in a rigorous way.

Table 2.17 reports the results of the Fama-MacBeth regression with the simulated data. We observe that an increase in streak length of the most recent price changes increases the magnitude of the sentiment prevailing in the current period. This confirms that streak length is a good proxy for the extrapolators' sentiment on a given day. The relationship is monotonic, consistent with the intuition that sentiment tends to be higher the longer a price-change streak lasts.

The model of Da, Huang, and Jin (2018) predicts further that extreme sentiment tends to be followed by price changes of the opposite sign, as sentiment comes back to non-extreme values in the absence of further extreme fundamental shocks. In Table 2.18, we test whether price-change streaks can be used as a proxy for sentiment to predict future price changes. Fama-MacBeth regressions show exactly this effect, since longer price-change streaks steadily increase the negative predictability of next period's price changes, for streaks with both negative and positive price changes. Further, we see that the streak dummies lose significance when we include the current sentiment $S_{i,t}$, confirming that price-change streaks per se do not convey relevant information. Rather, streaks serve as easy observable proxies for the current sentiment of extrapolators in our simulated data.

Table 2.17: Sentiment and streak length

Fama-MacBeth regressions testing the relationship between sentiment on the last period of a streak and the streak length are shown. The variable $Streak_5^+$ takes on the value 1 if the price changes of a given asset in the past 5 periods have been positive. The index $t-1$ highlights that the streaks are based on past price changes. The streak variables are constructed in such a manner that, when a stock has had 5 periods of positive price changes in the past, $Streak_5^+$ is one, while $Streak_4^+$, $Streak_3^+$, and $Streak_2^+$ are 0. The variable $Streak_5^-$ takes on the value 1 if the price changes of a given asset in the past 5 periods have been positive. To avoid the dummy trap caused by perfect multicollinearity in the streak dummy variables, the $Streak_{1,t-1}^+$ variable is removed from the specification in the third column.

	$Sentiment_t$		
$Streak_{1,t-1}^+$	0.195***		
	48.263		
$Streak_{1,t-2}^+$	0.301***		0.105***
	(50.904)		(16.661)
$Streak_{1,t-3}^+$	0.386***		0.190***
	(47.956)		(22.932)
$Streak_{1,t-4}^+$	0.427***		0.232***
	(40.211)		(20.954)
$Streak_{1,t-5}^+$	0.491***		0.296***
	(42.895)		(25.237)
$Streak_{1,t-1}^-$		−0.191***	−0.115***
		(−44.982)	(−24.462)
$Streak_{1,t-2}^-$		−0.309***	−0.233***
		(−60.494)	(−41.485)
$Streak_{1,t-3}^-$		−0.387***	−0.311***
		(−45.053)	(−35.856)
$Streak_{1,t-4}^-$		−0.452***	−0.376***
		(−36.147)	(−30.078)
$Streak_{1,t-5}^-$		−0.509***	−0.433***
		(−44.653)	(−35.999)
Constant	1.524***	1.795***	1.719***
	(157.939)	(181.097)	(177.780)

Table 2.18: Relationship between price change, sentiment, and price-change streaks

Fama-MacBeth regressions with simulated price changes, $Price\ change_t$, as dependent variable. The variable $Streak^+_{5,t-1}$ takes on the value 1 if the price changes of a given asset in the past 5 days have been positive. The index $t-1$ highlights that the streaks are based on past price changes. The streak variables are constructed in such a manner that, when a stock has had 5 days of positive price changes in the past, $Streak^+_{5,t-1}$ is one, while $Streak^+_{4,t-1}$, $Streak^+_{3,t-1}$, and $Streak^+_{2,t-1}$ are 0. The variable $Streak^-_5$ takes on the value 1 if the price changes of a given asset in the past 5 days have been positive. As in Da, Huang, and Jin (2018), $Sentiment_{t-1}$ is the sentiment on the last day of the price-change streak. To avoid the dummy trap caused by perfect multicollinearity in the streak dummy variables, the $Streak^+_{1,t-1}$ variable is removed from the two specifications which includes the positive and negative $Streak$ dummy variables.

			$Price\ change_t$			
$Streak^+_{1,t-1}$	-0.142^{***}		-0.054	-0.037^{***}		-0.054^{*}
	(-14.598)		(-1.626)	(-3.561)		(-1.897)
$Streak^+_{1,t-2}$	-0.214^{***}		-0.127^{***}	-0.053^{***}		-0.071^{**}
	(-17.047)		(-3.663)	(-3.856)		(-2.346)
$Streak^+_{1,t-3}$	-0.206^{***}		-0.118^{***}	-0.019		-0.038
	(-11.926)		(-3.243)	(-1.037)		(-1.146)
$Streak^+_{1,t-4}$	-0.243^{***}		-0.155^{***}	-0.039		-0.057
	(-9.756)		(-3.802)	(-1.495)		(-1.529)
$Streak^+_{1,t-5}$	-0.216^{***}		-0.129^{***}	-0.001		-0.020
	(-8.377)		(-3.164)	(-0.031)		$(-0.513\ )$
$Streak^-_{1,t-1}$		0.138^{***}	0.050		0.031^{***}	-0.025
		(14.163)	(1.507)		(2.997)	(-0.887)
$Streak^-_{1,t-2}$		0.210^{***}	0.122^{***}		0.054^{***}	-0.002
		(16.527)	(3.522)		(3.969)	(-0.060)
$Streak^-_{1,t-3}$		0.223^{***}	0.135^{***}		0.040^{**}	-0.016
		(12.422)	(3.679)		(2.142)	(-0.506)
$Streak^-_{1,t-4}$		0.238^{***}	0.151^{***}		0.038	-0.018
		(9.289)	(3.659)		(1.437)	(-0.486)
$Streak^-_{1,t-5}$		0.273^{***}	0.186^{***}		0.056^{**}	
		(10.164)	(4.419)		(1.960)	
$Sentiment_{t-1}$				-0.227^{***}	-0.223^{***}	-0.224^{***}
				(-27.599)	(-27.394)	(-26.466)
Constant	0.088^{***}	-0.087^{***}	0.000	0.391^{***}	0.347^{***}	0.404^{***}
	16.641	-16.431	0.000	31.612	20.727	14.492

Table 2.19: Event study with simulated data based on Da, Huang, and Jin (2018) model

This table reports the average price difference, shocks, and sentiment for simulated data based on the Da, Huang, and Jin (2018) model. The parameters used are the following: $\gamma = 0.01$ and $\mu^E = 0.5$. $\lambda_{i,1}$ is sampled from a normal distribution with mean 1, standard deviation 1, and the condition that $\lambda_{i,1}$ cannot be smaller than 0.5 or larger than 5. Furthermore, $\lambda_{i,2}$ is sampled from a normal distribution with mean 0.7 and standard deviation 0.2 and conditioned to be larger than 0 and smaller than 1. The values of $\lambda_{i,1}$ and $\lambda_{i,2}$ are chosen so that $(\mu^E/\mu^F)\lambda_{i,1}(1-\lambda_{i,2})$ is smaller than 1. Each variable value is reported for a positive and negative price-change streak of up to 5 days.

Panel B: Positive streaks in returns

	1-day positive streak				2-day positive streak				3-day positive streak				4-day positive streak				5-day positive streak			
	ΔPrice	Shocks	Sentiment	Trading volume	ΔPrice	Shocks	Sentiment	Trading volume	ΔPrice	Shocks	Sentiment	Trading volume	ΔPrice	Shocks	Sentiment	Trading volume	ΔPrice	Shocks	Sentiment	Trading volume
t-5	-0.010	-0.009	1.633	1.123	-0.029	-0.027	1.617	1.109	-0.067	-0.055	1.589	1.086	-0.146	-0.120	1.534	1.040	0.900	0.720	1.828	0.982
t-4	-0.019	-0.018	1.628	1.123	-0.053	-0.047	1.602	1.102	-0.122	-0.104	1.550	1.071	0.928	0.736	1.856	1.030	0.898	0.775	2.022	0.737
t-3	-0.032	-0.028	1.620	1.121	-0.117	-0.097	1.564	1.092	0.940	0.746	1.883	1.051	0.912	0.789	2.052	0.758	0.876	0.801	2.132	0.637
t-2	-0.086	-0.069	1.590	1.116	0.957	0.759	1.912	1.084	0.923	0.802	2.082	0.772	0.899	0.822	2.168	0.663	0.887	0.828	2.215	0.611
t-1	0.991	0.785	1.953	1.118	0.957	0.827	2.124	0.803	0.937	0.853	2.209	0.686	0.930	0.863	2.262	0.635	0.931	0.873	2.288	0.605
t	-0.089	-0.006	1.790	1.121	-0.128	-0.001	1.876	1.167	-0.130	0.009	1.940	1.174	-0.143	0.008	1.978	1.193	-0.149	0.020	2.008	1.165
t+1	-0.032	-0.0001	1.731	1.118	-0.044	0.004	1.788	1.111	-0.070	-0.004	1.825	1.100	-0.067	0.001	1.854	1.072	-0.058	0.014	1.882	1.062
t+2	-0.015	-0.003	1.705	1.115	-0.031	-0.003	1.743	1.100	-0.031	-0.0003	1.774	1.070	-0.058	-0.017	1.791	1.053	-0.058	-0.007	1.816	1.044
t+3	-0.014	-0.006	1.691	1.114	-0.021	-0.008	1.717	1.094	-0.039	-0.017	1.737	1.061	-0.044	-0.016	1.753	1.045	-0.067	-0.034	1.763	1.025
t+4	-0.010	-0.009	1.681	1.119	-0.027	-0.018	1.698	1.094	-0.029	-0.014	1.713	1.077	-0.047	-0.028	1.724	1.062	-0.050	-0.029	1.732	1.023
t+5	-0.007	-0.008	1.677	1.115	-0.007	-0.004	1.690	1.101	-0.015	-0.010	1.700	1.080	-0.010	-0.004	1.713	1.067	-0.021	-0.011	1.715	1.021

Panel B: Negative streaks in returns

	1-day negative streak				2-day negative streak				3-day negative streak				4-day negative streak				5-day negative streak			
	ΔPrice	Shocks	Sentiment	Trading volume	ΔPrice	Shocks	Sentiment	Trading volume	ΔPrice	Shocks	Sentiment	Trading volume	ΔPrice	Shocks	Sentiment	Trading volume	ΔPrice	Shocks	Sentiment	Trading volume
t-5	0.011	0.010	1.650	1.118	0.033	0.030	1.664	1.101	0.061	0.053	1.685	1.078	0.148	0.118	1.728	1.039	-0.913	-0.731	1.406	1.013
t-4	0.019	0.016	1.655	1.120	0.056	0.046	1.678	1.100	0.153	0.123	1.733	1.070	-0.918	-0.729	1.402	1.024	-0.875	-0.758	1.252	0.717
t-3	0.033	0.025	1.664	1.121	0.136	0.108	1.723	1.105	-0.941	-0.743	1.388	1.067	-0.900	-0.777	1.236	0.738	-0.910	-0.822	1.134	0.648
t-2	0.087	0.070	1.695	1.127	-0.965	-0.760	1.363	1.102	-0.928	-0.801	1.209	0.770	-0.925	-0.838	1.115	0.662	-0.917	-0.859	1.048	0.597
t-1	-0.998	-0.792	1.330	1.124	-0.963	-0.834	1.173	0.805	-0.954	-0.868	1.079	0.690	-0.955	-0.892	1.017	0.638	-0.945	-0.896	0.975	0.597
t	0.090	0.0002	1.515	1.120	0.134	-0.0005	1.427	1.173	0.149	-0.009	1.366	1.204	0.167	-0.004	1.321	1.218	0.186	0.005	1.291	1.210
t+1	0.033	-0.006	1.579	1.123	0.055	-0.008	1.525	1.127	0.071	-0.005	1.485	1.121	0.087	-0.003	1.453	1.104	0.086	-0.006	1.429	1.095
t+2	0.015	-0.008	1.608	1.125	0.031	-0.004	1.573	1.120	0.047	-0.001	1.546	1.100	0.042	-0.008	1.522	1.083	0.054	0.002	1.501	1.072
t+3	0.014	-0.002	1.627	1.124	0.031	0.002	1.605	1.105	0.027	-0.003	1.583	1.079	0.043	0.007	1.566	1.057	0.060	0.015	1.539	1.066
t+4	0.010	-0.004	1.639	1.118	0.010	-0.007	1.622	1.098	0.024	0.003	1.605	1.081	0.027	0.002	1.584	1.067	0.020	-0.009	1.570	1.058
t+5	0.007	-0.002	1.647	1.120	0.021	0.007	1.637	1.102	0.015	-0.002	1.620	1.083	0.031	0.005	1.610	1.055	0.062	0.026	1.612	1.043

Table 2.20: Price change after positive and negative streaks

For the streak portfolio with different streak lengths of positive and negative price changes, this table reports portfolio price changes relative to the average market price change, standard deviations, t-stats, and average number of assets in the portfolio. The length of a streak is measured in number of periods ranging from 1 to 5. The values reported are those recorded in the period following the streak. The portfolios are formed using a simulated price process from the model by Da, Huang, and Jin (2018). The parameters used are the following: $\gamma = 0.01$ and $\mu^E = 0.5$. $\lambda_{i,1}$ is sampled from a normal distribution with mean 1, standard deviation 1, and the condition that $\lambda_{i,1}$ cannot be smaller than 0.5 or larger than 5. Furthermore, $\lambda_{i,2}$ is sampled from a normal distribution with mean 0.7 and standard deviation 0.2 and is conditioned to be larger than 0 and smaller than 1. The values of $\lambda_{i,1}$ and $\lambda_{i,2}$ need to strictly fulfill the condition that $(\mu^E/\mu^F)\lambda_{i,1}(1 - \lambda_{i,2})$ is smaller than 1. The t-statistics are Newey-West t-statistics corrected for serial correlation and heteroskedasticity in the error term.

	Length of streak (days)				
	1	2	3	4	5
Price changes after positive streaks	-0.091	-0.129	-0.132	-0.143	-0.149
Std. dev.	0.003	0.006	0.008	0.015	0.023
t-stat	-30.816	-21.526	-16.623	-9.623	-5.295
No. of risky assets	502	237.700	110.500	51.400	23.700
Price changes after negative streaks	0.092	0.131	0.147	0.166	0.177
Std. dev.	0.003	0.007	0.012	0.020	0.026
t-stat	29.416	19.041	12.476	8.304	6.920
No. of risky assets	498	233.800	106.200	47.800	21.500

2.7.4 Fama-French 3-Factor Alphas

Table 2.21: Times series FF3-alphas of streak portfolios

For the streak portfolios with different streak lengths, this table reports the Fama-French three-factor alphas and the associated t-statistic. The length of a streak is measured in number of days ranging from 1 to 5. The t-statistics are Newey-West t-statistics corrected for serial correlation and heteroskedasticity in the error term. Daily data of stocks listed on NYSE, AMEX, or NASDAQ is collected from CRSP for the sample period from January 1, 1997 to October 31, 2017.

	Length of streak (days)				
	1	2	3	4	5
Alpha of returns after positive streaks in returns	-0.009	-0.036	-0.052	-0.060	-0.084
t-stat	-2.224	-4.530	-4.937	-5.215	-5.344
Alpha of returns after negative streaks in returns	0.008	0.043	0.065	0.101	0.125
t-stat	1.930	5.831	6.144	7.406	6.985

2.7.5 Weighting Streak Portfolios by Streak Returns

Table 2.22: Streak portfolios weighted by streak returns

This table reports each streak portfolio's average return, standard deviation and average number of stocks. The portfolios are constructed with positive and negative return streaks of different lengths. The length of a streak is measured in number of days ranging from 1 to 5. The values reported are those of the holding day after the streak. These portfolios are weighted by the absolute value of the sum of streak returns, following Nagel (2012). Portfolio returns are based on closing prices. *No. of stocks* is the average number of stocks in each portfolio each day. Portfolio returns and their standard deviation are expressed as percentages.

	Length of streak (in days)				
	1	2	3	4	5
Portfolio returns after negative streaks	0.596	0.562	0.540	0.529	0.547
Std. dev.	1.574	1.788	1.819	1.962	2.206
t-stat	16.013	15.371	16.755	16.769	15.876
No. of stocks	2,400	1,187	579	283	138
Portfolio returns after positive streaks	-0.388	-0.289	-0.240	-0.198	-0.189
Std. dev.	1.675	1.625	1.665	1.749	1.929
t-stat	-11.106	-9.261	-8.268	-7.305	-6.924
No. of stocks	2,251	1,037	477	220	103

2.7.6 Streak Length & Holding Day Returns: Fama-MacBeth Regression

We use the Fama and MacBeth (1973) regression to examine the increases in returns occurring after longer streaks in returns. We replicate the Fama-MacBeth regression in Table 2.18, applying it to the US stock market data. The dependent variable is the daily stock return r_t minus the risk free rate r_f. The dummies take on value 1 if there was a streak between t-1 and t-5. Column 1 reports the standard Fama-MacBeth coefficients, and in column 2 the observations are weighted by the previous day's market value. The coefficients of these dummies support the monotonically increasing return patterns observed in the portfolio sorts.[22] These empirical results are analogous to the Fama-MacBeth results based on the simulated price data in Table 2.18. The empirical results are consistent with the theoretical model, where an increase in streak length increases the size of the predicted returns.

[22]Due to the fact that our dummies use forward-looking information, the estimated coefficients in Table 2.23, column 1 and 2, do not add up to the portfolio returns reported in Table 2.2, Panel C. In our strategy we also hold a stock that has a 4-day streak after just 2 and 3 days. Only for a 5-day streak the coefficients do add up to the portfolio returns, because in this case the dummy variable and the portfolio strategy pick exactly the same stocks.

Table 2.23: Fama-MacBeth regressions testing the relationship between holding day return and streak length

Fama-MacBeth regressions with daily stock returns, R_t, as dependent variable. In the first two columns, the regression results are presented with the right-hand side variables as dummy variables indicating the length of a streak in returns a stock has had and whether they were positive or negative. The variable $Streak_5^+$ takes on the value 1 if the returns of a given stock in the past 5 days have been positive. The dummy variables are constructed in such a manner that, when a stock has had 5 days of positive returns in the past, $Streak_5^+$ will be one, while $Streak_4^+$, $Streak_3^+$, and $Streak_2^+$ will be zero. The Fama-Macbeth regression is calculated twice: once without weighting the observations (in columns 1), and once weighting each observation by the market value of the previous day (t-1). The coefficients are expressed as percentages and all coefficients are significant at the 1% level.

	(1) Not weighted	(2) Weighted
$Streak_5^+$	-0.074	-0.085
$Streak_4^+$	-0.095	-0.041
$Streak_3^+$	-0.121	-0.045
$Streak_2^+$	-0.149	-0.022
$Streak_1^+$	-0.121	0.014
$Streak_5^-$	0.262	0.131
$Streak_4^-$	0.237	0.078
$Streak_3^-$	0.219	0.035
$Streak_2^-$	0.203	0.026
$Streak_1^-$	0.114	-0.025

2.7.7 Rolling Betas

Figure 2.4 plots the time-varying market beta of the value-weighted long-short streak portfolio over time. A 6-month rolling window is used for the estimation. A large spike in the estimated beta can be observed in the early 2000's, most likely related to the burst of the dotcom bubble. The period of the 2008 financial crisis is not associated with comparable high market betas. Overall, beta remains relatively low and, in some instances, the trading strategy becomes a hedge to the market portfolio, with a negative beta.

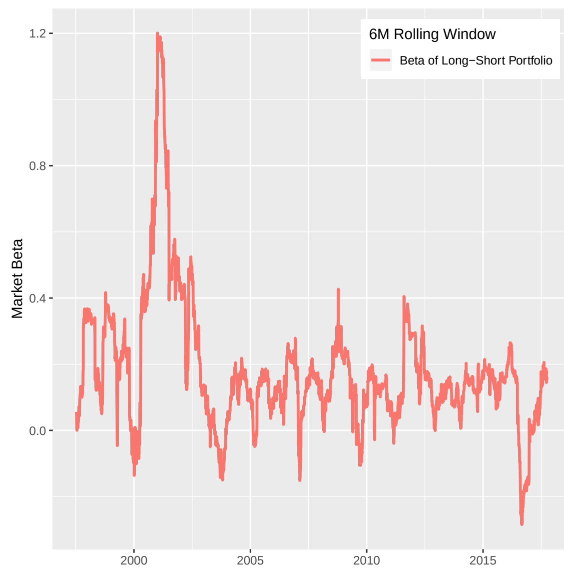

Figure 2.4: Rolling betas of long-short streak portfolio

Six-month moving average of rolling betas of the value-weighted long-short streak portfolio, as in Table 2.3. Six months of daily observations are used to compute the portfolio's beta.

2.7.8 Streaks vs. Cumulative Return

Table 2.24: Streaks vs. cumulative return: Fama-MacBeth regressions

This table reports the Fama-MacBeth regression coefficients for eight different regressions. In each regression, the market-adjusted return in t is the dependent variable. In each regression, a positive streak dummy, a negative streak dummy, and the cumulative returns for the n-days before t are the independent variables. Regressions reported in Panels B and D have the market-adjusted, previous-day return of a stock as an additional control variable. The regressions are conducted for variables based on an n of two to five days. Panels A and B report coefficients of equally-weighted regressions. Panels C and D report coefficients of value-weighted regressions. The value-weighting is conducted on the basis of the last days market value. The coefficients are expressed as percentages and all coefficients are significant at the 1% level.

	2 days	3 days	4 days	5 days
Panel A: Equally-weighted				
Intercept	-0.0005	0.005	0.014	0.017
n-day positive streak	0.126	-0.033	0.203	0.221
n-day negative streak	-0.016	0.039	-0.034	-0.029
n-day cumulative return	-4.893	-0.285	-2.963	-2.439
Panel B: Equally-weighted				
Intercept	0.003	0.0004	0.017	0.019
n-day positive streak	0.123	-0.588	0.193	0.207
n-day negative streak	-0.024	0.0004	-0.047	-0.044
n-day cumulative return	-2.346	-0.588	-1.464	-1.178
AdjRet_{t-1}	-5.094	0.0004	-5.694	-5.874
Panel C: Value-weighted				
Intercept	-0.004	-0.001	-0.001	0.001
n-day positive streak	-0.007	-0.018	-0.015	-0.032
n-day negative streak	0.026	0.040	0.070	0.077
n-day cumulative return	-0.578	-0.586	-0.563	-0.545
Panel D: Value-weighted				
Intercept	-0.005	-0.001	-0.001	0.001
n-day positive streak	-0.005	-0.016	-0.013	-0.027
n-day negative streak	0.026	0.038	0.067	0.075
n-day cumulative return	-0.939	-0.768	-0.691	-0.631
AdjRet_{t-1}	0.556	0.313	0.187	0.064

2.7.9 Further International Evidence

Table 2.25 reports the value-weighted holding day returns for 10 countries. The countries with the highest number of stocks traded are reported first, followed, in descending order, by countries with fewer reported stocks.

Streak strategies work in most countries. China is an exception in the sense that portfolio returns are significantly positive after positive streaks. Overall, streak strategies seem to work better in larger stock markets. Furthermore, the success of streak strategies comes predominately from the long leg. Returns after negative streaks are statistically significant in all countries. This asymmetry is consistent with the US results. Table 2.26 reports the equally-weighted streak portfolio returns for international markets.

Table 2.25: Value-weighted international streak portfolios by country

This table presents value-weighted streak portfolios with positive and negative return streaks of different length for 10 countries: Canada, UK, Hong Kong, Germany, China, France, Sweden, Italy, Switzerland, and Spain. This table reports returns, standard deviations, and t-statistics of streak portfolios with positive and negative returns streaks of different lengths. The length of a streak is measured in number of days, ranging from 1 to 5. The values reported are those recorded on the day following the streak. *No. of stocks* is the average number of stocks in each portfolio each day. Portfolio returns and their standard deviation are reported in percent. The t-statistics are Newey-West t-statistics corrected for serial correlation and heteroskedasticity in the error term.

