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Trading strategies and dynamic interactions under long-term volatility

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Markets can remain irrational longer than you can remain solvent.
John Maynard Keynes

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List of Abbreviations

1 s.e.	One standard error
ADF	Augmented Dickey-Fuller
AIC	Akaike information criterion
ARCH	Autoregressive conditional heteroscedasticity
AUD	Australian dollar
BG	Breusch-Godfrey
Brexit referendum	United Kingdom European Union membership referendum
BRL	Brazilian real
CAD	Canadian dollar
CET	Central European Time
CHF	Swiss franc
DBH	Deutsche Banks's PowerShares DB G10 Currency Harvest
DCC	Dynamic conditional correlation
df	Degrees of freedom
EGARCH	Exponential generalized autoregressive conditional heteroscedasticity
EUR	Euro
FX	Foreign exchange market
G-10	Group of Ten
GARCH	Generalized autoregressive conditional heteroscedasticity

GBP	British pound sterling
GCI	HSBC Global FX Carry Index
GED	Generalized error distribution
GIRF	Generalized impulse response function
GVAR	Global vector autoregression
HKD	Hong Kong dollar
$I(1)$	Integrated of order one
ICI	Barclays Capital's Intelligent Carry Index
iid	Independent identically distributed
INR	Indian rupee
J-B	Jarque-Bera
JPY	Japanese yen
KRW	South Korean won
LATAM	Latin America
LM	Lagrange multiplier
LR	Likelihood ratio
MEA	Middle East and Africa
MGARCH	Multivariate generalized autoregressive conditional heteroscedasticity
MSDR	Markov-switching dynamic regression
MXN	Mexican peso
MYR	Malaysian ringgit
NOK	Norwegian krone
NZD	New Zealand dollar
OIRF	Orthogonalized impulse response function
OLS	Ordinary least squares

P/E	Price earnings ratio
SEK	Swedish krona
SGD	Singapore dollar
SW	Shapiro-Wilk
THB	Thai baht
TRY	Turkish lira
TTRI	UBS G-10 Carry Trade Total Return Index
TWD	New Taiwan dollar
UIP	Uncovered interest parity
USD	United States dollar
VAR	Vector autoregression
VARX	Vector autoregression model with exogenous variables
VECM	Vector error correction model
VIX	CBOE Volatility Index
ZAR	South African rand

Introduction

This dissertation aims to investigate trading strategies and dynamic interactions under long-term volatility. Noise and unanticipated changes provide new information for market participants. The amount of information is growing and leads to an increase in price volatility as stated by Ross (1989). Stock prices do not follow a random walk and do not respond to intrinsic values in irrational markets. The efficient market hypothesis falls into disrepute as a result of market events and growing empirical evidence of inefficiencies according to Stout (2005). Furthermore, Mendel and Shleifer (2012) state that shocks move prices away from fundamental values and affect the market equilibrium. Former studies investigate return patterns in complete isolation without a dynamic model setting. In order to achieve an accurate understanding, autocorrelation patterns and state-dependencies have to be explored first because trading decisions are based on market conditions. On this basis, feedback and currency carry trading as widespread anomalies are part of the further investigation. In contrast to previous work, the project introduces dynamic interactions between assets, countries, and trading strategies by using state of the art econometric models. The link to behavioral finance theory is of high interest and sets out to find advantageous investment opportunities as well as to understand mutual effects arising from trading decisions within the scope of this research project.

Chapter 1 depicts investors' behavior and interactions of trading decisions under distress with changing volatility levels. Thereby, stock return patterns are difficult to predict with standard asset pricing models due to market anomalies among others. First, we use a world market model to analyze autocorrelation patterns in stock returns by interconnecting countries and capturing global market movements. Second, we analyze whether Bitcoin can be seen as a safe haven by employing state-dependent regressions. We offer a continuative examination of investment opportunities by taking autocorrelation patterns and diversification capabilities under distress into account.

Serial autocorrelation is deeply connected with feedback trading and the existence of feedback traders influences the partial predictability of aggregate stock

returns. Therefore, we explore the interaction between return autocorrelations and volatility from two new angles in chapter 2. We decompose the overall return premium and assume interconnectedness between multiple countries by implementing a global feedback trading model. Uncertainty shifts risk across periods by allowing for dynamic effects with spillovers. Hence, this chapter sheds light on investors' strategy and provides an alternative framework about price fluctuations.

Currency carry trading presents a widespread trading strategy and refers to the forward premium puzzle. Investors benefit from arbitrage opportunities by borrowing low-yielding currencies with the aim to invest in high-yielding ones. Investors' selection is closely linked with risk sentiment and fundamentals. Consequently, a shock can cause changes in the risk premium and affects expected returns. Furthermore, asset classes and market interconnectedness influence the risk sentiment due to market volatility. This implies that a one-to-one relationship does not exist between interest rate differentials and expected changes in exchange rates. On this basis, we explore the interaction between currency carry trading, futures, exchange rates, and commodities through structural shocks in chapter 3.

A better theoretical understanding of trading strategies and dynamic interactions advances not only the science but is also of high practical relevance. It is important to understand irrational behavior beforehand in order to remain at least solvent given market circumstances.

Chapter 1

Trading decisions: Autocorrelation and state-dependence under distress[1]

1.1 Introduction

Stock market anomalies have long been recognized to be inconsistent with standard asset pricing models due to market inefficiencies. Certainly, interest in the predictability of stock returns is substantial and has been growing over recent years. Multiple studies focus on anomalies in order to identify stock return patterns because trading strategies differ when market conditions change over time. However, little attention has been paid to reasons for investors' behavior and interactions of trading decisions despite a fast-growing literature. Hence, an integration of capital market theory with behavioral finance should offer meaningful conclusions and provide explanations for irrational financial decisions.

Trading decisions are based on market conditions with changing volatility levels. Periods with low volatility induce positively autocorrelated returns and autocorrelations turn negative during periods of high volatility. This phenomenon will be the initial point in order to depict investors' behavior under distress. Thereby, the United Kingdom European Union membership referendum (Brexit referendum) serves as a potential stock market crash to identify higher volatility in returns. The first step consists of autocorrelation patterns in stock returns by using a world market model. The inclusion of a world market index accounts for interconnectedness between countries and captures global market movements in contrast to previous studies. The next step entails currency exchange rates as well as price fluctuations of gold, Bitcoin, and bonds in order to address the

[1]This chapter is based on Kusen (2018). Trading decisions: Autocorrelation and state-dependence under distress. *Unpublished working paper.*

question whether traders can diversify or even minimize risk when investing in other assets aside of stocks, especially during market downturns. Furthermore, we analyze whether Bitcoin can be seen as a safe haven by employing state-dependent regressions.

Our research project aims to investigate mutual effects by taking autocorrelation under distress and asset classes into consideration. On this basis, the structure of this chapter proceeds as follows. Stock return patterns and investors' behavior with a connection to autocorrelation are provided in section 1.2 besides previous empirical work. In section 1.3, we present descriptive statistics of the applied data and propose specific hypotheses. In order to achieve an accurate understanding, return patterns have to be explored because trading decisions are based on market conditions and asset classes. Therefore, section 1.4 illustrates the methodology of the world market model and the Markov-switching model for our further analysis. Section 1.5 forms the main part of this chapter by providing empirical results for autocorrelation patterns and by including absolute as well as relative returns for state-dependent regressions. A continuative outlook is provided in section 1.6 after a sophisticated robustness check. Section 1.7 concludes.

1.2 Literature Review

Stock return behavior is the origin for deviations from a simple random walk in matters of means, variance, correlations, and non-linearities. Former studies explain altered return patterns by seasonality (Keim (1983)), time horizon (Summers (1986) or Fama and French (1988)), information arrival (French and Roll (1986)), trading volume (Lamoureux and Lastrapes (1990)), stock size (Lo and MacKinlay (1990)), transaction costs (Mech (1993)), monetary policy (Patelis (1997)), and institutional ownership (Sias and Starks (1997)) among others. In addition, autocorrelation reveals intriguing properties. Conrad et al. (1991) reconcile autocorrelation patterns in stock returns. On the one hand, returns are predictable when positive autocorrelation exists (Conrad and Kaul (1988) and Conrad and Kaul (1989)). On the other hand, returns tend to be negatively autocorrelated (Fama (1965), French and Roll (1986), or Lo and MacKinlay (1990)). Simultaneously, differences exist when considering long- and short-horizons. Negative autocorrelation is induced by a slow mean-reverting process according to Fama and French (1988). Thereby, the effect is stronger for long-horizon returns and in line with the slowly decaying stationary component hypothesis. Ding et al. (1993) justify that stock markets returns exhibit a long memory property. Consequently, autocorrelation reflects market inefficiency and LeBaron (1992) identifies higher autocorrelations for periods of lower volatility.

Trading strategies affect prices due to negative and positive autocorrelations arising from value investing and trend following, respectively. Jegadeesh and Titman (1993) document that investors earn significant positive returns when buying good performing and selling bad performing stocks from the past. On the one hand, an active trading strategy[2] assumes short-term movements and captures market trends by trying to beat the market average. On the other hand, a buy-and-hold strategy ignores short-term movements due to higher return expectations over the long-term. Active trading has the potential to capture profit opportunities in contrast to a buy-and-hold strategy according to Kwon and Kish (2002). Investors follow strategies of actively picking and trading stocks as pointed out by Lakonishok et al. (1992). Thereby, they affirm rather strong evidence for feedback trading than for herding. In contrast, Ellis and Parbery (2005) state that returns of a long-run passive strategy are larger while examining the comparative performance of an adaptive moving average strategy due to the cost of trading. Nevertheless, investors sell winners too early and ignore losses in value according to Shefrin and Statman (1985). Market risk stems not only from news (De Long et al. (1989)) but also from disclosures (Meulbroek (1992)), insider trading (Fishman and Hagerty (1992)), irrational noise trading (Campbell and Kyle (1993)), investor's type (Farmer and Joshi (2002)), investor's sentiment (Baker and Wurgler (2006)), firm-specific information (Baruch et al. (2007)), and liquidity (Chan et al. (2013)) among others.

Investors do not only adopt strategies but also diversify their portfolios among different asset classes. Besides the already well-known traditional classes, cryptocurrencies are becoming increasingly important and generate confusion around their classification.[3] Gronwald (2014) analyzes market characteristics and price jumps of Bitcoin. He identifies extremely unstable price movements as actually observed in immature markets. Additionally, Bitcoin can be seen as an alternative asset or speculative investment rather than a currency. Luther and White (2014) go one step further and state that Bitcoin can become a medium of exchange due to alternative payment systems with possibilities for non-state money. Elendner et al. (2018) investigate properties of cryptocurrencies as financial assets and find that the diversification of portfolios is improved due to marginal co-movements with established assets. Dyhrberg (2016), Bouri et al. (2017), and Bouri et al. (2017) clarify that Bitcoin is useful for risk-averse investors by indicating hedging capabilities – serving as a safe haven against extreme downward movements.

[2]Day trading, position trading, swing trading, range trading, breakout trading, reversal trading, trend trading, herding, and scalping are the most common types of active trading.

[3]We will not dive into the specifics of the technology, but rather disclose the economic aspects despite the little academic research.

Previous research confirms that investors' behavior has a major impact on stock returns with different strategies due to changing market conditions. On this basis, we offer a continuative examination by taking autocorrelation patterns and diversification capabilities under distress into account. First, we apply a world market model in order to disclose autocorrelation without to specify an explicit measure of volatility. Sentana and Wadhwani (1992), Koutmos (1997), or Koutmos and Saidi (2001) confirm that trading rules change in response to market conditions. Autocorrelation tends to be negative during periods of high volatility with negatively correlated stock returns. Second, the Markov-switching model depicts differences for estimated volatilities of various asset classes due to non-linear dynamics and sudden changes. This research sheds light on asset classification with respect to return patterns and investors' behavior. To the best of our knowledge, such an investigation with distress has not been considered in the literature.

1.3 Data

1.3.1 Sample and Estimation Window

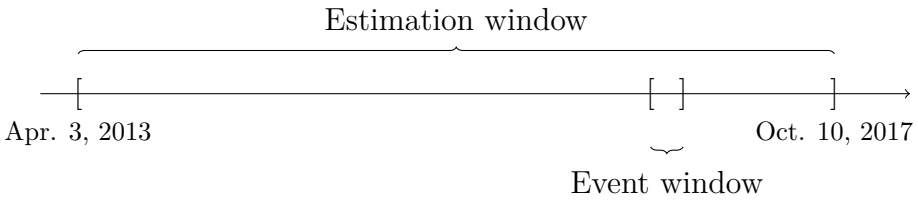
Our sample for the empirical investigation contains daily closing prices of gold, Bitcoin, bonds, and common stock market indices from different countries as well as dollar-euro exchange rates. In particular, the stock market sample consists of DAX 30 (Germany), FTSE 100 (UK), S&P 500 (US), SSE A (China), Nikkei 225 (Japan), RTSI (Russia), and MSCI World (World). Following MacKinlay (1997), we construct the estimation window large enough because the variance of sampling error of the parameters converges to zero. Therefore, we collect stock prices, gold prices, long-term 10-year US government bond yields, and exchange rate data from Thomson Reuters Datastream and Bitcoin prices from Coindesk Price Index on a daily frequency in United States dollar (USD) from April 3, 2013, to October 10, 2017, with 1119 trading days.[4] Later on, we assume S&P 500 as an appropriate benchmark for equity, the dollar-euro exchange rate is considered as the base currency, and the MSCI World index as the world market index.[5]

[4]Starting in 2008, Bitcoin prices only weakly increased in the following years due to a limited usage and distribution. A graphical illustration of prices and returns is provided in Figure A.1 on page 84 in the Appendix. We start our estimation on April 3, 2013, when the price exceeded USD100 for the first time. In comparison with stock market activity, Bitcoin trading is not time restricted and takes place on the weekend as well. Therefore, we adjust and correspondingly match trading days not only in matters of public holidays and trading called offs.

[5]S&P 500 is the world's most-tracked index and represents approximately 52% of the world market capitalization.

Figure 1.1 illustrates the model timeline with both the estimation and event window. The identification of a relevant event is helpful for the proposed research question, which might have impacted prices. Therefore, we provide a preliminary evidence on the link between volatility and autocorrelation of returns by illustrating market fluctuations during the whole period and the market crash. In particular, June 23, 2016, is the relevant event day when the Brexit referendum took place with the known result to leave the EU by a reception of 51.9%. The outcome of this election induced the largest single-day decline for share prices since the Chinese stock market crash starting with the stock market bubble on June 12, 2015. Consequently, share price volatility, measured by the standard deviation of returns, experienced an obvious rise. The deviation was between 1.130 and 6.086 during the event. Without to specify an explicit measure of volatility and in line with former studies, preliminary evidence for autocorrelation of returns can be shown by assuming the Brexit referendum as a potential stock market crash.[6]

Figure 1.1: Model timeline



Note: This figure shows the timeline for both the estimation and the event window. The estimation window consist of 1119 trading days and the Brexit referendum, as the event window, contains the days prior, during, and after the crash day.

1.3.2 Descriptive Statistics

Descriptive statistics of market indices are captured in Table 1.1. The mean is only negative for RTSI with a value of -0.021. The reasons, therefore, are economic and financial sanctions beginning in July, 2014, with the collapse of the Russian ruble. All return distributions are skewed and leptokurtotic relative to the normal distribution as expected for financial time series. Thereby, values of the Jarque-Bera (J-B) test, as a goodness-of-fit measure, range from 370.986*** to 9702.295*** for S&P 500 and FTSE 100, respectively.[7] The Augmented Dickey-Fuller (ADF) test confirms stationarity for all returns. Values of the t-statistics have similar negative values between -28.652*** and -43.859*** – a unit root can

[6]Note that the event window for the outlined crash contains the days prior, during, and after the crash day (June 22 to 24).

[7]We can neglect an overly sensitive chi-squared approximation due to the sufficient large sample size.

be rejected. As a result, returns of market indices follow a mean-reverting process with diminishing stochastic shocks over time. A serial correlation exists only for the FTSE 100 index according to the Breusch-Godfrey (BG) Lagrange multiplier (LM) test for up to two lags.

Table 1.1: Descriptive statistics of equity returns

	DAX 30	FTSE 100	S&P 500	SSE A	Nikkei 225	RTSI	MSCI World
Mean	0.036	0.001	0.043	0.320	0.033	−0.021	0.031
SD	1.167	1.080	0.777	1.533	1.278	1.890	0.696
Skewness	−0.578	−1.168	−0.440	−1.220	−0.256	−0.160	−0.805
Kurtosis	7.865	17.235	5.680	10.438	6.265	10.685	7.844
J-B	1165.838***	9702.295***	370.986***	2857.061***	509.255***	2758.411***	1214.881***
ADF	−33.203***	−30.908***	−33.978***	−31.468***	−43.859***	−31.779***	−28.652***
BG LM (2)	1.300	6.149**	0.448	0.181	0.323	1.354	1.224

Note: This table provides the sample statistics for each market using daily returns from April 3, 2013 to October 10, 2017 with a sample size of 1119 days. All series are in logarithmic first differences and expressed as a percentage on a daily basis. J-B matches the skewness and kurtosis to the normal distribution. ADF is the Augmented Dickey-Fuller test for a unit root and BG LM (2) is the Breusch-Godfrey test of order 2 for detecting serial correlation. Stars indicate significance as follows: *10%, **5%, ***1%.

Table 1.2 presents Pearson correlation coefficients for different asset classes with absolute and relative returns in panel (A) and (B), respectively. As it can be seen in panel (B), the correlation is significantly negative between equity and gold as well as between gold and currency with values of -0.091*** and -0.382***, respectively. Simultaneously, we find a positive relationship between equity and currency. This implies that returns behave similarly for both asset classes and investors probably adopt currency as a more risky investment like equity. The correlation between equity and bond helps to improve investors' allocation decisions. The negative correlation at the 1% level verifies that bonds can immunize asset allocations by hedging stock portfolios when the economy is in a bad state. Same reasoning can be applied for gold. Interesting is the positive correlation between gold and Bitcoin at the 10% level. A similar return pattern illustrates the possibility of a substitution of Bitcoin for gold. Not surprisingly, all significant correlations are positive and mostly higher in panel (A) due to the usage of absolute returns. However, a meaningful interpretation is not possible and requires further considerations.[8] Therefore, we only conclude the intensity of the correlation coefficients.

[8]Suppose we generalize the problem and introduce assets A and B without loss of generality. Four possibilities arise for a positive correlation when considering absolute returns. Returns of A and B go up (down) or returns of A go up (down) and down (up) for B.

Table 1.2: Correlation matrix for asset classes

	Equity	Gold	Currency	Bitcoin	Bond
(A) Absolute returns					
Equity	1				
Gold	0.146***	1			
Currency	0.148***	0.247***	1		
Bitcoin	0.056*	0.136***	−0.021	1	
Bond	0.267***	0.155***	0.205***	0.014	1
(B) Relative returns					
Equity	1				
Gold	−0.091***	1			
Currency	0.071**	−0.382***	1		
Bitcoin	−0.021	0.053*	0.007	1	
Bond	−0.326***	0.281***	−0.162***	0.020	1

Note: This table contains correlations for absolute and relative returns of different asset classes in panel (A) and (B), respectively. Stars indicate significance as follows: *10%, **5%, ***1%.

1.3.3 Hypotheses

First, we test for autocorrelation of index returns by capturing global market movements. Given the world market model, an explicit measure of volatility can be neglected because the Brexit referendum serves as a suitable event with enormously increased volatility in returns. The initial point is to depict investors' behavior under distress. Periods with low volatility should induce positively autocorrelated returns and autocorrelations should turn negative during periods of high volatility. Comprising these thoughts leads directly to the hypotheses:

H0: Serial correlation of index returns does not exist. The Brexit referendum has no impact on return patterns.

H1: Serial correlation exists for index returns. The Brexit referendum has an impact on return patterns.

Second, if autocorrelation exists for index returns in as well as across markets, then the question arises whether returns of different asset classes behave similarly. Furthermore, do asset classes have a mutual relationship with each other and can investors diversify risk by investing in different classes or select a suitable class? Dyhrberg (2016) states that Bitcoin is useful for risk-averse investors for diversification purposes and comprises advantages as a medium of exchange. We use state-dependent regressions in order to test the following hypotheses:

H2: Returns of different asset classes behave similarly. A mutual relationship is not present and investors cannot diversify their portfolios in order to minimize risk.

H3: Returns of different asset classes behave differently. A mutual relationship is present and investors can diversify their portfolios by minimizing risk.

Third, we can investigate further implications of Bitcoin if hypothesis 2 is rejected. Investment attractiveness intensifies the demand for Bitcoin with increasing trust and acceptance as well as decreasing transaction costs and uncertainty according to Ciaian et al. (2016). Furthermore, Bouri et al. (2017) argue that Bitcoin serves as a strong safe haven during market distress due to the independence from financial systems. Investors seek refuge in Bitcoin if the system is under threat – similar to gold. For this reason, a low-volatility and a high-volatility state are used to discover the classification of Bitcoin.