	Length of streak (days)				
	1	2	3	4	5
Canada					
Value-weighted portfolio returns after negative streaks	-0.017	0.026	0.044	0.058	0.083
Std. dev.	0.528	0.740	0.926	1.203	1.580
t-stat	-2.212	2.466	3.174	3.167	3.468
No. of stocks	444	221	108	52	25
Value-weighted portfolio returns after positive streaks	0.013	-0.021	-0.019	-0.034	-0.032
Std. dev.	0.512	0.696	0.924	1.180	1.664
t-stat	1.796	-2.085	-1.413	-2	-1.299
No. of stocks	401	178	78	35	15
UK					
Value-weighted portfolio returns after negative streaks	-0.017	0.027	0.035	0.032	0.039
Std. dev.	0.396	0.625	0.874	1.155	1.377
t-stat	-2.768	2.979	2.820	2.058	2.076
No. of stocks	719	386	206	111	61
Value-weighted portfolio returns after positive streaks	0.020	-0.013	-0.036	-0.047	-0.027

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Table 2.25 – (continued from previous page)

	Length of streak (days)				
	1	2	3	4	5
Std. dev.	0.374	0.578	0.780	1.095	1.328
t-stat	3.283	-1.688	-3.124	-3.212	-1.561
No. of stocks	643	312	151	72	35
Hong Kong					
Value-weighted portfolio returns after negative streaks	-0.044	0.023	0.058	0.092	0.113
Std. dev.	0.449	0.702	0.910	1.203	1.591
t-stat	-6.569	2.088	4.052	4.723	4.423
No. of stocks	497	258	132	68	34
Value-weighted portfolio returns after positive streaks	0.051	0.015	-0.022	-0.059	-0.017
Std. dev.	0.454	0.791	1.048	1.345	1.877
t-stat	7.679	1.237	-1.330	-2.934	-0.585
No. of stocks	427	189	83	37	17
Germany					
Value-weighted portfolio returns after negative streaks	0.006	0.035	0.054	0.101	0.123
Std. dev.	0.551	0.802	1.002	1.285	1.936
t-stat	0.732	3.350	3.764	5.347	4.575
No. of stocks	354	181	92	47	24
Value-weighted portfolio returns after positive streaks	0.003	-0.038	-0.073	-0.077	-0.111
Std. dev.	1.182	0.768	0.998	1.523	2.177
t-stat	0.176	-3.752	-5.816	-3.824	-3.532
No. of stocks	310	138	61	27	12
China					
Value-weighted portfolio returns after negative streaks	-0.039	0.002	0.031	0.051	0.113
Std. dev.	0.441	0.609	0.745	0.889	1.133
t-stat	-4.269	0.223	2.307	3.311	5.583
No. of stocks	373	197	101	51	26
Value-weighted portfolio returns after positive streaks	0.039	0.034	0.054	0.088	0.083
Std. dev.	0.474	0.701	0.937	1.248	1.675
t-stat	4.133	2.842	3.483	4.231	3.091
No. of stocks	323	148	66	29	13
France					
Value-weighted portfolio returns after negative streaks	0.005	0.042	0.074	0.106	0.133
Std. dev.	0.389	0.613	0.881	1.147	1.490
t-stat	1.022	5.753	6.521	6.542	6.250
No. of stocks	406	210	108	55	28
Value-weighted portfolio returns after positive streaks	-0.010	-0.044	-0.102	-0.111	-0.095
Std. dev.	0.395	0.640	0.893	1.212	1.634
t-stat	-1.860	-4.881	-7.944	-6.466	-4.379
No. of stocks	368	172	80	36	17
Sweden					
Value-weighted portfolio returns after negative streaks	0.018	0.069	0.099	0.167	0.221
Std. dev.	0.565	0.848	1.072	1.439	2.084
t-stat	2.058	5.270	6.682	7.855	6.526
No. of stocks	176	88	42	20	10

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Table 2.25 – (continued from previous page)

	Length of streak (days)				
	1	2	3	4	5
Value-weighted portfolio returns after positive streaks	-0.021	-0.054	-0.068	-0.051	-0.094
Std. dev.	0.550	0.807	1.087	1.424	2.230
t-stat	-2.477	-5.145	-4.176	-2.384	-2.787
No. of stocks	162	74	33	15	7
Italy					
Value-weighted portfolio returns after negative streaks	0.003	0.025	0.068	0.072	0.110
Std. dev.	0.437	0.693	0.957	1.351	1.798
t-stat	0.439	2.444	4.987	3.555	3.836
No. of stocks	123	62	31	15	8
Value-weighted portfolio returns after positive streaks	0.001	-0.008	-0.054	-0.028	0.023
Std. dev.	0.452	0.723	1.033	1.447	2.488
t-stat	0.173	-0.738	-3.449	-1.250	0.614
No. of stocks	112	51	23	10	5
Switzerland					
Value-weighted portfolio returns after negative streaks	-0.028	0.004	0.054	0.108	0.114
Std. dev.	0.507	0.740	0.988	1.376	1.815
t-stat	-3.593	0.336	3.578	4.903	4.138
No. of stocks	103	51	25	13	6
Value-weighted portfolio returns after positive streaks	0.029	0.007	-0.054	-0.061	-0.096
Std. dev.	0.490	0.695	0.933	1.262	1.705
t-stat	3.818	0.613	-3.569	-3.151	-3.559
No. of stocks	100	47	22	10	5
Spain					
Value-weighted portfolio returns after negative streaks	-0.028	0.005	0.011	0.025	0.044
Std. dev.	0.733	0.907	1.119	1.454	1.976
t-stat	-2.531	0.446	0.692	1.070	1.369
No. of stocks	66	34	18	9	5
Value-weighted portfolio returns after positive streaks	0.021	0.022	0.036	0.069	0.091
Std. dev.	0.520	0.804	1.148	1.688	2.211
t-stat	2.356	1.672	1.832	2.276	2.151
No. of stocks	61	29	14	7	3

Table 2.26: Equally-weighted international streak portfolios by country

This table presents equally-weighted portfolios with different streak length for 10 countries: Canada, UK, Hong Kong, Germany, China, France, Sweden, Italy, Switzerland, and Spain. For each portfolio with different streak length of positive and negative returns, this table reports returns, standard deviation, and t-statistics. The length of a streak is measured in number of days ranging from 1 to 5. The values reported are those recorded on the day following the streak. *No. of stocks* is the average number of stocks in each portfolio each day. Portfolio returns and their standard deviation are reported in percent. The t-statistics are Newey-West t-statistics corrected for serial correlation and heteroskedasticity in the error term.

	Length of streak (days)				
	1	2	3	4	5
Canada					
Equally-weighted portfolio returns after negative streaks	0.441	0.565	0.599	0.613	0.616
Std. dev.	0.852	0.979	1.145	1.411	1.848
t-stat	14.140	15.035	16.286	17.927	19.343
No. of stocks	444	221	108	52	25
Equally-weighted portfolio returns after positive streaks	-0.276	-0.318	-0.277	-0.220	-0.178
Std. dev.	0.811	0.914	1.133	1.397	1.883
t-stat	-11.781	-11.910	-10.878	-9.308	-6.128
No. of stocks	401	178	78	35	15
UK					
Equally-weighted portfolio returns after negative streaks	0.194	0.236	0.247	0.229	0.217
Std. dev.	0.854	0.857	0.911	1.033	1.288
t-stat	11.226	12.928	14.370	12.712	10.109
No. of stocks	643	312	151	72	35
Equally-weighted portfolio returns after positive streaks	-0.146	-0.138	-0.120	-0.101	-0.075
Std. dev.	0.788	0.804	0.874	0.993	1.228
t-stat	-10.998	-8.747	-7.434	-5.607	-3.533
No. of stocks	719	386	206	111	61
Hong Kong					
Equally-weighted portfolio returns after negative streaks	0.084	0.145	0.181	0.219	0.245
Std. dev.	0.927	1.023	1.137	1.332	1.743
t-stat	4.781	7.076	7.848	8.776	8.734
No. of stocks	497	258	132	68	34
Equally-weighted portfolio returns after positive streaks	0.020	0.049	0.103	0.151	0.220
Std. dev.	0.955	1.086	1.259	1.611	2.247
t-stat	1.032	2.203	4.149	4.940	5.841
No. of stocks	427	189	83	37	17
Germany					
Equally-weighted portfolio returns after negative streaks	0.212	0.301	0.357	0.381	0.396
Std. dev.	0.887	0.981	1.172	1.595	2.521
t-stat	13.102	15.648	16.940	14.565	10.172
No. of stocks	354	181	92	47	24
Equally-weighted portfolio returns after positive streaks	-0.175	-0.186	-0.128	-0.060	-0.012
Std. dev.	0.909	1	1.238	1.724	2.495
t-stat	-11.285	-9.093	-5.622	-1.952	-0.275

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Table 2.26 – (continued from previous page)

	Length of streak (days)				
	1	2	3	4	5
No. of stocks	310	138	61	27	12
China					
Equally-weighted portfolio returns after negative streaks	-0.001	0.065	0.106	0.122	0.181
Std. dev.	0.767	0.826	0.903	1.056	1.373
t-stat	-0.103	4.105	5.593	5.624	6.691
No. of stocks	373	197	101	51	26
Equally-weighted portfolio returns after positive streaks	0.052	0.033	0.061	0.115	0.144
Std. dev.	0.717	0.800	0.928	1.153	1.580
t-stat	3.721	2.226	3.282	4.719	4.606
No. of stocks	323	148	66	29	13
France					
Equally-weighted portfolio returns after negative streaks	0.067	0.111	0.145	0.201	0.221
Std. dev.	0.828	0.835	0.967	2.282	4.271
t-stat	6.551	9.595	10.376	6.166	3.699
No. of stocks	406	210	108	55	28
Equally-weighted portfolio returns after positive streaks	0.027	0.042	0.051	0.093	0.122
Std. dev.	0.905	0.939	1.029	1.241	1.649
t-stat	2.697	3.378	3.426	5.021	4.737
No. of stocks	368	172	80	36	17
Sweden					
Equally-weighted portfolio returns after negative streaks	0.198	0.289	0.334	0.384	0.461
Std. dev.	0.855	0.979	1.204	1.567	2.394
t-stat	14.936	18.358	15.435	14.331	11.544
No. of stocks	176	88	42	20	10
Equally-weighted portfolio returns after positive streaks	-0.126	-0.152	-0.121	-0.085	-0.112
Std. dev.	0.926	1.015	1.254	1.743	2.606
t-stat	-8.462	-7.896	-5.087	-2.747	-2.832
No. of stocks	162	74	33	15	7
Italy					
Equally-weighted portfolio returns after negative streaks	0.054	0.083	0.108	0.123	0.140
Std. dev.	0.688	0.739	0.885	1.178	1.633
t-stat	5.484	7.543	7.700	6.663	5.360
No. of stocks	123	62	31	15	8
Equally-weighted portfolio returns after positive streaks	-0.050	-0.033	-0.001	0.042	0.071
Std. dev.	0.781	0.899	1.128	1.582	2.534
t-stat	-4.499	-2.489	-0.044	1.706	1.877
No. of stocks	112	51	23	10	5
Switzerland					
Equally-weighted portfolio returns after negative streaks	0.108	0.149	0.187	0.201	0.208
Std. dev.	0.678	0.723	0.905	1.290	1.717
t-stat	10.080	12.880	12.372	9.800	7.616
No. of stocks	103	51	25	13	6
Equally-weighted portfolio returns after positive streaks	-0.048	-0.059	-0.070	-0.072	-0.096
Std. dev.	0.751	0.825	0.982	1.327	1.707

Continued on next page

Table 2.26 – (continued from previous page)

	Length of streak (days)				
	1	2	3	4	5
t-stat	-4.062	-4.410	-4.406	-3.545	-3.723
No. of stocks	100	47	22	10	5
Spain					
Equally-weighted portfolio returns after negative streaks	0.020	0.052	0.072	0.083	0.082
Std. dev.	0.736	0.825	1.095	1.482	1.944
t-stat	1.663	3.778	4.335	3.656	2.651
No. of stocks	66	34	18	9	5
Equally-weighted portfolio returns after positive streaks	-0.003	0.015	0.057	0.100	0.111
Std. dev.	0.795	0.987	1.272	1.801	2.312
t-stat	-0.227	0.895	2.494	2.905	2.370
No. of stocks	61	29	14	7	3

3 Media Attention and Short Selling around the Brexit Referendum

Single authored

3.1 Introduction

This paper takes the Brexit referendum on June 23, 2016 as a case study in which the effect of media attention for publicly shorted stocks on the post-referendum return is investigated. The Brexit referendum is the first major negative financial event which took place after the enforcement of the short selling disclosure regime. The extreme reactions of the financial market to its unexpected outcome made short selling a profitable strategy, thus increasing the already lively interest of the financial public for disclosed short positions.[23] Moreover, the Brexit referendum outcome received extensive media coverage, in particular regarding its implications for the financial market as well as specific firms. Embedding these two aspects in the context of a financial upheaval, the referendum offers an unparalleled opportunity to study the impact media attention can have on the reaction and performance of shorted stocks.

For the analyses conducted in this paper I collect all of the public short positions disclosed since the introduction of the *EU regulation No 236/2012 (...) on short selling and certain aspects of credit default swaps*, on November 1, 2012, which requires short positions larger than 0.5% of outstanding shares to be made public. Furthermore, the media attention data made available through the BBC *The Juicer* API is matched to shorted and non-shorted stocks to analyze the effect of media attention for shorted stocks. The BBC API allows access to 850 RSS (Rich Site Summary) feeds of media outlets both in the UK and Europe. The number of articles are collected in which the name of the stock and the term Brexit are tagged. The Brexit referendum offers a unique possibility to analyze the news coverage of a stock in relation to an event that is common to all firms.

[23]Christine Lagarde, International Monetary Fund chief, called the price movements following the referendum "violent and brutal" (Jopson, 2016). The British pound dropped to a 31-year low, and stocks worldwide plummeted likewise: for instance, Barclays lost 20.68% on June 24 alone. On June 27, 2016, the Monday following the referendum, the price drop of Barclays and RBS stocks was so fast that it triggered automatic circuit breaks on the market: for five minutes, it was not possible to trade the stocks of these banks (Sheffield, 2016). Following these events, the rating agencies S&P and Fitch downgraded the UK's rating based on the expected negative impact of the referendum on the economic growth of the UK in the short run. Moreover, the betting markets were showing odds in favor of a Remain vote until late into the evening of June 23, 2016 (Hughes, 2016, Shaddick, 2016).

The publicly traded airline EasyJet is a compelling example of the combined impact of media attention and disclosed short positions on stock returns after the Brexit referendum. On June 24, 2016, EasyJet was discussed manifold in the media due to the profit warnings it issued in the wake of the referendum (see, e.g., Elliott, 2016). Furthermore, on June 24, 2016, a total of 1.49% of the outstanding EasyJet stock was held short in public short positions. The EasyJet stock lost significantly after the referendum: the 5-day, market-adjusted, cumulative post-referendum return of EasyJet is -20.736%. By contrast, Wizz Air, another publicly traded UK based airline, did not receive media attention on the day after the referendum and was not shorted publicly at the time of the referendum; in the 5 days after the referendum, its stock outperformed the market by 2.515%. To the extent that it lends itself to generalization, this example illustrates the rationale for the analysis of the joint effect of media attention and open short positions on market movements and reactions.

Investigating the disclosed short positions around the events of the Brexit referendum is of interest also from a regulatory point of view. The short-selling disclosure regime has raised concerns. On one hand, fears were voiced that it could deepen and worsen the price reactions that follow negative events by provoking herding behavior (European Central Bank, 2010). Another envisioned risk of the short position disclosure regime is that it would direct additional media attention towards shorted stocks due to the increased visibility generated by the mandatory disclosures, especially in times of financial market instability. Websites such as ShortTracker+ or WhaleWisdom,[24] for instance, make the public short positions easily accessible and further heighten their visibility. This increased coverage would sharpen the interest of the informed public, whose reactions to the media coverage would in turn influence market and stock price development. It is well documented that mass media play a role in shaping stock market activity by influencing investors' sentiment and trade. Many of the results presented in the literature, for instance, suggest that media coverage often

[24] ShortTracker+ conveniently report the UK short positions reported on the FCA's webpage. ShortTracker+ can be found at https://shorttracker.co.uk/, last accessed July 20, 2019. WhaleWisdom summarizes – among others – the short positions reported in the UK, Germany, and France and can be found at https://whalewisdom.com/short_position, last accessed July 20, 2019.

has a positive effect on stock returns in the short run (Hillert and Ungeheuer, 2018, Barber and Odean, 2008, Fang and Peress, 2009). Therefore, in the context of short selling, the disclosure regime and the media coverage evidently interplay and reciprocally strengthen their effect – be it positive or negative – making more detailed research worthwhile.

Overall, for a stock neither receiving media attention nor being excessively shorted seems to be reliably associated with negative returns after the Brexit referendum. However, shorted stocks that additionally receive media attention (treatment stocks) significantly underperform control stocks that were shorted but not covered in the media. The 2-day, cumulative, market-adjusted return of a portfolio of shorted stocks that received negative media attention around the Brexit referendum is -7.8%. In contrast, shorted stocks in the same sector that were matched to the treatment stocks based on market capitalization underperformed the market a mere -0.9%. The effect is only observable over a few days, consistent with the idea that negative Brexit media attention creates short-term selling pressure. There is no such effect of media attention among non-shorted stocks.

Additional separate analyses are performed: one conducted on stocks in general (i.e. shorted and not shorted) to obtain the impact of media attention on returns, and the other conducted on stock with short positions independently from media attention. Their results show that, in the UK, stocks with a disclosed short position outperform non-shorted stocks with similar size and industry affiliation. This could be caused by the high number of short positions reductions disclosed on the day after the referendum. Only in Europe, however does media attention in relation to the Brexit lead all stocks to lose significantly more than those without media coverage in the same sector and with a similar size.

To date, there has been no previous paper examining the performance of stocks receiving high levels of media attention in the period around the Brexit referendum, let alone of shorted stocks with open short positions. In the literature, the available studies investigating the potential effect of a Brexit mostly analyze its economic and political effects in the UK and the EU (see, e.g., Docherty, 2016, Ottaviano, Pessoa, Sampson, Reenen, and Vaitilingam, 2014, Dhingra, Ottaviano, Sampson, and Van Reenen, 2016, Oliver, 2016). On the other hand, other studies analyzing reported short positions have done so over a long-time horizon of several years during which, however, no big-impact political event followed by a market-wide downturn has taken place (Jones, Reed, and Waller, 2016, Jank and Smajlbegovic, 2017, Jank, Roling, and Smajlbegovic, 2017). Another expanding branch of literature is the effect of media attention on stock returns. It is well documented that mass media play a role in shaping stock market activity by influencing investors' sentiment and trade. Many of the results presented in the literature, for instance, suggest that media coverage often has a positive effect on stock returns (Hillert and Ungeheuer, 2018, Barber and Odean, 2008, Fang and Peress, 2009).

3.2 Literature

Three fields of literature are central for this paper, which intends to investigate the question whether media attention directed at shorted stocks has a negative effect on the post-Brexit referendum returns. Firstly, the literature on Brexit offer insight into what effects could have been expected from a Leave vote. Secondly, the existing literature on the disclosure regime is essential for a solid basis on how the disclosure of short positions affect the returns of the shorted stocks in calmer periods. Lastly, the literature on media coverage plays an important role in understanding its effect on stocks returns.

In the literature, the referendum and the possible effects on Europe and the United Kingdom of the withdrawal of the UK from the EU are discussed manifold. All authors have reached a consensus that a Brexit would damage not only the UK and European economy, but the global economy as well, although the first to a higher degree than the other two (see, e.g., Jensen and Snaith, 2016, Oliver, 2016, Dhingra, Ottaviano, Sampson, and Van Reenen, 2016, Ottaviano, Pessoa, Sampson, Reenen, and Vaitilingam, 2014).

Most literature, however, discusses rather the economic and political than the financial effects on the stock market. The Brexit is expected to create political instability and risk (Oliver, 2016, Jensen and Snaith, 2016). Furthermore, trade levels between the UK and the EU are predicted to drop, leading to a substantial GDP and household income loss in the UK (Dhingra, Ottaviano, Sampson, and Van Reenen, 2016, Van Reenen, Dhingra, Ottaviano, and Sampson, 2015). In an earlier paper, Ottaviano, Pessoa, Sampson, Reenen, and Vaitilingam (2014) also analyze the potential effects of the Brexit on the GDP of the UK, concluding that it could lead to a loss similar in extent to the one experienced during the 2008/2009 financial crisis. Considering the less than optimistic scenarios outlined by these analyses, there is evidence that a Leave vote would cause negative price pressure on stocks returns. Since the referendum outcome turned Brexit from a possibility to a fact, with all the resulting upheaval, the short selling disclosure regime allows to analyze the behavior of investors with large short positions in times of financial stress.

Already before the referendum, the academic literature has not only been discussing the effects of a Brexit on the economy in general, but also trying to identify its most probable losers, which are to be found mainly in sectors that produce inside the UK and are directly subject to losses due to a GBP/EUR depreciation from the Brexit. For instance, the car industry in the UK is predicted to falter in case of a Brexit (Van Reenen, Dhingra, Ottaviano, and Sampson, 2015, Docherty, 2016). More specifically, sectors with the highest likelihood of losses will be real estate, banks, retail, insurance, travel and leisure, auto parts, and financial services (Docherty, 2016). In this paper I find that the sectors in which short positions are increased are indeed those identified by Docherty (2016).

Although some sectors are expected to be affected more than others by a Brexit, the literature shows that a Brexit would affect all firms in the UK and Europe. The Brexit referendum offers a unique possibility to investigate the effect of media attention on shorted stocks because it is an unexpected event affecting all firms in the UK and Europe. The fact that the Brexit referendum outcome was unexpected means that the stock price adjustments to the news take place simultaneously in a short time span after the referendum. This makes the Brexit referendum a suitable natural experiment to test the effect of media attention on shorted stocks. Similarly, Wagner, Zeckhauser, and Ziegler (2018) make use of the US presidential election in 2016 to test the effect of tax policies on the stock returns. The fact that the outcome of the 2016 presidential election was unexpected and the two candidates had very different tax policy plans, offers an almost ideal experimental setting in which to test the effect of tax policy on asset prices.

The literature on disclosure regimes is still growing. In Europe, the short position disclosure regime has not proven to be a means for coordinated manipulative attacks (Jones, Reed, and Waller, 2016). However, the reported short selling positions analyzed only go back until the end of 2013. Consequently, their sample does not include large price-drop events such as the Brexit referendum. Moreover, considering that the European short position disclosure regime was introduced to *"ensure the proper functioning ... with regard(s) to the financial markets, and to ensure a high level of consumer and investor protection"* (The European Parliament, 2012, p. 1), it is essential to test whether it fulfils this end also in periods of economic turmoil. So far, judging by the results in Jones, Reed, and Waller (2016), there is no evidence that the financial market suffered under the disclosure regime due to manipulative attacks by short sellers. Whether this holds also for the time period after the Brexit referendum will be investigated in this paper, which will compare the post-referendum returns of stocks with and without disclosed short positions. Using data from the disclosure regime in Japan, Boehmer, Duong, and Huszár (2018) offer evidence that the short position reductions have a positive effect on the stock price.

Another branch of research investigating European disclosure regimes focuses on the characteristics of the short seller as an investor. Short sellers, such as hedge funds, are found to be informed and sophisticated investors that outperform other investors (Jank and Smajlbegovic, 2017, Boehmer, Jones, and Zhang, 2008). Furthermore, short sellers have also proven to be investors with an edge over other market participants thanks to their ability to analyze new information, a skill that sets them apart from the average investor. For example, short sellers are found to analyze and incorporate the information of future earnings announcements correctly (Christophe, Ferri, and Angel, 2004). Not only during earnings seasons do short sellers invest smartly: Dechow, Hutton, Meulbroek, and Sloan (2001) also find that they are able to identify stocks with future negative stock returns on the basis of their fundamentals. Furthermore, Boehmer, Erturk, and Sorescu (2007) add to the empirical evidence in Diamond and Verrecchia (1987) that short sellers are sophisticated investors that incorporate relevant information into the valuation of a company, ensuring that the price reflects the fair value. Boehmer, Erturk, and Sorescu (2007) find that the informativeness of short seller is due to institutions being active short sellers.

Hence, on the basis of the assumption that short sellers are informed and sophisticated traders, it could be argued that analyzing the development of disclosed short positions around the Brexit referendum may carry informational value: this is reinforced by the academic literature offering evidence that short position disclosures also carry additional informational value about stock prices (Jones, Reed, and Waller, 2016, Boehmer, Duong, and Huszár, 2018). In fact, such an analysis performed on the short positions disclosed on the day of the referendum shows how some short sellers were smart enough to position themselves to win from a "Leave" outcome as well. Up to this point, however, no investigation of short position disclosures has taken into consideration the media coverage awarded to the stocks concerned, although media attention might influence the effect of short position disclosures on stock returns.

As a matter of fact, with the market turmoil around the Brexit which made short selling a profitable strategy, short sellers became increasingly subject to media attention. For example, Odey Asset Management LLP was reported in online articles by the Financial Times to have profited from their short positions in Intu Properties and Berkley Group; further, the hedge funds Marshall Wace and TT International were also showcased as short sellers. This media coverage drew attention to the profitability of short selling around the referendum (see e.g., Jopson, 2016, Johnson, Agnew, and Childs, 2016, *Reuters*, June 24, 2016 and *Financial Times*, June 26, 2016).

After the referendum, not only short sellers were brought into the limelight, but also the coverage of the effects of the referendum on UK and European firms increased drastically. The referendum outcome sparked an increase in news articles speculating in what way firms and industry sectors will react to the new developments ahead. The literature is rich in insight concerning the interactions of media and returns. The stocks of firms with media coverage are bought proportionately more often (see, e.g., Barber and Odean, 2008, Hillert and Ungeheuer, 2018, Peress, 2014, Yuan, 2015). Not only media coverage is an indicator for attention: also Google searching volume is found to be a strong predictor for extreme positive returns (Da, Engelberg, and Gao, 2011). Overall, the finance literature finds that the level and changes in media coverage have predictive power about stock returns. This paper adds to this literature and finds that post-referendum returns in Europe are negatively affected by media attention. Although a majority of the research on media attention is conducted for the US market, Griffin, Hirschey, and Kelly (2011) find in their cross-country analysis that on days with news the stock prices fluctuate more. Investigating the effect of media attention on stock returns poses the challenge of disentangling the effect of the event being reported from the news coverage itself. Engelberg and Parsons (2011) address this in their study and find that especially local media coverage predicts local trading activity. However, in this paper the media attention data does not reveal the source of the media attention.