H4: Bitcoin does not serve as a safe haven against extreme downward movements. Investors can neglect this specific asset class in their portfolios.

H5: Bitcoin serves as a safe haven against extreme downward movements. Investors should incorporate this specific asset class in their portfolios.

1.4 Methodology

1.4.1 World Market Model

A benchmark model is used to estimate parameters for stock return behavior. Due to a wide variety of different models in the literature, we apply a modified world market model as discussed in Park (2004). He links the return of an asset to the return of a global market portfolio, a domestic market portfolio, and the currency exchange rate in order to provide significant autocorrelation effects. Here, lagged returns of the applied index are used instead of a domestic market portfolio and the exchange rate is left out of our adjusted model because the currency conversion is done separately. Due to the inclusion of a world market index, we account for interconnectedness between countries and macroeconomic conditions.

Various indices can be used for the world market index in order to capture global market movements. Researchers developed their own indices by combining stock returns of a few countries (e.g. Jorion and Schwartz (1986) or Solnik

(1974)) or used both equally- and value-weighted global market indices, which are readily available on the market. Yang et al. (1985) and Chen et al. (1986) document that the mentioned choice of weighting does not create significant differences. However, one important issue has to be taken into account when using ready-made global market indices. Researchers have to make the global market index orthogonal to the domestic market index by subtracting the influence of local returns from global returns if domestic shares are included in the global market index. Orthogonality supports the regression coefficients of the global market index to be unbiased. If orthogonality is not achieved, then coefficients may be biased downward because the aggregated world market factor includes effects that are related to domestic components of total rates of returns. Other macroeconomic factors, such as inflation, interest rate, consumption, or industrial production have a marginal or an insignificant impact on stock returns.[9] One explanation while examining daily stock returns is the fact that most economic data are available on a monthly or quarterly basis and tend to limit possible effects due to missing volatility. The adjusted world market model is specified by the following equation:

$$r_{m,t} = \alpha_m + (\beta_{0,m} + \beta_{1,m} Crash_t) r_{m,t-1} + (\beta_{2,m} + \beta_{3,m} Crash_t) r_{w,t-1} + \epsilon_{m,t} \quad (1.1)$$

with $E[\epsilon_{m,t}] = 0$ and $Var[\epsilon_{m,t}] = \sigma^2_{m,t}$. $r_{m,t}$ is the return of index m in period t and $r_{w,t-1}$ is the world market index return on day $t-1$. $Crash$ is a dummy variable and takes the value one during the crash event and zero otherwise. $\epsilon_{m,t}$ is the zero-mean error term at time t. The country-specific parameters of the regressions are α_m and $\beta_{n,m}$ with $n \in \{0, 1, 2, 3\}$ and $m \in \{$DAX 30, FTSE 100, S&P 500, SSE A, Nikkei 250, RTSI$\}$. Returns are calculated continuously compounded as the percent logarithmic by:

$$r_{l,t} = \ln(\frac{p_{l,t}}{p_{l,t-1}}) * 100, \quad (1.2)$$

where $p_{l,t}$ is the price at time t and $l \in \{m, w\}$. The estimation of the model parameters is done through the ordinary least squares (OLS) method. MacKinlay (1997) argues that OLS is a consistent estimation procedure under general assumptions and moreover efficient.

[9] See Wasserfallen (1990), Chang (1991), Roll (1992), Ferson and Harvey (1994), or Garcia and Ghysels (1998) for a broader discussion.

1.4.2 Markov-switching Model

Financial time series are subject to non-linear dynamics and sudden changes. Given the Markov-switching regression framework, parameters vary over states and are often unobserved. Quandt (1972) and Goldfeld and Quandt (1973) initially introduced the model, which was extended by Hamilton (1989) for an autoregressive process. When applying a specific series, the transitions follow a Markov process over a finite set of k unobserved states by starting from their ergodic distribution $\pi = \{\pi_1, ..., \pi_k\}$.[10] Thereby, the duration of one particular state and the transition between states are random. The estimation is similar to the Kalman filter, where the likelihood function is updated at each period after predicting all probabilities of the unobserved states. However, a non-linear algorithm is applied in contrast to linear updates on latent variables. A general specification of the Markov-switching dynamic regression (MSDR) model in state s at time t is written as:

$$y_t = \mu_{s_t} + \beta_{s_t} z_t + \varepsilon_{s_t}, \tag{1.3}$$

where y_t is the dependent variable, μ_{s_t} the state-dependent intercept, β_{s_t} the state-dependent coefficient for the exogenous variable z_t, and ε_{s_t} the independent identically distributed (iid) normal error with mean zero and state-dependent variance $\sigma^2_{s_t}$.[11] In particular, we implement the MDSR model in matrix notation as follows:

$$\underbrace{\begin{bmatrix} r_{t,equity} \\ r_{t,gold} \\ r_{t,currency} \\ r_{t,bitcoin} \\ r_{t,bond} \end{bmatrix}}_{\boldsymbol{y_t}} = \underbrace{\begin{bmatrix} \mu_{s_t,equity} \\ \mu_{s_t,gold} \\ \mu_{s_t,currency} \\ \mu_{s_t,bitcoin} \\ \mu_{s_t,bond} \end{bmatrix}}_{\boldsymbol{\mu_{s_t}}} + \underbrace{\begin{bmatrix} r_{t-1,equity} & r_{t,gold} & r_{t,currency} & r_{t,bitcoin} & r_{t,bond} & Crash_t \\ r_{t,equity} & r_{t-1,gold} & r_{t,currency} & r_{t,bitcoin} & r_{t,bond} & Crash_t \\ r_{t,equity} & r_{t,gold} & r_{t-1,currency} & r_{t,bitcoin} & r_{t,bond} & Crash_t \\ r_{t,equity} & r_{t,gold} & r_{t,currency} & r_{t-1,bitcoin} & r_{t,bond} & Crash_t \\ r_{t,equity} & r_{t,gold} & r_{t,currency} & r_{t,bitcoin} & r_{t-1,bond} & Crash_t \end{bmatrix}}_{\boldsymbol{z_t}} \underbrace{\begin{bmatrix} \beta_{s_t,equity} \\ \beta_{s_t,gold} \\ \beta_{s_t,currency} \\ \beta_{s_t,bitcoin} \\ \beta_{s_t,bond} \\ \beta_{s_t,crash} \end{bmatrix}}_{\boldsymbol{\beta_{s_t}}} + \underbrace{\begin{bmatrix} \varepsilon_{s_t,equity} \\ \varepsilon_{s_t,gold} \\ \varepsilon_{s_t,currency} \\ \varepsilon_{s_t,bitcoin} \\ \varepsilon_{s_t,bond} \end{bmatrix}}_{\boldsymbol{\varepsilon_{s_t}}}, \tag{1.4}$$

where $r_{t,(\cdot)}$ and $r_{t-1,(\cdot)}$ are the particular returns at time t and $t-1$, respectively. As before, $Crash$ is a dummy variable and takes the value one during the crash event and zero otherwise. Thereby, the matrix $\boldsymbol{z_t} \in \mathbb{R}^{5\times 6}$ includes all six variables for the five asset classes and the dummy variable with 30 variables in total. The probability that s_t is equal to $j \in \{1, ..., k\}$ for $t = 1, 2, ..., T$ only depends on the lagged realization s_{t-1} and is given by:

$$Pr(s_t = j | s_{t-1} = i) = p_{i,j}. \tag{1.5}$$

The $k \times k$ matrix $\boldsymbol{P}$ collects all possible traces from state i to state j with:

[10] The number of states is imposed apriori.

[11] The variable z_t in Eq. (1.3) can be considered as a matrix and can contain lags of y_t.

$$\boldsymbol{P} = \begin{bmatrix} p_{1,1} & \cdots & p_{k,1} \\ p_{1,2} & \cdots & p_{k,2} \\ \vdots & \ddots & \vdots \\ p_{1,k} & \cdots & p_{k,k} \end{bmatrix}, \tag{1.6}$$

where each column sums to one and all elements of $\boldsymbol{P}$ are non-negative. Based on this, the duration D_i denotes the number of periods the system is in state i for $i = 1, ..., k$ and follows a geometric distribution. The expected duration is expressed by:

$$E[D_i] = \sum_{i=1}^{\infty} iPr(s_t = i) = \sum_{i=1}^{\infty} ip_{i,i}^{i-1}(1 - p_{i,i}) \approx \frac{1}{1 - p_{i,i}}. \tag{1.7}$$

The conditional density of y_t depends only on the current state and can be written as:

$$f(y_t|s_t = i, y_{t-1}; \boldsymbol{\theta}) \tag{1.8}$$

with k conditional densities for k states. $\boldsymbol{\theta}$ is a vector of parameters and estimated by changing the conditional likelihood after applying a non-linear filter. The marginal density is:

$$f(y_t|\boldsymbol{\theta}) = \sum_{i=1}^{k} f(y_t|s_t = i, y_{t-1}; \boldsymbol{\theta})Pr(s_t = i; \boldsymbol{\theta}), \tag{1.9}$$

where the conditional densities are weighted by their respective probabilities. Following Hamilton (1996), the log-likelihood is obtained as:

$$L(\boldsymbol{\theta}) = \sum_{t=1}^{T} logf(y_t|y_{t-1}; \boldsymbol{\theta}). \tag{1.10}$$

1.5 Empirical Results

We present results for autocorrelation patterns of different country indices and consider state-dependent regressions later on.

1.5.1 Autocorrelation

The significance of country-specific parameters is derived from the adjusted world market model as described in Eq. (1.1). Table 1.3 presents serial correlation in returns and Table 1.4 serial correlation of joint parameters for all previously discussed market indices. Without exception, all estimated parameters β_2 are statistically significant positive at least at the 10% level. These results suggest that the world market index exhibits positive serially correlated returns for the

whole estimation window. The highly significant coefficients for the world crash dummy, namely -3.358*** and -4.232*** for DAX 30 and FTSE 100, respectively, imply a high volatility on the days between the Brexit referendum.[12] The joint distribution of the parameters β_2 and β_3 confirms that the total effect of serially correlated returns is significant at the 1% level for both indices. Therefore, positive foreign effects influence the German and British market during the event. As a direct consequence of the crash, domestic traders invest less in stocks because investors adapt their behavior according to new market conditions under distress. Stock prices drop and this goes hand in hand with an even larger stock selling. Volatility is rising and this phenomenon boosts market uncertainty. The joint parameter $\beta_0 + \beta_1$ is statistically significant negative by taking the values -3.295*** and -4.113*** for DAX 30 and FTSE 100, respectively.

We cannot find any autocorrelation in returns in the US given the parameter β_0 for the whole estimation window. As it can be seen from Table 1.4, the joint parameter distribution for $\beta_0 + \beta_1$ is significant negative in this market. This implies that the crash in Europe reduced investors' efforts to invest in domestic stocks. The domestic market is positively influenced by the world market index with a positive coefficient of 0.039* for $r_{w,t-1}$. Nevertheless, the joint parameter $\beta_1 + \beta_3$ is statistically significant negative with a value of -1.826*** and rather implies a downturn movement due to negative autocorrelation.

In China, domestic returns exhibit positive autocorrelation according to the statistically significant value 0.090** for the parameter β_0. Surprisingly at first glance, the Brexit referendum has no impact on domestic investors' behavior in China. The joint distribution of the parameters β_0 and β_1 is insignificant and intensifies the general assumption that emerging stock markets are still less connected to crashes.[13] Domestic returns in China are primarily driven by foreign returns. The coefficient of $r_{w,t-1}$ with 0.221*** is highly significant. The combination of the parameters β_0 and β_2 clarifies that the aggregated effect is significant positive even at the 1% level. Chinese domestic investors account for positive serially correlated returns when considering international stock price movements.

Stock return patterns behave almost similar between Japan and the UK. Nevertheless, two crucial differences arise for Japan. First, we find negative autocorrelation in domestic stock returns with a value of -0.335*** for the parameter β_0. Second, the crash event only has a significantly negative impact on returns due to foreign returns arising from the world market index. The joint distribu-

[12] Not provided calculations support that the impact reduces during periods of low volatility. Estimated parameters show insignificant first order return autocorrelation when increasing the event window.

[13] Effects on emerging markets with a still not completed liberalization process are only partially covered in literature and most studies are based on the sample of free economic markets. Emerging markets, nowadays, are systemically crucial and should be examined in more detail to diminish ongoing market uncertainty.

tion of $\beta_2 + \beta_3$ implies that the negative effect of the sharp downturn during the Brexit referendum is larger than the positive effect from the world market index. The value of -2.360*** is statistically significant at the 1% level.

In Russia, the parameter β_0 is statistically significant positive at the 10% level. Returns exhibit positive serial correlation. The joint distribution of $\beta_0 + \beta_1$ shows that positive effects from the world market index cannot offset domestic trading strategies. Returns are negatively correlated during the crash, as the joint parameter $\beta_1 + \beta_3$ shows. A significant value of -3.726*** indicates that the Brexit referendum has a major negative impact on domestic returns even so the parameter β_2 is positive with a value of 0.287***.

Table 1.3: Serial correlation in returns

Regressor	DAX 30	FTSE 100	S&P 500	SSE A	Nikkei 250	RTSI
α	0.046	0.013	0.047	0.035	0.036	-0.018
	(0.033)	(0.030)	(0.023)	(0.045)	(0.032)	(0.056)
β_0	0.023	0.102***	-0.007	0.090**	-0.335***	0.099*
	(0.033)	(0.030)	(0.023)	(0.045)	(0.032)	(0.056)
β_1	-3.318***	-4.215***	-3.209***	-1.904	-0.217	-2.955
	(0.563)	(0.545)	(1.158)	(2.741)	(0.985)	(2.981)
β_2	0.212***	0.224***	0.039*	0.221***	0.571***	0.287***
	(0.033)	(0.030)	(0.023)	(0.045)	(0.032)	(0.056)
β_3	-3.358***	-4.232***	1.383	-1.320	-2.931***	-0.771
	(0.046)	(0.814)	(1.587)	(0.868)	(0.527)	(0.056)
Adj. R^2	0.088	0.148	0.022	0.022	0.281	0.029
F-value	26.69***	49.42***	7.17***	7.32***	110.07***	8.25***

Note: The estimated parameters rely on the model $r_{m,t} = \alpha_m + (\beta_{0,m} + \beta_{1,m} Crash_t) r_{m,t-1} + (\beta_{2,m} + \beta_{3,m} Crash_t) r_{w,t-1} + \epsilon_{m,t}$. Stars indicate significance as follows: *10%, **5%, ***1%. In parentheses: standard errors.

Table 1.4: Serial correlation of joint parameters

Regressor	DAX30	FTSE100	S&P500	SSE A	Nikkei 250	RTSI
$\beta_0 + \beta_1$	−3.295***	−4.113***	−3.216***	−1.814	−0.552	−2.856
$\beta_2 + \beta_3$	−3.146***	−4.008***	1.422	−1.099	−2.360***	−0.484
$\beta_0 + \beta_2$	0.235***	0.326***	0.032	0.311***	0.236***	0.386***
$\beta_1 + \beta_3$	−6.676***	−8.447***	−1.826***	−3.224	−3.148***	−3.726**

Note: The estimated parameters rely on the model $r_{m,t} = \alpha_m + (\beta_{0,m} + \beta_{1,m} Crash_t) r_{m,t-1} + (\beta_{2,m} + \beta_{3,m} Crash_t) r_{w,t-1} + \epsilon_{m,t}$. Stars indicate significance as follows: *10%, **5%, ***1%.

The next step entails currency exchange rates as well as price fluctuations of gold, Bitcoin, and bonds in order to address the question how different asset classes can diversify or even minimize risk and if Bitcoin can be seen as a safe haven, especially during market downturns.

1.5.2 State-dependent Regressions

We use daily absolute returns in our MSDR model due to a lower sensitivity of outliers for the estimated variance and compare the outcome with results of relative returns afterwards. Table 1.5 provides state-dependent regressions for absolute returns and Table 1.6 for relative returns according to Eq. (1.4). Thereby, we assume apriori two states, a low-volatility and a high-volatility period, with unequal variances. As it can be seen from Table 1.5, σ_1 is always smaller than σ_2 for all asset classes – implying that state 1 is the low-volatility state.[14] The estimated standard deviations range from 0.108 to 1.046 and from 0.245 to 5.560 for state 1 and state 2, respectively. Not surprisingly, the largest values correspond to Bitcoin due to sharp price fluctuations and the lowest values refer to bond. $p_{1,1}$ $(1-p_{2,1})$ illustrates the estimated probability of staying in state 1 (2) in the next period given that the process is in state 1 (2) in the current period according to Eq. (1.5). For all asset classes, state 1 is persistent in contrast to state 2. The highest (lowest) value is 0.750 (0.535) for Bitcoin (currency) with respect to state 1. The Akaike information criterion (AIC) implies that our statistical model discloses a transitive relation. The relative quality of estimated parameter coefficients is highest for bond – followed by currency, equity, gold, and Bitcoin. All dynamic regressions have two things in common. First, the state-dependent mean is always significantly positive at the 1% level for both states and higher for the high-volatility state. Second, equity has a significant effect on all asset classes at least at the 5% level with respect to state 2.

Now we turn our focus on the dependent coefficients given a particular asset class. Equity is only affected by gold in state 1 and by lagged returns of equity, gold, currency, bond, and the crash in state 2. Thereby, the highest value of 0.905^{***} corresponds to the crash and illustrates that market distress plays a significant role for the high-volatility state. Simultaneously, autocorrelation influences returns during this period. Gold is independent of all other asset classes in state 1. In contrast, the parameter coefficient is statistically significant for equity, currency, and Bitcoin for the high-volatility state. Surprisingly, the Brexit referendum has no impact on gold returns at all. As a result, gold should be considered neither as a safe haven nor as a risky asset in our sample when considering absolute returns. For the low-volatility state, only equity affects currency. This outcome suggests that the currency rate is somehow given and settled down when an economy is rather in an upward movement. When considering state 2, a difference appears. Equity, gold, bond, and lagged currency rates

[14] State-specific predictions of absolute and relative returns are higher in state 2 than in state 1 due to more risk as illustrated in Figure A.2 and Figure A.3 on page 85f. in the Appendix.

affect today's rates. The highest value is 0.222^{***} for $\beta_{2,bond}$. Bitcoin is embossed by its own lagged returns in the low-volatility state. In addition, the crash has an enormous effect with a value of 2.977^{***} for $\beta_{1,crash}$. Interesting is that this impact is only significant in state 1 despite a smaller standard deviation. For state 2, equity, gold, and lagged returns of Bitcoin are the main drivers. We refer that autocorrelation exists in this state. The last asset class, namely bond, depends on equity in the low-volatility state and also on gold and currency in the high-volatility state.

A different picture arises when considering relative returns from Table 1.6. All estimated standard deviations are higher for relative than absolute returns due to the existence of negative values. With respect to the estimated probability, state 1 is highly persistent for gold, currency, and Bitcoin and state 2 only for currency and Bitcoin. The AIC is smaller for absolute returns compared to relative returns.

The interpretation of dependencies is simplified by adopting relative returns because the parameter coefficient sign contains the direction of possible effects. Notably is the fact that equity has a negative effect on itself and bond with values ranging from -0.077^{**} to -0.237^{***}. This risky asset class illustrates that autocorrelation patterns exist and that other classes help to diversify a specific portfolio. A strong economy (state 1) gives rise to inflation due to rising bond yields and gold should be used as a hedge against inflation. Nevertheless, we find a positive relationship between bond and gold because of changes in the confidence in the fiat dollar-dominated system. Investors diversify their investments among gold and bonds. As predicted, the Brexit referendum has a statistically significant negative effect on equity and a positive one on gold as well as currency in state 2 even at the 1% level. Market distress verifies that gold is still considered as a safe haven by investors. Gold and currency are positively affected by Bitcoin with values of 0.124^{***} and 0.015^{**}, respectively, for $\beta_{2,bitcoin}$. Simultaneously, gold has a positive effect on Bitcoin in state 2 at the 5% level. As assumed, we find a significant negative relationship between gold and currency. The mutual impact is higher in state 2 than in state 1. Furthermore, currency has a more intense effect on gold than gold on currency with values of -0.566^{***} as well as -1.695^{***} for $\beta_{1,currency}$ and $\beta_{2,currency}$, respectively. More surprisingly is the fact that the market crash has no impact on Bitcoin even for the high-volatility state. Hence, Bitcoin is indeed a novel asset class positioned in between a safe haven and a risky investment. Investors should consider Bitcoin during sudden downward movements.