Also sentiment and tone of the media coverage affect the subsequent stock returns (Tetlock, 2007, Fang and Peress, 2009, Gurun and Butler, 2012, Tetlock, Saar-Tsechansky, and Macskassy, 2008, Ferguson, Philip, Lam, and Guo, 2015). Tetlock (2007) analyzes how the tone of a central *Wall Street Journal* column affects daily stock returns: A pessimistic tone in the column results in lower stock returns compared to days with an optimistic column. Not only the tone of the column plays a role: Dougal, Engelberg, Garcia, and Parsons (2012) find that also the author of the *Wall Street Journal* column has explanatory power in the returns of the Dow Jones Industrial Averages.[25] Chan (2003) and Tetlock, Saar-Tsechansky, and Macskassy (2008) focus on negative words used in article headlines and news stories, respectively. Both articles find that the use of negatively slanted words predicts stock returns and trading behavior. In this paper the sentiment of the online articles cannot be investigated. The data collected through the BBC *the Juicer* API only shows the number of articles published on a particular stock in combination with the Brexit. However, the additional information on the shorting activity in the stocks presents itself as a possible proxy for the articles sentiment.

3.3 Data

The short selling disclosure regime, introduced in 2012 in all European countries, imposes a two step disclosure: to the local regulatory authority in case of a negative net position amounting to at least 0.2% of the issued shares, and to the public in general if the position is larger than 0.5% of the issued shares. Furthermore, the regulation requires that short position changes that exceed the next 0.1% increment must be reported as well (EU, No. 236/012, Art 5[2] and Art 6[2]). Also, if short seller reduces a short position and surpasses a 0.1% increment again, the short position must be disclosed again. In consequence, many of the disclosures are corrections of existing short positions, such as position increase, reduction or close out. Each European regulatory entity has been provided with a convenient downloading option in comma-separated values (csv) format. For the following analysis, I collect the disclosed short positions from all countries in the European Union[26] from November 1, 2012 (day of the introduction of the disclosure regime) to November 1, 2016. For each position, the

[25] Similarly, Uhl (2014) finds that the sentiment of *Reuters* articles also predict Dow Jones Industrial Averages stock index returns.

[26] Table 3.10 in the Appendix lists the links to the short position data for all countries analyzed in this study. Further, Figure 3.3 in the appendix plots the number of short positions reported from November 05, 2012 to November 1, 2016. For the considered time span, in the UK the day after the referendum marks the date with the highest number of short position disclosures.

position holder, the issuer, the ISIN, as well as the date of the position trade and the position size in percentage are reported. The issuer of a position is the shorted firm. The reported position size is the entire net short-selling position value of a position holder, expressed as percentage of the total issued stocks shares. Moreover, once collected, the data must be filtered extensively by hand. There are vast differences in the quality of the reported short positions: in Germany, for example, there have been some reports of short positions of the STOXX index, and an individual trader has disclosed to have shorted 100% of UniCredit. Such positions must be removed from the sample, because a 100% position is implausible and a STOXX index cannot be directly shorted.[27]

On the basis of the stock positions owned by individual short sellers, it is possible to determine the total amount of shorted shares of each single stock by adding up each individual position held by the short sellers. For this computation, a position that is reduced to 0.5% or below is considered to be closed, and so taken out of the calculation. After the Brexit referendum, the number of disclosed short position changes has increased drastically, as the barplot in Figure 3.3 in the Appendix shows. Especially in the UK, the highest number of short position trades subject to disclosure has been reported on the day after the referendum (June 24, 2016). This shows that short sellers did in fact react to the surprising referendum outcome.

Thomsons Reuters Datastream provides ISIN, name, daily returns and market capitalization for all stocks traded on European markets. The daily trading turnover is calculated using the number of shares outstanding, number of shares traded, and adjustment factor.

[27] Overall, the sample consists of 66,851 reported disclosures: among them, 44 occurrences can be found in which the reported date of the disclosed position falls on a Saturday or Sunday (by definition not trading days, see section 2), although the EU regulation clearly states that the reported date needs to be the trading day of the position. The German Federal Financial Supervisory Authority has assured me that the positions reported on a weekend occur due to mishaps by the position holders. Among the 44 short positions with the trading date set on a Saturday or Sunday, 38 are reported by different short position holders, thus eliminating the possibility that a short seller used this method to systematically conceal information. To include these disclosures, I set these positions on the preceding Friday, because this is the latest possible trading day. If the position has already been disclosed on that Friday, I choose the characteristics of the later reported disclosure, consequently interpreting the later short position report as a correction.

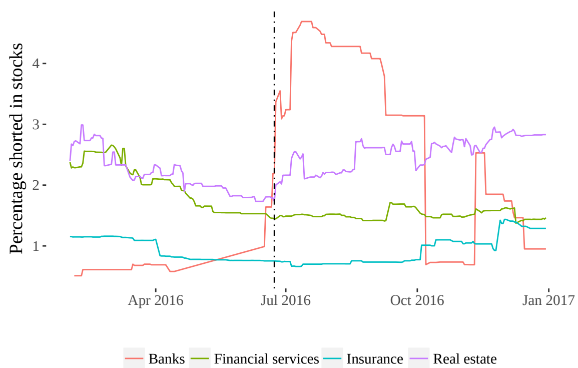
Appendix 3.6.2 provides a detailed account of the calculation of the trading turnover, which reports the proportion of shares that have been traded in a day.[28] To control for industry, the Industry Classification Benchmark (ICB) is downloaded for each stock. The ICB has four different levels of classification: industry, supersector, sector, and subsector. In this study, the supersector level is used.

The stock-specific data collected from Datastream is matched with the disclosed short positions according to the ISIN and the date. Of the 55,191 gathered short positions, 8% (4,415.28) cannot be matched to the corresponding stock information, because the reported ISIN is not found in the Datastream dataset. The data for all the stocks in the considered countries are gathered to ensure a comparison between the return of stocks with at least one disclosed short position and the return of stocks without any reported short position.[29]

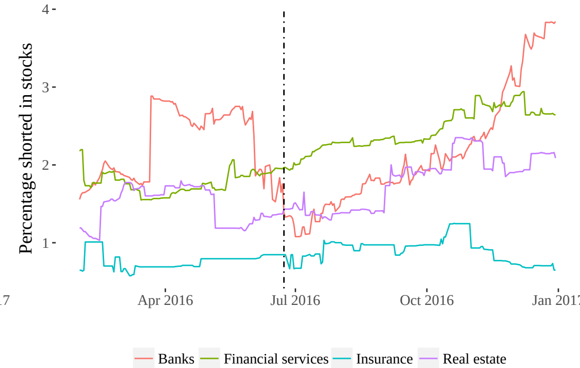
Figure 3.1 plots the development of the short positions from January 2016 to January 2017 within each supersector. For the UK, in Panels (a), (c), and (e) the total short positions held in each supersector show a clear short-term increase in the supersectors real estate, banks, retail and construction. This supports the prognosis by Docherty (2016), who identifies these supersectors as the ones most likely to lose from a Leave vote. For Europe, Panels (b), (d), and (f) plot the total short positions over time. Similarly, here we see a short-term increase in reported short positions in the bank, insurance, financial services and telecommunications supersectors.

[28] Appendix 3.6.3 tests the data quality for the trading volume collected from Datastream. For Germany, I compare the trading volume reported by the Deutsche Börse to the trading volume collected from Datastream.

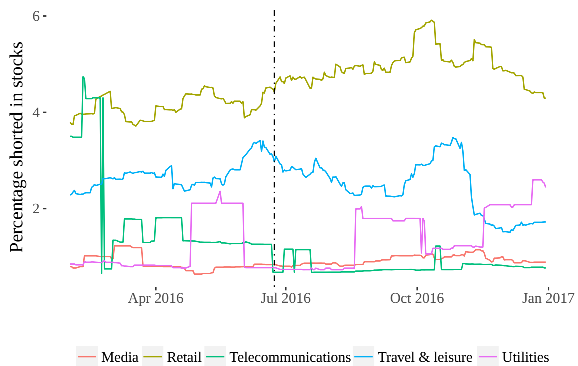
[29] In the Appendix, Figure 3.5 plots the changes in disclosed short positions and the stock price of Aixtron since the introduction of the short position disclosure regime. This figure shows the data stock return and short selling data available.



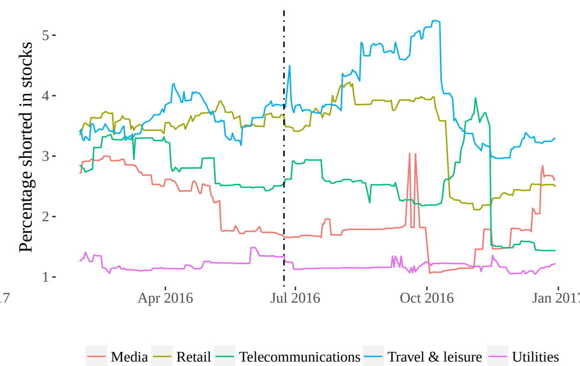
(a) UK: Financials



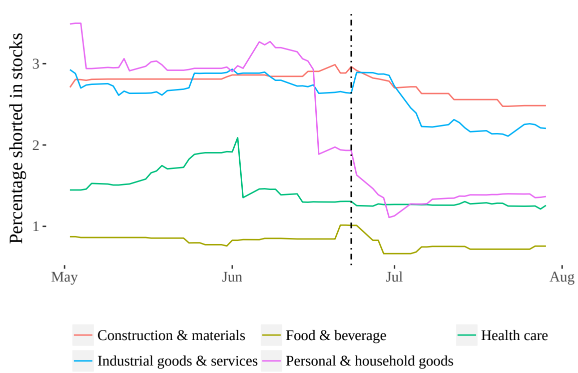
(b) EU: Financials



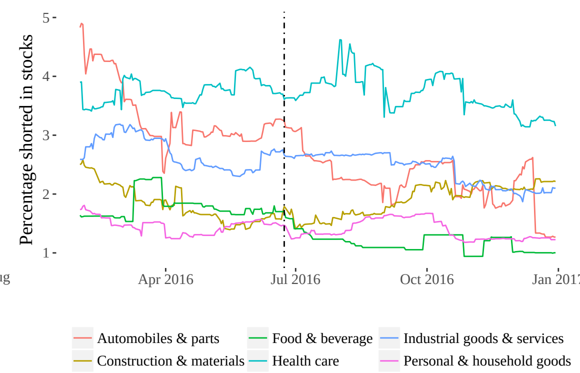
(c) UK: Consumer services & utilities



(d) EU: Consumer services & utilities



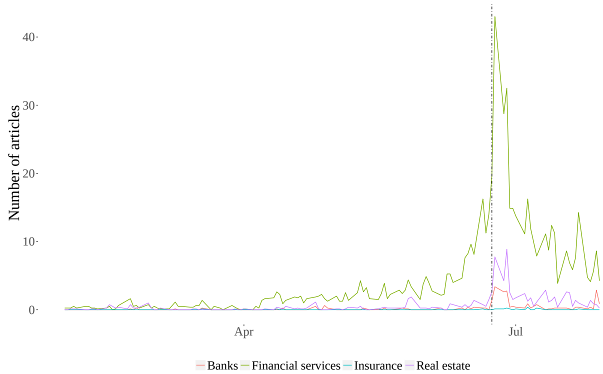
(e) UK: Consumer goods & health care



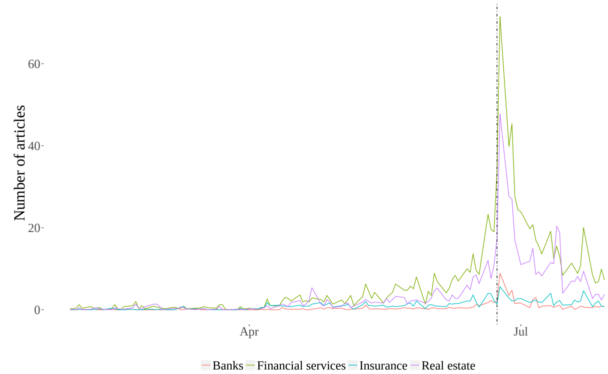
(f) EU: Consumer goods & health care

Figure 3.1: Total percentage of shorted stocks by supersector

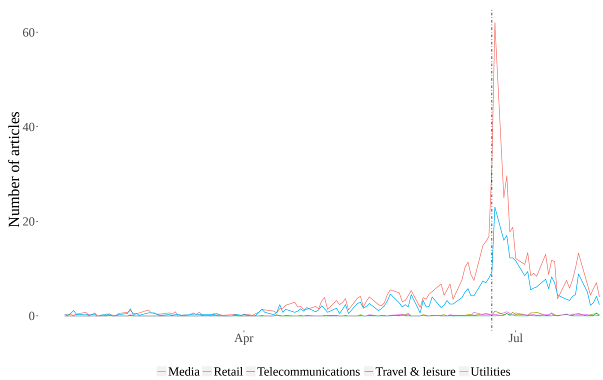
This figure plots the number of reported short sale positions divided by the total number of outstanding shares of the shorted stocks for each supersector. The short positions are grouped by ICB supersector and plotted from January 1, 2016 to January 1, 2017. The development of the short positions is calculated by cumulating the difference in disclosed short positions in the UK (left panels) and the EU (right panels) before and after the Brexit referendum, grouped by supersector. If the number of short positions drops below 0.5% of the total number of outstanding shares, the position is considered closed. The total of the short positions in a supersector is measured as number of shares shorted divided by number of shares outstanding in all the shorted stocks. The dashed vertical line indicates the day of the Brexit referendum.



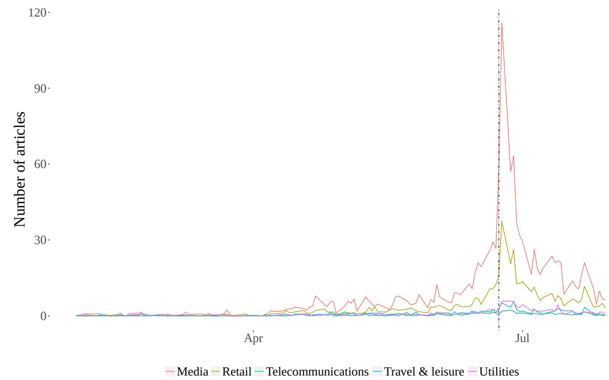
(a) UK: Financials



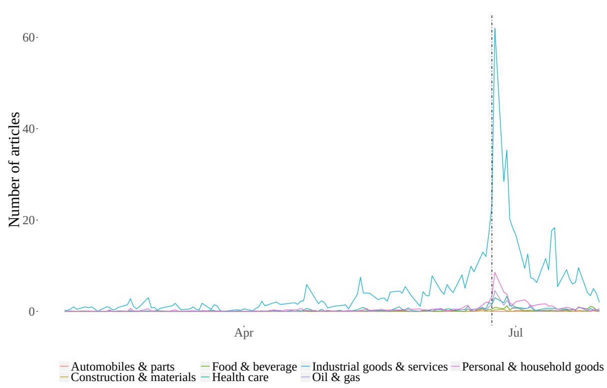
(b) EU: Financials



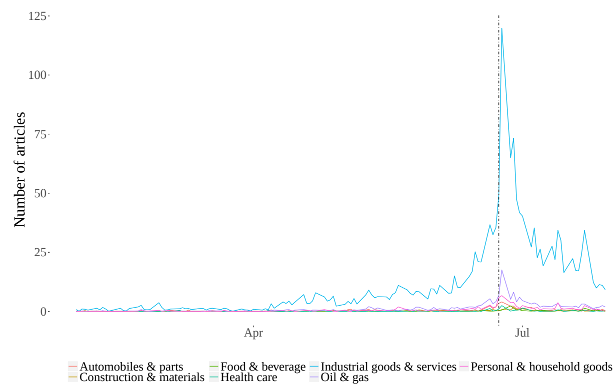
(c) UK: Consumer services & utilities



(d) EU: Consumer services & utilities



(e) UK: Consumer goods & health care



(f) EU: Consumer goods & health care

Figure 3.2: Total number of published news articles joining Brexit and a company name by supersector

Number of published articles tagged with *"Brexit"* and *"company name"* and dealing with stocks traded on European stock exchanges. For each supersector, the numbers of articles are aggregated and plotted from January 1, 2016 to January 1, 2017.

Table 3.1: Summary of media attention and disclosed short position by supersector

This table reports the change in number of articles published, average disclosed short positions, 2-day cumulative return and average change in short positions of the stocks in each ICB supersector. Each value is reported for the day after the referendum (June 24, 2016); the differences are between the values reported on the day of the referendum and on the day after it.

Sector	No. of articles	Average short position	2-day cumulative return	Average change in short positions
UK				
Real estate	8	1.457	-6.611	0.470
Automobiles & parts	0	0.000	-5.061	0.000
Banks	5	1.123	-4.492	-0.070
Construction & materials	3	1.270	-3.834	-0.040
Financial services	44	1.151	-3.561	0.000
Retail	4	2.453	-3.425	-1.780
Insurance	1	0.677	-2.315	-0.110
Technology	2	0.789	-1.434	-0.010
Industrial goods & services	63	1.331	-1.047	-0.260
Telecommunications	0	1.312	-1.013	-0.140
Travel & leisure	23	1.320	-0.940	0.110
Media	62	0.483	-0.428	-0.130
Basic resources	1	0.666	2.619	-0.300
Food & beverage	4	0.627	4.759	0.000
Oil & gas	4	1.211	5.086	0.000
Personal & household goods	9	0.649	5.372	-0.150
Utilities	0	1.170	5.709	0.000
Health care	3	0.801	6.182	0.160
EU				
Travel & leisure	3	1.368	-3.164	-0.020
Insurance	4	0.347	-2.994	0.000
Banks	5	0.916	-2.956	0.370
Automobiles & parts	5	1.052	-2.792	-0.240
Industrial goods & services	65	1.577	-1.181	-0.090
Construction & materials	5	1.105	-0.227	-0.080
Financial services	37	1.785	0.055	0.000
Basic resources	5	1.438	0.303	-0.120
Technology	20	1.352	0.628	-0.080
Media	34	1.493	0.743	0.100
Oil & gas	11	2.131	0.853	0.060
Retail	20	1.491	1.010	-0.130
Personal & household goods	5	1.084	1.300	-0.200
Telecommunications	2	1.471	1.686	0.210
Food & beverage	1	0.622	2.210	-0.330
Health care	1	1.325	2.252	0.110
Utilities	2	0.585	2.284	-0.170
Real estate	26	1.070	2.611	0.000

For this study, media coverage about the Brexit is gathered when it includes explicit references to a company traded on a European stock exchange. To this purpose, I collect articles tagged with the name of the stock and the term *"Brexit"*.[30] This ensures that the media coverage of the stock is mentioning the company in combination with the Brexit. The data is gathered through the BBC Application Programming Interface (API) called *The Juicer*,[31] which collects, with the help of an algorithm, all articles published on 850 RRS (Rich Site Summary) feeds of national, international, and local publications, tags them with relevant keywords, and then gives access to this information. For every stock, the name of the company is taken from the Datastream variable NAME; moreover, in order to find the most accurate matches, all general abbreviations such as PLC, GmbH or LLP are removed from the company name.

Figure 3.2 plots the collected number of articles that are published on the companies in each ICB supersector from January 1, 2016 to 1 January 1, 2017. For most supersectors, there is a sharp increase in the number of articles published after the Brexit referendum. For the UK, Panel (a) shows that the number of articles increases significantly for the supersectors banks, financial services, and real estate; interestingly, the banks and real estate supersectors experience a simultaneous increase in shorted stocks. Panel (b) reports the number of articles on financial services published in Europe, excluding the UK, and here we see a significant increase in articles mentioning stocks from the financial services and real estate supersectors.

In Panel (c) and (d) of Figure 3.2, the number of published articles addressing the consumer services and utilities industry is plotted for the UK and the rest of the European Union, respectively. In the consumer services industry, the retail supersectors is discussed particularly often in the media with regards to the Brexit, in both Europe and the UK.

[30]In the Appendix 3.6.5, the number of articles tagged with the words *"Brexit"*, *"referendum"* and *"Brexit and referendum"* are reported, showing that the pattern is very similar for all three tags. However, the number of articles tagged with the term *"Brexit"* is consistently higher.

[31]Information on the API can be fund at http://bbcnewslabs.co.uk/projects/juicer/, last accessed February 26, 2019.

In Panel (e) and (f), the supersector with the most extreme reaction to the referendum is industrial goods & services. Overall, the graphical summaries of both the short positions and the number of articles published after the Brexit confirm that the concentration does lie in supersectors that would stand to lose from the GDP/EUR depreciation, as predicted by Docherty (2016).

Table 3.1 reports, for each supersector, the total disclosed short positions in percentage, the change in number of articles published, the 2-day cumulative return, and the average change in short positions over the referendum. As Docherty (2016) predicted and the 2-day cumulative returns after the referendum confirm, supersectors which sustained losses after the Brexit referendum were banks, travel & leisure, retail, and construction. In the supersectors with the lowest returns, an average stock has a high number of short positions; however, at the same time, short positions are also high in stocks which usually attract more investments in periods of market downturn, such as those in the supersectors utilities, oil & gas, and basic resources.

Furthermore, it can be observed that short sellers shorted both stocks that would lose in case of a Leave vote and stocks that would lose with a Remain vote: this shows that, as a group of investors, they were preparing for both possible outcomes. Table 3.1 shows that especially companies in the UK and other the EU countries that are expected to lose from a prospective Brexit have strong negative 2-day, cumulative, post-referendum returns.

To answer the question whether media attention towards a stock with disclosed short positions leads to a significant underperformance of returns after the referendum, it is necessary to look at the stocks with both media attention and disclosed short positions. In the summary presented in Table 3.2, the number of stocks with both a disclosed short position and media attention, their value-weighted post-referendum return, and their average market capitalization are reported. Furthermore, Table 3.2 also give the summary statistics for stocks with no disclosed short position and no media attention, stocks with no disclosed short position but with media attention, and stocks with a disclosed short position and no media attention. In both the UK and the other European countries, the largest number of stocks have no disclosed short position. Overall, in the UK, 170 stocks had disclosed short positions open at the time of the Brexit referendum. Of the 170 shorted stocks, 21 also had media attention. Stocks with both an open short position and media attention have a return of -7.908%, which is perceptibly lower compared to the shorted stocks with an open short position and no media attention or stocks without an open short position but with media attention. For the EU stocks, a similar observation can be made. In the other European countries, the total number of stocks shorted at the time of the referendum is higher with a total of 229 firms. However, only 11 of these are also covered in the media. A total of 204 stocks are covered in the media in the European countries in connection with the Brexit. This preliminary summary of the data suggests that especially publicly shorted stocks that receive media attention have significant negative returns after the referendum. However, it is important to note that the number of stocks with both an open short position and media attention are only 21 in the UK and 11 in the other European countries.

Table 3.2: Summary of media attention and publicly disclosed stocks

This table reports summary statistics for the groups of stocks with and without disclosed short positions that have media attention or not. For each of the four groups, the no. of stocks, the post-referendum returns, and the average market value are reported. *No. of stocks* is the number of stocks comprised in the group with media attention and disclosed short position characteristics. The *Post-referendum return* is the value-weighted, 2-day, cumulative, market-adjusted returns after the Brexit referendum. The average market value of the stocks is reported in millions. Panel A reports the summary statistics for the UK stocks and Panel B reports the summary statistics for the European countries without the UK.

Panel A: UK			
		Not shorted	Shorted
No media attention	No. of stocks	1,631	149
	Post-referendum return	0.878	-3.385
	Avg. market value	1,124	3,062
Media attention	No. of stocks	99	21
	Post-referendum return	0.904	-7.809
	Avg. market value	5,043	3,825
Panel B: EU			
		Not shorted	Shorted
No media attention	No. of stocks	6,567	193
	Post-referendum return	0.081	-0.169
	Avg. market value	3,052	8,397
Media attention	No. of stocks	218	11
	Post-referendum return	-0.425	-3.696
	Avg. market value	7,137	9,111

3.4 Empirical Results

This section is divided into two subsections. The first subsection presents the main result of this paper, namely that media attention directed at shorted stocks affects negatively their post-referendum returns. The second presents auxiliary results which show that, in the UK, stocks with open short positions significantly underperform the market; however, they have significantly higher returns than stocks matched on their market value and ICB supersector. Furthermore, small stocks with media attention in the UK significantly underperform the market but do not underperform stocks of similar size and industry affiliation. In the EU, open short positions have a negative effect on smaller stocks, and media attention has a negative effect on larger stocks.

3.4.1 Main Results

In this section I will show that, when it comes to UK, the post-referendum returns of shorted stocks are negatively affected by media attention. First, evidence will be given by a diff-in-diff analysis. Second, a matching approach will offer further evidence of the effect of media attention given to a publicly shorted stock compared to other stocks with similar size and the same industry affiliation.

Table 3.3 shows the results of the diff-in-diff regression, where the dependent variable is the 2-day, cumulative, market-adjusted return after the referendum.[32] Assuming that investors read the articles on a company on June 24, 2016 and then trade on this new information, this should then be reflected in the 2-day, cumulative, market-adjusted return. The variables *Short position* and *Media attention* indicate whether there is a disclosed short position in the stock on the day after the referendum (June 24, 2016) or a published article mentioning jointedly the company and the referendum. *Short position* is a dummy variable which has the value 1 for stocks with a disclosed short position larger than 0.5% of outstanding shares. Furthermore, *Media attention* is a dummy variable with the value 1 if the stock has been covered in the media in relation to the referendum on June 24, 2016. To control for the cross-sectional difference in size and trading volume in each stock, the market value and the turnover are included as control variables. More specifically, the logarithm of the market value and the logarithm of the turnover plus 1 are included. The trading turnover is transformed into $log(1 + turnover)$ to account for the possibility of a stock having a trading volume of zero. This diff-in-diff regression shows the effect a disclosed short position or media attention has on stocks in the cross-section and also the effect both a disclosed short position and media attention can have on the post-referendum returns of these stocks.