Table 1.5: Markov-switching dynamic regressions for absolute returns

Coefficient	Equity	Gold	Currency	Bitcoin	Bond
μ_1	0.198***	0.357***	0.171***	0.977***	0.135***
	(0.022)	(0.032)	(0.016)	(0.100)	(0.013)
$\beta_{1,equity}$	0.026	0.031	-0.023*	-0.090	0.040**
	(0.018)	(0.024)	(0.013)	(0.080)	(0.018)
$\beta_{1,gold}$	0.029**	0.006	0.008	0.093	-0.005
	(0.014)	(0.020)	(0.009)	(0.064)	(0.008)
$\beta_{1,currency}$	-0.020	0.035	-0.002	0.076	0.022
	(0.024)	(0.038)	(0.017)	(0.113)	(0.018)
$\beta_{1,bitcoin}$	0.001	0.004	0.001	0.114***	0.002
	(0.002)	(0.003)	(0.001)	(0.017)	(0.001)
$\beta_{1,bond}$	0.061	0.086	0.032	0.201	0.023
	(0.041)	(0.054)	(0.028)	(0.177)	(0.028)
$\beta_{1,crash}$	-0.060	-0.179	-0.084	2.977***	-0.047
	(0.174)	(0.222)	(0.126)	(0.890)	(0.159)
μ_2	0.439***	0.502***	0.357***	4.858***	0.299***
	(0.062)	(0.113)	(0.047)	(0.697)	(0.033)
$\beta_{2,equity}$	0.303***	0.334***	0.098***	1.357**	0.151***
	(0.048)	(0.113)	(0.032)	(0.663)	(0.032)
$\beta_{2,gold}$	0.058*	0.074	0.153***	1.653***	0.046**
	(0.033)	(0.067)	(0.023)	(0.422)	(0.020)
$\beta_{2,currency}$	0.176**	0.751***	0.122**	-0.537	0.136***
	(0.074)	(0.128)	(0.052)	(1.001)	(0.036)
$\beta_{2,bitcoin}$	0.004	0.064***	-0.005	0.336***	0.000
	(0.006)	(0.013)	(0.004)	(0.052)	(0.003)
$\beta_{2,bond}$	0.558***	0.222	0.222***	-1.907	0.011
	(0.095)	(0.211)	(0.069)	(1.336)	(0.057)
$\beta_{2,crash}$	0.905**	-0.247	0.168	0.381	-0.016
	(0.383)	(0.936)	(0.279)	(5.793)	(0.193)
σ_1	0.171	0.303	0.118	1.046	0.108
σ_2	0.519	0.826	0.370	5.560	0.245
$p_{1,1}$	0.596	0.670	0.535	0.750	0.593
$p_{2,1}$	0.518	0.785	0.502	0.541	0.496
AIC	1.037	1.628	0.393	4.769	-0.249
Log-likelihood	-561.918	-891.964	-201.427	-2647.690	157.306

Note: This table presents parameter coefficients for the MSDR model for two states by using absolute returns. The model is estimated according to Eq. (1.4). Stars indicate significance as follows: *10%, **5%, ***1%. In parentheses: standard errors.

Table 1.6: Markov-switching dynamic regressions for relative returns

Coefficient	Equity	Gold	Currency	Bitcoin	Bond
μ_1	0.098***	-0.007	-0.003	0.237**	0.079***
	(0.019)	(0.025)	(0.014)	(0.096)	(0.017)
$\beta_{1,equity}$	-0.077**	-0.044	-0.035	-0.062	-0.237***
	(0.038)	(0.036)	(0.023)	(0.127)	(0.024)
$\beta_{1,gold}$	-0.031	-0.072***	-0.213***	-0.103	0.055***
	(0.025)	(0.024)	(0.016)	(0.107)	(0.017)
$\beta_{1,currency}$	-0.068	-0.566***	0.004	-0.006	-0.080**
	(0.043)	(0.051)	(0.032)	(0.180)	(0.035)
$\beta_{1,bitcoin}$	-0.004	-0.004	-0.004	-0.010	-0.003
	(0.003)	(0.004)	(0.003)	(0.039)	(0.002)
$\beta_{1,bond}$	-0.364***	0.473***	-0.169***	0.182	-0.142***
	(0.065)	(0.074)	(0.041)	(0.241)	(0.054)
$\beta_{1,crash}$	0.376	-0.414	-0.430*	-10.327	-0.099
	(0.327)	(0.506)	(0.247)	(9.560)	(0.377)
μ_2	-0.023	-0.058	0.019	0.526	-0.047*
	(0.060)	(0.224)	(0.042)	(0.536)	(0.024)
$\beta_{2,equity}$	0.024	0.369	0.117**	-0.350	-0.093***
	(0.051)	(0.257)	(0.047)	(0.735)	(0.029)
$\beta_{2,gold}$	0.080	0.633**	-0.215***	1.111**	0.129***
	(0.055)	(0.284)	(0.037)	(0.520)	(0.025)
$\beta_{2,currency}$	0.247**	-1.695***	-0.029	0.777	-0.005
	(0.102)	(0.414)	(0.053)	(1.026)	(0.041)
$\beta_{2,bitcoin}$	-0.002	0.124***	0.015**	0.014	0.004
	(0.011)	(0.048)	(0.007)	(0.056)	(0.004)
$\beta_{2,bond}$	-0.906***	0.649	0.103	-0.727	-0.056
	(0.147)	(0.548)	(0.107)	(1.531)	(0.047)
$\beta_{2,crash}$	-3.150***	7.296***	3.080***	-1.960	0.233
	(1.131)	(2.120)	(0.756)	(5.790)	(0.336)
σ_1	0.460	0.713	0.347	2.310	0.232
σ_2	1.062	1.599	0.722	9.650	0.454
$p_{1,1}$	0.038	0.914	0.971	0.941	0.125
$p_{2,1}$	0.920	0.924	0.065	0.132	0.864
AIC	2.014	2.492	1.325	5.702	0.772
Log-likelihood	-1107.726	-1374.968	-722.603	-3169.553	-413.448

Note: This table presents parameter coefficients for the MSDR model for two states by using relative returns. The model is estimated according to Eq. (1.4). Stars indicate significance as follows: *10%, **5%, ***1%. In parentheses: standard errors.

Table 1.7 depicts the average days a series remains in a given state using Eq. (1.7). Panel (A) discloses that state 1 always persists longer than state 2. Values range from 2.151 (1.274) to 3.992 (2.015) for currency (gold) and Bitcoin (bond), respectively, given state 1 (2). We conclude that Bitcoin persists for about one day longer in the low-volatility state than gold and is with 1.850 days in between gold and bond during the high-volatility state on average. Possible explanations for this are the independence from financial systems as well as overreaction patterns on the part of investors. Obviously, Bitcoin still has a many times smaller market capitalization than all other assets with fewer market participants investing in the finite resource. Therefore, momentum and speculations play a crucial role and drive the price stronger, especially during the low-volatility state – the expected duration extends and the particular state persists longer. The average length increases for relative returns as provided in panel (B). The highest persistence has currency for both states with 34.996 and 15.439 days on average. This phenomenon results from a decelerated adjustment during expansion as well as recession states. Moreover, macroeconomic factors have a supporting role for changes in currency rates. Again, the expected duration of Bitcoin exceeds gold by about five days in state 1. In state 2, Bitcoin persists 7.354 days in state 2 compared to 1.083 and 12.529 days for gold and equity, respectively.

Table 1.7: Expected duration

	$E[D_i]$			
Asset	State 1	State 2	State 1	State 2
	(A) Absolute returns		(B) Relative returns	
Equity	2.474	1.931	26.554	12.529
	(0.302)	(0.139)	(7.506)	(3.324)
Gold	3.029	1.274	11.664	1.083
	(0.366)	(0.082)	(3.871)	(0.086)
Currency	2.151	1.992	34.996	15.439
	(0.264)	(0.144)	(18.608)	(9.748)
Bitcoin	3.992	1.850	16.856	7.571
	(0.360)	(0.154)	(3.759)	(1.769)
Bond	2.459	2.015	8.017	7.354
	(0.379)	(0.306)	(2.939)	(2.494)

Note: This table indicates the expected duration in days for absolute as well as relative returns in panel (A) and (B), respectively, derived by Eq. (1.7). In parentheses: standard errors.

1.6 Robustness and Outlook

We examine our model fit by comparing actual returns with fitted values and corresponding residuals for all asset classes with respect to the return type.[15] As mentioned before, daily absolute returns have a lower sensitivity of outliers for the estimated variance in our MSDR model – residuals account for less of the variation in the dependent returns. More problematic is the case for Bitcoin with enormously high values, especially when applying relative returns. Therefore, we apply the Shapiro-Wilk (SW) test and the J-B test for normality as provided in Table 1.8. Both tests show that residuals of fitted returns are nonnormally distributed. Nevertheless, we confirm that values are located close to zero.[16] Here, residuals of relative returns have almost the shape of a normal density. Residuals of Bitcoin are again out of the ordinary. We conclude two important findings. First, absolute returns tend to diminish the sensitivity of outliers in the specified model. Second, residuals of fitted relative returns are closer to a normal density than residuals of fitted absolute returns. Hence, both return types should be considered when applying the MSDR model.

Table 1.8: Tests of normality for residuals

	Equity	Gold	Currency	Bitcoin	Bond
(A) Fitted absolute returns					
SW	0.757***	0.750***	0.745***	0.541***	0.833***
J-B	10035.639***	74414.911***	8846.497***	177416.990***	6114.384***
(B) Fitted relative returns					
SW	0.970***	0.978***	0.975***	0.830***	0.984***
J-B	223.816***	270.357***	209.002***	6645.062***	148.388***

Note: This table contains tests of normality for residuals of fitted absolute and relative returns in panel (A) and (B), respectively, regarding different asset classes. Stars indicate significance as follows: *10%, **5%, ***1%.

The applied dummy analysis does not specify an explicit measure of volatility. Certainly, reported existing autocorrelations cannot be fully convincing given the fact of a predefined estimation window and an arbitrarily chosen crash dummy. An explicit measure of volatility could, in turn, affirm a more precise analysis. As we have seen in Table 1.1, the normality of returns' distribution is rejected for the time series of all indices. Therefore, the model should incorporate heteroscedasticity or follow a fat-tailed distribution.

[15] Figure A.4 illustrates the model fit for absolute returns and Figure A.5 for relative returns on page 87f. in the Appendix.

[16] The kernel density shows that residuals seem to be close to zero as Figure A.6 and Figure A.7 show on page 89f. in the Appendix.

Investors' strategy is based on certain preferences. Without loss of generality, preferences can differ across traders and the total feasible demand corresponds coevally to the total supply on the market. Therefore, it is necessary to take various trading strategies besides different asset classes into consideration. Furthermore, the effect of foreign market indices on the domestic index is important to consider. Most researchers separate their samples without any interconnection for different markets. A cross-country comparison is based on national and international stock price movements with the aim to disclose both spillover effects and investors' behavior.

In addition, hedging capabilities of Bitcoin against portfolios and asset classes should be investigated for different market conditions. As we have seen, a permanent change of volatility in returns implies a not constant diversification ability over time. Chan and Maheu (2002) study time-varying jump dynamics in returns by using an autoregressive moving average form. Thereby, the main advantage lies in the predictability of jumps before market downturns and improved forecasts of volatility.

We leave the suggested extensions for future research because a detailed discussion would exceed the scope of this chapter. It should be noted that, irrespective the approach, Bitcoin should be included in order to obtain extensive evidence.

1.7 Conclusion

Stock market anomalies have long been recognized to be inconsistent with standard asset pricing models due to market inefficiencies. Certainly, interest in the predictability of stock returns is substantial and has been growing over recent years. Trading decisions are based on market conditions with changing volatility levels. Periods with low volatility induce positively autocorrelated returns and autocorrelations turn negative during periods of high volatility. Our research project aims to investigate mutual effects by taking autocorrelation under distress and asset classes into consideration.

Relying on a world market model, evidence for autocorrelation of index returns is provided by capturing global market movements without to specify an explicit measure of volatility. Thereby, the Brexit referendum serves as a suitable event with enormously increased volatility in returns. The inclusion of the world market index accounts for interconnectedness between countries and captures global market movements in contrast to previous studies. In detail, serial correlation in returns exists for all previously discussed market indices from the world market index. As a direct consequence of the crash, domestic traders invest less in stocks

because investors adapt their behavior according to new market conditions under distress. Volatility is rising and this phenomenon boosts market uncertainty. Surprisingly at first glance, the Brexit referendum has no impact on domestic investors' behavior in China. This phenomenon intensifies the general assumption that emerging stock markets are still less connected to crashes.

Indeed, asset classes have a mutual relationship with each other. Thereby, the dependency is affected by both the return type and the particular state. Keeping this in mind, investors can diversify risk by investing in different asset classes or select a suitable class given a particular state. To be more precise, we argue that Bitcoin can be seen as in between a safe haven and a risky investment. The expected duration illustrates that Bitcoin persists longer in a low-volatility state in contrast to all other assets given absolute returns. In addition, the duration of a high-volatility state is shorter than for equity or currency. For relative returns, Bitcoin is more employable than gold in state 1 and than equity as well as currency in state 2. Therefore, investors should incorporate Bitcoin in their portfolios not only during an expansion in order to minimize risk and increase expected returns despite intensive fluctuations.

We examine our model fit by comparing actual returns with the fitted values and corresponding residuals for all asset classes with respect to the return type. As indicated, daily absolute returns have a lower sensitivity of outliers for the estimated variance in our MSDR model. In contrast, residuals of fitted relative returns have almost the shape of a normal density. Therefore, both return types should be considered when applying the MSDR model. For further research, hedging capabilities of Bitcoin against portfolios and asset classes should be investigated for different market conditions.

Chapter 2

Feedback trading: Strategies during day and night with global interconnectedness[1]

2.1 Introduction

Feedback trading strategies have gained much popularity among researchers in the last decades and are used to illustrate how new information based on returns is reflected in the markets. This behavioral approach adopts the view that stock prices are influenced by irrational trading or noise (e.g. Beja and Goldman (1980) or Thaler (1999)) and is in contrast to Fama (1970) with his notion of an efficient capital market by stating that security prices fully reveal all available information.

The literature on feedback trading is extensive and its implied effects have still been the subject of research in recent years. Cutler et al. (1990) use a model with feedback traders to account for possible links between volatility and serial correlation. They confirm that fluctuations in speculative prices cannot be predicted under the efficient market hypothesis as demonstrated at least with stock market crashes. Price determination relies on the existence of heterogeneous investors – e.g. informed traders, liquidity traders, fundamental traders, and naive (noise) traders. Thereby, noise investors base their portfolio decisions on serial correlation properties of stock returns by discovering trends in past stock prices. The so-called feedback traders pursue their own strategy, given explicit market conditions. Positive feedback traders actively buy (sell) stocks in a rising (falling) market while negative feedback traders adhere to a "buy low and sell high" investment strategy.

[1]This chapter is based on Kusen and Rudolf (2019a). Feedback trading: Strategies during day and night with global interconnectedness. *Research in International Business and Finance 48*, 438-463. The paper was presented at the 2017 Paris Financial Management Conference.

Stock return autocorrelation increases in the presence of feedback traders. The more feedback traders are active the higher is the autocorrelation due to a greater effect on prices. Hence, the existence of feedback traders influences the partial predictability of aggregate stock returns. Literature and experimental findings support the existence of positive feedback traders while empirical evidence is divided with respect to different stock markets and changing return behavior.[2]

We offer an informative framework for exploring feedback trading from two new angles. First, we decompose the overall return premium into day and night returns. Prices are more efficient and more information is revealed during the day. Market closures, on the other hand, affect the mean and standard deviation of returns due to risk compensations when trading overnight. Second, we assume interconnectedness between multiple countries and introduce a global feedback trading model. Dynamic effects with spillovers shed light on investors' strategy and provide justifications for price fluctuations.

This chapter has the following structure: The foundations of feedback trading and previous empirical work is discussed in section 2.2. Section 2.3 states the methodology and extends the feedback trading model. In section 2.4, analyzed data concerning different market indices and descriptive statistics are provided in addition to developed hypotheses. The main part of this chapter consists of the analysis by separating day from night returns in the presence of global interconnectedness in section 2.5. Furthermore, a robustness check and ideas for future research are presented in this section. Section 2.6 concludes.

2.2 Literature Review

The behavior of different types of investors is a popular field of research in financial studies, especially the study of trading strategies. Several hypotheses and models try to explain the theoretical foundation of feedback strategies, where the distribution of returns depends on current and past performance (see Campbell and Kyle (1993), Conrad et al. (1991), Farmer and Joshi (2002) Jegadeesh and Titman (1993), Kwon and Kish (2002), De Long et al. (1989), and Shefrin and Statman (1985) among others). Unanticipated changes provide new information for market participants and corresponding stock price changes help to inform traders' strategies during both up and down price movements. Noise in the market induces more liquidity and simultaneously more risk, expressed through

[2]Experimental and survey evidence can be found in Shiller (1988), Kroll et al. (1988), De Bondt (1993), or Bange (2000). Shiller et al. (1984), Cutler et al. (1990), De Long et al. (1990), or Campbell and Kyle (1993) among others provide theoretical models on feedback trading.

higher volatility. Shiller et al. (1984) and Shiller (1990) state that fundamentals, i.e. dividends, earnings, and debt, cannot explain asset price volatility. Returns are rather predictable because stock prices do not follow a random walk in irrational markets due to investors' overreactions. This view is confirmed by De Long et al. (1990) who show that prices do not correspond to intrinsic values. Noise trading leads to large price deviations from fundamental values. Thereby, informed traders cannot fully offset the impact of noise traders in a high-risk environment because risk also rises, especially during short-time horizons.

Different forms of noise trading exist. A destabilizing effect occurs when noise trading strategies correlate in the market. This is the case when market participants conclude relevant information from analyzing same indicators, thus ending up with highly correlated trades and influencing price fluctuations – known as spurious herding according to Wermers (1999).[3] One of the most common destabilizing forms of noise trading is feedback trading. Positive feedback traders actively buy (sell) stocks in a rising (falling) market while negative feedback traders adhere to a "buy low and sell high" investment strategy. The feedback trading model, originally introduced by Sentana and Wadhwani (1992), allows for changing trading rules in response to market conditions and investors' past experiences.[4] They find a positive feedback trading behavior. Stock prices overreact to news and exhibit excessive volatility. In line with Koutmos (1997), periods with low volatility induce positively autocorrelated returns while autocorrelations turn negative during periods of high volatility. Thereby, the magnitude of autocorrelation is driven by the level of volatility. The inverse relationship between autocorrelation and volatility is mainly due to the interaction between rational expected utility maximizers and trend chasing traders. As a consequence, investors perform a forced liquidation (depyramiding) by withdrawing unprofitable positions with the aim to minimize losses. More feedback trading is expected because most investors insure high-performing assets in their portfolios. The existence of autocorrelation accounts beside non-synchronous trading in most studies for the presence of feedback trading. However, the reason for return autocorrelation is not as elementary as generally assumed according to Conrad et al. (1991) and LeBaron (1992) inversely relates serial return correlations to conditional volatilities by reporting significant nonlinear first moment dependencies.

Overall, strong evidence is found in previous research that feedback trading ex-

[3]Correlated noise can also be the result of the systematic influence of biases as stated by Barber et al. (2009).

[4]The model is based on Cutler et al. (1990) who realize that dynamic price movements arise from heterogeneous investors.

ists in bond markets (Dean and Faff (2008)), emerging and mature stock markets (Bohl and Siklos (2008)), options markets (Tavakkol (2000)), exchange-traded fund markets (Charteris et al. (2014)), index futures markets (Antoniou et al. (2005)), mutual funds markets (Hsieh et al. (2011)), commodity markets (Chau et al. (2015)), and real estate markets (Koulakiotis and Kiohos (2016)). Several determinants of feedback trading can be considered feasible. First, information risk motivates feedback trading in smaller stocks due to less information being available about them according to Wermers (1999).[5] Brennan and Cao (1997) show that foreign investors often resort to feedback trading when trading in overseas markets to mitigate against the perceived informational superiority of domestic investors in these markets. Second, cognitive and behavioral biases support positive feedback trading. Investors ignore conflicting opinions while recalling information that supports their preexisting beliefs (confirmation bias) and mistakenly believe that the future investment performance depends only on the past performance (trend-chasing bias).[6] Third, reputational and career related concerns influence managers' propensity to engage in feedback trading behavior. Boyson (2010) shows that managers have a higher probability of failure when deviating from the herd. They end up selling losers and buying winners in a "window dressing" fashion and thereby sacrifice the potential to perform better as stated by Lakonishok et al. (1992).[7] Fourth, style investing can also promote feedback trading. Bennett et al. (2003) argue that institutional investors change their preferences over time and adjust their applied strategies. The intensity of feedback trading is driven by institutional investors (Lakonishok et al. (1992) and Spiegel and Subrahmanyam (1995)), arbitrage opportunities (Chau et al. (2015)), margin requirements (Watanabe (2002)), investor's sentiment (Chau et al. (2011) and Kurov (2008)), cost of credit (Antoniou and Koutmos (2014)), stop-loss orders (Koutmos (2014)), and short sale constraints (Bohl et al. (2013)).