[32] Table 3.13 in the Appendix reports the same diff-in-diff regression with a post-referendum return of 5-days.

For the UK, the coefficient of the interaction term between *Short position* and *Media attention* is significantly negative, indicating that the combination of a disclosed short position with media attention for any shorted stock affects negatively the post-referendum return of that stock. Without controlling for trading turnover and market value, the media attention in the UK has a slightly significant positive effect, which is in line with the literature that finds media attention to be good for stock returns (Hillert and Ungeheuer, 2018). Overall, this result offers some evidence that media attention for a stock that has been shorted has a negative effect on that stock's return, as indicated by this analysis of the post-referendum results.

Table 3.3: Media attention, short selling, and post-referendum returns

This table reports the results of the diff-in-diff regression. The dependent variable is the 2-day, cumulative, market-adjusted return after the Brexit referendum. The variable *Short position* is a dummy variable with the value 1 if the stock has a disclosed short position on June 24, 2016. The variable *Media attention* is a dummy variable with the value 1 if the stock is covered in the media in relation to the Brexit referendum on the day after the referendum, June 24, 2016. *Short position * Media attention* is the interaction term between the two variables. The variables *log(MV)* and *log(1 + turnover)* are the logarithm of the market capitalization of the stock and the logarithm of the trading turnover of the stock, respectively. The trading turnover is the quotient of number of shares traded to the number of shares outstanding in a stock. The first two columns report the regression results for all UK stocks, and the last two columns for all countries in the EU excluding the UK. The t-statistics are reported in brackets below the coefficient values.

	UK		EU	
Short position	0.061	0.117	0.072	0.280***
	(0.702)	(1.379)	(0.749)	(3.265)
Media attention	0.284	0.377*	−0.120	0.136
	(1.456)	(1.878)	(−0.559)	(0.668)
Short position * Media attention	−0.398*	−0.437**	−0.003	−0.196
	(−1.676)	(−2.167)	(−0.001)	(−0.725)
log(MV)	0.041***		0.038**	
	(4.149)		(2.353)	
log(1 + turnover)	−1.655***		2.581***	
	(−3.803)		(4.573)	
Constant	−0.227***	−0.047**	−0.376***	−0.208***
	(−3.828)	(−2.172)	(−4.471)	(−6.756)

In the other European countries, the results differ from the ones in the UK. Media attention for a shorted stock does not have a significant effect on the post-referendum returns. Furthermore, stocks with media attention in relation to the referendum do not significantly under- or outperform the market. The coefficient of the short position variable is only significant if the control variables are not added into the regression. Furthermore, neither a disclosed short position nor media attention have an added significant effect on the post-referendum returns.

In the following, the analysis will concentrate on the effect media attention has on the post-referendum returns of stocks with a disclosed short position. For this reason, the stocks with a disclosed short position and media attention are matched to stocks with an open short position but no media attention (Barber and Lyon, 1997). The matching approach allows to compare the return of stocks with short positions and/or media attention while controlling for unobserved factors that may influence the stocks returns. The treatment stocks – namely stocks with a disclosed short positions and media attention – are matched to stocks with a disclosed short position and no media attention (control stocks) according to the stock's size and the supersector it belongs to. Conducting the matching based on supersectors is in this case especially important because the outcome of the referendum has affected supersector in significantly different ways. Suitable control stocks are identified among all those with a disclosed short position and no media attention by first identifying all stocks in the same ICB supersector, and then selecting among these the one with the market value closest to that of the treatment stocks.

Table 3.4 reports the results for the UK stocks, both value- and equally-weighted. Aggregating the stocks on a value- and equally-weighted basis allows to investigate the different effect of media on shorted stocks with a larger and smaller market capitalization, respectively. For example, Ferguson, Philip, Lam, and Guo (2015) find that the effect of media attention is higher for larger firms, motivating the analysis of the value-weighted and equally-weighted aggregation. Table 3.4 shows that after the referendum stocks with media attention and an open short position underperform their matched stocks significantly. This means that media attention in a publicly shorted stock in the UK has a negative effect on the stock returns after the referendum. This may be due to the fact that the media attention in this case is more likely negative, because the open short positions show that investors have a bearish outlook on this stock. This effect is similar irrespective of whether the mean post-referendum return is value- or equally-weighted, suggesting that this effect is independent of size. In Table 3.4 the returns of stocks with an open short position and media attention reverse slightly. The 5-day, market-adjusted, cumulative returns are less negative than the 2-day cumulative return. Although this reversal is not significant, it is consistent with a negative price pressure caused by negative media attention that is not backed up by fundamentals.

Table 3.5 reports the results of the same matching approach for the other countries in the European Union. As for the UK, also in the rest of the EU media attention for a shorted stock has a negative effect on its post-referendum returns compared to the matched stocks. In magnitude, however, this effect is smaller than for the UK stocks. In contrast to the results of the diff-in-diff regression, this result for the EU stocks shows that, unlike what happens with the matches, media attention for a shorted stock has a negative effect on the post-referendum returns. In the EU, the effect of media attention on a shorted stock is more significant in larger stocks, supporting results of Ferguson, Philip, Lam, and Guo (2015) that the effect of media attention is more extreme in larger stocks.

Overall, the analysis presented shows evidence that media attention for a shorted stock does influence negatively its post-referendum returns, be it because journalists are aware of the disclosed short positions, or because they are as well informed as analysts and therefore direct their interest to similar stocks. The presence of webpages such as the short interest tracker by Castellain Capital LLP called ShortTracker+ or WhaleWisdom[33] make the public short positions easily accessible. Easier accessibility of the short data may lead to media attention being directed at shorted stocks because of the short positions themselves.

[33] The ShortTracker+ can be found at https://shorttracker.co.uk/, last accessed July 20, 2019. WhaleWisdom can be found at https://whalewisdom.com/short_position, last accessed July 20, 2019.

Table 3.4: Matching approach to examine the effect of media attention on shorted stocks in the UK

For UK stocks, Panel A (Panel B) reports the post-referendum, cumulative, value-weighted (equally-weighted), market-adjusted returns of treatment stocks and control stocks. The treatment stocks are all stocks with media attention and any open short positions on the day of the referendum, whereas the control stocks have an open short position but no media attention. The control stocks are matched to the treatment stocks based on size and supersector. The first (second) column reports the value-weighted (equally-weighted) returns of the control stocks and treated stocks, respectively. The third column reports the difference in returns between the two. Returns are expressed as percentages. T-statistics are reported in brackets below the estimates.

	Control	Treatment	Treatment - Control
Panel A: Value-weighted			
5-day cumulative return	-2.098	-3.777	-1.962
	(-1.785)	(-1.565)	(-0.605)
4-day cumulative return	-1.465	-4.416	-3.185
	(-1.344)	(-2.205)	(-1.146)
3-day cumulative return	-1.085	-6.050	-5.127
	(-0.965)	(-3.415)	(-2.099)
2-day cumulative return	-0.899	-7.809	-7.065
	(-1.000)	(-3.180)	(-2.477)
1-day return	0.004	-0.047	-0.052
	(0.961)	(-2.902)	(-3.338)
Panel B: Equally-weighted			
5-day cumulative return	0.156	-4.625	-4.781
	(0.229)	(-1.359)	(-1.492)
4-day cumulative return	0.739	-4.667	-5.406
	(1.203)	(-1.428)	(-1.740)
3-day cumulative return	1.447	-5.606	-7.053
	(1.259)	(-2.88)	(-3.227)
2-day cumulative return	0.84	-5.886	-6.726
	(0.690)	(-2.178)	(-2.544)
1-day return	0.017	-0.032	-0.049
	(2.480)	(-1.810)	(-3.157)

Table 3.5: Matching approach to examine the effect of media attention on shorted stocks in the EU (excluding UK)

For European stocks excluding UK stocks, Panel A (Panel B) reports the post-referendum, cumulative, value-weighted (equally-weighted), market-adjusted returns of treatment stocks and control stocks. The treatment stocks are all stocks with media attention and any open short positions on the day of the referendum, whereas the control stocks have an open short position but no media attention. The control stocks are matched to the treatment stocks based on size and supersector. The first (second) column reports the value-weighted (equally-weighted) returns of the control stocks and treated stocks, respectively. The third column reports the difference in returns between the two. Returns are expressed as percentages. T-statistics are reported in brackets below the estimates.

	Control	Treatment	Treatment - Control
Panel A: Value-weighted			
5-day cumulative return	-0.503	-3.515	-3.989
	(-0.296)	(-2.004)	(-2.127)
4-day cumulative return	-0.49	-3.401	-3.666
	(-0.390)	(-2.016)	(-2.155)
3-day cumulative return	-0.212	-4.391	-4.599
	(-0.244)	(-3.277)	(-3.248)
2-day cumulative return	-0.336	-3.696	-3.684
	(-0.378)	(-2.440)	(-1.988)
1-day return	-0.001	-0.028	-0.026
	(-0.114)	(-3.043)	(-2.200)
Panel B: Equally-weighted			
5-day cumulative return	-2.420	-4.258	-1.838
	(-1.304)	(-3.415)	(-1.708)
4-day cumulative return	-1.746	-3.974	-2.228
	(-1.077)	(-2.907)	(-2.458)
3-day cumulative return	-0.797	-3.811	-3.014
	(-0.840)	(-2.203)	(-1.902)
2-day cumulative return	-0.894	-2.837	-1.943
	(-0.887)	(-1.606)	(-0.931)
1-day return	-0.002	-0.014	-0.012
	(-0.253)	(-1.529)	(-0.977)

3.4.2 Further Results

For a further analysis, the treatment sample includes four groups of stocks: stocks with open short positions (independently from media attention), stocks with media attention (independently from short positions), stocks with media attention and short positions, and stocks with open short positions but no media attention. The possible control stocks are to be chosen among all stocks that cannot be included in the treatment sample considered because they do not have the characteristics required. They are found by first identifying all stocks in the same ICB supersector, and then selecting among these the one with the market value closest to that of the treatment stocks. This procedure is applied for each different group in the treatment sample.

Table 3.6 and Table 3.7 present the average cumulative return of the 4 different groups of treatment stocks and of the matched control stocks for the UK and for other EU countries, respectively. The treatment stocks in Panel A are all stocks with open short positions; in Panel B, all stocks with media coverage; Panel C includes all stocks with media attention and disclosed short positions, and Panel D all stocks with open short positions and no media attention. The cumulative returns are the 1-day to 5-day, cumulative, market-adjusted returns after the Brexit referendum.

For the UK, Panel A in Table 3.6 shows that, after the referendum, stocks with an open short position did not exhibit significantly higher losses compared to non-shorted stocks in the same supersector with a similar size. Furthermore, Table 3.8 Panel A shows that larger firms with an open short position actually significantly outperform after the referendum compared to their matches without short positions. This could be attributed to the large number of short position reductions after the referendum. The average percentage of short position in the month before the Brexit is 1.11%, but in the month after the Brexit this value is reduced to 1.08%. The difference of 0.17 percentage points is significant (t-stat=2.973) and indicates that a stock with an open short position is much more likely to profit from the positive return effect of a short position reduction (see, Boehmer, Duong, and Huszár, 2018, for an example on the Japanese disclosure regime).

Furthermore, Panel B in Table 3.6 shows that, compared to their matches, stocks with media attention did not suffer significantly higher losses; this result also holds for larger stocks. In Panel C, the treatment stocks are stocks with both media attention and an open short position on the day after the referendum. After the referendum, stocks with media attention and an open short positions also did not lose to a significantly higher degree than their matches. The same holds for stocks with an open short position and no media attention. For larger stocks, Table 3.8 shows that the post-referendum returns are -2.87 percentage points lower for stocks with media attention and an open short position. However, this effect is not statistically significant. Overall, these results show that, on an equally-weighted basis, in the UK public short positions did not worsen the post-referendum adverse reaction of shorted stocks compared to their matches; moreover, the same can be said of media attention in general, which also had no negative influence on post-referendum returns. These results do not test the additional effect media attention has on a shorted stock, therefore they do not stand in contrast to the main results reported above.

Table 3.7 reports the results of the matching approach for all EU countries excluding the UK. In Panel A, stocks with an open short position are shown to underperform their matches. For large stocks, the difference in return is not statistically significant. This stands somewhat in contrast to the UK results, where stocks with an open short position do not significantly underperform the matched stocks. This may be because in the EU the number of short position reductions after the referendum are fewer than in the UK.[34]

[34]The barplot in Panel B, Figure 3.7, confirms the lower number of short position reductions (downticks) in the other European countries excluding the UK after the referendum.

Table 3.6: Equally-weighted matching approach results for UK stocks

This table reports the cumulative, equally-weighted, market-adjusted returns after the Brexit referendum of treatment stocks and control stocks. The treatment stocks are: in Panel A all stocks with at least an open short position on the day of the referendum, in Panel B all stocks with media coverage, in Panel C all stocks with media attention and disclosed short positions, and in Panel D all stocks with short positions and no media attention. The first column reports the equally-weighted returns of the control stocks. The second column reports the equally-weighted returns of the treatment stocks. The third column reports the difference in returns between the two. Stock are matched on market value and supersector. Returns are expressed as percentages. T-statistics are reported in brackets below the estimates.

	Control stocks	Treatment	Treatment - Control
Panel A: Short positions			
5-day cumulative return	-6.162	-5.265	0.897
	(-5.597)	(-7.608)	(0.667)
4-day cumulative return	-5.351	-5.351	0.000
	(-5.159)	(-7.989)	(0.000)
3-day cumulative return	-4.541	-4.926	-0.385
	(-6.615)	(-7.292)	(-0.458)
2-day cumulative return	-4.638	-5.218	-0.580
	(-6.328)	(-7.384)	(-0.667)
1-day return	-0.018	-0.022	-0.004
	(-3.758)	(-5.108)	(-0.713)
Panel B: Media attention			
5-day cumulative return	-5.101	-5.170	-0.069
	(-3.639)	(-3.545)	(-0.612)
4-day cumulative return	-4.578	-4.635	-0.057
	(-4.820)	(-4.781)	(-0.519)
3-day cumulative return	-2.057	-2.135	-0.077
	(-3.457)	(-3.735)	(-0.293)
2-day cumulative return	0.342	0.397	0.054
	(0.560)	(0.708)	(0.174)
1-day return	0.006	0.006	0.000
	(1.710)	(1.767)	(-0.178)
Panel C: Media attention and short positions			
5-day cumulative return	-8.292	-4.625	3.667
	(-2.547)	(-2.915)	(1.449)
4-day cumulative return	-7.185	-4.667	2.518
	(-2.271)	(-3.777)	(0.840)
3-day cumulative return	-6.062	-5.606	0.456
	(-1.626)	(-2.880)	(0.130)
2-day cumulative return	-5.766	-5.886	-0.120
	(-1.292)	(-2.178)	(-0.030)
1-day return	-0.026	-0.032	-0.006
	(-1.046)	(-1.810)	(-0.276)
Panel D: Short positions and no media attention			
5-day cumulative return	-6.037	-5.307	0.730
	(-5.104)	(-5.314)	(0.550)
4-day cumulative return	-5.175	-5.395	-0.220
	(-4.752)	(-5.998)	(-0.187)
3-day cumulative return	-4.619	-4.882	-0.263
	(-6.800)	(-6.881)	(-0.305)
2-day cumulative return	-3.859	-5.174	-1.316
	(-5.569)	(-7.051)	(-1.504)
1-day return	-0.013	-0.021	-0.008
	(-2.927)	(-4.794)	(-1.422)

Table 3.7: Equally-weighted matching approach results for EU (excluding UK) stocks

This table reports the cumulative, equally-weighted, market-adjusted returns after the Brexit referendum of treatment stocks and control stocks. The treatment stocks are: in Panel A all stocks with at least an open short position on the day of the referendum, in Panel B all stocks with media coverage, in Panel C all stocks with media attention and disclosed short positions, and in Panel D all stocks with short positions and no media attention. The first column reports the equally-weighted returns of the control stocks. The second column reports the equally-weighted returns of the treatment stocks. The third column reports the difference in returns between the two. Stock are matched on market value and supersector. Returns are expressed as percentages. T-statistics are reported in brackets below the estimates.

	Control	Treatment	Treatment - Control
Panel A: Short positions			
5-day cumulative return	0.373	-0.874	-1.247
	(0.682)	(-2.203)	(-1.950)
4-day cumulative return	0.325	-0.698	-1.023
	(0.679)	(-1.783)	(-1.779)
3-day cumulative return	0.513	-0.326	-0.839
	(1.377)	(-0.916)	(-1.816)
2-day cumulative return	0.912	-0.153	-1.065
	(2.375)	(-0.427)	(-2.338)
1-day return	0.010	0.006	-0.004
	(3.871)	(2.226)	(-1.406)
Panel B: Media attention			
5-day cumulative return	2.089	1.876	-0.214
	(4.588)	(3.803)	(-1.695)
4-day cumulative return	2.000	1.827	-0.174
	(5.249)	(4.277)	(-1.309)
3-day cumulative return	2.970	2.748	-0.222
	(7.934)	(6.895)	(-1.818)
2-day cumulative return	3.665	3.516	-0.149
	(8.783)	(8.134)	(-1.204)
1-day return	0.022	0.021	-0.001
	(7.489)	(6.836)	(-1.711)
Panel C: Media attention and short positions			
5-day cumulative return	1.763	-4.258	-6.021
	(1.098)	(-2.286)	(-5.694)
4-day cumulative return	1.681	-3.974	-5.655
	(1.011)	(-2.193)	(-3.577)
3-day cumulative return	0.353	-3.811	-4.164
	(0.397)	(-2.203)	(-2.439)
2-day cumulative return	0.818	-2.837	-3.655
	(0.707)	(-1.606)	(-2.677)
1-day return	0.011	-0.014	-0.024
	(1.918)	(-1.529)	(-2.582)
Panel D: Short positions and no media attention			
5-day cumulative return	-5.519	-0.680	4.838
	(-2.685)	(-1.081)	(2.347)
4-day cumulative return	-4.964	-0.510	4.454
	(-2.403)	(-0.887)	(2.155)
3-day cumulative return	-4.504	-0.126	4.378
	(-5.393)	(-0.351)	(4.898)
2-day cumulative return	-3.716	0.000	3.717
	(-4.464)	(0.001)	(4.302)
1-day return	-0.013	0.007	0.019
	(-2.549)	(2.591)	(3.604)

Table 3.8: Value-weighted matching approach results for UK stocks

This table reports the cumulative, value-weighted, market-adjusted returns after the Brexit referendum of treatment stocks and control stocks. The treatment stocks are: in Panel A all stocks with at least an open short position on the day of the referendum, in Panel B all stocks with media coverage, in Panel C all stocks with media attention and disclosed short positions, and in Panel D all stocks with short positions and no media attention. The first column reports the value-weighted returns of the control stocks. The second column reports the value-weighted returns of the treatment stocks. The third column reports the difference in returns between the two. Stock are matched on market value and supersector. Returns are reported in percentage. T-statistics are reported in brackets below the estimates.

	Control	Treatment	Treatment - Control
Panel A: Short positions			
5-day cumulative return	-5.064	-2.474	2.881
	(-5.587)	(-3.291)	(2.862)
4-day cumulative return	-4.366	-2.519	2.017
	(-5.392)	(-3.724)	(2.217)
3-day cumulative return	-4.42	-2.884	1.592
	(-5.934)	(-4.315)	(1.822)
2-day cumulative return	-5.061	-3.736	1.536
	(-6.181)	(-5.137)	(1.643)
1-day return	-0.031	-0.014	0.018
	(-5.829)	(-2.891)	(2.716)
Panel B: Media attention			
5-day cumulative return	-1.053	0.108	-0.097
	(-0.675)	(0.074)	(-0.168)
4-day cumulative return	-0.41	0.481	-0.201
	(-0.299)	(0.371)	(-0.367)
3-day cumulative return	0.335	0.857	-0.476
	(0.26)	(0.663)	(-0.861)
2-day cumulative return	0.024	0.923	-0.218
	(0.016)	(0.68)	(-0.357)
1-day return	-0.013	0.001	0.004
	(-1.333)	(0.119)	(1.134)
Panel C: Media attention and short positions			
5-day cumulative return	-1.445	-3.777	0.014
	(-0.209)	(-1.565)	(0.003)
4-day cumulative return	-1.004	-4.416	-1.523
	(-0.157)	(-2.205)	(-0.308)
3-day cumulative return	-1.924	-6.050	-2.873
	(-0.376)	(-3.415)	(-0.691)
2-day cumulative return	-0.764	-7.809	-5.720
	(-0.123)	(-3.180)	(-1.224)
1-day return	-0.001	-0.047	-0.039
	(-0.030)	(-2.902)	(-1.503)
Panel D: Short positions and no media attention			
5-day cumulative return	-3.502	-2.361	1.996
	(-5.268)	(-2.992)	(1.972)
4-day cumulative return	-2.668	-2.356	1.103
	(-4.430)	(-3.309)	(1.168)
3-day cumulative return	-2.925	-2.612	1.160
	(-4.842)	(-3.713)	(1.256)
2-day cumulative return	-3.209	-3.385	0.323
	(-5.340)	(-4.480)	(0.344)
1-day return	-0.020	-0.011	0.008
	(-4.653)	(-2.204)	(1.257)

Table 3.9: Value-weighted matching approach results for EU (excluding UK) stockss

This table reports the cumulative, value-weighted, market-adjusted returns after the Brexit referendum of treatment stocks and control stocks. The treatment stocks are: in Panel A all stocks with at least an open short position on the day of the referendum, in Panel B all stocks with media coverage, in Panel C all stocks with media attention and disclosed short positions, and in Panel D all stocks with short positions and no media attention. The first column reports the value-weighted returns of the control stocks. The second column reports the value-weighted returns of the treatment stocks. The third column reports the difference in returns between the two. Stock are matched on market value and supersector. Returns are reported in percentage. T-statistics are reported in brackets below the estimates.

	Control	Treatment	Treatment - Control
Panel A: Short positions			
5-day cumulative return	0.357	-0.351	-0.669
	(0.962)	(-0.987)	(-1.536)
4-day cumulative return	0.155	-0.194	-0.331
	(0.465)	(-0.585)	(-0.837)
3-day cumulative return	-0.187	-0.251	-0.012
	(-0.606)	(-0.856)	(-0.033)
2-day cumulative return	-0.305	-0.388	-0.064
	(-1.016)	(-1.270)	(-0.177)
1-day return	0.002	-0.003	-0.005
	(1.258)	(-1.459)	(-2.213)
Panel B: Media attention			
5-day cumulative return	-2.21	-2.645	-0.463
	(-5.438)	(-6.336)	(-3.022)
4-day cumulative return	-2.039	-2.46	-0.448
	(-5.189)	(-6.032)	(-2.86)
3-day cumulative return	-2.024	-2.528	-0.525
	(-5.531)	(-6.623)	(-3.231)
2-day cumulative return	-2.19	-2.593	-0.421
	(-5.524)	(-6.438)	(-2.977)
1-day return	-0.017	-0.02	-0.003
	(-6.113)	(-7.116)	(-3.176)
Panel C: Media attention and short positions			
5-day cumulative return	0.397	-3.515	-4.284
	(0.333)	(-2.004)	(-3.236)
4-day cumulative return	0.567	-3.401	-4.322
	(0.551)	(-2.016)	(-3.047)
3-day cumulative return	0.200	-4.391	-4.854
	(0.260)	(-3.277)	(-4.108)
2-day cumulative return	-0.238	-3.696	-3.462
	(-0.257)	(-2.440)	(-3.157)
1-day return	0.004	-0.028	-0.032
	(1.225)	(-3.043)	(-3.750)
Panel D: Short positions and no media attention			
5-day cumulative return	-0.035	-0.141	-0.167
	(-0.087)	(-0.394)	(-0.341)
4-day cumulative return	-0.281	0.019	0.240
	(-0.793)	(0.057)	(0.550)
3-day cumulative return	-0.419	0.023	0.408
	(-1.269)	(0.079)	(1.030)
2-day cumulative return	-0.399	-0.169	0.146
	(-1.186)	(-0.552)	(0.359)
1-day return	0.002	-0.001	-0.003
	(0.835)	(-0.492)	(-1.19)

In Panel B, stocks with media attention on June 24, 2016, directly after the referendum, seem to outperform the market returns; however, their return is still significantly lower than that of the matched stocks. The value-weighted returns in Table 3.9, Panel B, show that large stocks with media attention significantly underperform the market and their matched counterparts as well. Compared to the UK, media coverage of EU stocks could be more unfavorable, causing the media attention to have a negative effect on the post-referendum returns, whereas in the UK the media coverage may be more balanced.

3.5 Conclusion

This analysis of the stock returns around the Brexit referendum is able to establish that media interest for publicly shorted stocks has proven to significantly intensify the negative reaction to the referendum outcome, this effect being more pronounced for the UK stocks. This finding strongly suggests that, in times of economic upheaval, media attention on stocks with a disclosed short position has a measurable influence on their returns. This reported effect can be seen as a risk arising from the European disclosure regime, whose stated aim is to ensure the transparency of short positions without *"unduly detracting from the benefits that short selling provides to the quality and efficiency of markets"* (European Securities and Markets Authorities, 2012, §(5) p.L86/2). In fact, the disclosure rules mandated by it, facilitating access and analysis of short-selling data previously out of reach of the wide public, also seem to have the unintended effect of developing and intensifying the interaction between media and markets. This case study offers first evidence of this phenomenon, showing that publicly shorted stocks are negatively affected by media attention after a market downturn.

The outcome of the Brexit referendum offers a unique possibility to study the effect of media attention on stocks with an open short position and this for two reasons. First, it came as a surprise and thus triggered sudden and complete stock price adjustments in the days following the referendum. Second, it affected all stocks in the European Union making this a unique example where media attention is similar for all stocks. This stands in contrast to the relatively small number of stocks with both media attention and an open short position. Extending the analysis to calmer periods will be necessary to be able to conclusively make an assertion on the effect of media attention on shorted stocks.

3.6 Appendix

3.6.1 Additional Tables

Table 3.10: Sources for national short position disclosure data

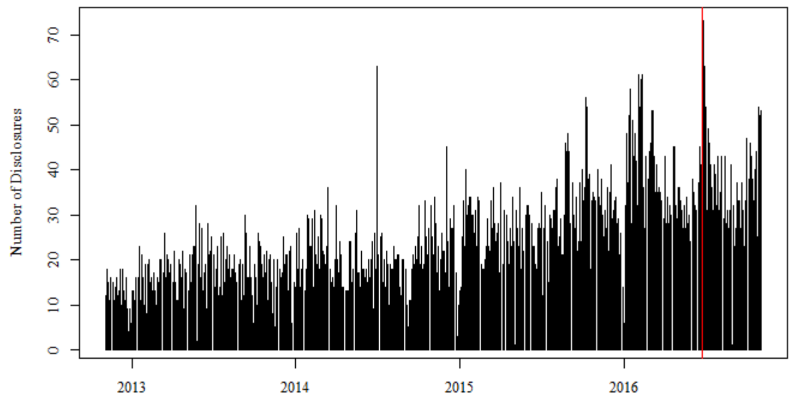
Weblinks to the regulatory authorities websites in the European Union countries. The short position data can be collected from these websites. These websites were last visited on January 27, 2018.

Country	Link
Austria	https://webhost.fma.gv.at/ShortSelling/pub/www/QryNetShortPositions.aspx
Belgium	http://www.fsma.be/en/Supervision/fm/ma/shortselling.aspx
Finland	http://www.finanssivalvonta.fi/en/Supervision/Market_supervision/Short_positions/Previous_positions/Pages/Previous_positions.aspx
France	http://www.amf-france.org/en_US/Acteurs-et-produits/Marches-financiers-et-infrastructures/Ventes-a-decouvert/Consolidation-des-publications.html
Germany	https://www.bundesanzeiger.de/ebanzwww/wexsservlet?page.navid=nlpstarttonlpstart_new&nlp_search_param.extended_search=true&session.sessionid=d29e7e68660725ada211383360a5c17d
Greece	http://www.hcmc.gr/en_US/web/portal/shortselling1
Hungary	https://www.kozzetetelek.hu/en/short_selling/list
Ireland	http://www.centralbank.ie/regulation/securities-markets/shortselling/Pages/PublicDisclosure.aspx
Italy	http://www.consob.it/mainen/markets/short_selling/intro_updated_data.html?queryid=ultimasegnalazioneSS&resultmethod=ultimavenditascoperto&maxres=1&search=1&symblink=/mainen/markets/short_selling/pnc_updated_data.html
Luxembourg	http://shortselling.cssf.lu/
Netherlands	http://www.afm.nl/en/professionals/registers/alle-huidige-registers.aspx?type=\protect\T1\textbraceleft129CD296-003C-4D56-8633-E1C7A83A9820\protect\T1\textbraceright
Poland	https://rss.knf.gov.pl/RssOuterView/
Portugal	http://web3.cmvm.pt/english/sdi/emitentes/shortselling/index.cfm
Spain	http://www.cnmv.es/portal/Consultas/Busqueda.aspx?id=29
Sweden	http://www.fi.se/Folder-EN/Startpage/Register/Short-Selling/
United Kingdom	http://www.fca.org.uk/firms/markets/international-markets/eu/short-selling-regulations/notifications-disclosures

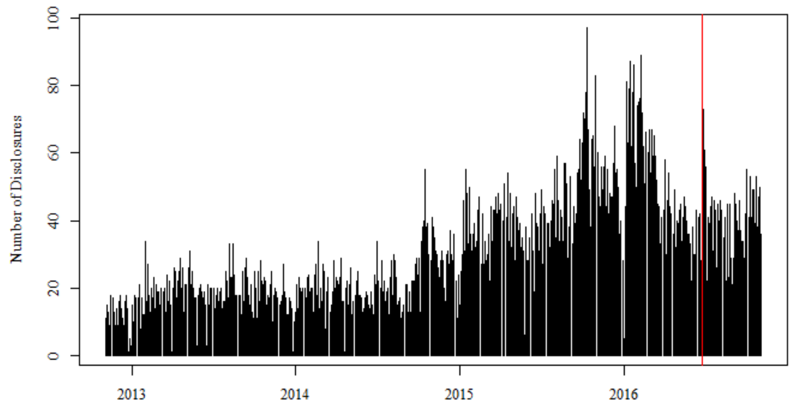
Table 3.11: Summary of the largest disclosed short positions after the Brexit

Summary of the largest disclosed short positions from June 23, 2016 (the day of the referendum) to June 29, 2016. For each day, the four largest positions are reported. For each positions, position holder, issuer and position size expressed as percentages are reported as they appear in the disclosures themselves. Furthermore, each position is labeled as a downtick or an uptick according to the previous disclosure. The uptick or downtick size is also expressed as percentages. The last column indicates the sector of the issuer firm.

Date	Position Holder	Issuer	Position Size in %	Downtick or Uptick	Size of Uptick or Downtick	Sector
June 23, 2016						
	Odey Asset Management LLP	Lancashire Holdings LTD	5.05	Downtick	-0.19	Financial Services
	Odey Asset Management LLP	Ashmore Group PLC	4.23	Downtick	-0.11	Financial Services
	Odey Asset Management LLP	Tullow Oil PLC	4.20	Downtick	-0.12	Oil and gas
	Discovery Capital Management, LLC	Ocado Group PLC	3.75	Uptick	0.06	Retail
June 24, 2016						
	Discovery Capital Management, LLC	Ocado Group PLC	3.90	Uptick	0.15	Retail
	Jericho Capital Asset Management L.P.	Ocado Group PLC	3.90	Downtick	-0.32	Retail
	Henderson Global Investors	Marston's plc	2.37	Downtick	-0.11	Travel
	Odey Asset Management LLP	INTU Properties PLC	2.26	Uptick	0.11	Real estate
June 27, 2016						
	Odey Asset Management LLP	Ashmore Group PLC	4.38	Uptick	0.15	Financial Services
	UBS Global Asset Management (UK) Ltd	New Melrose Industries PLC	3.93	Downtick	-0.44	Construction and materials
	Odey Asset Management LLP	INTU Properties PLC	2.36	Uptick	0.1	Real estate
	BlackRock Investment Management (UK) Limited	Carillion PLC	2.31	Uptick	0.06	Industrial goods
June 28, 2016						
	Discovery Capital Management, LLC	Ocado Group PLC	4.09	Uptick	0.19	Retail
	Jericho Capital Asset Management L.P.	Ocado Group PLC	4.02	Uptick	0.12	Retail
	Odey Asset Management LLP	INTU Properties PLC	2.40	Uptick	0.04	Real estate
	BlackRock Investment Management (UK) Limited	Brammer PLC	2.30	Uptick	0.01	Industrial goods
June 29, 2016						
	Schroder Investment Management Limited	J.D. Wetherspoon PLC	1.41	Uptick	0.03	Travel
	BlackRock Investment Management (UK) Limited	BBA Aviation PLC	1.10	Uptick	0.04	Travel
	BlackRock Institutional Trust Company, National Association	Firstgroup PLC	1.03	Downtick	-0.25	Travel
	Marshall Wace LLP	CYBG PLC	1.03	Uptick	0.05	Banks



(a) Panel A: UK



(b) Panel B: Europe

Figure 3.3: Short position disclosures

This figure shows the daily total number of short position disclosures from November 5, 2012 to November 1, 2016. Panel A shows the short positions disclosed in the UK and Panel B those disclosed in all other EU countries. The red vertical line indicates the day of the Brexit referendum, June 23, 2016.

3.6.2 General Turnover Calculation

In the empirical analysis, I compute turnover as the value of daily traded stocks divided by their respective market capitalization. In Datastream codes this translates in $(VO * P * U.P)/MV$, where VO is the daily number of shares traded adjusted for capital changes; P is the adjusted price; U.P reports the units in which the price is reported, and MV is the market capitalization of the stock. For Germany, VO cannot be used because it only reports the trading volume on the Frankfurt stock exchange (a detailed analysis of the German trading volume can be found in the next subsection of the appendix). The price variable P must be multiplied with U.P (reported units of P) because for some companies in the UK price is not reported in pounds but rather in pence, making this adjustment necessary.

In the existing literature, Ferreira and Matos (2008) calculate the daily turnover using the number of stocks traded and the number of shares outstanding. In Datastream codes, the turnover is calculated as follows: $VO/(NOSH/AF))$, where NOSH is the number of shares outstanding not adjusted for capital changes and AF is the adjustment factor, which indicates which kind of capital changes have been made, so that the number of shares outstanding can be adjusted for this factor.

I compare these two methods for calculating the turnover and find that they obtain the same trading turnover measure. This exercise assesses the data quality in Datastream and confirms that the datatypes in Datastream are correctly coordinated, because calculating the trading turnover using different variables does not change the result.

3.6.3 Germany Trading Volume

Since Ince and Porter (2006) reviewed the data quality of Datastream (DS) – examining the return data in Datastream and comparing it to the data for the US market available on CRSP, – and found significant data errors, the importance of data screenings has become evident. For the German market, I have access to monthly trading volume data available from the Deutsche Börse (German Stock Exchange, from here on DB) and use it to investigate the quality of the trading volume data gathered from Datastream.

For Germany, downloading the trading volume data presents a challenge in itself, due to the different data type codes. For other countries except Japan, the trading volume has data code VO, whereas in Germany four different data codes are available for the trading volume measured in number of shares: VZ, VO, VC and VQ. Table 3.12 summarizes the available data codes in Datastream for the German volume in number of shares. Choosing the code to use in order to select the data required some reflection. VO is not appropriate for Germany because, returning only the number of shares traded on the Frankfurt stock exchange, it significantly underestimates the number of shares traded, since the Frankfurt stock exchange is neither the only nor the largest stock exchange in Germany. VQ only reports the trading volume on the stock exchange on which the stock is predominantly traded, and therefore misses again a large part of the trading volume. Furthermore, the stock exchange with the highest trading volume for a given stock may change over time. VZ counts every trade double because it counts the sell side and buy side of a trade, thus inflating the total trading volume of a stock. VC returns the total trading volume of the stock across all German stock exchanges and is therefore the code which generates the most accurate picture of stock demand on the German market.

Table 3.12: List of available German trading volume variables in Datastream

This Table summarizes the data codes in Datastream associated with German trading volume measured in the number of shares.

Data code	Data description
VZ	Trading volume on all stock exchanges, sell side and buy side.
VO	Trading volume in Frankfurt
VC	Entire trading volume of any given stock on all exchanges
VQ	Trading volume of a stock on the exchange it is mostly traded on

The trading volume data gathered from the DB[35] reports the trading volume of a stock in one month for the Frankfurt stock exchange and the Xetra stock exchange, as well as the sum of these two stock exchanges. For my purposes, I compare the data from DB to the VC Datastream code. Since the latter includes a larger number of stock exchanges, I expect the trading volume obtained from Datastream VC data to be larger on average than that from the DB.

To allow a meaningful comparison with the trading volume reflected by the DB data, the trading volume obtained with Datastream has to be adapted, since the Datastream data is adjusted for capital changes while the DB data is not. This means that, in order to compare the trading volume from the two data sources, I have to either remove the adjustment of the Datastream trading volume or measure it in Euro, which has the same effect because, after a capital change, the value of the shares stays the same. To remove the adjustment for capital changes, Datastream VC data has to be multiplied with the adjustment factor (data code AF). Furthermore, to check the validity of the Datastream data, it is necessary to convert the trading volume in number of shares into trading volume in value: to this end it has to be multiplied with the adjusted price of the same trading date (data code P). Lastly, I have to aggregate to a monthly level the daily data I gathered, by calculating the sum over all

[35]The trading volume reported by the Deutsche Börse can be found at: http://www.deutsche-boerse-cash-market.com/dbcm-en/instruments-statistics/statistics/cash-market-statistics/order-book-statistics, last accessed July 20, 2019.

trading days. To account for missing data in Datastream, I only compare the months with more than 20 trading days.

Figure 3.4 compares the monthly trading volume in number of shares between DB and DS. As expected, the DB volume is in general lower because it does not include the trading volume of smaller stock exchanges such as the Stuttgart, Berlin or Hamburg stock exchanges. The correlation between the DS and DB trading volume over time is 0.989, confirming that the data quality available in DS is high. Therefore, to measure the trading activity in German stocks it is reasonable to use the trading volume variable VC available in DS.

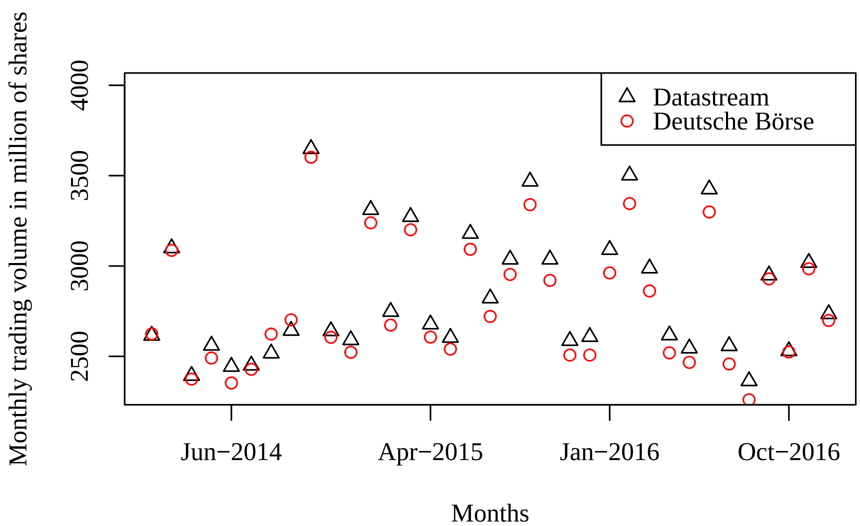


Figure 3.4: Comparison between monthly Deutsche Börse and Datastream trading volumes in number of shares traded

The monthly volume reported on the Deutsche Börse website for each stock traded is aggregated and compared to the Datastream trading volume of the same stocks. The Datastream data is daily data aggregated at monthly level. The monthly number of shares traded are reported in millions.

3.6.4 Short Positions and Stock Returns

Figure 3.5: Aixtron short position reductions and increases vs. stock price

This figure shows the daily short positions reductions and increases disclosed from November 05, 2012 to January 23, 2017. Each color in the barplots shows the different short sellers. The line graph is the stock price of the Aixtron stock.

3.6.5 Brexit vs. Referendum

When investigating the media coverage of the shorted stocks, it is important to choose accurately which term to use in order to find an appropriate measure for the media coverage. In Figure 3.6, the number of articles with the tags *"Brexit"*, *"Referendum"*, and *"Brexit and Referendum"* is plotted. For each of these three tags, we observe an increase in number of articles after the day of the Brexit referendum. The tag "Brexit" is consistently used more frequently than the other two. This indicates that, although the Brexit itself will not happen for a few years after the referendum, the media coverage and the tagging algorithm from the BBC Juicer is using the term Brexit in connection to the outcome of the referendum, justifying the use of the "Brexit" tag to analyze the media coverage of shorted stocks in connection to the Brexit referendum outcome.

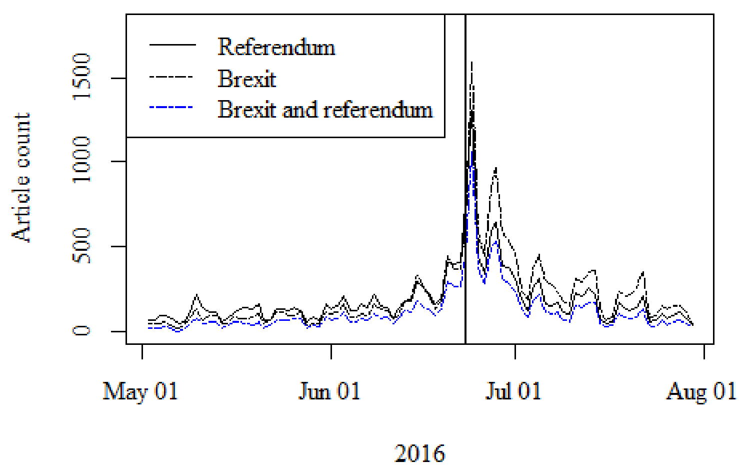


Figure 3.6: Comparison of media coverage with the term *"referendum"* vs. *"Brexit"*

This line graph plots the number of articles published with the tag *"referendum"* (solid black line), the tag *"Brexit"* (dashed black line) and the tag *"Brexit and referendum"* (blue line). The articles with these tags are collected from the BBC Juicer API.

3.6.6 Robustness Check

Table 3.13: Media attention, short selling, and post-referendum returns (5 days)

This table reports the results of the diff-in-diff regression. The dependent variable is the 5-day, cumulative, market-adjusted return after the Brexit referendum. The variable *Short position* is a dummy variable with the value 1 if the stock has an open short position on June 24, 2016. The variable *Media attention* is a dummy variable with the value 1 if the stock is covered in the media with relation to the Brexit referendum on the day after the referendum, June 24, 2016. *Short position * Media attention* is the interaction term between the two variables. The variables *log(MV)* and *log(1 + turnover)* are, respectively, the logarithm of the market capitalization of the stock and the logarithm of the trading turnover of the stock. The trading turnover is the quotient of number of shares traded to the number of shares outstanding in a stock. The first two columns report the regression results for all UK stocks and the last two columns for all countries in the EU excluding the UK. The t-statistics are reported in brackets below the coefficient values.

	UK		EU	
Short selling	0.300**	0.111	0.168	0.592***
	(2.524)	(0.901)	(1.139)	(4.470)
Media attention	0.927***	0.706**	−0.131	0.362
	(3.002)	(2.285)	(−0.398)	(1.151)
*Short position * Media attention*	−0.957**	−0.791*	−0.098	−0.465
	(−2.019)	(−1.680)	(−0.228)	(−1.115)
log(MV)		0.042***	0.050**	
		(3.421)	(2.016)	
log(1 + turnover)		−2.136	70.867***	
		(−0.355)	(7.356)	
Constant	−0.037	−0.163**	−0.439***	−0.242***
	(−1.383)	(−2.211)	(−3.390)	(−5.075)

3.6.7 Event Study

In order to analyze the returns yielded by stocks shorted during the period around the Brexit referendum, I conduct event studies using a market model whose parameters (intercept and slope) are estimated within the period from November 1, 2012 (introduction of the disclosure regime) to June 22, 2016 (day preceding the Brexit referendum). This pre-event window has been chosen because it allows for a long estimation horizon and excludes the post-Brexit observations. The daily abnormal returns, i.e. the difference between the actual stock returns and the expected (normal) returns predicted by the market model, are then used to estimate the cumulative abnormal returns (CARs) across the event window. The CARs are calculated for the UK and all other European countries separately, using appropriate market returns for each CAR calculation.

The biases arising from the use of CARs in long-term event studies have been discussed by Barber and Lyon (1997); however, most of them are not relevant for the short event window chosen for these event studies.[36] Furthermore, Fama (1998) argues that CARs reduce the "bad-model" problem that arises from using asset-pricing models to estimate expected returns. The risk of a "bad model" problem is further reduced by the use of the market model, which estimates the expected returns on a firm-specific level instead of using methods that put constraints on the cross-section of expected returns (Fama, 1998). Applying this event study methodology will give a representative summary of the effect of the Brexit referendum result on the stock returns of shorted stocks.

A possible alternative to the CARs would be to use the buy-and-hold returns (BAHRs), but the two methods obtain very similar results for short-horizon studies like the present one. In Figure 3.7, the number of disclosed short positions is presented in a barplot that

[36]CARs ignore compounding, which will only results in significantly different results over longer time horizons. This means that the CARs in this case test the null hypothesis that the daily abnormal returns are not equal to zero, but not that the abnormal returns over the entire testing periods are equal to zero. However, for this short time period of daily returns the difference is minimal.

indicates whether a short position is a downtick, an uptick or a new position. The cumulative abnormal returns of the stocks with a disclosed short position between June 1, 2016 and July 24, 2016 are plotted in red on top of the barplot. The event studies for the UK and for all other EU countries are conducted separately.

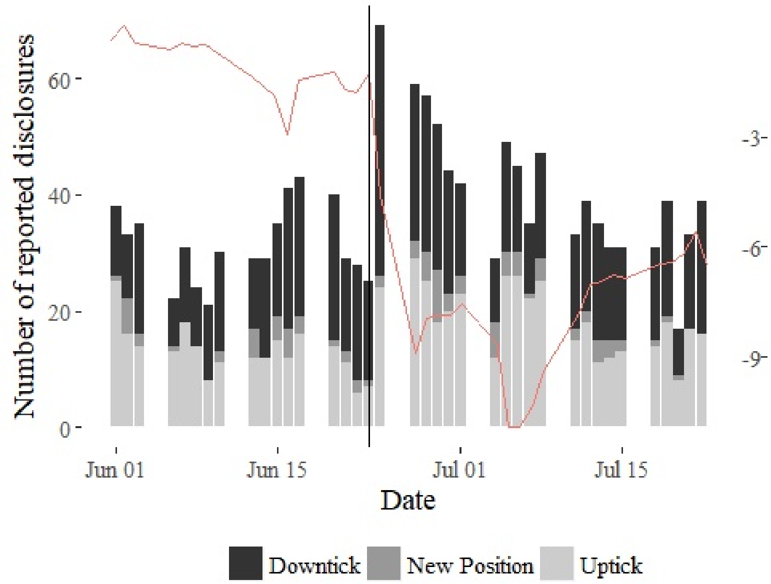
The event study for the UK, reported in Panel A of Figure 3.7, shows in the line graph that the day after the referendum the stocks with a disclosed short position had significantly negative returns compared to the market return. Before the referendum, these stocks had a slightly negative trend: in this period (June 1, 2016 to June 23, 2016), the cumulative abnormal return was -1.437% ($t = -2.325^{***}$). During the period after the referendum, between June 24, 2016 and July 6, 2016, the cumulative abnormal return is -8.736% ($t = -7.518^{***}$): this unambiguously confirms that the shorted stocks underperformed significantly their expected return. Some evidence of overreaction to the news of the UK planning to leave the EU can be found in the cumulative abnormal returns until July 6, 2016, during which period the prices fall and then rebound, although never to the pre-Brexit level. Overall, the shorted stocks markedly underperform compared to the market return, before rebounding between July 7, 2016 and July 23, 2016 with a cumulative abnormal return of 4.4239% ($t= 7.262^{***}$).

The barplot in Figure 3.7, Panel A, reports the disclosed short-selling positions in the UK, differentiating between uptick, downtick, and new positions. There is a clear spike of disclosures on June 24, 2016, mostly downticks and, at the same time, the returns fall significantly. The high number of downticks after the referendum may depend on it being a Friday: since short sellers are not permitted to trade over the weekend, they would close some of their positions on Fridays in order to reduce the risk, as pointed out by Chen and Singal (2003), who find that speculative short sellers contribute to the weekend effect by covering their short positions on a Friday – so that they are not short over the weekend – and reopening the position on the following Monday. This behaviour of short sellers contributes to the weekend effect, which entails positive returns on a Friday and then negative returns on the following Monday (Chen and Singal, 2003). The weekend following the Brexit referendum, the short sellers behave according to the weekend effect – covering short positions on Friday and reopening them on Monday – although this does not have a positive effect on the stock return on Friday, which is compelling evidence that the majority of other traders is still selling these stocks. This theory is supported by the increased number of upticks on the Monday following the Brexit referendum, June 27, 2016. On this Monday, the number of disclosures falls to 64, with more upticks than downticks, and the stock returns continue to fall. Furthermore, in the UK 66 new short positions are opened between June 24, 2016 and July 23, 2016, a high number compared to mere 10 during the same time in the other European countries.