Nevertheless, the feedback trading behavior is not considered separately for day and night returns. Multiple studies confirm that market closures affect investors' trading decisions and return patterns (e.g. Oldfield Jr. and Rogalski (1979), Wood et al. (1985), Stoll and Whaley (1990), Madhavan et al. (1997), and Hong and Wang (2000)). Consequently, overnight returns exceed intraday returns despite a lower volatility during the nighttime period according to Kelly and Clark (2011) or Berkman et al. (2012). Longstaff (1995) justifies that investors receive

[5]Shi et al. (2012) use firm size as a proxy for firm information uncertainty and verify a higher degree of positive feedback trading for firms with a greater degree of uncertainty. This implies that firm size effects correlate with high credit risk stocks.

[6]The confirmation bias causes investors to follow a trend even when the price already exceeds the fundamental value.

[7]Choi and Sias (2009) confirm that institutions follow similar classified institutions which is in line with reputational herding.

a higher reward overnight due to less liquidity. This finding is robust across different market structures and asset classes as stated by Cooper et al. (2008). A positive relationship between volatility and trading volume is shown by Foster and Viswanathan (1993) and Lee and Rui (2002) in general. French and Roll (1986) find that private information causes a higher volatility during exchange trading hours because more informed investors trade. The rate of information flow is about seven times higher for the daytime period and corresponds to 85% of the weighted price contribution (e.g. George and Hwang (2001), Barclay and Hendershott (2003), and Barclay and Hendershott (2004)). Furthermore, the information at opening hours is not equivalent to the prior day closure because firms strategically time the release of information.[8]

The composition of the investment population differs across the day. Institutional liquidity providers are less active during the night and liquidity traders as well as professionals mostly dominate the after-hours session (e.g. Barclay and Hendershott (2004), Giannetti et al. (2006), and Lou et al. (2019)). Chen et al. (2012) show that trades in the after-hours have a more informed nature, but are rather based on short-lived private information or scheduled news. Thereby, the population's behavior has an effect on prices. For example, semiprofessional traders reestablish their positions in the morning after selling them at the end of the previous day (Kelly and Clark (2011)) and retail investors push up opening prices in high-attention stocks (Berkman et al. (2012)).

Motivated by the fact that return dynamics are more versatile than originally assumed, we seek to examine the existence of feedback trading during daytime and overnight periods in a multi market setting. On the one hand, Lachance (2015) argues that feedback trading is profitable at night even when transaction costs are taken into account. However, taxes and regulatory fees are not included and need to be considered in order to evaluate the profitability of overnight strategies. On the other hand, individual liquidity traders congregate during the trading day and have less incentives to trade after hours due to higher adverse selection. This circumstance deters feedback trading at night. Based on the foregoing discussion, we expect less feedback trading during the night because of higher risk, lower volatility, and less trading activity. This chapter tackles the important issue of exploring the existence of feedback trading: Investors could use the results for conditional strategies and the timing of trades.

[8]Firms' disclosure of news is strategically planned. According to Patell and Wolfson (1982), firms disclose negative news rather overnight or on Fridays and benefit from a lack of available attention due to less trading activity. This opportunistic approach is used to reduce the associated market penalty. In contrast, Doyle and Magilke (2009) state that late announcements depend on institutional factors rather than being a result of hiding purposes.

2.3 Methodology

An appropriate measure for volatility effects on the serial correlation of returns is essential in order to answer the proposed research questions. Improvements have been made throughout the years and provide justified approaches to explain potential departures from the efficient market hypothesis.

2.3.1 Feedback Trading Model

In simple terms, several types of investors carry different implications for the autocorrelation pattern of stock returns. The feedback trading model, as historically proposed by Sentana and Wadhwani (1992), is based on the existence of two types of investors. Thereby, this approach captures investors' behavior due to stock price changes over a certain period of time. In order to be accurate while using this technique, we consider three heterogeneous groups and develop a dynamic feedback trading model using the following procedure. Thereby, we estimate the dynamic conditional correlation (DCC) between countries at each point in time.

Rational utility maximizers (smart money or rational speculators) with an arbitrary von Neumann-Morgenstern utility function hold a fraction of shares of the market portfolio given by:

$$Y_{1,t} = \frac{E_{t-1}(R_t) - r_f}{\theta \sigma_t^2} \qquad \theta > 0, \tag{2.1}$$

where $Y_{1,t}$ is the fraction of shares held by rational speculators at time t, R_t the ex-post stock return at t, and E_{t-1} the expectation as of time $t-1$. r_f is the risk-free rate of return, σ_t^2 the conditional variance (risk) at t, and θ the coefficient of risk aversion. The required risk premium is defined by the product $\theta\sigma_t^2$ and takes into account that individuals are risk-averse as implied under the expected utility theory.[9]

The second group includes feedback traders. Positive feedback traders actively buy (sell) stocks in a rising (falling) market while negative feedback traders adhere to a "buy low and sell high" investment strategy. The feedback function assumes that demand is simply proportional to past return changes of the asset and affected by sentiment in an additive way:

$$Y_{2,t} = \gamma(R_{t-1} - r_f) + \beta B_t \qquad \gamma > 0, \tag{2.2}$$

where $Y_{2,t}$ is the fraction of shares demanded by feedback traders at time t. γ is the basic feedback parameter and discriminates between two types of feedback

[9] If all investors have the same demand function given by Eq. (2.1), the market equilibrium yields the Intertemporal Capital Asset Pricing Model as stated by Merton (1973).

traders: $\gamma < 0$ implies a negative feedback behavior while $\gamma > 0$ refers to the case of positive feedback trading. B_t is a dummy variable taking the value one or zero for optimistic and pessimistic investors' sentiment, respectively, at t. The coefficient β measures the sensitivity of feedback traders to the sentiment state.

The third group consists of investors who base their decisions on fundamental values regarding future returns. They increase their demand for shares when fundamental values are absolutely higher in contrast to prices. The underlying demand function for such investors can be expressed as:

$$Y_{3,t} = \delta(f_{t-1} - P_{t-1}) \qquad \delta > 0, \tag{2.3}$$

where $Y_{3,t}$ is the fraction of shares held by fundamental traders at time t. f_{t-1} and P_{t-1} are the fundamental value and the price, respectively, at time $t-1$. The parameter δ measures the degree of investment.

Given the assumption of market clearing and that all shares must be held at any period, it follows from Eq. (2.1) - (2.3):

$$Y_{1,t} + Y_{2,t} + Y_{3,t} = 1 \tag{2.4}$$

or alternatively

$$\frac{E_{t-1}(R_t) - r_f}{\theta\sigma_t^2} + \gamma(R_{t-1} - r_f) + \beta B_t + \delta(f_{t-1} - P_{t-1}) = 1. \tag{2.5}$$

A regression equation with a stochastic error term can be achieved by setting $R_t - r_f = r_t$ and $E_{t-1}(R_t) - r_f = r_t + \varepsilon_t$:

$$r_t = \theta\sigma_t^2 - \gamma\theta\sigma_t^2 r_{t-1} - \beta\theta\sigma_t^2 B_t - \delta\theta\sigma_t^2(f_{t-1} - P_{t-1}) + \varepsilon_t. \tag{2.6}$$

The term $-\gamma\theta\sigma_t^2 r_{t-1}$ shows that positive (negative) feedback trading induces negative (positive) first-order autocorrelation in returns and the intensity is driven by σ_t^2. The regression equation can be simplified into the following form:

$$r_t = b_0 + b_1\sigma_t^2 + b_2\sigma_t^2 r_{t-1} + b_3\sigma_t^2 B_t + b_4\sigma_t^2 f_{t-1}^* + \varepsilon_t \tag{2.7}$$

with $b_0 = 0$, $b_1 = \theta$, $b_2 = -\gamma\theta$, $b_3 = -\beta\theta$, $b_4 = -\delta\theta$, and $f_{t-1}^* = f_{t-1} - P_{t-1}$. The coefficient b_1 illustrates the presence of rational speculators and should be positive according to risk aversion under the expected utility theory. b_2 should have a negative (positive) sign when the majority of traders in the market consists of positive (negative) feedback traders. Thereby, high volatility impacts the magnitude of negative autocorrelation. Cyclical market conditions influence investors' sentiment. The coefficient b_3 can either be positive or negative according to significant volatility movements. Simultaneously, a high degree of volatility

impacts the presence of fundamental traders because prices move away from fundamental values. The sign of b_4 can be expected to turn in both directions. It is worth mentioning that volatility movements are intensified through the interaction of the three investor types with changing trading behavior. Unlike a statical consideration, an increased volatility from feedback behavior shifts the required rate of return for rational speculators and impacts fundamental values.

Normality of returns' distribution is oftentimes rejected for stock indices.[10] An appropriate method to overcome this issue is the incorporation of the volatility term σ^2 into the mean equation. The conditional variance of the error term is an essential component in Eq. (2.7). This chapter uses the exponential generalized autoregressive conditional heteroscedasticity (EGARCH) model from Nelson (1991) in order to model the conditional variance for a single country by:

$$ln(\sigma_t^2) = \alpha_0 + \sum_{l=1}^{p} \gamma_l ln\sigma_{t-l}^2 + \sum_{l=1}^{q} \alpha_l[|z_{t-l}| - E|z_{t-l}|] + \sum_{l=1}^{q} \xi_l z_{t-l} \qquad (2.8)$$

with $z_{t-l} = \epsilon_{t-l}/\sigma_{t-l}$ as the standardized residual at time $t-l$ and l as the number of lags. $ln(\cdot)$ is the natural logarithm. The main advantage is that asymmetric effects are included between positive and negative returns.[11] Campbell and Hentschel (1992) argue that positive shocks in returns lead to lower volatility than negative shocks given the same magnitude. Furthermore, the EGARCH specification does not require any parameter restrictions. Thereby, this approach is robust against volatility changes and long-run memory effects arising from time-varying clustering in financial time series.

Standardized residuals are rather leptokurtic than normally distributed for financial time series. Distributions with flatter tails induce more reliable tests in comparison to standard t-tests. Therefore, the computation is based on the generalized error distribution (GED) with the density function:

$$f(\mu_t, \sigma_t^2, \nu) = \frac{\nu}{2}[\Gamma(3/\nu)]^{\frac{1}{2}}[\Gamma(1/\nu)]^{\text{-}\frac{3}{2}}(1/\sigma_t)exp\{\text{-}[\Gamma(3/\nu)/\Gamma(1/\nu)]^{\frac{\nu}{2}}|z_t|^{\nu}\}, \qquad (2.9)$$

where μ_t is the conditional mean, σ_t^2 the conditional variance, and $\Gamma(\cdot)$ the gamma function. ν is an endogenously estimated scale parameter and depicts the degrees of freedom (df) under GED. The GED yields the normal distribution, the Laplace distribution[12], and converges pointwise to a uniform density for $\nu = 2$, $\nu = 1$ and $\nu \to \infty$, respectively.

The maximization of the log-likelihood function with given values of ε_t and

[10] See Officer (1972), Hagerman (1978), Peiró (1994), and Longin (2005) for more discussion.

[11] Unanticipated price decreases (negative innovations) are less destabilizing than positive innovations if $\alpha_l < \xi_l$. Moreover, different signs suggest the presence of asymmetric volatility.

[12] The Laplace distribution is often called the double exponential distribution.

σ_t^2 over the sample period induces the fixed parameters in Eq. (2.1) - (2.9) and can be expressed as:

$$\mathcal{L}(\theta) = \sum_{t=1}^{T} logf(\mu_{t-l}, \sigma_{t-l}^2, \nu). \tag{2.10}$$

The estimation can be interpreted as a quasi-maximum likelihood method as proposed by White (1982) because error terms are nonnormally distributed.[13] The numerical maximization technique follows either the Broyden-Fletcher-Goldfarb-Shanno or the Berndt-Hall-Hall-Hausman algorithm to avoid nonconcave regions when maximizing the likelihood function. Berndt et al. (1974) justify their approach by a nonlinear log-likelihood function in the parameters.

2.3.2 Global Feedback Trading Model

In order to estimate the dynamic effects between multiple countries, a multivariate generalized autoregressive conditional heteroscedasticity (MGARCH) model is used. Following Bollerslev et al. (1988), the MGARCH model is a multivariate extension of the generalized autoregressive conditional heteroscedasticity (GARCH) model with m regression equations. Conditional variances and covariances of the error terms are dynamic and follow an autoregressive moving average structure. The general MGARCH model is given by:

$$\begin{aligned} \boldsymbol{r}_t &= \boldsymbol{A}\boldsymbol{x}_t + \boldsymbol{\epsilon}_t \\ \boldsymbol{\epsilon}_t &= \boldsymbol{H}_t^{1/2}\boldsymbol{\nu}_t, \end{aligned} \tag{2.11}$$

where $\boldsymbol{r}_t$ is an $m \times 1$ vector of dependent variables, $\boldsymbol{A}$ an $m \times k$ matrix of parameters, $\boldsymbol{x}_t$ a $k \times 1$ vector of independent variables, $\boldsymbol{\epsilon}_t$ an $m \times 1$ vector of residuals, $\boldsymbol{H}_t^{1/2}$ the Cholesky factor of the time-varying conditional covariance matrix $\boldsymbol{H}_t$, and $\boldsymbol{\nu}_t$ an $m \times 1$ vector with zero-mean, unit variance, and independent identically distributed (iid) innovations at time t for m countries. Thereby, the trade-off between parsimony and flexibility has to be considered when applying a specific parameterization due to existing comovements of returns. A wide range of parameterizations exists in the literature.[14] Engle (2002) introduces a MGARCH model with DCC. The diagonal elements in the matrix $\boldsymbol{H}_t$ represent univariate GARCH models and the off-diagonal elements are modeled as nonlinear functions of the diagonal terms:

$$h_{ij,t} = \rho_{ij,t}\sqrt{h_{ii,t}h_{jj,t}}, \tag{2.12}$$

[13] Bollerslev and Wooldridge (1992) identify that standard errors are robust under given estimation procedure.

[14] See Bauwens et al. (2006), Silvennoinen and Teräsvirta (2009), or Caporin and McAleer (2012) for a meaningful distinction between various MGARCH models.

where $h_{ii,t}$ and $h_{jj,t}$ follow an univariate and $\rho_{ij,t}$ a dynamic process for the (i,j)th element. The DCC MGARCH model is given by:

$$\begin{aligned}
\boldsymbol{r}_t &= \boldsymbol{A}\boldsymbol{x}_t + \boldsymbol{\epsilon}_t \\
\boldsymbol{\epsilon}_t &= \boldsymbol{H}_t^{1/2}\boldsymbol{\nu}_t \\
\boldsymbol{H}_t &= \boldsymbol{D}_t^{1/2}\boldsymbol{R}_t\boldsymbol{D}_t^{1/2} \\
\boldsymbol{R}_t &= diag(\boldsymbol{Q}_t)^{-1/2}\boldsymbol{Q}_t diag(\boldsymbol{Q}_t)^{-1/2} \\
\boldsymbol{Q}_t &= (1-\lambda_1-\lambda_2)\boldsymbol{R} + \lambda_1\tilde{\boldsymbol{\epsilon}}_{t-1}\tilde{\boldsymbol{\epsilon}}_{t-1}^T + \lambda_2\boldsymbol{Q}_{t-1}.
\end{aligned} \tag{2.13}$$

$\boldsymbol{D}_t$ is a diagonal matrix of conditional variances:

$$\boldsymbol{D}_t = \begin{bmatrix} \sigma_{1,t}^2 & 0 & \dots & 0 \\ 0 & \sigma_{2,t}^2 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \sigma_{m,t}^2 \end{bmatrix} \tag{2.14}$$

with

$$\sigma_{i,t}^2 = \alpha_{0,i} + \sum_{l=1}^{p_i}\beta_l\sigma_{i,t-l}^2 + \sum_{l=1}^{q_i}\alpha_l\epsilon_{i,t-l}^2. \tag{2.15}$$

$\boldsymbol{R}_t$ is a symmetric matrix of conditional quasi correlations[15] and can be expressed as:

$$\boldsymbol{R}_t = \begin{bmatrix} 1 & \rho_{12,t} & \dots & \rho_{1m,t} \\ \rho_{12,t} & 1 & \dots & \rho_{2m,t} \\ \vdots & \vdots & \ddots & \vdots \\ \rho_{1m,t} & \rho_{2m,t} & \dots & 1 \end{bmatrix}, \tag{2.16}$$

where $|\rho_{ij,t}| = |\frac{q_{ij,t}}{\sqrt{q_{ii,t}q_{jj,t}}}| \leq 1$ and $q_{ij,t}$ are the underlying elements in $\boldsymbol{Q}_t$. $\tilde{\boldsymbol{\epsilon}}_t$ is an $m \times 1$ vector of standardized residuals calculated by $\boldsymbol{D}_t^{-1/2}\boldsymbol{\epsilon}_t$ at time t with $\tilde{\boldsymbol{\epsilon}}_t \sim \mathcal{N}(\boldsymbol{0}, \boldsymbol{R}_t)$. $\boldsymbol{R} = Cov[\tilde{\boldsymbol{\epsilon}}_t\tilde{\boldsymbol{\epsilon}}_t^T] = E[\tilde{\boldsymbol{\epsilon}}_t\tilde{\boldsymbol{\epsilon}}_t^T]$ is the unconditional covariance matrix of $\tilde{\boldsymbol{\epsilon}}_{\boldsymbol{t}}$ and expressed as a weighted average:

$$\boldsymbol{R} = \frac{1}{T}\sum_{t=1}^{T}\tilde{\boldsymbol{\epsilon}}_t\tilde{\boldsymbol{\epsilon}}_t^T. \tag{2.17}$$

The nonnegative parameters λ_1 and λ_2 control the conditional quasi correlations. A necessary condition for nonnegativity is satisfied by $0 \leq \lambda_1 + \lambda_2 < 1$. In addition, $\boldsymbol{Q}_0$, as the starting value of $\boldsymbol{Q}_t$, has to be positive definitely to guarantee $\boldsymbol{H}_t$ and $\boldsymbol{R}_t$ to be positive definite. If $\boldsymbol{\nu}_t$ follows a multivariate t-distribution with *df* greater than two, then the conditional log-likelihood function is:

[15] Aielli (2013) shows that $\boldsymbol{R}$ is neither an unconditional mean nor an unconditional correlation matrix of $\boldsymbol{Q}_t$.

$$\begin{aligned}\mathcal{L}(\theta) = &\sum_{t=1}^{T} log\Gamma\left(\frac{df+m}{2}\right) - log\Gamma\left(\frac{df}{2}\right) - \frac{m}{2}log[(df-2)\pi] \\ &- \frac{1}{2}log[det(\boldsymbol{R}_t)] - log[det(\boldsymbol{D}_t^{1/2})] - \frac{df+m}{2}log\left(1 + \frac{\tilde{\boldsymbol{\epsilon}}_t \boldsymbol{R}_t^{-1} \tilde{\boldsymbol{\epsilon}}_t^T}{df-2}\right).\end{aligned} \tag{2.18}$$

The global feedback trading model represents an extension of the feedback trading model by using the DCC MGARCH methodology. Thereby, m regression equations of Eq. (2.7) are implemented with respect to different countries. The DCC MGARCH model with m countries yields the following matrix expression for the global feedback trading model:

$$\underbrace{\begin{bmatrix} r_{1,t} & 0 & \dots & 0 \\ 0 & r_{2,t} & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & r_{m,t} \end{bmatrix}}_{\boldsymbol{r_t}} = \underbrace{\begin{bmatrix} b_{1,0} & b_{1,1} & b_{1,2} & b_{1,3} & b_{1,4} \\ b_{2,0} & b_{2,1} & b_{2,2} & b_{2,3} & b_{2,4} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ b_{m,0} & b_{m,1} & b_{m,2} & b_{m,3} & b_{m,4} \end{bmatrix}}_{\boldsymbol{A}} \underbrace{\begin{bmatrix} 1 & 1 & \dots & 1 \\ \sigma_{1,t}^2 & \sigma_{2,t}^2 & \dots & \sigma_{m,t}^2 \\ \sigma_{1,t}^2 r_{1,t-1} & \sigma_{2,t}^2 r_{2,t-1} & \dots & \sigma_{m,t}^2 r_{m,t-1} \\ \sigma_{1,t}^2 B_{1,t} & \sigma_{2,t}^2 B_{2,t} & \dots & \sigma_{m,t}^2 B_{m,t} \\ \sigma_{1,t}^2 f_{1,t-1}^* & \sigma_{2,t}^2 f_{2,t-1}^* & \dots & \sigma_{m,t}^2 f_{m,t-1}^* \end{bmatrix}}_{\boldsymbol{x_t}} \circ \boldsymbol{I}_m + \underbrace{\begin{bmatrix} \epsilon_{1,t} & 0 & \dots & 0 \\ 0 & \epsilon_{2,t} & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \epsilon_{m,t} \end{bmatrix}}_{\boldsymbol{\epsilon_t}}. \tag{2.19}$$

An implementation of all matrices in Eq. (2.13) would exceed the scope of this chapter and is therefore not presented here.[16]

2.4 Data

2.4.1 Sample and Variable Construction

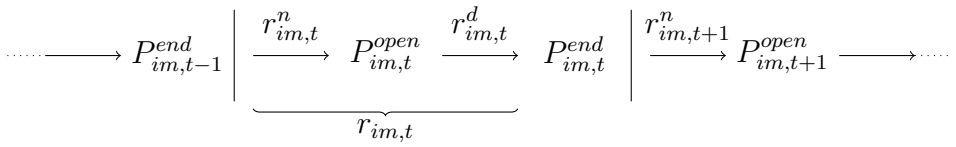
We decompose the overall return premium and compute returns for full trading days (daily returns), trading periods (day returns) and nontrading periods (night returns) as provided in Eq. (2.20). Returns are calculated continuously compounded by:

$$\begin{aligned} r_{im,t} &= ln\left(\frac{P_{im,t}^{end}}{P_{im,t-1}^{end}}\right) * 100 \\ r_{im,t}^{d} &= ln\left(\frac{P_{im,t}^{end}}{P_{im,t}^{open}}\right) * 100 \\ r_{im,t}^{n} &= ln\left(\frac{P_{im,t}^{open}}{P_{im,t-1}^{end}}\right) * 100 \\ r_{im,t} &= r_{im,t}^{d} + r_{im,t}^{n} \end{aligned} \tag{2.20}$$

[16] It is obvious that the global feedback trading model follows the same structure as under Eq. (2.13) by assuming $\boldsymbol{r}_t$ as the dependent variable matrix, m as the number of countries, and k as the number of different parameters of independent variables for each country with $k \times m$ parameters in total. To be precise, the $m \times m$ matrix $\boldsymbol{r_t}$, the $m \times 5$ matrix $\boldsymbol{A}$, the $5 \times m$ matrix $\boldsymbol{x}_t$, and the $m \times m$ matrix $\boldsymbol{\epsilon}_t$ are provided in Eq. (2.19). Note that the matrix $\boldsymbol{x}_t$ is defined as the Hadamard product between independent variables and the identity matrix $\boldsymbol{I}_m \in \mathbb{R}^{m \times m}$.

with $r_{im,t}$ as the daily return, $r^d_{im,t}$ as the day return, and $r^n_{im,t}$ as the night return of index i in period t for country m. $P^{end}_{im,t}$ and $P^{open}_{im,t}$ are the closing and opening prices of index i in period t for country m. Figure 2.1 illustrates the timeline of all three return types according to the definitions in Eq. (2.20).