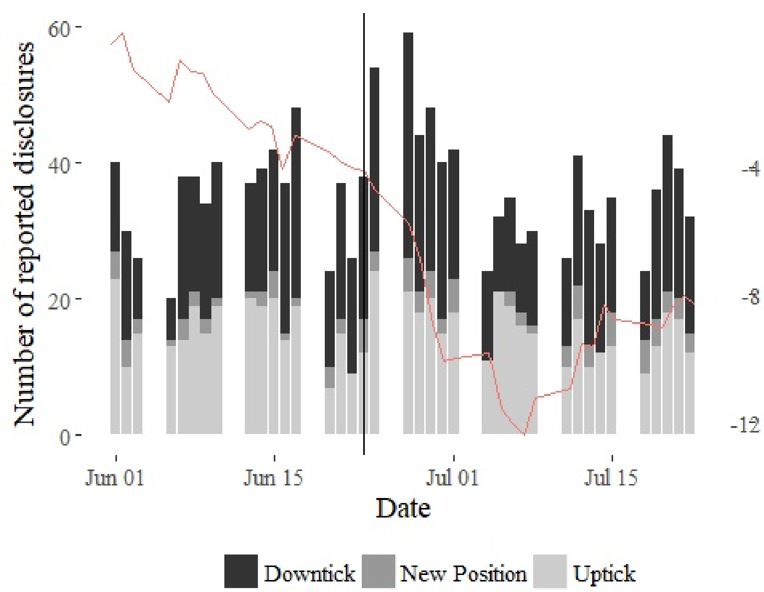
In Panel A, it emerges also that the number of new positions increases substantially after the Brexit referendum, going from 7 between June 20 and June 23, 2016, to 17 in the four trading days after the referendum (an increase of 142%). This surge in short positions and the corresponding cumulative abnormal returns of these stocks in the UK are evidence that short sellers have good stock picking and timing ability.

In Panel B, the same event study is conducted for the stocks with a disclosed short position in all other EU countries, in order to illustrate the different reaction in these countries. Before the referendum, between June 1, 2016 and June 23, 2016, the shorted stocks have a cumulative abnormal return of -4.1262 ($t = -8.521^{***}$); after the referendum, we see both an increase in short positions, although not as drastic as in the UK, and also a decrease in cumulative abnormal returns, again less extreme than in the UK. In non-UK European countries, the cumulative abnormal return from the day after the referendum to July 6, 2016 amounts to -7.6167% ($t = -12.16^{***}$) which is, again, lower than the cumulative abnormal return observed in the UK. In these European countries, the weekend effect is also observed: on Friday there is a higher number of downticks than upticks. Even so, the cumulative return does not decrease on the Friday after the referendum, and so the downticks cause a positive price pressure on these stock markets. The following Monday, the number of upticks increases compared to downticks, and the returns are significantly negative. In the European countries the effect of the referendum outcome on the returns is significantly less extreme.

The returns in Europe and the UK differ significantly before the Brexit referendum: the shorted stocks in the UK present returns that remain close to zero, whereas the returns in Europe are significantly negative and such as one would expect from stocks that are being shorted. Thus, the returns in the UK before the Brexit suggest that short-seller in the UK are actively shorting those stocks that would react strongly to the outcome of the Brexit referendum. In contrast, in the other European countries considered, short sellers are less focused on shorting stocks that would react strongly to the Brexit referendum outcome, otherwise the returns before the Brexit would be less negative than in the UK. I do not see an increase in shorting before the referendum; however, the returns in the UK shows that a preparation for the Brexit referendum has been made.



(a) Panel A: UK



(b) Panel B: EU

Figure 3.7: Cumulative returns, new positions, downticks, and upticks around the Brexit referendum

The line graph shows the cumulative log returns over time of all firms with a disclosed short position around the Brexit. The barplot shows the reported disclosures on each trading day since June 1, 2016 until July 15, 2016. Each bar is subdivided into number of downticks (black), number of new positions (dark grey), and number of upticks (light grey) reported on each day. The highest bar with 74 disclosures is on the day after the referendum, June 24, 2016. Panel A shows the reported short position changes and the stock return for Great Britain and Panel B for the rest of the European Union.

4 Procyclical Leverage in Europe and its Role in Asset Pricing

Coauthored by: Markus Baltzer and Stefan Reitz

4.1 Motivation

Banks' leverage is procyclical. This is emphasized in the paper by Adrian and Shin (2010), which demonstrates that financial intermediaries manage their balance sheets so as to adjust to changes in asset prices and value-at-risk calculations. Using some simple arithmetics, the authors show that during a market downturn banks face the devaluation of their assets as well as a decline in their equity. Assuming relatively constant liabilities, the resulting leverage increase forces banks to sell assets. Since leverage constraints are binding for all banks, sales across all risky assets are to be expected, which are bound to provoke further deleveraging: this mechanism has been dubbed the "loss spiral" by Brunnermeier and Pedersen (2009). However, the procyclicality of leverage also contributes to the acceleration of market upturns. With increasing asset prices, a decline in leverage leaves room for additional asset purchases financed by short-run debt. This expansion of the balance sheet recovers leverage but also tends to increase asset prices, again revealing the mutually reinforcing nature of the relationship between market liquidity and leverage. In fact, as has been observed during the financial crisis, these accelerating dynamics have severe consequences outside the financial sector, too.

Thus far, the procyclicality of financial intermediaries' balance sheet management has been empirically documented mainly on the US market. Adrian and Shin (2010) and Adrian, Etula, and Muir (2014) show that asset growth and leverage growth exhibit a strong positive co-movement for US broker-dealer banks, in contrast to non-financial firms and households. The last group, in particular, seems to abstain from active balance sheet management, leading to a negative correlation between asset growth and leverage. While the reinforcing balance sheet behavior of financial intermediaries has been identified in Adrian and Shin (2010), Adrian, Etula, and Muir (2014) investigate the role of broker-dealer leverage in asset pricing. Thanks to their findings, which corroborate the exceptionally high explanatory power of the leverage factor for pricing a large cross-section of US portfolios, the authors are able to close the outlined feedback loop of banks' balance sheets and asset market liquidity.

This paper adds empirical evidence from non-US financial markets to this important relationship between asset prices and financial intermediary leverage. Using German and European data, we follow the approach taken by Adrian, Etula, and Muir (2014) and test whether shocks to leverage are a useful pricing kernel in a different geographical setting. As a starting point, Figure 4.1 presents the growth rates of total assets and leverage, defined as $(TotalAssets)/(TotalAssets - TotalLiabilities)$ of different groups of German and European financial firms.[37]

Figure 4.1 unambiguously confirms that increases in asset values are associated with increases in leverage, supporting the view that financial firms actively manage their balance sheets during market upturns and downturns.[38] In the rest of the paper, we will show that the procyclicality of German broker-dealer leverage explains the excess returns of a large cross-section of test assets. Applying standard two-pass regressions to data ranging from 1971 to 2016, we find that broker-dealer leverage on the German cross-section of stock market portfolios has an explanatory power similar to competitor models such as the Fama-French three-factor framework. This is remarkable in the sense that the time series of shocks to leverage might be quite noisy, while the latter factors are derived from the underlying test asset returns. The results are confirmed using data from European broker-dealers with somewhat lower R^2s due to the shorter sample ranging from 1999 to 2016. Thus, our results lend support to the feedback loop described by Brunnermeier and Pedersen (2009) and stress the potential of financial intermediaries' balance sheet management to accelerate booms and busts in asset markets.

In addition, recent theoretical contributions such as Danielsson, Shin, and Zigrand (2010) and Adrian and Boyarchenko (2015) suggest that the leverage price of risk is time-varying in a predictable fashion. In times of tight funding constraints such as those experienced during the financial crisis, the balance sheet exposure of intermediaries is low, implying a high marginal value of wealth. Given that low asset prices allow higher expected future returns,

[37]For details on the grouping of banks see the data section of this paper.

[38]For example, the Pearson correlation coefficient is 0.73 for German broker-dealer banks.

broker-dealer leverage should forecast future asset returns. Applying the dynamic asset pricing (DAPM) model of Adrian, Crump, and Moench (2015a), we test for this systematic time-variation in the price of risk. In line with Adrian, Moench, and Shin (2016), we find that German broker-dealer leverage negatively forecasts one-quarter-ahead returns, thereby lending support to the proposition that this balance sheet factor is also a driver of the market price of risk.

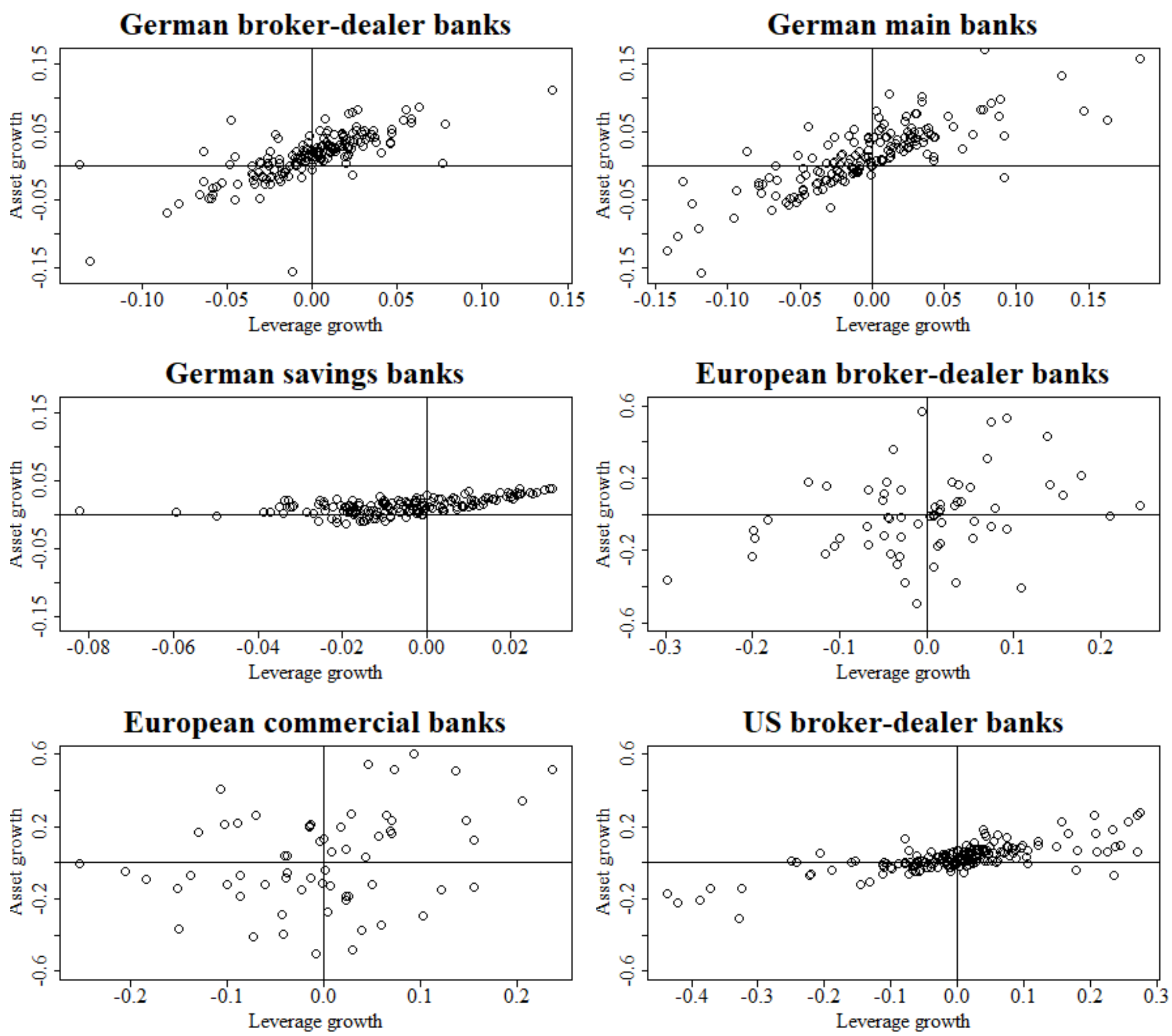


Figure 4.1: Leverage growth vs. asset growth

The graphs plot leverage growth (x-axis) against asset growth (y-axis). The first three report the relationship of the leverage and asset growth for German broker-dealer, main, and savings banks. The fourth and fifth plots report the relationship for European broker-dealer and commercial banks. The last plot shows the relationship for US broker-dealers.

The remainder of this paper is structured as follows: The next section describes the related literature; this is followed by an overview of the cross-sectional empirical approach and the data used for Germany and Europe; we then develop a DAPM framework for the different regional areas; the last section concludes.

4.2 Related Literature

In his presidential address to the American Finance Association, Cochrane (2011) delivers a plea for reconsidering the concept of the average investor and discusses intermediated markets. Investors finance intermediaries with different types of claims such as debt and equity. When losses appear, the managers of intermediaries will try to avoid bankruptcy by selling risky assets, thus possibly provoking so-called "fire sales" and "illiquidity spirals": hence the importance of balance sheet data from leveraged intermediaries.

Adrian, Etula, and Muir (2014) take these considerations into account and shift their attention from measuring the stochastic discount factor (SDF) of the average household to measuring the SDF of financial intermediaries. Financial intermediaries fit the assumptions of modern finance theory nicely, being sophisticated investors capable of using the whole spectrum of investment strategies. The authors link information from broker-dealers' balance sheets data – namely the leverage ratio defined as the ratio of assets to equity – to explain the cross-sectional variation of asset returns. Indeed, they are able to show that intermediary leverage has strong pricing potential in the cross-section of US asset returns.

There are several theoretical models that assume that financial intermediaries influence asset prices. In Brunnermeier and Pedersen (2009), the authors show how funding liquidity enters the pricing kernel when investors are risk-neutral and face funding constraints. Their model is concerned with market and funding liquidity. Investors may experience initial losses which cause funding problems to arise, requiring them to reduce their positions. Under some circumstances, the result can be liquidity spirals, i.e. the drying up of liquidity when several investors have to reduce leverage. Adrian, Etula, and Muir (2014) argue that the leverage of financial intermediaries can be used as a proxy for funding conditions. Another approach by Danielsson, Shin, and Zigrand (2010) also considers risk-neutral intermediaries subjected to a value-at-risk (VaR) constraint. In their model, investors' risk appetite may be time-varying because of the VaR-constraints even if preferences are constant. Asset prices depend on the level of effective risk aversion and hence on the leverage of the intermediaries – in times of low intermediary leverage, effective risk aversion is high. As a result, financial intermediary leverage directly enters the equilibrium SDF.

Adrian and Boyarchenko (2015) develop an equilibrium model of the macroeconomy where intermediaries are subjected to risk-based funding constraints that give rise to an equilibrium representation, with intermediary leverage as a key state variable. The equilibrium pricing kernel can be expressed as a function of shocks to financial intermediary leverage, which represents funding conditions, and shocks to output. When intermediaries experience an adverse shock to their funding, their effective risk aversion endogenously increases as their leverage declines. Therefore, Adrian and Boyarchenko (2015) predict that the price of risk of intermediary leverage is positive, which is consistent with our empirical results.

An alternative approach to modeling an intermediary pricing kernel is proposed by He and Krishnamurthy (2013). In their setup, intermediary wealth, rather than intermediary leverage, is the key state variable. They argue that financial intermediaries are the marginal investor, and, as a result, the SDF is proportional to the wealth growth of the intermediary sector, giving an intermediary CAPM. Brunnermeier and Oehmke (2014) develop a closely related equilibrium asset pricing model with financial intermediaries where intermediation arises as an outcome of principal-agent problems. Their model also predicts that shocks to intermediary wealth are the relevant measure of systematic risk. In addition, both He and Krishnamurthy (2013) and Brunnermeier and Oehmke (2014) feature countercyclical intermediary leverage, thus predicting a negative price of risk of intermediary leverage.

The finding that financial institutions' balance sheets contain information about the real economy and expected asset returns has only recently received more attention in empirical studies. Adrian and Shin (2010) examine the relationship between asset growth and leverage growth for different investor groups. They document that, unlike private households, for example, security broker-dealers adjust their financial leverage aggressively as economic conditions change. Broker-dealers' active balance sheet management practices result in highly procyclical leverage, whereas households exhibit a more passive balance sheet management. Recently, Adrian, Etula, and Shin (2015b), Adrian, Moench, and Shin (2010), Adrian, Moench, and Shin (2016), and Etula (2013) have shown that broker-dealer leverage has a strong predictive power for asset prices. Furthermore, equity forecasts and risk premia of intermediaries are especially high around financial crises (Muir, 2013). The predictive power of intermediaries' balance sheets for stock and bond returns indicates that they contain valuable information about the evolution of risk premia over time. Adrian, Etula, and Muir (2014) connect the cross-section of returns to the exposures to broker-dealer leverage shocks, showing that broker-dealer leverage can price assets. An adverse shock to the leverage of intermediaries increases their effective risk aversion endogenously, so that the equilibrium pricing kernel can be expressed as a function of shocks to the intermediaries' leverage.

Lastly, but importantly, Haddad and Muir (2018) show that the relationship between intermediaries' balance sheet factors and asset returns is not merely a co-movement. The authors document a larger resiliency of the risk premia of intermediated assets, such as credit default swaps and FX, to changes in intermediary risk appetite, implying that intermediary funding constraints have a strong impact on assets that households can hardly access.

4.3 Data

To conduct our analysis, we need two sets of information: the data to calculate the balance sheet factor, and the portfolio returns on which to test the leverage factor.

We follow Adrian, Etula, and Muir (2014) and use shocks to the leverage of intermediaries as a proxy for shocks to the pricing kernel. Broker-dealer (BD) leverage is defined as:

$$Leverage_t^{BD} = \frac{TotalAssets_t^{BD}}{TotalAssets_t^{BD} - TotalLiabilities_t^{BD}} = \frac{TotalAssets_t^{BD}}{TotalEquity_t^{BD}} \tag{4.1}$$

and the leverage factor is then computed as the residual of the AR(1) process of the leverage series.

We collect leverage and portfolio data for both the European and German market. In the following, we will give some details on the data used in our analysis.

4.3.1 Leverage

Starting with German financial institutions, a relatively long time series comparable to the database of US studies is available. Aggregate quarterly balance sheet data from June 1971 to June 2016 of German financial intermediaries are obtained from the Deutsche Bundesbank's banking statistics, which groups banks according to their role in the German financial system. The group of banks closest to the US broker-dealers are classified as depository institutions larger than savings banks but smaller than the big or money center banks. These financial institutions provide services such as securities brokerage, investment banking, insurance sales, and mutual fund and pension fund management, which is why in the following we refer to them as "broker-dealer banks". This group of banks comprises relevant financial intermediaries that play a decisive role in the German broker-dealer business. As a robustness test, we also investigate the role of savings banks' leverage for German asset pricing. Since this group of financial institutions is focused on the regional supply of mortgages and loans to small-size firms, the time series of leverage shocks should not provide any explanatory power in Fama-MacBeth regressions.[39] The Deutsche Bundesbank database also reports the leverage of the big money center banks – called 'main banks' – which are substantially engaged in providing loans to the public and private sector: for this reason, and due to the German universal banking system, their business is more balanced. Their aggregate balance sheet indicators are also used for comparison purposes.

To apply our analysis to a European context, we also build a sample of European broker-dealers. We use bank-level data of the constituents of the Europe Stoxx600 Banks, which is a sector index of the Europe Stoxx600 comprising European companies in the banking sector whose activity is expected to have a significant impact on financial markets. We cover the period ranging from the beginning of this index in January 2000 up to June 2016. The construction of this dataset requires the aggregation of two sources: Datastream for market data and Bloomberg for the financial statements of the financial companies. The sample consists of 80 listed banks operating in continental Europe – including Switzerland – plus the United Kingdom, Denmark, and the Scandinavian countries.

Since the prevailing European business model is universal banking, where investment banking and commercial banking co-exist, albeit in different proportions, in the same institution, we have to investigate whether and how different proportions of investment versus commercial banking affect leverage procyclicality. In our sample, there are banks where the traditional commercial banking activity is prevalent and other financial institutions which are more focused on investment banking. To identify the latter, we follow the strategy of Baglioni, Beccalli, Boitani, and Monticini (2013) to distinguish commercial banks from investment banks. Investment banks are defined as intermediaries whose ratio between interest income and net revenues is below the median ratio of the whole sample of banks; consequently, commercial banks have a ratio above the median. We check this ratio quarterly and allocate the respective financial institution to one of the two groups.

[39]As a first indication, we observe a Pearson correlation coefficient of 0.07 between the changes in leverage ratios of German broker-dealers and savings banks, which reflects a difference in leverage management.

The banks in the sample are the largest in Europe, and after our classification into investment and commercial banks, many significant differences emerge. Over the whole sample period, commercial financial institutions have a median total asset size of 129 billion euro, whereas the second group, classified as investment banks, covers a median total asset size of 204 billion euro. The median ratio between interest income and net revenues significantly exceeds 50%, thus confirming the prevalence of the universal banking business model. The median level of leverage, measured as total assets over equity for each quarter, is 20.5 for commercial and 24.7 for investment banks.

Figure 4.2 displays long-term leverage movements for US, German, and European financial institutions. For comparability, we standardize each series, setting mean to zero and using a unit variance. To capture long-term developments, we use five-year averages. Note that, due to the limited data availability, the long-term series for European financial institutions do not start before 2004, which excludes these series from a long-term comparison. For the much longer series for US and German financial institutions, we interestingly find comparable financial cycles. We observe dips both around the 1987 stock market crash and during the recent financial crisis. Moreover, there also seems to be a widespread long-term consensus developing in support of the idea of common (global) financial cycles followed by the internationally-oriented financial institutions (Rey, 2015). Correlation between the long-term leverage of US and German broker-dealers exceeds 70%, whereas German main banks and US broker-dealers show a slightly negative correlation. Even German main banks and broker-dealers have a comparable low correlation, not exceeding 28%.

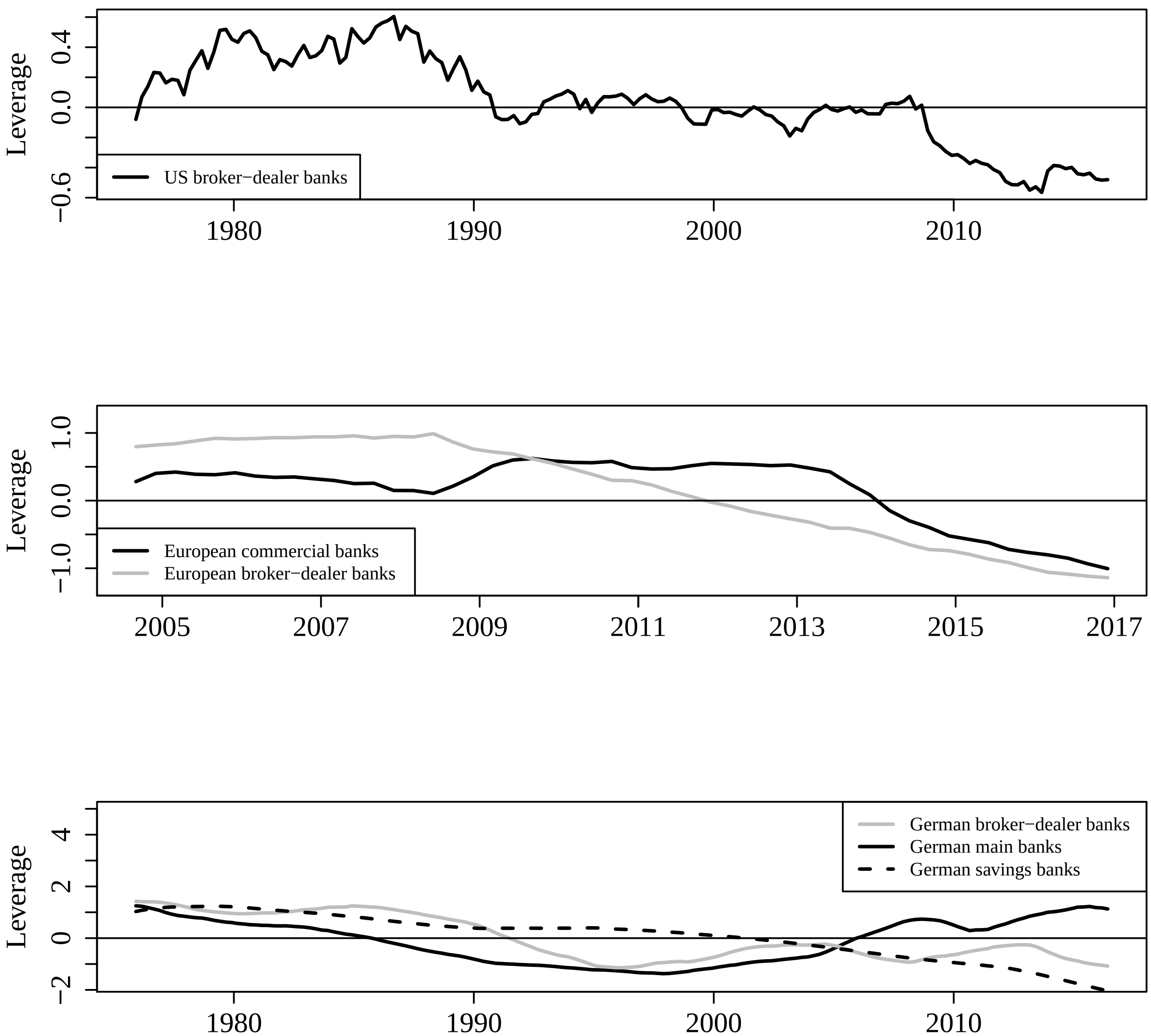


Figure 4.2: Long-term leverage movements

Long-term leverage movements for US, German, and European financial institutions. The first plot reports the leverage movements of US broker-dealer banks, the second those of European broker-dealer and commercial banks, and the last plot the leverage movements of German broker-dealer, savings and main banks. Each series is standardized to have a mean of zero and a unit variance.

To identify the potential procyclical behavior of banks' balance sheets, as briefly outlined in the motivation of this paper, Figure 4.1 plots leverage growth against asset growth. As confirmed by Table 4.1, containing the respective correlation coefficients, we find positive correlation for all regions and across all banks' business models, with coefficients ranging between 0.31 and 0.85. This strongly supports the view that financial institutions in general actively manage their balance sheets during market upturns and downturns. Of course, this does not imply that all banks might be perceived as marginal investors on asset markets. The literature reviewed above suggests that, rather than regional savings banks, for instance, it is the broker-dealers that offer the most promising data for analyzing asset portfolio returns, due to their strong trading activity and constant presence on asset markets.

The difference in business models can be illustrated by the impact of the financial crisis on the associated balance sheet changes. German savings banks report for 2008 the amount of 247 billion euro of stocks (68 billion euro) and bonds (179 billion euro), while loans to non-banks accumulate to 726 billion euro. Total assets sum up to 1071 billion euro in 2008. After major stock markets plummeted and the financial crisis had fully unfolded in the balance sheets of banks, tradable assets (stocks and bonds) even increased to 270 billion euro. As a result, total assets also slightly increased and savings banks' balance sheets seem to be largely unaffected.

When looking at the respective group of German broker-dealers, in contrast, the following interesting observations can be made. These banks report a total of 145 billion euro of stocks and bonds and total assets amounting to 791 billion euro in 2008. In 2009, a strong decrease of 47.1% in stocks induced a significant decline (-9.5%) of total assets in this banking group to 723 billion euro.

A similar picture emerges when looking at balance sheet positions of main banks. Total assets also significantly declined by 11.7%, mainly driven by the strong balance sheet's dependence on financial assets. However, main banks are much bigger than the above mentioned group of German broker-dealers. The four main banks comprise a sum of total assets of 1,292 billion euro at the end of 2009. These figures already show that these banks have a much broader business model and are much more universal than the financial institution involved in the broker-dealer business. Therefore, we also provide empirical results for this group of banks as a further robustness test.

With respect to Figure 4.1, the difference between banks' business models emerges from the size of the growth rates of leverage and banks' assets. While we find growth rates for broker-dealers quite often exceeding 5%, growth rates for savings banks are typically confined to lower numbers. This is mirrored in the respective average absolute growth rates. In contrast to average absolute growth rates of 2.2% (leverage) and 2.4% (assets) for broker-dealers, the average absolute growth rates for savings banks are 1.3% and 1.6%. Again, the reason for this difference in growth rates is the structure of the bank group balance sheets.

Table 4.1: Correlation of leverage and asset growth

This table presents the correlation of intermediaries' leverage growth with asset growth. For German broker-dealers, main, and savings banks, the correlation is calculated for the period from Q3 1971 to Q2 2016. For the European commercial and broker-dealer banks, the correlation is calculated from Q1 2000 to Q4 2016. For comparison purposes, the correlation between US broker-dealer leverage growth and asset growth is reported for the period from Q3 1971 to Q2 2016. For German data, we exclude extreme values/outliers linked to the unification (Q2-Q3 1990) and to the introduction of the Euro (Q1 1999).

	Germany			Europe		USA
	Broker-dealer	Main banks	Savings banks	Investment	Commercial	Broker-dealer
Rho	0.73	0.85	0.61	0.31	0.35	0.75
(p-value)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)

Overall, savings banks, which focus on regional supply of mortgages and loans to small firms, typically lack a substantial balance sheet position for market-traded assets such as stocks and bonds. The contrary is true for broker-dealers, by whom a relatively large fraction of traded financial assets can be found. These substantial differences in the impact of the financial crisis on banking groups' balance sheets suggest that it should be broker-dealer leverage that explains asset prices. By contrast, there is very little room for German savings banks to act as marginal investors. We use the latter proposition as an opportunity for robustness tests.

4.3.2 Portfolios and Factors

In order to test whether the leverage of intermediaries is able to explain the cross-section of asset returns, we use for the European market the stock return data of 25 size and book-to-market portfolios from Kenneth French's data library.[40] For the German market, we obtain portfolio stock return data from Richard Stehle's website of the Humboldt University of Berlin.[41] Here, the asset portfolios are the intersections of German stocks double-sorted in 4 groups by size and 4 groups by book-to-market value. Summing up all possible combinations, we get the returns of a total of 16 portfolios. In addition, 10 portfolios sorted on momentum (the past 12 months return) are constructed as in Fama and French (2012). For the European and the German sample, we choose to include additional German government bond portfolios with a maturity of 2, 3, 4, 5, 6, 7, and 10 years, as a representative investment in a risk-free European asset. While the European data set ranges from 2000 to 2016, the German sample already starts in 1971.

[40]Kenneth French's data library can be found at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html, last accessed July 20, 2019.

[41]A description of the dataset is given by Brückner, Lehmann, Schmidt, and Stehle (2015), found at https://www.wiwi.hu-berlin.de/de/professuren/bwl/bb/data/fama-french-factors-germany, last accessed August 3, 2019.

In a first step, we explain these return data with well-known asset pricing models: the CAPM, the three-factor model of Fama and French (1993), and the four-factor model of Carhart (1997). For the CAPM, we construct the market factor as the difference between the market return and the return of a risk free asset. In the Fama-French three-factor model, we additionally add a small-minus-big factor (SMB), which is based on firm size and measures return differences between portfolios with small vs. big capitalized companies. The third factor, high-minus-low (HML), is based on the book-to-market ratio and measures return differences between portfolios with high book-to-market ratios minus portfolios with low book-to-market ratios. Finally, for the Carhart four-factor model we add a momentum factor (MOM) based on the return difference between the winner and the loser portfolios of the past 12 months. All these factors are available for the European data from the Kenneth French's website and for the German data from Richard Stehle's website.

4.4 Empirical Results from a Linear Factor Model

We investigate the role of broker-dealer leverage in pricing the cross-section of asset returns using a standard linear factor model.[42] As a starting point, the asset pricing literature assumes that there exists a stochastic discount factor M_{t+1} so that

$$E_t[M_{t+1}R_{i,t+1}] = 0, \tag{4.2}$$

where $R_{i,t+1}$ denotes the return of asset i in excess of the risk-free rate.[43] The associated beta representation can be derived using the covariance definition, so that

$$E_t[R_{i,t+1}] = -\frac{Cov[M_{t+1}R_{i,t+1}]}{E_t[M_{t+1}]}. \tag{4.3}$$

[42]The derivation of the estimators follows Adrian, Crump, and Moench (2015a).
[43]See, for instance, Cochrane (2005).

If the percentage shocks to the pricing kernel are linear in the shocks to the vector of k risk factors (f_{t+1}), i.e.

$$\frac{M_{t+1} - E_t[M_{t+1}]}{E_t[M_{t+1}]} = \lambda_t \Sigma_f^{-1/2} f_{t+1} \tag{4.4}$$

and assuming a constant $\lambda_t = \Sigma_f^{-1/2} \lambda_f$,[44] we find

$$E_t[R_{i,t+1}] = \beta_{i,f}' \lambda_f. \tag{4.5}$$

Regarding the set of risk factors, this paper focuses on an empirical model combining financial intermediaries' balance sheet indicators and the market return to explain the excess returns of test assets. This is motivated by the theoretical contributions reviewed above, namely that the market return, as a long-run risk factor, and the intermediaries' balance sheet measure, as an important medium-term risk factor, are both a proxy for shocks to consumption growth. Aside from their theoretical contributions showing how balance sheet factors enter the pricing kernel, Adrian, Etula, and Muir (2014) stress the importance of information and transaction costs. The latter prevent the average household from participating regularly in asset markets, which is why a stochastic discount factor based on the marginal value of household wealth alone will not accurately reflect differences in assets' excess returns. This argumentation leaves room to introduce broker-dealers into the analysis, since they may be perceived as highly-informed agents trading heavily in financial markets. The potential importance of information and transaction costs also allows for a robustness test, with which we estimate the asset pricing model using balance sheet factors of German and European credit banks not focussing on the broker-dealer business.[45] Given that these financial institutions have a strong focus on monitoring their borrowers, their balance

[44] In the next section, the time-variation of prices of risk is explicitly taken into account.

[45] Unfortunately, data on German household wealth are unavailable.

sheet factors should be less informative in pricing the cross-section of stocks. All balance sheet factors are compared using the Fama-French three-factor (FF) and Carhart four-factor (FF&MOM) models as a benchmark (Fama and French, 1993, Carhart, 1997).[46] Reflecting the ongoing discussion in the literature about the exact specification of the intermediaries' balance sheet factor, we will also provide results for both book equity and leverage.[47]

The risk exposures β_i and the prices of risk λ_f of the above model are estimated using the Fama and MacBeth (1973) two-pass procedure. As a first step, risk exposures are derived from the time-series regression of excess returns $R_{i,t}$ on the k risk factors f_t for each asset i = 1,...,N:

$$R_{i,t} = c_i + \beta'_{i,f} f_t + \epsilon_{i,t}, \quad i = 1, ..., N. \tag{4.6}$$

To estimate the cross-sectional price of risk associated with the factors f, the second step is a cross-sectional regression of time-series excess return means on risk factor exposures

$$E[R_{i,t}] = \beta'_{i,f} \lambda_f + \zeta_i, \quad i = 1, ..., N, \tag{4.7}$$

yielding estimates of cross-sectional prices of risk λ.

In line with most of the related literature, we measure the size of pricing errors by means of the cross-sectional adjusted R^2 ($adjR^2 = 1 - \frac{\sigma_\zeta^2}{\sigma_R^2}(\frac{N-1}{N-k})$) and the mean absolute pricing error ($MAPE = \frac{1}{N}\Sigma\,|\zeta|$) . In order to correct the standard errors for the pre-estimation of betas, we report the t-statistics of Shanken (1992). Indeed, shocks to intermediary leverage stem from a large set of different sources, such as a capital regulation, making the leverage factor a noisy regressor. Although Adrian, Etula, and Muir (2014) argue that this feature affects the quality of the first-stage time-series regression but not the cross-sectional regression, Kleibergen and Zhan (2015) indeed stress a potential upward bias of second-stage R^2s.

[46]It has to be borne in mind that, in contrast to the intermediary leverage model, the competitor models apply factors derived from the returns of the set of test assets.

[47]Since a large subset of German intermediaries are not listed, however, we are unable to use market capitalization as a balance sheet factor. See the discussion on book equity versus market capitalization in Adrian, Moench, and Shin (2016).

To deal with the problem, we perform the suggested likelihood ratio (LR) test, with which we test the null-hypothesis of whether the leverage factor betas are all equal to zero against the alternative hypothesis that the leverage factor betas are unequal to zero.

In the following subsections, we will outline the results of the geographical and temporal extensions we have made to the work of Adrian, Etula, and Muir (2014). First, we apply and calculate the leverage factor model to data from Germany and, second, we test the application of the leverage factor model to the broader but shorter sample of European data.

4.4.1 Broker-Dealer Leverage

Table 4.2 presents the cross-sectional prices of risk for the factor models from Germany. The table is split into two panels. Panel A presents the pricing performance of the different factor models with respect to our set of 33 test portfolios, including equity and bond portfolios, while Panel B reports the results obtained using only the equity portfolios sorted on size and book-to-market as well as momentum. This allows for the identification of a potential specialization of German broker-dealers on stock markets.

Starting the discussion with Panel B, we find that the Fama-MacBeth two-step regression with broker-dealer leverage as single factor performs fairly well in explaining the cross-sectional excess returns with an adjusted R^2 of 53%. The positive and significant estimate λ confirms the findings of Adrian, Etula, and Muir (2014) and reveals the reinforcing balance sheet behavior of the broker-dealers in Germany. By contrast, the market factor exhibits low explanatory power. The leverage factor model also outperforms the FF model, which yields an adjusted R^2 of 18.2%. Only the FF&MOM model does better, obtaining an adjusted R^2 of 78.5%. Regarding the alpha coefficient, we find a statistically significant and relatively large estimate of 10.2%, which is somewhat bigger than in the CAPM model but smaller than in the FF model.[48] Overall, our findings suggest that the FF&MOM model does better

[48]Only the FF&MOM yields a statistically insignificant intercept.

in explaining the excess returns of the cross-section of test assets than the leverage factor model. However, as pointed out in Lewellen, Nagel, and Shanken (2010), the high adjusted R^2 may be misleading, because a relatively large number of factors may easily capture the variation of returns of highly correlated test assets.[49]

Table 4.2: Fama-MacBeth regressions for German broker-dealer leverage

This table presents the results of the Fama-MacBeth regression for Germany. Panel A reports the results for 16 size and book-to-market portfolios, 10 momentum portfolios and 7 German bond portfolios sorted by maturity. The factors used are market, small-minus-big (*SMB*), high-minus-low (*HML*), momentum (*MOM*) and leverage (*LevFac*). Panel B presents only the results of the Fama-MacBeth regression for 16 size and book-to-market portfolios and 10 momentum portfolios, excluding the 7 German bond portfolios. The 33 portfolios in Panel A and the 26 portfolios in Panel B are used to test the performance of the following five factor models: CAPM, Fama-French three-factor model (*FF*), Fama-French three-factor model with momentum factor (*FF&MOM*), leverage factor model (*Lev*), and leverage factor model with market factor (*Lev&Mrkt*). Portfolios, Fama-French and momentum factors are provided by the Humboldt University of Berlin. The leverage is calculated from the monthly German broker-dealer balance sheet data obtained from the Bundesbank and then aggregated to quarterly data. *LevFac* is the residual of the AR(1). The results are for annualized quarterly data from Q3 1971 to Q2 2016. The Shanken t-statistics are reported under the Fama-MacBeth prices of risk. The likelihood ratio (*LR*) test statistics and p-values are reported in the last row. The one-percent critical value for the *LR* test is 134.64 (bonds included) and 109.96 (bonds excluded).

	Panel A: Bond portfolios included					Panel B: Bond portfolios excluded				
	CAPM	FF	FF&MOM	Lev	Lev&Mrkt	CAPM	FF	FF&MOM	Lev	Lev&Mrkt
Constant	1.719***	1.678***	0.415***	8.102***	2.144***	7.826**	16.541***	−6.009	10.165***	10.973**
	(3.833)	(6.464)	(2.418)	(4.138)	(4.146)	(2.443)	(3.696)	(−1.311)	(4.041)	(2.666)
Market	9.459***	9.162***	11.189***		11.058***	2.242	−6.463	18.093***		1.158
	(3.133)	(3.052)	(3.723)		(3.639)	(0.508)	(−1.146)	(3.135)		(0.224)
SMB		−3.253*	−2.862				−3.626**	−2.623		
		(−1.805)	(−1.565)				(−2.010)	(−1.437)		
HML		2.980	5.537***				4.013**	5.653***		
		(1.608)	(2.937)				(2.182)	(3.000)		
MOM			9.410***					9.910***		
			(3.398)					(3.523)		
LevFac				9.827***	9.541**				11.594***	11.775***
				(3.088)	(2.336)				(3.679)	(2.801)
Adj. R^2	0.526	0.514	0.906	0.128	0.662	-0.026	0.182	0.785	0.532	0.515
MAPE	15.653	13.862	12.806	26.057	15.602	19.255	16.918	15.857	30.974	19.195
LR	711.68	1642.74	1956.46	32.88	746.28	702.60	1596.01	1904.03	25.99	731.25
p-Value	0	0	0	1	0	0	0	0	1	0

[49] Estimating asset pricing models with each of the factors individually shows that the closest competitor to the leverage factor is the momentum factor, which yields an adjusted R^2 of 30%.

When incorporating the seven bond portfolios, as in Panel A of Table 4.2, the leverage single-factor model is inferior, while the CAPM substantially gains in explanatory power. With respect to the information and transaction costs argument of Adrian, Etula, and Muir (2014), it can be concluded that German broker-dealers seem to concentrate on stock markets. Incorporating the market factor into the leverage factor model, the Fama-MacBeth two-step regression with leverage factor again outperforms the FF factor model with an adjusted R^2 of 66.2%. In addition, we also observe a substantial decline in the estimated constant, as well as in the $MAPE$ statistic. The associated LR test statistic of 746.28 has a zero p-value, implying a strong rejection of the null hypothesis that all betas are jointly zero.

Table 4.3 presents the results of the time-series regressions for the German asset pricing model using market and leverage factor. We report the average return of each portfolio, beta and t-statistic of the leverage factor, and the R^2 of the time-series regression. Confirming the LR test statistic, the results reveal a reasonable fit of the first-stage regressions, using a noisy variable such as intermediaries' leverage.

In conclusion, broker-dealers in Germany seem to be informed market participants strongly involved in asset market trading. Thus, a stochastic discount factor based on their leverage can reasonably be expected to help explain the variation of excess returns in the respective test portfolios. The positive and significant leverage price of risk supports the view that the balance sheet behavior of the broker-dealers in Germany is reinforcing booms and busts in asset markets. For the broader set of test assets, we find the factor model with both leverage and market factor to be the superior approach over the model with leverage as the single factor. Its relatively small constant in Table 4.2 further supports this conclusion. The greater ability to explain the cross-sectional variation in expected returns of stocks and bonds thus confirms the choice of our preferred model, stressing the importance of the role of a long-run factor combined with a medium-term factor as motivated by the theoretical contributions reviewed in the literature section.

Table 4.3: Time-series betas for Germany

Results of the time-series regression for the model $R^e_{i,t} = c_i + \beta'_{i,Levfac} LevFac_t + \beta'_{i,Market} Market_t + \epsilon_{i,t}$. This table reports betas and t-statistics of the leverage factor. The R^2 of the leverage and market factor time-series regressions are expressed as percentages. The time-series regression is estimated for each of the 33 portfolios.

	Low	Book-to-Market		High
Average return				
Small	3.882	6.476	7.834	11.288
Size	7.601	8.715	10.593	11.520
	6.895	9.566	9.404	14.672
Big	7.891	11.108	10.872	13.587
Betas, $\beta'_{i,Levfac}$				
Small	-0.415	-0.447	-0.288	-0.247
Size	-0.085	-0.192	-0.292	-0.264
	-0.240	-0.205	-0.450	-0.125
Big	-0.192	0.048	-0.024	0.051
t-stat				
Small	-1.993	-2.398	-1.560	-1.159
Size	-0.532	-1.268	-1.818	-1.451
	-1.676	-1.409	-3.046	-0.707
Big	-1.298	0.382	-0.229	0.445
R^2 in %				
Small	29.159	32.347	49.967	42.622
Size	47.267	53.175	51.144	52.384
	53.793	58.222	60.860	60.716
Big	75.546	82.231	84.917	82.113

Momentum portfolios				Bond portfolios			
Average return	Betas	t-stat	R^2	Average return	Betas	t-stat	R^2
6.746	-0.552	-2.102	56.803	0.199	-0.004	-0.752	2.239
3.584	-0.525	-2.319	60.599	0.398	-0.005	-0.804	2.199
9.231	-0.415	-2.527	72.459	0.583	-0.006	-0.816	2.213
6.260	-0.106	-0.721	71.997	0.691	-0.007	-0.936	2.355
8.599	-0.308	-2.059	71.531	0.827	-0.008	-0.987	2.426
8.726	-0.175	-1.293	73.659	0.947	-0.009	-1.016	2.450
11.822	0.157	1.128	68.292	1.133	-0.010	-1.054	2.516
11.813	-0.051	-0.352	65.452				
12.493	0.016	0.109	66.368				
19.284	0.300	1.305	48.728				

We now extend our analysis to the European asset market. Table 4.4 reports the results of the Fama-MacBeth regressions for Europe. The returns of the twenty-five stock and seven bond portfolios are denominated in euro in order to eliminate a potential exchange rate effect. The leverage factor arises from European broker-dealers as defined in the data section. In the first column of Panel A, which includes the seven German bond portfolios sorted on maturity, the market return is the sole pricing factor; in the second column, the Fama-French three-factors are used as pricing factors and achieve an adjusted R^2 of 75.3%. As it was the case for Germany, the Fama-French three-factor model plus momentum factor in column three obtains the highest adjusted R^2 value of 84.8%. In the fourth column, the only pricing factor is the European leverage factor based on broker-dealer banks, while the fifth column represents the preferred model where the market factor is also considered. The empirical results concur with those of Germany as presented above. The adjusted R^2 of the model using the leverage factor alone is low, while in the fifth column we see the adjusted R^2 increase to 46.1%. This again suggests that, in order to account for cross-sectional variation in the returns of bond portfolios, it is important to include the market return as a long-run risk factor. For the Fama-MacBeth results reported in Panel B, which does not include the bond portfolios, the adjusted R^2 of the leverage factor model is 24.1%, and adding the market factor substantially lowers the $MAPE$. Overall, the second-stage regressions deliver relatively high adjusted R^2s for our preferred model including the market factor together with the leverage factor, making the latter a useful SDF for European asset pricing.

Table 4.5 reports the results of the time-series regressions for the European asset pricing model using market and leverage. Similarly to the time-series results of Adrian, Etula, and Muir (2014), we see an increase in the betas of the leverage factor and an increase in its t-statistic when the average return of the portfolios increases. The pattern of significant betas in the time-series regression indicates that our results are unlikely to be due to a spurious regression. Overall our sample, circumscribed to European data, largely confirms the above findings for Germany and those for the US presented in Adrian, Etula, and Muir (2014).

Table 4.4: Fama-MacBeth regressions for European broker-dealer leverage

This table presents the results of the Fama-MacBeth regressions for the European market. Panel A reports the Fama-MacBeth regression results for 25 European equity portfolios sorted on size and book-to-market plus 7 German bond portfolios sorted on maturity. Panel B presents only the results of the Fama-MacBeth regression for 25 test portfolios sorted on size and book-to-market for Europe. The 25 portfolios sorted on size and book-to-market, the Fama-French factors and the momentum factor come from the data library curated by Kenneth French. The factors used are market, small-minus-big (*SMB*), high-minus-low (*HML*), momentum (*MOM*) and leverage (*LevFac*). The leverage factor is the residual of the AR(1) process of the natural logarithm of the leverage of the investment banks in the Stoxx600 Europe Banks Index. The results are reported in quarterly frequency from Q1 2000 to Q4 2016. Risk premia and returns are reported as yearly variables. The Shanken t-statistics are reported under the Fama-MacBeth prices of risk. The likelihood ratio (*LR*) test statistics and p-values are reported in the last row. The one-percent critical value for the *LR* test is 131.14 (bonds included) and 106.39 (bonds excluded).

	Panel A: Bond portfolios included					Panel B: Bond portfolios excluded				
	CAPM	FF	FF&MOM	Lev	Lev&Mrkt	CAPM	FF	FF&MOM	Lev	Lev&Mrkt
Constant	1.165***	0.853***	0.508***	6.003	1.067***	24.564***	14.687**	1.219	9.975	22.584***
	(6.469)	(4.803)	(4.140)	(1.536)	(5.012)	(3.696)	(2.040)	(0.134)	(1.417)	(2.865)
Market	6.020	5.211	6.671		4.084	−16.413**	−8.115	5.948		−16.309*
	(1.317)	(1.159)	(1.487)		(0.906)	(−2.039)	(−0.964)	(0.591)		(−1.810)
SMB		13.792*	14.215				13.005*	14.169		
		(1.839)	(1.572)				(1.713)	(1.585)		
HML		19.576**	18.611*				18.267**	18.585*		
		(2.567)	(2.013)				(2.356)	(2.037)		
MOM			18.416*					17.949*		
			(1.907)					(1.876)		
LevFac				−0.488	22.512**				24.586**	23.447**
				(−0.024)	(2.131)				(1.992)	(2.226)
Adj. R^2	0.337	0.753	0.84	-0.033	0.461	0.142	0.657	0.7	0.241	0.313
MAPE	10.687	8.639	8.540	26.044	10.282	12.829	10.210	9.951	31.433	12.296
LR	436.803	818.046	891.334	1.219	516.592	405.93	770.47	828.611	0.980	469.916
p-val	0	0	0	1	0	0	0	0	1	0

Table 4.5: Time-series betas for Europe

Results of the time-series regressions for the model $R^e_{i,t} = c_i + \beta'_{i,Levfac} LevFac_t + \beta'_{i,Market} Market_t + \epsilon_{i,t}$ for Europe. This table reports betas and t-statistics of the leverage factor. The R^2 of the leverage and market factor time-series regressions is expressed as percentages. The time-series regressions are estimated for each of the 33 portfolios.

	Low	Book-to-Market			High
			Average Return		
Small	−2.537	3.423	6.375	8.688	11.570
	3.135	7.511	9.536	11.557	13.090
Size	3.608	8.155	9.829	11.172	12.260
	6.463	8.395	10.159	10.914	9.790
Big	1.960	5.727	4.849	7.560	6.407
			Betas, $\beta'_{i,Levfac}$		
Small	0.106	0.149	0.132	0.202	0.212
	0.066	0.136	0.127	0.161	0.186
Size	0.107	0.101	0.113	0.159	0.148
	0.024	0.083	0.041	0.110	0.095
Big	-0.046	0.019	-0.076	-0.059	-0.017
			t-stat		
Small	1.531	2.444	2.801	4.086	3.871
	0.877	2.618	2.621	2.928	2.917
Size	1.534	2.240	2.685	3.554	2.363
	0.444	2.429	1.001	2.292	1.355
Big	-0.867	0.578	-2.309	-1.254	-0.262
			R^2 in %		
Small	82.059	84.225	89.436	86.879	82.575
	80.502	88.970	87.945	84.621	79.761
Size	82.678	89.689	90.155	88.983	81.460
	87.418	92.870	89.982	87.657	80.063
Big	82.258	91.356	93.759	88.279	85.375

Bond Portfolios			
Average return	Betas	t-stat	R^2
0.049	-0.002	-0.994	16.327
0.181	-0.004	-1.288	20.160
0.359	-0.004	-1.175	18.907
0.503	-0.004	-1.137	19.190
0.672	-0.004	-1.062	19.312
0.800	-0.004	-1.014	18.778
1.109	-0.004	-0.960	21.129

4.4.2 Other Banking Groups' Leverage and Equity Factor

The balance sheet data available for Germany and Europe give us the opportunity, firstly, to further investigate to what extent information and transaction costs influence the suitability of financial intermediary leverage as an asset pricing factor and, secondly, to collect empirical evidence in order to answer the question as to whether leverage or equity is the appropriate factor for cross-sectional asset pricing.