Figure 2.1: Return timeline



Note: Continuously compounded returns are presented in this figure. Thereby, $P^{end}_{im,t-1}$ and $P^{end}_{im,t}$ are the closing prices of index i for country m in period $t-1$ and t, respectively. The corresponding opening prices are specified as $P^{open}_{im,t}$ and $P^{open}_{im,t+1}$ at time t and $t+1$. $r_{im,t}$ is the daily return, $r^d_{im,t}$ the day return, and $r^n_{im,t}$ the night return of index i in period t for country m.

Daily observations are used in this chapter for stock price indices of five major stock exchanges. The observed group[17] consists of Germany, the UK, the US, Japan, and Hong Kong. We examine individual and mutual interactions of heterogeneous investors and how their actions drive stock prices in these countries. In particular, we use the following indices: DAX 30 (Germany), FTSE 100 (UK), S&P 500 (US), Nikkei 500 (Japan), and Hang Seng Index (Hong Kong). The composition of stocks varies in each index, but still covers at least 80% of the free float-adjusted market capitalization in a specific country. Daily opening and closing prices were collected from Thomson Reuters Datastream. We employ a long estimation window because the variance of the sampling error of the parameters converges to zero. In our case, the sample period covers 2165 trading days and spans from June 27, 2007, to March 7, 2017.[18] Returns are calculated as logarithmic first differences and expressed in percentage terms as shown in Eq. (2.20).

Daily dividend yield and price earnings ratio (P/E) data are taken from Datastream for the same time frame. We calculate dividend payments, D_t, and earnings, E_t, from mentioned fundamental value indicators in order to construct reasonable proxies for financial fundamentals for each period t.[19] We implement

[17] All presented markets are classified as advanced economies according to the International Monetary Fund.

[18] The starting date depends on the availability of all further variables in order to guarantee the same time frame. Public holidays and trading called offs are already excluded. Trading days are correspondingly matched to obtain an equal number of observation days for every market index. The loss of observations differs across markets ranging between 8.8% and 12.2% for Japan and Germany, respectively.

[19] A general agreement on an appropriate proxy for the fundamental value is missing despite a large body of academic literature. In addition, it is worth mentioning that earnings and dividends are only to some extent correlated. Additional information can be derived from

two different measures for fundamental values to assure robustness of the results. Proxies for financial fundamentals are defined as follows:

$$f_{1,t} = \frac{1}{d-g} D_t$$
$$f_{2,t} = eE_t,$$

where $1/(d-g)$ is a constant multiple with d as the required rate of return and g as the growth rate according to the constant growth model of Gordon (1959) and implemented by Koutmos (2012). To be in line with previous research and justified by Cutler et al. (1990), we use the inverse of the dividend yield as an equivalent constant multiple. e depicts the long-term average earnings multiple as used by Fama and French (2002). The average trailing P/E is adopted for the long-term multiple as an alternative to a discounted cash flow analysis.

Investor's sentiment has a direct impact on the demand function. We identify optimistic and pessimistic periods by calculating the put call ratio.[20] An optimistic (pessimistic) period implies that the current sentiment indicator is smaller (greater) than one. The sentiment-driven dummy variable B_t indicates whether a market is in a bullish or bearish condition by taking the value one and zero, respectively, at time t.

2.4.2 Descriptive Statistics

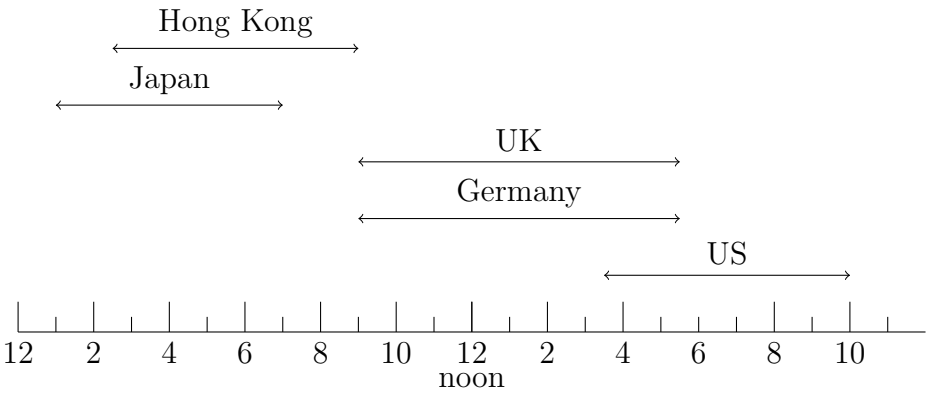
Trading hours differ across international markets and stock exchanges operate at the same time or one after the other. Due to the trading hours overlap and different time zones illustrated in Figure 2.2, markets cannot be regarded in isolation which can lead to problems with the interpretation of results. The separation of daily returns is potentially misleading for the following two reasons. First, it is not possible to distinguish adequately between lagged and contemporaneous effects. Second, information randomly accrues during opening or closing hours of a particular stock exchange and foreign quotes cannot always adjust immediately. Suitable return types are necessary to test for the transmission of information between markets. We eliminate these pitfalls by using independent as well as unbiased day and night returns of stock indices with respect to trading hours. To be precise, we conduct correlations between day and night returns as well as between domestic day (night) and foreign day (night) returns.[21]

earnings due to alternative dividend payments, such as repurchases, which are not reflected in the dividend yield.

[20] See Baker and Wurgler (2006, 2007) for a detailed analysis of the most renowned sentiment measures.

[21] The calculations include lagged and leading returns with respect to trading hours and time zones. Day returns of Germany, the UK, and the US are mapped to leading night returns

Figure 2.2: Trading hours of stock exchanges



Note: This figure highlights trading hours of major stock exchanges around the world in Central European Time (CET). Lunch break is between 3:30 a.m. and 4:30 a.m. and between 5:00 a.m. and 6:00 a.m. at the Tokyo Stock Exchange and the Stock Exchange of Hong Kong, respectively, in CET.

Pearson correlation coefficients are presented in Table 2.1 for the selected market indices. It can be noticed that most correlations are highly significant.[22] This feature implies both a tight stock market interconnectedness and a strong dependency between return types. Several dependencies show higher correlations between day returns compared to night returns. The highest correlation is 0.708^{***} (0.694^{***}) between Germany and the UK with respect to day (night) returns. Not less interesting is the interaction among return types for a particular country and on a cross-country basis. Day returns of Japan are significantly negative correlated with night returns of Japan (-0.056^{***}) and Hong Kong (-0.403^{***}). In contrast, only day returns of Hong Kong illustrate a negative correlation to night returns of Japan (-0.163^{***}). Different trading hours and time zones have a strong impact on the cross-country comparison. Leading as well as lagged returns have to be considered due to nonsynchronous opening hours. The respective stock exchanges in Germany, the UK, and the US operate while the exchanges in Japan or Hong Kong are closed and vice versa. Consequently, the majority of correlations are higher between those day and night returns since price momentum is driven by day returns outside a particular country. The correlation is 0.137^{***} between day returns of Germany and night returns of the UK and 0.492^{***} when considering night returns of Hong Kong. The largest value is identified for the interaction between day returns of the US and night returns of Hong Kong.

of Japan and Hong Kong. On the contrary, night returns of Japan and Hong Kong are matched with lagged day returns of Germany, the UK, and the US.

[22] High correlations are not due to the fact that we only consider developed countries. Unreported calculations entail similar findings for emerging markets as well. Thereby, we apply three market indices – namely the MSCI Emerging Markets index, the MSCI Emerging Markets ex Asia index, and the MSCI World index. The highest correlation is 0.840^{***} (0.785^{***}) between the MSCI World index (DAX) and the MSCI Emerging Markets ex Asia index.

Table 2.1: Correlation matrix for stock market returns

	Day returns						Night returns				
	Germany	UK	US	Japan	Hong Kong		Germany	UK	US	Japan	Hong Kong
(A) Day returns						(C) Day returns					
Germany	1					Germany	.075***	.137***	.142***	.425***	.492***
UK	.708***	1				UK	.396***	.177***	.252***	.392***	.385***
US	.587***	.548***	1			US	.162***	.129***	.052**	.467***	.656***
Japan	.076***	.318***	.149***	1		Japan	.406***	.252***	.331***	-.056***	.403***
Hong Kong	.148***	.289***	.284***	.340***	1	Hong Kong	.217***	.087***	.151***	-.163***	.007
(B) Night returns						(D) Night returns					
Germany	.075***	.396***	.162***	.406***	.217***	Germany	1				
UK	.137***	.177***	.129***	.252***	.087***	UK	.694***	1			
US	.142***	.252***	.052**	.331***	.151***	US	.472***	.504***	1		
Japan	.425***	.392***	.467***	-.056***	-.163***	Japan	.220***	.189***	.042*	1	
Hong Kong	.492***	.385***	.656***	-.403***	.007	Hong Kong	.520***	.439***	.399***	.403***	1

Note: The overall return premium is decomposed into day and night returns. Trading hours differ across international markets. Therefore, panel (A) illustrates the correlation between day returns and (D) the correlation between night returns. (B) presents correlations for the combinations between night and day returns, whereas lagged day returns from Germany, the UK, and the US are mapped to night returns in Japan and Hong Kong. In contrast, (C) shows the correlation matrix for day and night returns with leading night returns of Japan and Hong Kong for day returns in Germany, the UK, and the US. Stars indicate significance as follows: *10%, **5%, ***1%.

Table 2.2: Descriptive statistics of stock market returns

	Germany	UK	US	Japan	Hong Kong
(A) Day returns					
Mean	−0.015	−0.010	0.015	−0.036	−0.071
St.Dev.	1.262	1.266	1.261	1.136	1.157
Skewness	0.049	−0.358	−0.565	−0.613	0.244
Kurtosis	8.940	9.189	12.267	15.303	17.339
J-B	3183.741***	3501.561***	7862.034***	13 789.867***	18 568.940***
ADF	−44.403***	−46.872***	−53.223***	−48.656***	−51.385***
BG LM (2)	0.684	2.736	0.302	9.989***	6.313**
Ljung-Box (12)	19.950*	16.896	18.698*	30.381***	18.668*
Ljung-Box^2 (12)	805.946***	2130.138***	1690.445***	1896.442***	1179.227***
LM ARCH (2)	173.425***	274.229***	135.172***	438.834***	455.072***
(B) Night returns					
Mean	0.024	−0.007	0.006	0.048	0.075
St.Dev.	1.293	0.957	0.563	0.988	1.357
Skewness	−0.009	1.460	4.837	−0.159	0.309
Kurtosis	22.514	39.532	116.987	5.189	16.903
J-B	34 351.019***	121 160.023***	180 522.400***	441.376***	17 471.129***
ADF	−50.078***	−45.419***	−46.845***	−59.175***	−49.614***
BG LM (2)	15.835***	5.697*	9.155**	9.737***	0.450
Ljung-Box (12)	34.588***	41.182***	63.492***	15.305	10.550
Ljung-Box^2 (12)	127.356***	59.529***	102.451***	105.029***	462:441***
LM ARCH (2)	33.726***	2.163	2.282	46.608***	155.807***

Note: This table provides the sample statistics for each market using day and night returns from June 27, 2007, to March 7, 2017, with a sample size of 2165 observations. All series are in logarithmic first differences form and expressed as a percentage on a daily basis. The J-B test matches the skewness and kurtosis to the normal distribution's. ADF is the Augmented Dickey-Fuller test for a unit root and BG LM is the Breusch-Godfrey test of order 2 for detecting serial correlation. The Ljung-Box statistic of order 12 for returns and squared returns is defined as Ljung-Box (12) and Ljung-Box^2 (12), respectively. LM ARCH (2) performs Engle's Lagrange multiplier (LM) test for the presence of autoregressive conditional heteroskedasticity. Stars indicate significance as follows: *10%, **5%, ***1%.

Table 2.2 provides a first analysis of major market indices in terms of descriptive statistics. Thereby, panel (A) depicts day returns and panel (B) night returns for all treated countries in order to compare on a cross-country and cross-return type basis.[23] Noteworthy is the difference between day and night returns when taking the mean into consideration. The mean is mostly negative for day returns and positive for night returns. This implies that returns are rather negative during trading hours than during closing periods for the following two reasons.[24] First, market uncertainty after market closures and a reduced possibility of liquidation have an impact on night return patterns. Intuitively, a positive risk premium is earned by taking naturally a riskier side of the trade. Second, institutions have a dominant market position and tend to trade intraday while individuals are more likely to trade overnight as shown in Giannetti et al. (2006). Thereby, institutional investors usually trade against the momentum during the day with lower and partially reverted momentum profits.[25] As expected for financial time series, all return distributions are skewed and leptokurtic relative to the normal distribution. A goodness-of-fit test is highlighted by the Jarque-Bera (J-B) test, which matches the skewness and kurtosis to the normal distribution. The values range from 3501.561^{***} to 18568.940^{***} and from 441.376^{***} to 180522.400^{***} for day and night returns, respectively. It is notable that the test statistics are at least 10 times higher for night returns of Germany, the UK, and the US than for the corresponding day returns. Nonnormal distributions are mainly driven through an increased kurtosis during overnight hours. Stationarity is confirmed by the Augmented Dickey-Fuller (ADF) test. The existence of a unit root can be rejected for all return series. T-statistics for day and night returns have similar significantly negative values between -44.303^{***} and -59.175^{***} in panels (A) and (B). Hence, the process is mean-reverting and stochastic shocks diminish with a nonpermanent effect over time. Serial correlation is present in most market indices as the Breusch-Godfrey (BG) Lagrange multiplier (LM) test for up to two lags confirms, especially when considering night returns. The largest dependency between lagged and present day returns can be observed in Japan (9.989^{***}) while in Germany for night returns (15.835^{***}). The Ljung-Box statistic illustrates intertemporal dependencies in both returns and squared returns

[23] Figure B.1 presents opening prices and day returns, whereas Figure B.2 highlights closing prices and night returns on page 92f. in the Appendix. The corresponding conditional variances of returns are provided in Figure B.3 on page 94.

[24] Unreported calculations confirm that daily returns are positive on average for every country. Furthermore, night returns' standard deviation is lower than day returns' with the exception of Germany. This is in line with Lachance (2015) who verifies that stocks with positive overnight biases in the past have lower risk and higher returns during the night. Here, a positive overnight bias occurs when firms' overnight returns are exceeding the average overnight return.

[25] See Badrinath and Wahal (2002) for a broader investigation of the trading behavior of institutional investors.

for up to 12 lags. Panels (A) and (B) show that autocorrelations of most return series are significantly different from zero – implying a dependent distribution. The test statistics for squared returns are smaller when considering night returns and range from 59.529*** to 462.441***. In contrast, values for day returns lie between 805.946*** and 2130.138***. The presence of autoregressive conditional heteroscedasticity (ARCH) is significant for all day returns at the 1% level by applying Engle's LM with two lags. LM-test values are only significant for Germany, Japan, and Hong Kong when considering night returns. The test statistics are obviously smaller for night returns than for day returns. The largest ARCH effects are detected for Hong Kong with values of 455.072*** and 155.807*** for day and night returns, respectively. Therefore, the sample is consistent with current asset pricing literature in terms of ARCH and volatility clustering.[26]

2.4.3 Hypotheses

Theoretically, serial correlation in returns can arise from other aspects besides feedback trading. Both nonsynchronous trading and investors' preferences are possible explanations for the observed serial correlations. However, negative autocorrelation in returns due to nonsynchronous trading of an individual security is dominated by positive cross-correlation.[27] The degree of risk aversion in preferences can be neglected because the estimation does not include any specific utility function or exogenous wealth. Hence, investors adapt their behavior differently to market conditions, past performance, and fundamental values. Cooper et al. (2008) argue that the rate of information flow changes around the clock. This in turn induces larger price volatility due to increased or decreased demand for particular stocks – away from the predetermined market equilibrium. Comprising these thoughts leads directly to the hypotheses:

H0: Effects of volatility on the serial correlation pattern of returns do not exist in the market. Feedback traders' behavior is irrelevant for the pricing of stocks and no feedback traders can be found in the market.

H1: Effects of volatility on the serial correlation pattern of returns exist in the market. Feedback traders change their behavior according to market conditions and past performance, which is in line with a feedback trading strategy.

[26] Correlograms of autocorrelations are provided for different stock markets with respect to the return type in Figure B.4 and Figure B.5 on page 95f. in the Appendix.

[27] See Lo and MacKinlay (1990) or Sentana and Wadhwani (1992) for a broader discussion.

Analyzing possible drivers of volatility implies a direct prediction concerning the rejection of the null hypothesis in favor of the alternative hypothesis. In addition, we can investigate further implications if the null hypothesis is rejected. Time differences can impact potentially on returns. Barclay and Hendershott (2003) identify asymmetric patterns. They argue that prices are less efficient and less information is revealed at night than during the day due to noise, but a single trade contains more information after hours.[28] Market closures affect the mean and standard deviation of returns because investors need to be compensated for the risk when trading overnight as stated by Blanc et al. (2014). Lou et al. (2019) confirm that a positive risk premium is earned at night and the premium offsets intraday average returns. The limited possibility of liquidation constricts night returns to be higher than day returns. Institutional liquidity providers are less active during the night and liquidity traders mostly dominate the after-hours session according to Giannetti et al. (2006). These can result in either a similar trading behavior or different strategies across the day.

H2: Feedback trading strategies behave similarly during a full trading day.

H3: Feedback trading strategies differ when taking the distinction between day and night returns into account.

Furthermore, the interconnectedness between multiple countries considers dynamic effects according to market spillovers. Price fluctuations in one country can certainly influence investors' strategy in another country with a mutual reaction to investors' behavior in the initiating country. Aretz and Bartram (2015) verify that prices are driven by day returns from abroad.[29] According to Frino and Hill (2000), overseas information releases and contagion effects are the main reasons for spillovers.[30] We apply a joint analysis of stock prices with matched day and night returns across countries to control for spillovers in volatility of the lagged returns from one stock exchange to another. Possible interrelations between countries are examined with the following hypotheses:

[28]Not surprisingly, the trading volume decreases and trading costs increase at night due to a lack of liquidity, larger quote spreads, uncertain prices, competition with professional traders, computer delays, and biases toward limit orders.

[29]The sample comprises 48,000 stocks from 35 countries and results are robust across countries as well as subsamples.

[30]Local traders react to foreign (public) information by observing price movements. Thereby, Becker et al. (1995) show that overseas macroeconomic information releases can not only increase asymmetries between overseas and local markets but also among market participants in the local market.

H4: Spillover effects across international markets do not change investors' behavior. Feedback trading patterns can be individually estimated for each particular country.