For the first purpose, we report in Table 4.6 the Fama-MacBeth regression results obtained using the leverage factor of main banks' and savings banks' balance sheets for Germany and commercial banks' balance sheet for Europe. Assuming that this group of financial intermediaries is mainly dealing with loans to the public and private sectors, the results of the asset pricing models should be less convincing than in the case of broker-dealer leverage. Since in the previous sections we find that the leverage factor plus market factor outperforms other specifications in explaining the cross-sectional variation in stock and bond portfolio returns, for this analysis we decided to add the market factor to the leverage factor of main and commercial banks.

In contrast to the results for broker-dealers discussed in the previous section, the results for Germany presented in Table 4.6 show no significant price of risk for the leverage factor based on main banks, which remains insignificant with both specifications with and without market factor. The leverage based on the savings banks also exhibits no significant price of risk for the leverage factor.[50] For the European market, the leverage model based on the commercial bank leverage produces a negative price of risk, which is in contrast to the theoretical work presented before. Overall, these findings support the suggestion that particularly broker-dealers in close proximity to asset markets might be viewed as marginal investors and their leverage as a significant pricing factor.

[50] In Germany, Sparkassen and Volksbanken are both savings banks. The results reported are for the Sparkassen group; however, the results are qualitatively the same for both groups.

Table 4.6: Fama-MacBeth regressions for non broker-dealer leverage

This table presents the results of the Fama-MacBeth regressions for the leverage factor based on the balance sheet leverage of German main and savings banks and European commercial banks. Test portfolios and market factor are provided by the Humboldt University of Berlin for Germany and by the Kenneth French data library for Europe. The results are reported in quarterly frequency from Q1 2000 to Q4 2016 for Europe, and from Q3 1971 to Q2 2016 for Germany. Risk premia and returns are reported as yearly variables. The Shanken t-statistics are reported under the Fama-MacBeth prices of risk.

	Germany				Europe	
	Main banks		Savings banks		Commercial banks	
	LevFac&Market	LevFac	LevFac&Market	LevFac	LevFac&Market	LevFac
Constant	1.713***	2.269**	1.529***	7.611**	0.954***	0.673
	(4.132)	(2.222)	(5.743)	(2.713)	(3.601)	(0.584)
Market	9.475***		9.265***		5.301	
	(3.141)		(3.038)		(1.149)	
LevFac	0.185	−8.481	-0.985	-0.486	−43.593**	−36.530
	(0.049)	(−1.116)	(-0.490)	(-0.104)	(−2.373)	(−1.256)
Adj. R^2	0.51	0.013	0.508	-0.032	0.504	0.514

To pursue our second aim of collecting further empirical evidence to answer the question of whether leverage or equity is the appropriate factor to use for cross-sectional asset pricing, we test a risk factor based on innovations to book equity of broker-dealers. Our approach is similar to the exercise for US data provided by Adrian, Moench, and Shin (2016), who conclude that the leverage factor is preferable when pricing a cross-section of assets.[51] On the basis of Adrian, Moench, and Shin (2016), in Table 4.7 we report the risk premia for the equity factor model both with the market factor and without it. For Germany, the results in Table 4.7 show that the equity factor for German broker-dealers fails to explain cross-sectional variation in the bond and equity market any better than the broker-dealer leverage factor. Furthermore, the risk premium of the equity factor is negative and contradicts the positive risk premia reported by Adrian, Moench, and Shin (2016) for the US market: this is

[51]Note that He and Krishnamurthy (2013) stress that market capitalization is the appropriate variable to use. However, this is unavailable for German and European broker-dealers. As a consequence, the results presented here have to be interpreted with caution.

an indication that the equity model fails to price the market in a correct way. For Germany, a low adjusted R^2 and insignificant equity factor coefficients show that the equity factor can do little to explain the cross-sectional variation of the test asset returns. For Europe, the adjusted R^2 of the factor model reaches 49.3% without the market factor and 47.0% with it; however, the risk premia of the equity factor remain negative for Europe as well. These results confirm the view that in Europe and Germany broker-dealer leverage is a more useful risk factor than book equity.[52]

Table 4.7: Fama-MacBeth regressions for German and European equity factor

This table presents the results of the Fama-MacBeth regressions with the equity factor (*EQFac*) for Germany and Europe. The test portfolios are those used for the Fama-MacBeth regression in the previous section without the 7 German bond portfolios. The factors used are market and equity (*Market* and *EQFac*). The results are reported in a quarterly frequency from Q1 2000 to Q4 2016 for Europe and from Q3 1971 to Q2 2016 for Germany. Risk premia and returns are reported as yearly variables. The Shanken t-statistics are reported under the Fama-MacBeth prices of risk.

	Germany		Europe	
	EQFac	EQFac & Market	EQFac	EQFac & Market
Constant	9.280	7.646**	13.629	13.056
	(1.489)	(2.271)	(1.650)	(1.108)
Market		2.510		−6.143
		(0.552)		(−0.472)
EQFac	−0.090	−0.087	−0.636*	−0.643
	(−0.638)	(−1.357)	(−1.806)	(−1.536)
Adj. R^2	-0.011	-0.041	0.493	0.47

[52]Note that data on market equity is unavailable for German broker-dealers.

4.4.3 Cross-Country Leverage

In Table 4.8 we test whether and to what extent a leverage factor based on broker-dealers of different countries affects German and European portfolios. Germany being part of the European Union, it may be plausible to employ the German broker-dealer leverage to price the European portfolios and vice versa. Furthermore, broker-dealer banks in the United States may be influential on the German and European markets as well. To test the explanatory power of US broker-dealer leverage, we use data from Table L.130 of the Federal Reserve Flow of Funds, Z.1 release, which corresponds to the broker-dealer leverage for the US.[53] All the Fama-MacBeth results are reported for both equity and bond portfolios and include the market return as a second risk factor.

The first three columns of Table 4.8 show the results obtained from testing the European and US leverage factor on the German market. The European leverage factor offers very little explanation for the cross-sectional variation of returns resulting in an adjusted R^2 of only 1.9%, indicating that the European broker-dealers' behavior has no explanatory power for the German equity and bond markets. The US leverage factor, by contrast, performs substantially better as a relevant risk factor for German equity and bond portfolios' returns. If we use the US leverage as the only factor in the model, we find an adjusted R^2 of 56.8% with a λ-coefficient significant at a 10% level. However, including both the German and the US leverage in the model shows that the US leverage factor seems not to carry any pricing information that the German leverage factor fails to capture. For the European equity and bond portfolios, the model with German broker-dealer leverage factor and market factor results in a negative price of risk, and the US broker-dealer leverage factor is statistically insignificant. Overall, there is very little evidence of cross-market influence of broker-dealer leverage. If the general notion of US investors' dominance on European asset market is true, then it does not appear to work through broker-dealer leverage.

[53] Since the study conducted by Adrian, Etula, and Muir (2014), the broker-dealer data has been moved from table L.129 to L.130 and the total liability calculation has also substantially changed.

Table 4.8: Fama-MacBeth regressions for cross-country leverage

Results of the cross-country Fama-MacBeth regressions for Germany and Europe. The factors used are the balance sheet leverage for Germany, the US, and Europe. The results are reported in quarterly frequency, from Q3 1990 to Q4 2016 for Europe and from Q3 1971 to Q2 2016 for Germany. When the European leverage factor is included, the time period goes only from Q1 2000 to Q4 2016 due to data availability. The leverage factors are the broker-dealer leverages for each country. All the specifications test the factor model on the equity and bond portfolios for Germany and Europe. The risk premia reported in column one are for the European leverage and German market factors; in column two those for US broker-dealer leverage and German market; and in column three for US leverage, German leverage and German market factor. For the European portfolios, column four reports the risk premia for German leverage and European market, and column five reports the risk premia for US leverage and European market factor. Column six reports the risk premia of US leverage, European leverage, and European market factor. Risk premia and returns are based on annualized quarterly data. The Shanken t-statistics are reported under the Fama-MacBeth prices of risk.

	Germany			Europe		
	EU LevFac	US LevFac	US & DE LevFac	DE LevFac	US LevFac	US & EU LevFac
Constant	6.657***	1.772***	2.159***	0.128	0.718***	0.664***
	(13.711)	(3.446)	(3.996)	(0.846)	(3.206)	(3.206)
Market	7.422	10.447***	11.018***	−2.303	6.167	5.080
	(1.436)	(3.460)	(3.630)	(−0.413)	(1.310)	(1.129)
US LevFac		1.662	-1.761		24.693*	18.930
		(1.662)*	(-0.162)		(1.720)	(1.488)
EU LevFac	0.023					14.353
	(0.829)					(1.164)
DE LevFac			2.489**	−7.984**		
			(2.539)	(−2.452)		
Adj. R^2	0.019	0.568	0.651	0.207	0.698	0.77

4.5 Empirical Evidence from a Dynamic Asset Pricing Model

The empirical results in the preceding section suggest that, in times of tight funding constraints, financial intermediaries have to deleverage, thereby raising their marginal value of wealth. Under these circumstances, assets that covary positively with leverage must provide a risk premium in terms of higher cross-sectional expected returns. Thus, showing a significantly positive price of risk and relatively low pricing errors, broker-dealer leverage seems to perform well as an intermediary stochastic discount factor. As argued by Adrian, Etula, and Muir (2014), however, a constant price of risk such as it emerges from the Fama-MacBeth regressions might be too restrictive. In fact, theoretical contributions point to a time-varying λ. For instance, Danielsson, Shin, and Zigrand (2010) derive a negative relationship between leverage and effective risk aversion when intermediaries are facing a value-at-risk constraint. In Adrian and Boyarchenko (2015), the deleveraging of broker-dealers further spurs volatility, thereby triggering a vicious cycle in financial markets, with the testable implication that the price of risk is a time-varying function of intermediary leverage.

To capture a time-varying price of risk, we follow Adrian, Moench, and Shin (2016) and apply the dynamic asset pricing model (DAPM) of Adrian, Crump, and Moench (2015a). The systematic part of an economy's risk is proxied by the time series of shocks arising from the vector autoregression (VAR) of risk factors and price of risk factors. Risk factors are defined as state variables that are contemporaneously correlated with returns, while price of risk factors show forecasting power for future excess returns in the time series, which is why they are also called forecasting factors. The DAPM framework is flexible in the sense that any given variable might be a risk factor, a price of risk factor, or both. Based on the results of the US market documented in Adrian, Moench, and Shin (2016) and the results in the preceding section, we concentrate on a specification that employs the market return (R^M) as a risk factor and the single balance sheet measure (BSF) both as risk and as price of risk factor.

Thus, the VAR is given by

$$\begin{pmatrix} R^M_{t+1} \\ BSF_{t+1} \end{pmatrix} = \begin{pmatrix} \mu_{R^M} \\ \mu_{BSF} \end{pmatrix} + \begin{pmatrix} \phi_{R^M,R^M} & \phi_{R^M,BSF} \\ \phi_{BSF,R^M} & \phi_{BSF,BSF} \end{pmatrix} \times \begin{pmatrix} R^M_t \\ BSF_t \end{pmatrix} + \begin{pmatrix} u^{R^M}_{t+1} \\ u^{BSF}_{t+1} \end{pmatrix}. \quad (4.8)$$

Assuming linearity of the pricing kernel and the prices of risk being affine in BSF_t, the beta representation of our DAPM model can be written as

$$R^i_{t+1} = \beta^{R^M}_i(\lambda^{R^M}_0 + \Lambda^{R^M,BSF}_1 BSF_t + u^{R^M}_{t+1}) + \beta^{BSF}_i(\lambda^{BSF}_0 + \Lambda^{BSF,BSF}_1 BSF_t + u^{BSF}_{t+1}) + e^i_{t+1}. \quad (4.9)$$

Equation (4.9) reveals that, in contrast to a standard beta representation, the price of risk is now time-varying. Thus, the expected excess return depends on the βs and the set of $\lambda_t = \lambda^i_0 + \Lambda^{i,j}_1 BSF_t$.[54] For the parameter estimations, we implemented the two-stage procedure of Adrian, Crump, and Moench (2015a). Aside from showing the consistency and asymptotic normality of estimated coefficients, the authors also provide heteroskedasticity-robust standard errors, which are used to calculate t-statistics of coefficients.

The following Table 4.9 and Table 4.10 contain the estimation results of the DAPM model for German and European data. In Panel A of each table, we report the results of simple regressions of the stock market return (R^M), the 10-year German government bond return ($BUND10$), the difference between $BUND10$ and the 3-month Euribor rate ($SPREAD$), and the return from a corporate bond portfolio (CBP) on lagged shocks to balance sheet factors. The intent behind this preliminary exercise is to reveal the potential suitability of the balance sheet measures to serve as forecasting factors. Panel B shows estimates of $\Lambda^{R^M,BSF}_1$

[54]The framework nests the Fama-MacBeth estimator as a constraint specification ($\Lambda^{i,j}_1 = 0$ and $\phi_{i,j} = 0$).

and $\Lambda_1^{BSF,BSF}$ together with the $MAPE$ for comparison purposes.[55] We also calculate the average prices of risk for the market return and the balance sheet factor, denoted by $\bar{\Lambda}^{R^M}$ and $\bar{\Lambda}^{BSF}$, respectively.

Panel A of Table 4.9 shows that the leverage of German broker-dealers exhibits potential to forecast future excess stock market returns, suggesting that this particular balance sheet factor is a successful driver of a time-varying price of risk. The negative coefficient is consistent with the expected role of the broker-dealer leverage. If broker-dealers are buying stocks, both their leverage and stock market prices increase. The price impact implies that future stock returns will be compressed. This funding constraint effect can also be observed with main banks, but in this case the forecasting power is related to the return of the German Bund. Here, improved funding conditions primarily trigger bond purchases. These funding constraint mechanics are in contrast to Haddad and Sraer (2018), who show that, if banks' balance sheet management is dominated by interest rate risk considerations, a larger than average net exposure of banks to long-term assets should be a predictor of larger bond risk premia. Interestingly, this is true for savings banks largely focusing on local credit supply. As a result, the estimation result reveals positive and significant coefficients in the case of German government bonds and corporate bonds, but not for the stock market return.

Panel B of Table 4.9 largely confirms these findings. The estimated coefficient measuring the influence of leverage on the market price of risk is statistically significant (at the 10% level) and negatively signed only with broker-dealers. Moreover, the unconditional prices of risk are all positive and the time-variation of λ obtains a slightly lower mean absolute pricing error compared to the Fama-MacBeth regressions.[56] The time series of $\lambda_t^{R^M,BSF}$ is presented in Figure 4.3 for illustration purposes. Due to the fact that market price of risk is supposed to be driven by shocks to broker-dealer leverage, it clearly shows substantial volatility around its long-run mean. Marked episodes, however, may be in accordance with

[55] The cross-section of absolute pricing errors is available from the authors upon request.

[56] Table 4.9 also reports the $Wald$-statistic (together with its p-value) of joint beta significance of the time-series regressions, as recommended by Adrian, Moench, and Shin (2016). The strong rejection of the null hypothesis of $\beta_i = 0$ suggests that weak instrument problems are not an issue here.

the above argumentation. For instance, in the run-up to the financial crisis, increasing asset prices led to a loosening of funding constraints, giving rise to a downward trending market price of risk to below-average levels. This trend is immediately corrected thereafter in the fourth quarter of 2008 when funding started to dry up.

Table 4.9: Time-varying price of risk for German intermediary leverage

This table contains the time-varying price of risk estimates for alternative German leverage factors: broker-dealer leverage ($LevBD$), main banks leverage ($LevMain$), and savings banks leverage ($LevSav$). $\bar{\Lambda}^{R^M}$ and $\bar{\Lambda}^{BSF}$ denote the unconditional price of risk for R^M and BSF, respectively. $\Lambda_1^{R^M,BSF}$ and $\Lambda_1^{BSF,BSF}$ are the estimated coefficients of the price of market risk on lagged balance sheet factors and the price of balance sheet risk on lagged balance sheet factors, respectively. $MAPE$ denotes the mean absolute pricing error. $Wald$ reports the test statistic (together with its p-value) of joint beta significance in the time-series regressions, as recommended by Adrian, Moench, and Shin (2016) (the 1% critical value for this F-test is 4.73). The sample ranges from Q1 1971 to Q4 2016. $***$, $**$, and $*$ denote significance at the 1%, 5%, and 10% level.

	$LevBD$	$LevMain$	$LevSav$
Panel A			
R^M	-0.49**	0.08	-0.06
	(1.97)	(0.45)	(0.11)
$BUND10$	0.01	-0.12**	0.36***
	(0.13)	(2.38)	(2.75)
$SPREAD$	-0.04	-0.01	-0.09
	(1.14)	(0.30)	(1.17)
CBP	0.01	-0.02**	0.10***
	(1.01)	(2.23)	(4.22)
Panel B			
$\Lambda^{R_M,BSF}$	-0.47*	0.22	0.03
	(1.80)	(1.11)	(0.06)
$\Lambda^{BSF,BSF}$	0.04	0.03	-0.82***
	(0.17)	(0.15)	(2.62)
$\bar{\Lambda}^{R^M}$	13.58***	11.60***	11.89***
	(4.29)	(3.76)	(3.94)
$\bar{\Lambda}^{BSF}$	9.06**	1.33	0.71
	(2.46)	(0.34)	(0.43)
$MAPE$	15.27	15.28	15.23
$Wald$	55.95	81.60	122.69
p-Value	0.00	0.00	0.00

In the case of savings bank leverage, Table 4.9 reports a significantly negative influence of leverage on the leverage price of risk, which is in line with Adrian and Boyarchenko (2015). The estimated unconditional prices of risk for leverage are statistically insignificant for main banks and savings banks, confirming the results of the Fama-MacBeth regressions above. Taken together, the empirical evidence from the DAPM model points to a time-variation of the prices of risk along the lines of the theoretical contribution of Adrian and Boyarchenko (2015). This confirms earlier results for the US market as documented in Adrian, Moench, and Shin (2016).

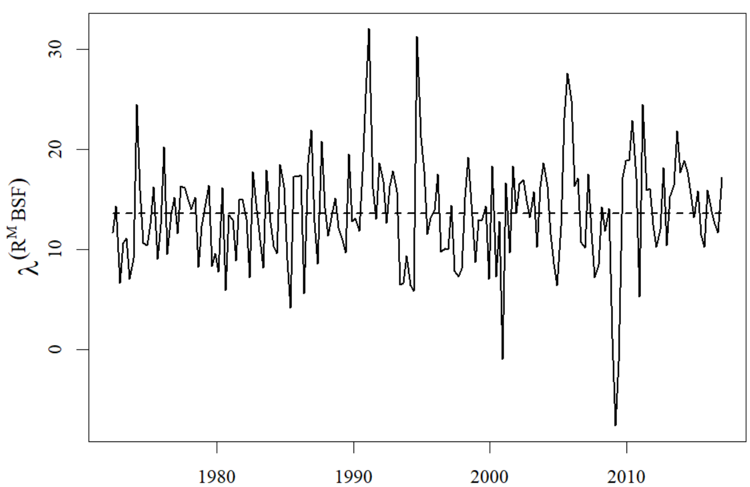


Figure 4.3: Time-varying lambda

The solid black line is the time series of $\lambda_t^{R^M,BSF}$ and the dashed line is its long-run mean expressed as percentages.

Table 4.10: Time-varying price of risk for European intermediary leverage

This table contains the time-varying price-of-risk estimates for two European balance sheet factors: broker-dealer leverage ($LevBD$) and commercial banks leverage ($LevCom$). $\bar{\Lambda}^{R^M}$ and $\bar{\Lambda}^{BSF}$ denote the unconditional price of risk for R^M and BSF, respectively. $\Lambda_1^{R^M,BSF}$ and $\Lambda_1^{BSF,BSF}$ are the estimated coefficients of the price of market risk on lagged balance sheet factors and the price of balance sheet risk on lagged balance sheet factors, respectively. $MAPE$ denotes the mean absolute pricing error. $Wald$ reports the test statistic (together with its p-value) of joint beta significance in the time-series regressions as recommended by Adrian, Moench, and Shin (2016) (the 1% critical value for this F-test is 4.99). The sample ranges from Q4 1999 to Q4 2016. $***$, $**$, and $*$ denote significance at the 1%, 5%, and 10% level.

	$LevBD$	$LevCom$
	Panel A	
R^M	0.16	-0.13
	(0.90)	(1.15)
$BUND10Y$	0.05**	0.04**
	(2.30)	(2.00)
$TERM$	0.001	0.01
	(0.06)	(0.72)
CBP	0.03	0.07***
	(1.18)	(3.37)
	Panel B	
$\Lambda_1^{R^M,BSF}$	0.20	-0.09
	(1.63)	(0.78)
$\Lambda 1^{BSF,BSF}$	-0.17	-0.26
	(0.58)	(0.69)
$\bar{\Lambda}^{R^M}$	5.34	7.16
	(1.23)	(1.48)
$\bar{\Lambda}^{BSF}$	23.37**	-39.98**
	(2.52)	(2.46)
$MAPE$	10.11	9.97
$Wald$	1,109.53	199.24
p-Value	0.00	0.00

The empirical results for European financial intermediaries are comparable to those of German main banks and savings banks. The positive relationship between banks' leverage and future returns of the German Bund shown in Panel A of Table 4.10 may be explained by resorting not only to interest rate risk management, as in Haddad and Sraer (2018), but also to a 'flight-to-quality' effect, as suggested by Brunnermeier and Pedersen (2009) and Acharya and Pedersen (2005). The latter work suggests that, in a market downturn, financial intermediaries face increasing liquidity risks of stock holdings, which lead them to substitute them with safe assets such as German government bonds and – in the case of main banks – also corporate bonds. Buying bonds in a situation of negative leverage shocks raises bond prices, thereby lowering future returns as signified by the positive sign.[57] A statistically significant influence of leverage on future stock returns, however, cannot be identified. This is also reflected in Panel B of Table 4.10. Although the $MAPE$s are slightly lower than in case of the Fama-MacBeth regressions, there is little evidence in favor of a significant time-variation of λ for European broker-dealers.

4.6 Conclusion

This paper provides empirical evidence on the reinforcing nature of financial intermediaries' balance sheet management during boom and bust cycles on European markets. We start by showing that the findings of Adrian, Etula, and Muir (2014) for US broker-dealers also hold for other important financial markets. Particularly, the Fama-MacBeth two-step regression reveals that including broker-dealer leverage as a risk factor explains German asset returns with an adjusted R^2 of up to 66%. To provide some additional evidence on the question of whether or not broker-dealers can be perceived as marginal investors, we also investigate the role of savings banks' leverage. Focusing on mortgage loans and loans to private-sector firms, this group of financial institutions is not strongly engaged in asset market trading. In line with this conjecture, the time series of leverage shocks does not provide any explanatory power in Fama-MacBeth regressions: This is supported by the empirical results from European data since 1999. In addition, a cross-country perspective does not reveal any indication of foreign broker-dealer influence.

Moreover, we consider the suggestions by Adrian, Moench, and Shin (2016), who stress that a constant price of risk as derived from Fama-MacBeth regressions might be too restrictive. To capture a time-varying price of risk, the authors' dynamic asset pricing model is applied to German and European data sets. Here, the systematic part of an economic risk is proxied by the time series of shocks arising from the vector autoregression of risk factors and price of risk factors. Risk factors are defined as state variables that are contemporaneously

[57] Given the low fraction of stocks in savings banks' balance sheets, a flight-to-quality effect is less likely.

correlated with returns, while price of risk factors show forecasting power for future excess returns in the time series. We find that the leverage of German broker-dealers exhibits potential for forecasting future excess stock market returns, suggesting this particular balance sheet factor as a successful driver of a time-varying price of risk.

From a policy perspective, it can be concluded that broker-dealer leverage shows procyclicality and significantly explains excess asset returns, thus supporting the view that financial intermediaries play a central role in propagating shocks in the financial sector and stressing the importance of macro- and microprudential policies.

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Erklärung zum selbständigen Verfassen der Arbeit

Ich erkläre hiermit, dass ich meine Doktorarbeit „Essays on Empirical Empirical Finance“ selbstständig und ohne fremde Hilfe angefertigt habe und dass ich als Koautor maßgeblich zu den weiteren Fachartikeln beigetragen habe. Alle von anderen Autoren wörtlich übernommenen Stellen, wie auch die sich an die Gedanken anderer Autoren eng anlehnenden Ausführungen der aufgeführten Beiträge wurden besonders gekennzeichnet und die Quellen nach den mir angegebenen Richtlinien zitiert.

Ort, Datum Unterschrift