H5: Interaction of specific markets has an influence on feedback trading patterns. Stock prices are dependent on business cycles and national economic shocks with cross-country spillover effects.

2.5 Empirical Results

In this part we investigate our implied hypotheses and present results with respect to market segmentation, time differences, and global interconnectedness. First, the serial correlation pattern of returns is analyzed for individual markets. Thereby, we distinguish between day and night returns and examine effects arising after market closures as well as during a trading day. We continue with a joint analysis of stock prices on a multi-country foundation in order to find spillovers in the volatility of lagged returns. Our study ends with a further outlook after applying sophisticated robustness checks.

2.5.1 Day and Night

Heterogeneous trading strategies of various market participants can have a significant impact on stock prices. The aim is to answer the question whether feedback trading is evident and if feedback trading strategies differ between the day and night. An examination of hypotheses 2 and 3 can only be performed when the null hypothesis is rejected. Proceeding from here, one can seek differences and similarities in serial correlation patterns for different return types. Table 2.4 and Table 2.3 report parameter estimation results for Eq. (2.7) and Eq. (2.8), respectively. In particular, Table 2.4 depicts mean equations' estimates for day and night returns with respect to the applied fundamental value, whereas Table 2.3 presents variance equations' estimates for the same underlying mean equation by applying an EGARCH$(1,1)$ model with GED. The technical reason for this is that conditional variances of stock returns are time-varying and depend asymmetrically on past estimates.

The Akaike information criterion (AIC) discloses low values around 2.744 and 2.645 for day and night returns, respectively. As a direct implication, our applied model with one lag is superior in terms of the trade-off between bias and variance in model construction as already demonstrated in Figure B.4 and Figure B.5. As

it can be seen by the sign of the mostly significant parameter ξ_1 in Table 2.3, an asymmetric response of the conditional variance to past residuals is observed for day and night returns. This implies that the conditional variance rises faster for negative residuals than for positive ones.[31] Thereby, the volatility feedback hypothesis serves as an important determinant of asymmetric volatility. Negative shocks and unexpected return changes lead to a higher volatility than positive innovations given an equal magnitude as mentioned by Campbell and Hentschel (1992) among others.

According to the endogenously estimated scale parameter ν, a distribution with flatter tails has to be assumed for all return types due to leptokurtic standardized residuals. *df* between 1.278^{***} (0.977^{***}) and 1.521^{***} (1.542^{***}) for day (night) returns imply rather a Laplace than a normal distribution. The quasi-maximum likelihood estimation yields values around -2910.867 on average with higher values for day than night returns in absolute terms.[32] Unfortunately, it is not possible to estimate valid results for night return patterns in the US due to a flat likelihood. A missing uphill direction with nonconcave regions illustrates obviously the complexity of the model. Nevertheless, it can be assumed that investors' behavior in the US is similar to all other discussed markets.[33]

The adjusted R^2 varies across markets, return types, and fundamental values. In general, the implied feedback trading model explains on average 2.2% (2.5%) of returns' variance during the day (night). Barclay and Hendershott (2003) confirm that a significant price discovery can be achieved after hours even with relatively little trading and noisier prices. At first glance, the fundamental value f_2 suits best when dealing with day returns and f_1 for night returns on average. Markets with different microstructures exhibit unequal price discovery processes after earnings and dividend announcements according to Greene and Watts (1996). They find that price responses to earnings announcements are mainly realized during the day. Along with Spiegel and Subrahmanyam (1995), institutional investors have a trading advantage and mainly trade at the open or during periods of unusual demand. Thereby, this group of investors typically prefers nonpaying dividend firms in contrast to individual investors as stated by Jain (2007).[34] For day returns, the highest values are 5.9% and 6% for Germany

[31] The news response functions reinforce an asymmetric pattern for both day and night returns in Figure B.6 on page 97 in the Appendix.

[32] Log-likelihoods are on average -2958.774 (-2850.011) and -2958.073 (-2852.834) for day (night) returns given f_1 and f_2, respectively.

[33] A similar return pattern with more volatile intraday returns can be found in the literature across different markets. Lachance (2015) identifies that overnight trading is persistent and pervasive in the US.

[34] First, the relative proportion of news releases is higher during the day than at night as Patell and Wolfson (1982) highlight. Second, Francis et al. (1992) find that disclosures contain less bad news and surprises during the day. Therefore, this systematic timing behavior has a direct impact on price changes and the adjustment process. Furthermore, Lamont (1998)

with respect to f_1 and f_2. In contrast, the smallest explanatory power is derived for Japan based on day returns. Values for night returns differ between 4.9% in Japan and 0.7% in the UK for f_1 and f_2, respectively. However, changes in the explanatory power arise when considering day returns. In Hong Kong, for example, the explanatory power with 2.5% is higher by taking f_1 as the fundamental value than under f_2 with an adjusted R^2 of 2.3%. Therefore, a consideration of only one of both fundamental values is, ceteris paribus, not Pareto efficient for further analysis.

We now turn our attention to traders' behavior by examining the effects of volatility on the serial correlation pattern of returns for the different return types and respective countries. Overall, findings affirm the presence of positive feedback traders in daily stock market prices. The coefficient parameter b_2 is mostly significantly negative with values ranging from -0.174*** to -0.007* in Table 2.4. The null hypothesis can be rejected in favor of the alternative hypothesis because traders change their behavior according to market conditions and past performance by actively buying (selling) stocks in a rising (falling) market. However, strategies of trend chasing investors differ with regards to trading time and allow us to investigate further implications. Achieving this objective involves, on the one hand, a differentiation between return types and, on the other hand, a consideration of the underlying fundamental value.

Fundamental values are instructive and serve as useful benchmarks for investors to measure over- or undervaluation in stock markets. The crucial parameter coefficient b_4 is mostly negative and statistically significant for all countries and return types when using f_1 or f_2 as the proxy. Only a positive value of 0.058** is estimated for day returns in the US, given f_1. Consistent results across markets suggest that findings are robust regarding fundamental traders.

The coefficient for the dummy variable B_t is always significantly positive except for day returns in Hong Kong with f_1 as the fundamental proxy. The sentiment level has a direct impact on trend chasing investors by providing a useful signal for trading. The simultaneous existence of positive feedback traders illustrates that investors rather buy stocks in a bullish market situation and vice versa. Therefore, this dummy confirms a significant linkage between the sentiment level and feedback trading and affirms the existence of positive feedback behavior. This finding is in line with Kurov (2008) who confirms that the degree of positive feedback trading is intensified by high-sentiment periods.

argues that earnings contain more information regarding business conditions and are embedded in press releases with many other bits of relevant information according to Patell and Wolfson (1984).

Table 2.3: Variance equations for day and night returns

Coefficient	Germany	UK	US	Japan	Hong Kong
(A) Day returns with f_1 as the fundamental proxy					
α_0	-0.101***	-0.144***	-0.134***	-0.164***	-0.100***
	(0.017)	(0.020)	(0.018)	(0.022)	(0.015)
α_1	0.133***	0.182***	0.162***	0.200***	0.127***
	(0.022)	(0.026)	(0.024)	(0.029)	(0.019)
ξ_1	-0.108***	-0.149***	-0.180***	-0.099***	-0.049***
	(0.015)	(0.017)	(0.020)	(0.018)	(0.012)
γ_1	0.979***	0.967***	0.973***	0.954***	0.989***
	(0.005)	(0.005)	(0.005)	(0.008)	(0.004)
ν	1.337***	1.521***	1.299***	1.285***	1.467***
	(0.052)	(0.071)	(0.053)	(0.031)	(0.066)
Log-likelihood	-3168.477	-3066.954	-2878.993	-2779.925	-2899.521
Adj. R^2	0.059	0.001	0.008	0.000	0.025
AIC	2.938	2.844	2.670	2.578	2.689
(B) Day returns with f_2 as the fundamental proxy					
α_0	-0.102***	-0.150***	-0.151***	-0.167***	-0.096***
	(0.017)	(0.021)	(0.019)	(0.022)	(0.015)
α_1	0.135***	0.190***	0.186***	0.204***	0.122***
	(0.022)	(0.027)	(0.026)	(0.029)	(0.019)
ξ_1	-0.109***	-0.139***	-0.161***	-0.093***	-0.052***
	(0.015)	(0.017)	(0.020)	(0.017)	(0.012)
γ_1	0.978***	0.968***	0.972***	0.954***	0.988***
	(0.005)	(0.006)	(0.005)	(0.008)	(0.004)
ν	1.339***	1.501***	1.278***	1.289***	1.468***
	(0.052)	(0.070)	(0.052)	(0.031)	(0.066)
Log-likelihood	-3168.725	-3062.940	-2880.079	-2780.636	-2897.983
Adj. R^2	0.060	0.013	0.023	0.003	0.023
AIC	2.938	2.840	2.671	2.579	2.688
(C) Night returns with f_1 as the fundamental proxy					
α_0	-0.091***	-0.076***		-0.097***	-0.107***
	(0.014)	(0.014)		(0.020)	(0.014)
α_1	0.129***	0.101***		0.120***	0.142***
	(0.020)	(0.019)		(0.025)	(0.019)
ξ_1	-0.008	-0.020*		-0.016	-0.066***
	(0.014)	(0.012)		(0.014)	(0.012)
γ_1	0.986***	0.990***		0.974***	0.990***
	(0.004)	(0.003)		(0.009)	(0.003)
ν	1.093***	0.977***		1.542***	1.208***
	(0.028)	(0.029)		(0.057)	(0.042)
Log-likelihood	-3124.226	-2313.100		-2898.319	-3064.398
Adj. R^2	0.018	0.008		0.049	0.034
AIC	2.897	2.147		2.688	2.841
(D) Night returns with f_2 as the fundamental proxy					
α_0	-0.086***	-0.070***		-0.101***	-0.107***
	(0.013)	(0.013)		(0.021)	(0.015)
α_1	0.121	0.089***		0.125***	0.142***
	(0.019)	(0.017)		(0.025)	(0.020)
ξ_1	-0.018	-0.026**		-0.018	-0.075***
	(0.014)	(0.012)		(0.015)	(0.013)
γ_1	0.987***	0.991***		0.973***	0.989***
	(0.004)	(0.003)		(0.009)	(0.003)
ν	1.097***	0.990***		1.537***	1.212***
	(0.028)	(0.029)		(0.056)	(0.042)
Log-likelihood	-3127.728	-2317.743		-2897.535	-3068.330
Adj. R^2	0.011	0.007		0.046	0.025
AIC	2.900	2.151		2.687	2.845

Note: This table presents parameter coefficients for the EGARCH(1,1) specification in order to estimate the conditional variance $ln(\sigma_t^2) = \alpha_0 + \gamma_1 ln\sigma_{t-1}^2 + \alpha_1[|z_{t-1}| - E|z_{t-1}|] + \xi_1 z_{t-1}$. The model is estimated simultaneously with Eq. (2.7) with respect to day and night returns as well as different fundamental proxies (f_1 and f_2). Stars indicate significance as follows: *10%, **5%, ***1%. In parentheses: standard errors.

Table 2.4: Mean equations for day and night returns

Coefficient	Germany	UK	US	Japan	Hong Kong
(A) Day returns with f_1 as the fundamental proxy					
b_0	0.077**	-0.019	0.071***	0.018	-0.050
	(0.039)	(0.026)	(0.023)	(0.027)	(0.030)
b_1	-0.120***	-0.131**	0.099**	-0.268***	0.015
	(0.057)	(0.059)	(0.045)	(0.076)	(0.085)
b_2	0.000	-0.010*	-0.016***	-0.013***	-0.014**
	(0.005)	(0.006)	(0.006)	(0.005)	(0.006)
b_3	0.280***	0.270***	0.119**	0.322***	0.046
	(0.031)	(0.032)	(0.061)	(0.035)	(0.037)
b_4	-0.019	-0.021	0.058**	-0.016**	0.011
	(0.019)	(0.017)	(0.026)	(0.007)	(0.024)
(B) Day returns with f_2 as the fundamental proxy					
b_0	0.093	-0.041	0.020	0.013	-0.063**
	(0.032)	(0.027)	(0.024)	(0.027)	(0.026)
b_1	-0.136***	-0.008	0.041	-0.067**	-0.007
	(0.030)	(0.031)	(0.030)	(0.038)	(0.032)
b_2	0.000	-0.010*	-0.018***	-0.014***	-0.013**
	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)
b_3	0.270***	0.280***	0.154***	0.324***	0.061*
	(0.031)	(0.032)	(0.055)	(0.035)	(0.035)
b_4	-0.011	-0.010***	-0.065	-0.008**	-0.027*
	(0.015)	(0.013)	(0.047)	(0.004)	(0.014)
(C) Night returns with f_1 as the fundamental proxy					
b_0	0.020	-0.030		-0.094*	0.049**
	(0.034)	(0.019)		(0.054)	(0.022)
b_1	-0.167***	-0.243***		-0.060	-0.210***
	(0.054)	(0.050)		(0.108)	(0.060)
b_2	-0.009**	0.003		-0.174***	-0.007*
	(0.004)	(0.006)		(0.016)	(0.004)
b_3	0.123***	0.081***		0.098*	0.067*
	(0.025)	(0.026)		(0.053)	(0.025)
b_4	-0.012**	-0.021***		-0.020**	-0.060***
	(0.017)	(0.016)		(0.010)	(0.017)
(D) Night returns with f_2 as the fundamental proxy					
b_0	0.071**	0.018		-0.106*	0.080
	(0.030)	(0.015)		(0.056)	(0.020)
b_1	-0.031	-0.029		0.214***	0.011
	(0.026)	(0.025)		(0.072)	(0.018)
b_2	-0.006	0.002		-0.174***	-0.006
	(0.004)	(0.007)		(0.016)	(0.004)
b_3	0.116***	0.064**		0.102*	0.056**
	(0.025)	(0.026)		(0.053)	(0.025)
b_4	-0.004	-0.001		-0.012**	-0.025**
	(0.016)	(0.010)		(0.005)	(0.010)

Note: The estimated parameters rely on the model $r_t = b_0 + b_1\sigma_t^2 + b_2\sigma_t^2 r_{t-1} + b_3\sigma_t^2 B_t + b_4\sigma_t^2 f_{t-1}^* + \varepsilon_t$. Parameters are estimated simultaneously with Eq. (2.8) with respect to day and night returns as well as different fundamental proxies (f_1 and f_2). Stars indicate significance as follows: *10%, **5%, ***1%. In parentheses: standard errors.

We conclude from the empirical results that feedback trading strategies differ across markets when taking day and night returns into account. Feedback traders behave similarly in Japan and Hong Kong during a full trading day, whereas Germany and the UK register a strong contrariness. For Japan and Hong Kong, panels (A) and (B) in Table 2.4 denote the presence of significantly negative b_2-values with respect to both fundamental proxies. Similar results are reported for night returns in panels (C) and (D). Of particular interest are the diverse strategies in Germany and the UK. No feedback trading is found to exist in Germany during trading hours because b_2 is insignificant according to f_1 and f_2. Simultaneously, the parameter is significantly negative at least at the 5% level for night returns when f_1 is the fundamental proxy. An inverse relationship is found in the UK. During the day, investors follow a positive feedback trading strategy as the significantly negative values of b_2 illustrate. The absence of feedback trading during night hours, as illustrated by insignificant b_2-values, can reflect a change in investors' behavior in this particular country. Furthermore, a reason can be the systematic trading behavior of different investor groups. Usually, institutional investors engage in positive feedback trading while individual investors follow a negative feedback behavior due to limit trade imbalances according to Lee (2016). Expected return reversals reinforce the negative feedback trading pattern in addition. The lack of feedback trading during the day in Germany and overnight in the UK can stem from the fact that positive and negative feedback trading strategies offset each other. This evidence supports our hypothesis that trading strategies are different between day and night hours across markets.

It is not surprising that positive feedback trading tends to occur more often for day than night returns. One possible explanation is the obvious decline in trading volume overnight arising from the clientele effect. On the one hand, trading in the after-hours session is the privilege of professional investors due to high risk levels as stated by Barclay and Hendershott (2003). On the other hand, less sophisticated market participants and institutions with a dominant market position prefer to trade during the day. Giannetti et al. (2006) show that institutional liquidity providers are less active during the night. Hence, a decline in the trading volume diminishes the attractiveness of the feedback behavior and the amount of trend chasing investors reduces.

In the next part of this analysis, we focus on day and night returns in Germany and the UK, respectively, to assess the impact of spillovers by taking market interconnectedness into consideration. The purpose is to explain potential changes in investors' strategies and to address the question whether feedback trading is still absent in these countries.

2.5.2 Global Interconnectedness

Examining the interaction of specific markets is a superior way to shed light on investors' behavior by taking spillover effects into account. We use the global feedback trading model to estimate parameters and present results in Table 2.5 as well as Table 2.6. Thereby, Table 2.5 incorporates combinations of day returns with respect to Germany and Table 2.6 night returns according to the UK.

In general, the necessary condition for nonnegativity is satisfied for all combinations and with regards to both fundamental proxies. Average values for $\lambda_1 + \lambda_2$ are between 0.577 and 0.952 for day and night returns, respectively, given f_2. An absent unit root in the variance, as the second necessary condition, is achieved according to $\alpha_1 + \beta_1 < 1$. All estimated values are significantly smaller and imply that past shocks diminish after periods of time.[35] Quasi correlations differ across country combinations. The value ρ is larger for the interconnectedness between Germany and the UK (or the US) than between Germany and Japan (or Hong Kong) according to day returns. This circumstance is justified by time-delayed opening and closing hours in a particular country. Day returns in Germany, the UK, and the US have an overlap time. Japan and Hong Kong, on the other hand, are ahead in time and act as leaders with leading signals. Same findings hold for night returns in Table 2.6.[36] Not surprisingly, likelihood estimations are larger in the global feedback trading model compared to the feedback trading model for both return types and fundamental values in absolute terms. In contrast to a GED assumption, ν_t follows here a multivariate t-distribution. All parameters in the model are estimated along with df. This approach is robust for leptokurtic standardized residuals and in addition justified in subsection 2.4.2. df is always larger than two by taking values between 6.417 (4.174) and 6.432 (4.183) on average for day (night) returns with respect to f_1 and f_2.

We analyze the impact of spillovers for each pair of countries according to the introduced DCC MGARCH$(1,1)$ model. The focus lies in changes of feedback trading during the day in Germany and the night in the UK. Thereby, results in Table 2.4 serve as a benchmark. For day returns, feedback trading still does not exist in Germany for all estimations as well as both fundamental proxies. In addition, the former positive feedback trading only disappears in the UK. Global

[35] The persistence of volatility can be measured by the concept of half-life, which discloses the number of periods it takes to move halfway towards the unconditional volatility, and is defined as: $halflife = \frac{-ln(2)}{ln(\alpha_1+\beta_1)}$. Volatility has a half-life of about 105 days on average with respect to day and night returns, whereas the mean reversion lasts longer for night returns (156 days) than for day returns (54 days).

[36] Note that night returns of the US are again not considered due to a flat likelihood in the previous feedback trading model.

interconnectedness between both markets induces a decline of trend chasing investors in the UK. Positive and statistically significant feedback trading is present in the US, Japan, and Hong Kong even with respect to day returns in Germany.

As a result, we identify two important findings for day returns – investors' behavior in Germany is not influenced by all other countries according to feedback trading, but day returns from Germany have an impact on feedback traders in the UK. The picture is partly different when considering night returns. The presence of positive feedback trading is confirmed in Germany, the US, Japan, and Hong Kong at least at the 5% level. More interesting is the interaction between night returns of Germany and the UK. We find a one-sided spillover effect from Germany to the UK when comparing with the benchmark model. The parameter coefficient b_2 is significant positive with a value of 0.010^* for the UK with respect to f_1 and f_2 in Table 2.6. This also means that rather negative feedback trading tends to occur in this particular country when including interactions with Germany. Hypothesis 4 can be partly rejected because of cross-country spillover effects as illustrated by the negative feedback trading behavior.[37]

The coefficients for B_t are in line with our previous estimations by taking mostly significant and positive values for night returns. Only a negative parameter coefficient of -0.047^* is determined for night returns in the UK with respect to f_2 and an interaction with Germany. Apart from that, the parameter coefficients for day returns are always positive except for Hong Kong as already shown in the feedback trading model.

Not surprisingly, the parameter coefficient b_4 is mostly insignificant for night returns according to f_2 and same reasoning can be applied as before. Significantly negative values are only reported for Japan when including the UK and Japan in the bivariate model. The parameter coefficient is less often insignificant for day returns and again only negative for Japan for the interaction between Japan and Germany. Consequently, fewer fundamental traders exist on average in general under global interconnectedness. A possible explanation for this outcome is that stock prices provide less information for fundamental traders. Hinterleitner et al. (2015) argue that a rising uncertainty about fundamental values overnight lowers market quality in terms of liquidity and mispricing. In addition, investors may rely on other fundamentals beside earnings and dividend announcements when considering a multi-country setting.

[37]Unfortunately, we cannot give any indication to what extent domestic trading behavior changes. Domestic traders in the UK can still engage equally in positive and negative feedback trading, adhere more to negative feedback trading, or pursue positive feedback trading patterns. However, the total effect discloses a significant amount of negative feedback trading behavior. Wylie (2005) and Blake et al. (2017) find that pension funds in the UK display a strong herding behavior with negative feedback trades.

Table 2.5: Day returns with global interconnectedness

Coefficient	Germany	UK	Germany	US	Germany	Japan	Germany	Hong Kong
(A) Day returns with f_1 as the fundamental proxy								
b_0	0.091**	0.031	0.045	0.057**	0.078*	0.037	0.069	-0.027
	(0.036)	(0.024)	(0.038)	(0.024)	(0.043)	(0.029)	(0.043)	(0.032)
b_1	-0.062	-0.070	-0.222***	-0.051	-0.282***	-0.292***	-0.298***	0.020
	(0.058)	(0.060)	(0.063)	(0.054)	(0.070)	(0.090)	(0.070)	(0.091)
b_2	0.005	-0.002	-0.001	-0.022***	-0.002	-0.017**	0.001	-0.015**
	(0.005)	(0.005)	(0.006)	(0.005)	(0.007)	(0.008)	(0.007)	(0.007)
b_3	0.112***	0.161***	0.192***	0.092*	0.295***	0.342***	0.292***	0.038
	(0.023)	(0.023)	(0.026)	(0.055)	(0.033)	(0.041)	(0.033)	(0.038)
b_4	0.003	-0.012	0.000**	0.000	0.000*	-0.017**	0.000**	0.000
	(0.018)	(0.017)	(0.020)	(0.000)	(0.022)	(0.008)	(0.043)	(0.000)
α_0	0.023***	0.026***	0.026***	0.022***	0.017**	0.037***	0.179***	0.011**
	(0.007)	(0.007)	(0.008)	(0.006)	(0.007)	(0.009)	(0.007)	(0.004)
α_1	0.075***	0.094***	0.087***	0.138***	0.079***	0.131***	0.081***	0.057***
	(0.011)	(0.013)	(0.014)	(0.019)	(0.015)	(0.020)	(0.015)	(0.011)
β_1	0.908***	0.886***	0.899***	0.853***	0.912***	0.834***	0.908***	0.934***
	(0.013)	(0.016)	(0.016)	(0.018)	(0.016)	(0.024)	(0.159)	(0.129)
ρ	0.674		0.573		0.036		0.108	
λ_1	0.016		0.011		0.002		0.000	
λ_2	0.978		0.981		0.921		0.896	
df	6.709		5.434		6.326		7.197	
Log-likelihood	-5589.084		-5651.589		-5960.890		-6098.745	
(B) Day returns with f_2 as the fundamental proxy								
b_0	0.084***	-0.005	0.105***	0.028	0.114***	0.023	0.117***	-0.041
	(0.029)	(0.026)	(0.031)	(0.024)	(0.035)	(0.029)	(0.035)	(0.272)
b_1	-0.058**	0.041	-0.096***	0.088***	-0.139***	-0.055	-0.141***	-0.005
	(0.025)	(0.026)	(0.028)	(0.028)	(0.034)	(0.040)	(0.033)	(0.033)
b_2	0.005	-0.003	0.000	-0.022***	-0.001	-0.017**	0.002	-0.015**
	(0.005)	(0.004)	(0.006)	(0.005)	(0.007)	(0.008)	(0.007)	(0.006)
b_3	0.107***	0.165***	0.186***	0.109**	0.280***	0.351***	0.277***	0.048
	(0.023)	(0.022)	(0.026)	(0.054)	(0.033)	(0.040)	(0.033)	(0.038)
b_4	-0.018	0.000	-0.004	0.000***	0.000	-0.011***	-0.022	0.000
	(0.013)	(0.011)	(0.015)	(0.000)	(0.019)	(0.004)	(0.019)	(0.000)
α_0	0.023***	0.025***	0.025***	0.022***	0.016**	0.037***	0.018***	0.107**
	(0.007)	(0.007)	(0.008)	(0.006)	(0.007)	(0.009)	(0.007)	(0.004)
α_1	0.073***	0.091***	0.086***	0.138***	0.079***	0.131***	0.080***	0.057***
	(0.011)	(0.013)	(0.014)	(0.019)	(0.015)	(0.020)	(0.015)	(0.011)
β_1	0.909***	0.890***	0.890***	0.853***	0.913***	0.834***	0.909***	0.934***
	(0.013)	(0.015)	(0.015)	(0.018)	(0.016)	(0.024)	(0.016)	(0.013)
ρ	0.674		0.574		0.035		0.109	
λ_1	0.016		0.011		0.010		0.015	
λ_2	0.978		0.981		0.296		0.002	
df	6.714		5.426		6.378		7.211	
Log-likelihood	-5580.503		-5648.747		-5960.044		-6099.705	

Note: This table presents parameter coefficients under the DCC MGARCH$(1,1)$ model. Parameters are estimated simultaneously between day returns of Germany and the UK (the US, Japan as well as Hong Kong) with respect to different fundamental proxies (f_1 and f_2) according to Eq. (2.18) and Eq. (2.19). Stars indicate significance as follows: *10%, **5%, ***1%. In parentheses: standard errors.

Table 2.6: Night returns with global interconnectedness

Coefficient	UK	Germany	UK	Japan	UK	Hong Kong
(A) Night returns with f_1 as the fundamental proxy						
b_0	-0.030	-0.008	-0.003	-0.058	-0.017	0.050**
	(0.022)	(0.030)	(0.024)	(0.052)	(0.024)	(0.023)
b_1	-0.156**	-0.122**	-0.208***	-0.105	-0.205***	-0.260***
	(0.065)	(0.049)	(0.076)	(0.105)	(0.076)	(0.063)
b_2	0.010*	-0.009**	0.006	-0.178***	0.003	-0.008**
	(0.005)	(0.004)	(0.006)	(0.016)	(0.006)	(0.004)
b_3	-0.040	0.063***	0.087***	0.099**	0.036	0.059**
	(0.025)	(0.022)	(0.031)	(0.048)	(0.030)	(0.026)
b_4	0.000***	0.000***	0.000**	-0.021**	0.000**	0.000***
	(0.023)	(0.015)	(0.000)	(0.009)	(0.000)	(0.000)
α_0	0.008***	0.025***	0.004***	0.022**	0.005***	0.010***
	(0.002)	(0.007)	(0.001)	(0.010)	(0.002)	(0.004)
α_1	0.029***	0.049***	0.018***	0.042***	0.022***	0.059***
	(0.006)	(0.009)	(0.004)	(0.012)	(0.005)	(0.011)
β_1	0.955***	0.933***	0.971***	0.943***	0.967***	0.940***
	(0.008)	(0.010)	(0.005)	(0.017)	(0.007)	(0.011)
ρ	0.512		0.204		0.154	
λ_1	0.029		0.027		0.013	
λ_2	0.928		0.894		0.961	
df	4.080		4.532		3.911	
Log-likelihood	-4878.089		-5121.652		-5237.738	
(B) Night returns with f_2 as the fundamental proxy						
b_0	0.010	0.038	0.030	-0.059	0.022	0.093***
	(0.017)	(0.029)	(0.018)	(0.052)	(0.018)	(0.021)
b_1	0.003	-0.001	-0.057**	0.161**	-0.028	0.013
	(0.025)	(0.024)	(0.028)	(0.064)	(0.027)	(0.018)
b_2	0.010*	-0.010***	0.006	-0.178***	0.003	-0.008**
	(0.005)	(0.004)	(0.006)	(0.016)	(0.006)	(0.004)
b_3	-0.047*	0.055***	0.082***	0.107**	0.028	0.042
	(0.025)	(0.021)	(0.031)	(0.048)	(0.030)	(0.026)
b_4	0.011	0.001	-0.002	-0.012***	0.007	0.000
	(0.009)	(0.015)	(0.011)	(0.005)	(0.011)	(0.000)
α_0	0.008***	0.026***	0.004***	0.027***	0.006***	0.010***
	(0.002)	(0.007)	(0.001)	(0.012)	(0.002)	(0.004)
α_1	0.029***	0.049***	0.018***	0.045***	0.023***	0.062***
	(0.006)	(0.009)	(0.004)	(0.013)	(0.005)	(0.012)
β_1	0.954***	0.931***	0.971***	0.936***	0.966***	0.937***
	(0.008)	(0.011)	(0.006)	(0.020)	(0.007)	(0.011)
ρ	0.514		0.199		0.158	
λ_1	0.030		0.025		0.014	
λ_2	0.927		0.901		0.959	
df	4.098		4.518		3.934	
Log-likelihood	-4882.328		-5122.664		-5247.037	

Note: This table presents parameter coefficients under the DCC MGARCH(1, 1) model. Parameters are estimated simultaneously between night returns of the UK and Germany (Japan as well as Hong Kong) with respect to different fundamental proxies (f_1 and f_2) according to Eq. (2.18) and Eq. (2.19). Stars indicate significance as follows: *10%, **5%, ***1%. In parentheses: standard errors.

2.5.3 Robustness and Outlook

We consider a modified demand function for feedback traders as well as different calculation methods for the deviation between the fundamental value and the price in order to verify a sufficient robustness check. With regard to the second verification, the impact of fundamental traders does not change when using a cumulative or weighted moving average of prices instead of actual prices. Based on this, the demand of fundamental traders is rather affected by the underlying fundamental proxy than by the calculation of prices. Koutmos (2012) uses two-year moving averages and the "Fed model"[38] as an additional proxy. He confirms that this proxy is only reliable for the US market. Based on the modification, we consider a demand function of feedback traders that is affected by sentiment in a multiplicative way:

$$Y_{2,t} = [\gamma B_t + \beta(1 - B_t)](R_{t-1} - r_f) \qquad \forall \gamma > 0. \tag{2.21}$$

Here, the existence of chasing investors depends on the sentiment state and varies for price changes if $\gamma \neq \beta$. Relying on the feedback trading model, we could not find tangible changes for day and night returns with respect to trading behavior. Therefore, we conclude that our suggested Eq. (2.2) is sufficient as the demand function for feedback traders.

Likelihood ratio (LR) tests are calculated to reinforce the relative explanatory power of an extended model. LR$=-2 * (L_0 - L_1)$ follows a chi-squared distribution[39], where L_0 is the value of the likelihood function under the null hypothesis and L_1 the value of the alternative hypothesis. Koutmos (2012) demonstrates that an extended model provides advantages in matters of explaining the impact of stock price movements. Here, we consider the GARCH model as the nested model and test the significance to alternative GARCH specifications. The EGARCH model yields improved log-likelihood values and performs best for most countries in order to calculate the conditional variance.[40]

Our findings are important in understanding investors' trading behavior and what types of indicators they use during different trading hours. The knowledge about the existence of positive or negative feedback trading is beneficial for traders in any given market. A more rational investor could use the diverse implications arising from day and night returns for own arbitrage opportunities by catching incipient trends in stock prices. Investors with low marginal trading

[38] The model calculates the yield spread between long-term government bonds and market earnings.

[39] *df* depend on the number of parameter restrictions required under the null hypothesis.

[40] All log-likelihood values and LR statistics are presented in Table B.1 and Table B.2 on page 98f. in the Appendix.

costs can develop profitable conditional strategies and time their buy and sell orders better. Thus, strategies have to be adjusted with respect to trading hours and the stock market of interest. An interesting aspect concerning strategies arises by considering intraday data and other asset classes. Market participants diversify their portfolio allocation and do not only invest in stocks. Therefore, a mixed combination with adjusted demand functions has to be developed. As indicated in subsection 2.4.1, more renowned sentiment measures can reveal a closer relationship between fundamental and feedback traders in addition. This interaction clarifies mainly why strategies differ across time and countries. All extensions suggest a future research involving behavioral preferences. A detailed discussion of this complex process, however, would exceed the scope of this chapter.

2.6 Conclusion

Feedback trading strategies are used to illustrate how new information based on returns is reflected in the markets. Positive feedback traders buy (sell) stocks in a rising (falling) market while negative feedback traders adhere to a contrarian strategy. Stock return autocorrelation increases in the presence of feedback traders. The more feedback traders are active the higher is the autocorrelation due to a greater effect on prices.
The feedback trading model, as historically proposed by Sentana and Wadhwani (1992), is based on the existence of two types of investors. In order to be accurate while using their model, we consider three heterogeneous groups and develop a dynamic feedback trading model by applying a DCC MGARCH model. Thereby, we offer an informative framework for exploring feedback trading from two new angles. First, we decompose the overall return premium into day and night returns. Second, we assume interconnectedness between multiple countries and introduce a global feedback trading model. Dynamic effects with spillovers shed light on investors' strategy and provide an alternative framework about price fluctuations.

Overall, findings confirm the presence of positive feedback traders in daily stock market prices. However, feedback trading strategies differ across markets when distinguishing between day and night returns. Positive feedback trading tends to occur more often for day than night returns due to a decline in trading volume overnight. Market closures affect the mean and standard deviation of returns because investors need to be compensated for the risk when trading overnight. The limited possibility of liquidation constricts night returns to be higher than day returns. A decline in the trading volume during the night diminishes the at-

tractiveness of feedback behavior and the amount of chasing investors is reduced. Feedback traders behave similarly in Japan and Hong Kong during a full trading day, whereas Germany and the UK register a strong contrariness. No feedback trading is found to exist in Germany during trading hours. Simultaneously, the parameter coefficient b_2 is significantly negative for night returns under f_1 as the fundamental proxy. An inverse relationship is found in the UK. During the day, investors follow a positive feedback trading strategy. Missing feedback trading during the night reflects a change in investors' behavior in this particular country. This evidence supports our hypothesis that feedback trading strategies differ between the day and night given a specific market.

Relying on the global feedback trading model, evidence for changing trading behavior is provided by examining the interaction of specific markets. For day returns, feedback trading still does not exist in Germany for all estimations as well as both fundamental proxies. In addition, the former positive feedback trading only disappears in the UK. Global interconnectedness between both markets induces a decline of trend chasing investors in the UK. Positive and statistically significant feedback trading is present in the US, Japan, and Hong Kong even with respect to day returns in Germany. As a result, we identify two important findings for day returns – investors' behavior in Germany is not influenced by all other countries according to feedback trading, but day returns from Germany have an impact on trend chasing investors in the UK. The picture is partly different when considering night returns. We find one-sided spillover effects from Germany to the UK when comparing with the benchmark model. The parameter coefficient b_2 is significantly positive for the UK with respect to f_1 and f_2. This also means that it is negative feedback trading that tends to occur in this particular country when including interactions with Germany.

All in all, feedback trading strategies differ between the day and night with spillover effects arising from market interactions. Future research should include a broader range of different asset classes and more renowned sentiment measures to understand behavioral preferences as well as intraday data to capture spillover effects during contemporaneous stock exchange openings.

Chapter 3

Global asset market interdependencies: A dynamic interaction[1]

3.1 Introduction

The uncovered interest parity (UIP) predicts a one-to-one relationship between interest rate differentials and expected changes in exchange rates. Unlike the covered interest parity, investors do not hedge against possible currency depreciation. Currency carry trading, often referred to as the forward premium anomaly (puzzle), presents a widespread trading strategy. Investors borrow low-yielding currencies with the aim to invest in high-yielding ones in order to benefit from arbitrage opportunities. Thereby, investors' behavior is reflected by risk sentiment, appetite, and fundamentals when seeking for high-yielding investments. Shocks globally change the risk premium and affect expected returns due to market dependencies. Consequently, the volatility increases, spills over, and boosts the effect. A simple relationship does not exist and the interconnectedness is complex in nature. For this reason, we explore the interaction between currency carry trading, futures, exchange rates, and commodities in an informative framework.

Exactly this interaction is oftentimes neglected by researchers and the main focus lies on (linear) interdependencies among time series without external shocks. Naturally, a shock can be considered as a signal and changes investors' risk appetites across markets. In order to fill this gap in the literature and to be in line with previous research, we apply a vector autoregression (VAR) model to capture possible interdependencies and analyze dynamic interactions between asset

[1]This chapter is based on Kusen and Rudolf (2019b). Global asset market interdependencies: A dynamic interaction. *Unpublished working paper*.

classes through structural shocks. The implementation of a global VAR (GVAR) model with generalized impulse response functions (GIRFs) helps to understand interactions by taking global interconnectedness into account. The aim is to model economic and financial interdependencies at national and international level with global indicators. The implementation of a GVAR model with GIRFs has not been considered to our knowledge in the literature.

The structure of this chapter is as follows. Section 3.2 presents previous empirical work concerning currency carry trading with respect to the UIP and interactions with different asset classes. In section 3.3, we state the methodology of the applied GVAR model as an extension in matters of global interconnectedness. The underlying data and descriptive statistics are presented in section 3.4. The model framework with individual specifications and the analysis comprise the main part of this chapter and consist of various statistics and dynamic interrelationships among variables in sections 3.5 and 3.6, respectively. A continuative outlook with ideas for further research is highlighted in addition. We conclude with section 3.7.

3.2 Literature Review

As history has shown, Japan faced low interest rates and the yen was a favorable carry trade funding currency before the financial crisis starting in 2007. Risk on the market reversed money flows because of investors' decisions under uncertainty. The yen currency inflated and depressed currency values with high-yielding margins. A fall in the US stock market was the consequence after the unwinding of the yen carry trade.

The forward premium puzzle has long been under investigation and relies on spot as well as forward rates. The law of one price is another way of justifying the concept of interest rate parities. Unfortunately, the UIP relationship fails to hold for different markets as well as in an integrated world. Most empirical studies confirm the existence of arbitrage opportunities and speculation.[2] It seems obvious that investors are risk-averse and uncertain about volatility's magnitude of their investment return due to the presence of exchange risk. Difficulties arise in finding a connection between trade and exchange rate exposure through time.

Engel (1996) rejects the forward exchange rate unbiasedness from the current floating exchange rate era and states that standard models cannot explain the

[2]See Plantin and Shin (2008), Burnside et al. (2008), Brunnermeier et al. (2008), or Jylhä and Suominen (2011) for a broader discussion.

implied risk premium. Most popular and justified explanations are peso problems (Lewis (1995)), irrational behavior of market participants (Cavaglia et al. (1993) and Engel (1996)), speculative bubbles (Frankel and Rose (1994)), liquidity (Brunnermeier and Pedersen (2008)), central banks (Engel (1996)), exchange risk (Hodrick (1987)), risk premium shocks (Fama (1984) and Meredith and Chinn (1998)), transaction costs (Baldwin (1990)), persistent autocorrelations (Baillie and Bollerslev (2000)), danger of currency crashes (Brunnermeier et al. (2008)), and the presence of country- and time-specific risk premium (Froot and Frankel (1989) and Sarantis (2006)).

As Baillie and Chang (2011) state, momentum and carry trade strategies explain market deviations from UIP during increased volatility. Furthermore, speculative dynamics magnify on the part of investors because carry trade losses are more likely during higher market volatility. In addition, financial integration induces bidirectional volatility interactions between markets according to the gradual information diffusion hypothesis proposed by Hong and Stein (1999). Spillover effects arise, among others, across international stock markets (Baele (2005) and Rapach et al. (2013)) and from commodity prices to stock markets (Driesprong et al. (2008)), especially during periods of high volatility. Melvin and Taylor (2009) show that an increased volatility in stock markets and in other asset classes has a deleveraging effect on currency markets. Thereby, the implied volatility depends on the relative size of carry profits and the adjustment speed. Empirical results of Christiansen et al. (2011) show that systematic risk depends on carry trade strategies with a high exposure to the stock market. Tse and Zhao (2012) examine the dependency between currency carry trades and US stocks. They confirm that currency carry trading is correlated with stock return movements due to volatility spillovers. Spillovers flow one-sided from the stock market and stronger in periods of high volatility. However, volatilities are driven by same factors, like funding or liquidity constraints, and mainly during cyclical shocks. In contrast to contemporaneous relations, Lu and Jacobsen (2016) focus on predictive relations of currencies, stock prices, and commodity prices by using VAR innovations. They find that common influences endure across markets with delayed reactions of investors.

Nevertheless, forecasts of investors' behavior across asset classes and for a large number of countries are rarely considered in a global setting. We offer a novel approach by exploring a dynamic interaction between currency carry trading, futures, exchange rates, and commodities in a multi-country setting. Here, the approach sheds light on both investors' behavior as well as spillover effects arising from shocks. Thereby, we examine whether the UIP hypothesis is still absent. In

former studies, the GVAR model has been applied to macroeconomics (Pesaran et al. (2004), Dees et al. (2007), Pesaran et al. (2007), Pesaran et al. (2009), and Dovern et al. (2016)), capital flows (Boschi (2012)), fiscal imbalances (Caporale and Girardi (2013)), output growth (Chudik et al. (2016)), industrial sectors (Hiebert and Vansteenkiste (2010)), oil prices (Basher et al. (2012)), bank capital (Groß et al. (2016)), credit supply (Eickmeier and Ng (2015)), energy supply (Souto et al. (2014)), bond markets (Favero (2013)), labor markets (Hiebert and Vansteenkiste (2010)), and housing markets (Vansteenkiste (2007)).

3.3 Methodology

In order to analyze spillovers between currency carry trading, futures, exchange rates, and commodities, we apply the GVAR model introduced by Pesaran et al. (2004) as an appropriate approach to reveal interdependencies and effects on investors' behavior after shocks. The main advantage compared to general VAR models lies in the practical global modeling framework. We provide a comprehensive methodical description and undertake a closer examination of the models.

3.3.1 VARX

The VAR model is attributed to Sims (1980) and captures joint dynamics of multiple variables without requiring strong identification assumptions. The VAR model with exogenous variables (VARX) can be seen as an extension. Without loss of generality, we state the general VARX(p_i,q_i) for region i with only two lags for the sake of simplification.[3] The individual VARX(2,2) can be expressed as:

$$\boldsymbol{x}_{i,t} = \boldsymbol{a}_{i0} + \boldsymbol{a}_{i1}t + \boldsymbol{\Phi}_{i1}\boldsymbol{x}_{i,t-1} + \boldsymbol{\Phi}_{i2}\boldsymbol{x}_{i,t-2} + \boldsymbol{\Lambda}_{i0}\boldsymbol{x}^*_{i,t} + \boldsymbol{\Lambda}_{i1}\boldsymbol{x}^*_{i,t-1} + \boldsymbol{\Lambda}_{i2}\boldsymbol{x}^*_{i,t-2} + \boldsymbol{u}_{i,t} \quad (3.1)$$

with $\boldsymbol{x}_{i,t}$ as a $k_i \times 1$ vector of domestic variables and $\boldsymbol{x}^*_{i,t}$ as a $k^*_i \times 1$ vector of foreign variables for $i = 0, 1, 2, ..., N$ regions at time t.[4] Thereby, foreign variables are calculated by:

$$\boldsymbol{x}^*_{i,t} = \sum_{j=0}^{N} w_{ij}\boldsymbol{x}_{j,t} \quad (3.2)$$

[3]The Akaike information criterion (AIC) is used to select the appropriate lag orders p_i and q_i for the domestic and foreign variables, respectively.

[4]Region 0 is assumed to be the numeraire region. Furthermore, we assume that $x^*_{i,t}$ is weakly exogenous at the individual country level because most countries are small to the world economy, but endogenous to the whole model. Global exogenous variables are not important for the estimation of the country-specific variables and are considered as weakly exogenous as well.

with $w_{ii} = 0$ and $\sum_{j=0}^{N} w_{ij} = 1$ for $j = 0, 1, 2, ..., N$.[5] $\boldsymbol{\Phi}_{i1}$ and $\boldsymbol{\Phi}_{i2}$ are the $k_i \times k_i$ matrices of the lagged coefficients of domestic variables, whereas $\boldsymbol{\Lambda}_{i0}$, $\boldsymbol{\Lambda}_{i1}$, and $\boldsymbol{\Lambda}_{i2}$ are the $k_i \times k_i^*$ matrices of coefficients of foreign variables with respect to region i. $\boldsymbol{a}_{i0}$ and $\boldsymbol{a}_{i1}$ are coefficient matrices of size $k_i \times 1$ for the intercepts and linear trends, respectively. $\boldsymbol{u}_{i,t}$ is a $k_i \times 1$ Gaussian noise vector of idiosyncratic country-specific shocks with $\boldsymbol{u}_{i,t} \sim \mathcal{N}(\boldsymbol{0}, \sum_{ii})$.

Covariance stationary implies that the first two moments of the variables are finite and time-invariant. In order to estimate all parameters, we introduce an vector error correction model (VECM) to investigate interrelationships both in the short- and long-run.[6] Engle and Granger (1987) establish a theorem by connecting autoregressive and error correction representations for cointegrated systems. A lagged error correction vector is added from the cointegrating regressions to express the disequilibrium from the long-run relationship. The length of cointegrating vector terms is equal to the number of cointegrating relationships between all series. The error correction form of the applied VARX(2,2) can be written as:

$$\triangle \boldsymbol{x}_{i,t} = \boldsymbol{c}_{i0} - \boldsymbol{\alpha}_i \boldsymbol{\beta}_i^T [\boldsymbol{z}_{i,t-1} - \boldsymbol{\gamma}_i (t-1)] + \boldsymbol{\Lambda}_{i0} \triangle \boldsymbol{x}_{i,t}^* + \boldsymbol{\Gamma}_i \triangle \boldsymbol{z}_{i,t-1} + \boldsymbol{u}_{i,t}, \tag{3.3}$$

where $\boldsymbol{z}_{i,t} = (\boldsymbol{x}_{i,t}^T, \boldsymbol{x}_{i,t}^{*T})^T$ is a $(k_i + k_i^*) \times 1$ vector of domestic and country-specific foreign variables at t, $\boldsymbol{\alpha}_i$ a $k_i \times r_i$ loading matrix, and $\boldsymbol{\beta}_i$ a $(k_i + k_i^*) \times r_i$ matrix of cointegrating vectors both of rank r_i. $\boldsymbol{c}_{i0}$ is a $k_i \times 1$ vector of fixed intercepts, $\boldsymbol{\gamma}_i$ a $(k_i + k_i^* + 1) \times 1$ vector of fixed constants, and $\boldsymbol{\Gamma}_i$ a $k_i \times 1$ vector associated with domestic and country-specific foreign variables. The corresponding long-run multiplier matrix is rank deficient and defined as:

$$\boldsymbol{\Pi}_i = \boldsymbol{\alpha}_i \boldsymbol{\beta}_i^T. \tag{3.4}$$

For estimation purposes, $\boldsymbol{z}_{i,t}$ is treated weakly exogenous and integrated of order one ($I(1)$).[7] Thereby, the rank of $\boldsymbol{\Pi}_i$ is denoted by $r_i = rank(\boldsymbol{\Pi}_i) \leq k_i$ and specifies the actual number of cointegrating relationships. The r_i error correction terms of the model can be specified by:

[5] We use fixed weighted averages for the underlying variables. A time-varying model would require a time-related evolution for future weights.

[6] Only the first differences of the variables are covariance stationary in our model. If several series are $I(1)$, a simple regression in first differences is misspecified without capturing long-run tendencies.

[7] Chudik and Pesaran (2011) decompose a high dimensional VAR model into country-specific VARXs by assuming a finite number of dominant countries and show that $\boldsymbol{x}_{i,t}$ is weakly exogenous.

$$\boldsymbol{\xi}_{i,t} = \boldsymbol{\beta}_i^T(\boldsymbol{z}_{i,t} - \boldsymbol{\gamma}_i t) = \boldsymbol{\beta}_{ix}^T \boldsymbol{x}_{i,t} + \boldsymbol{\beta}_{ix^*}^T \boldsymbol{x}_{i,t}^* - (\boldsymbol{\beta}_i^T \boldsymbol{\gamma}_i)t, \tag{3.5}$$

where $\boldsymbol{\xi}_{i,t}$ is a mean zero $r_i \times 1$ vector and illustrates deviations from the long-run equilibrium. Cointegration in country-specific models can occur within $\boldsymbol{x}_{i,t}$, between $\boldsymbol{x}_{i,t}$ and $\boldsymbol{x}_{i,t}^*$, or across $\boldsymbol{x}_{i,t}$ and $\boldsymbol{x}_{j,t}$ for $i \neq j$. Therefore, VARXs can be separately estimated for each country with respect to $\boldsymbol{x}_{i,t}^*$. Given an estimated cointegrating vector $\boldsymbol{\beta}_i$, all remaining parameters can be obtained by ordinary least squares (OLS) regressions of the form:

$$\triangle \boldsymbol{x}_{i,t} = \boldsymbol{c}_{i0} + \boldsymbol{\delta}_i ECM_{i,t-1} + \boldsymbol{\Lambda}_{i0} \triangle \boldsymbol{x}_{i,t}^* + \boldsymbol{\Gamma}_i \triangle \boldsymbol{z}_{i,t-1} + \boldsymbol{u}_{i,t}, \tag{3.6}$$

where $ECM_{i,t-1}$ are the error correction terms of region i for the corresponding r_i at time $t-1$.

3.3.2 GVAR

The GVAR model combines individual VECMs by linking all domestic and foreign variables in a consistent manner for forecast purposes. As discussed earlier, individual estimations are done on a country by country basis. On the contrary, all variables are endogenous in the global system and can be solved for the world as a whole in the GVAR(2) model. We use Eq. (3.1) for each region i to illustrate the model by:

$$\boldsymbol{A}_{i0} \boldsymbol{z}_{i,t} = \boldsymbol{a}_{i0} + \boldsymbol{a}_{i1} t + \boldsymbol{A}_{i1} \boldsymbol{z}_{i,t-1} + \boldsymbol{A}_{i2} \boldsymbol{z}_{i,t-2} + \boldsymbol{u}_{i,t}, \tag{3.7}$$

where $\boldsymbol{A}_{i0} = (\boldsymbol{I}_{k_i}, -\boldsymbol{\Lambda}_{i0})$, $\boldsymbol{A}_{i1} = (\boldsymbol{\Phi}_{i1}, \boldsymbol{\Lambda}_{i1})$, and $\boldsymbol{A}_{i2} = (\boldsymbol{\Phi}_{i2}, \boldsymbol{\Lambda}_{i2})$ with $k_i \times (k_i + k_i^*)$ dimensions and $rank(\boldsymbol{A}_{i0}) = k_i$. Furthermore, $\boldsymbol{z}_{i,t}$ is defined as:

$$\boldsymbol{z}_{i,t} = \begin{pmatrix} \boldsymbol{x}_{i,t} \\ \boldsymbol{x}_{i,t}^* \end{pmatrix} = \boldsymbol{W}_i \boldsymbol{x}_t, \tag{3.8}$$

where $\boldsymbol{x}_t = (\boldsymbol{x}_{0,t}^T, \boldsymbol{x}_{1,t}^T, ..., \boldsymbol{x}_{N,t}^T)^T$ is a $k \times 1$ vector with all endogenous variables for $k = \sum_{i=0}^{N} k_i$ and $\boldsymbol{W}_i$ a $(k_i + k_i^*) \times k$ matrix related to the weights w_{ij}. Eq. (3.7) can now be written as:

$$\begin{aligned} \boldsymbol{A}_{i0} \boldsymbol{W}_i \boldsymbol{x}_t &= \boldsymbol{a}_{i0} + \boldsymbol{a}_{i1} t + \boldsymbol{A}_{i1} \boldsymbol{W}_i \boldsymbol{x}_{t-1} + \boldsymbol{A}_{i2} \boldsymbol{W}_i \boldsymbol{x}_{t-2} + \boldsymbol{u}_{i,t} \\ \boldsymbol{G}_0 \boldsymbol{x}_t &= \boldsymbol{a}_0 + \boldsymbol{a}_1 t + \boldsymbol{G}_1 \boldsymbol{x}_{t-1} + \boldsymbol{G}_2 \boldsymbol{x}_{t-2} + \boldsymbol{u}_t. \end{aligned} \tag{3.9}$$

Given the regular matrix $\boldsymbol{G}_0$[8], the inverse $\boldsymbol{G}_0^{-1}$ is applied for Eq. (3.9) in order

[8] $\boldsymbol{G}$ is a $k \times k$ matrix and of full rank. Chudik et al. (2016) investigate the case when the matrix $\boldsymbol{G}_0$ is not invertible and conclude that additional equations, which can be specified as VAR models, are required to uniquely determine $\boldsymbol{x}_t$.

to obtain the GVAR(2) model:

$$\boldsymbol{x}_t = \boldsymbol{b}_0 + \boldsymbol{b}_1 t + \boldsymbol{F}_1 \boldsymbol{x}_{t-1} + \boldsymbol{F}_2 \boldsymbol{x}_{t-2} + \boldsymbol{\epsilon}_t, \tag{3.10}$$

where $\boldsymbol{F}_1 = \boldsymbol{G}_0^{-1}\boldsymbol{G}_1$, $\boldsymbol{F}_2 = \boldsymbol{G}_0^{-1}\boldsymbol{G}_2$, $\boldsymbol{b}_0 = \boldsymbol{G}_0^{-1}\boldsymbol{a}_0$, $\boldsymbol{b}_1 = \boldsymbol{G}_0^{-1}\boldsymbol{a}_1$, and $\boldsymbol{\epsilon}_t = \boldsymbol{G}_0^{-1}\boldsymbol{u}_t$. The covariance matrix $\sum_\epsilon$ is in general unrestricted and can be computed by:

$$\widehat{\sum}_\epsilon = \boldsymbol{G}_0^{-1}\widehat{\sum}_u \boldsymbol{G}_0^{-1^T} \tag{3.11}$$

since $\boldsymbol{\epsilon}_t = \boldsymbol{G}_0^{-1}\boldsymbol{u}_t$, $\widehat{\sum}_u = \sum_{t=1}^{T} \hat{\boldsymbol{u}}_t \hat{\boldsymbol{u}}_t^T / T$, and $\hat{\boldsymbol{u}}_t$ is a $k_i \times 1$ vector of estimated residuals.[9]

3.4 Data

3.4.1 Sample

We use monthly observations of futures contracts for stock price indices traded on major stock exchanges in developed as well as emerging markets. The country sample in this chapter consists of Australia, Brazil, Canada, Germany, Hong Kong, India, Japan, Malaysia, Mexico, New Zealand, Norway, Singapore, South Africa, South Korea, Sweden, Switzerland, the United Kingdom, the United States, Taiwan, Thailand, and Turkey. With the focus on not only developed countries we can infer a better understanding of spillover effects under global interconnectedness. To be more precise, we examine mutual interactions of investors given their trading behavior and the interdependent effects of returns from a global perspective. The data is collected from Thomson Reuters Datastream as well as Thomson Reuters Eikon on a monthly basis and spans the period from May 1, 2007, to August 1, 2017, with 124 observations. As generally applied, returns are calculated in logarithmic first differences and expressed in percent after adjusting all prices for cash distributions and reinvestments. Thereby, settlement and opening prices are used to obtain particular monthly returns. The United States dollar (USD) is the applied currency basis by taking the average between the bid and ask exchange rate.[10]

The foreign exchange market (FX) provides a diverse array of carry trade indices and certificates with an overwhelming differentiation in the construction.[11] We make use of the most approved and consistent currency carry trading

[9] $\widehat{\sum}_u$ is a positive definite matrix because the dimension of all endogenous variables is smaller than the time series dimension ($k < T$).

[10] The USD is the most traded currency and involved in over 80% of all foreign exchange transactions – amounting to approximately USD2.7 trillion per day.

[11] A domination is observed in the market by a handful of systemically important banks. Thereby, weighting, number and type of used currencies, or degree of leverage are important specifications for the provided trading products.

strategies available on the FX. Understanding specific FX instruments is the first step to disclose major differences for investors' decisions and to highlight interdependencies as well as spillover effects. To be in line with former research[12], we collect closing prices from Datastream for the following strategies: Deutsche Banks's PowerShares DB G-10 Currency Harvest (DBH), Barclays Capital's Intelligent Carry Index (ICI), UBS G-10 Carry Trade Total Return Index (TTRI), and HSBC Global FX Carry Index (GCI). The DBH portfolio, as the simplest strategy, contains a short (long) position in the three lowest-yielding (highest-yielding) currencies from the Group of Ten (G-10) by using an equally weighted approach.[13] Long positions are financed by equal short positions in the ICI portfolio by applying an individual weighting scheme from -100% to 100% for each G-10 currency with a mean-variance optimization process. The TTRI, as a cash-neutral investment strategy, avoids an adverse drawdown during market stress by considering several risk factors and volatility spreads. Like for the DBH, the three lowest-yielding (highest-yielding) currencies are selected from the G-10 universe. In contrast, the GCI portfolio consists of 32 liquid currencies[14] and applies two algorithm mechanisms. Volatility is monitored by defining different world states and a stop-loss trigger excludes currencies below a certain threshold. Every currency carry trading strategy is reallocated every month by applying the underlying rule approaches.

We use monthly exchange rates per USD for the following foreign currencies: the Australian dollar (AUD), the Brazilian real (BRL), the Canadian dollar (CAD), the Swiss franc (CHF), the euro (EUR), the British pound sterling (GBP), the Hong Kong dollar (HKD), the Indian rupee (INR), the Japanese yen (JPY), the South Korean won (KRW), the Mexican peso (MXN), the Malaysian ringgit (MYR), the Norwegian krone (NOK), the New Zealand dollar (NZD), the Swedish krona (SEK), the Singapore dollar (SGD), the Thai baht (THB), the Turkish lira (TRY), the New Taiwan dollar (TWD), and the South African rand (ZAR). Currencies are grouped according to established classifications and economic areas – the Middle East and Africa (MEA), Latin America (LATAM), Asia, and G-9.[15]

Oil and gold prices, as global indicators, are taken from Datastream on a monthly frequency for the same sample period. The West Texas Intermediate

[12]See Burnside et al. (2008), Clarida et al. (2009), or Barroso and Santa-Clara (2015) among others for a broader discussion in matters of carry trade strategies.

[13]The G-10 currencies are the euro, the United States dollar, the Australian dollar, the New Zealand dollar, the Canadian dollar, the Japanese yen, the Swiss franc, the Norwegian krone, the Swedish krona, and the British pound sterling.

[14]The universe includes not only G-10 currencies but also currencies from Asia, Latin America, the Middle East, India, and Africa.

[15]Table C.1 groups all treated countries according to established classifications and economic areas on page 108 in the Appendix.

is commonly used as the underlying commodity benchmark for crude oil and expressed in USD per barrel. Individual fundamentals influence the market supply and demand for this particular oil future contract traded on the New York Mercantile Exchange. The gold price is determined on the London Bullion Market and expressed in USD per troy ounce. We consider gold as a safe haven for investors who secure investment portfolios against market swings.[16]

For the construction of the region-specific weighting matrix, we consider both exports and imports as the total trade. The trading volume measures the integration of the respective economic area and influences the performance of stock markets because investors base their decisions not only on fundamental but also on economic factors. A relative share of the global amount is calculated for each individual country for the matrix in order to compute foreign-specific variables as depicted in Eq. (3.8). Simultaneously, the relative share for each individual country is linked to the selected regions and shows the dependency on the remaining countries as well as regions.

3.4.2 Descriptive Statistics

Investors rely on carry trade strategies in order to make use of arbitrage opportunities. Therefore, the identification of suitable currencies goes along with positive future returns by forming expectations about appreciations and depreciations. Table 3.1 depicts the descriptive statistics of spot exchange rates in USD within and across economic areas. Panel (A) indicates that returns of exchange rates behave unequal in the G-9 portfolio. NZD, JPY, and CHF depreciate while all other rates appreciate when considering the mean. The change in value lies between 0.336% and -0.186% for EUR and CHF, respectively, and is 0.077% for the whole subsample by using an equal weighting. Same findings are observed for panel (B), whereat more currencies depreciate in terms of the USD and induce a smaller positive return on average. Panel (C) and (D) illustrate differences due to only positive exchange rate returns. MEA and LATAM have the highest mean on average with values of 0.644% and 0.371%, respectively. This circumstance is not surprisingly because these currencies tend to be more speculative and can attract investors with higher returns. The Jarque-Bera (J-B) test illustrates the fluctuation of returns by matching the skewness and kurtosis to the normal distribution. As indicated, the following two statements result. First, rather smaller values occur for G-9 and Asia countries. Second, returns of spot exchange rates are normally distributed for SEK, NOK, JPY, and THB. The smallest (largest) value of 1.344 (73.235***) is identified for THB and MXN, respectively.

[16]Both commodities have a huge effect on global economies and have to be considered when analyzing dynamic interactions with arbitrage opportunities.

Table 3.1: Descriptive statistics of spot exchange rates

	Mean	St.Dev.	Skewness	Kurtosis	J-B
(A) G-9					
EUR	0.115	3.140	0.254	3.869	5.193*
GBP	0.336	2.941	0.477	5.031	25.805***
AUD	0.029	4.154	0.400	4.340	12.482***
NZD	−0.009	4.391	0.272	4.893	19.882***
SEK	0.154	3.634	−0.040	3.777	3.127
NOK	0.227	3.543	0.267	3.570	3.127
CAD	0.096	2.975	0.333	4.947	21.701***
JPY	−0.068	2.962	0.365	3.532	4.182
CHF	−0.186	3.374	0.082	6.376	58.549***
∅	0.077	3.457	0.268	4.482	12.729***
(B) Asia					
HKD	−0.001	0.132	−0.497	6.130	55.273***
MYR	0.183	2.434	0.499	2.959	5.113*
KRW	0.151	3.853	0.248	6.084	50.005***
INR	0.359	2.631	0.233	4.195	8.432**
SGD	−0.093	1.921	0.690	6.103	59.107***
TWD	−0.079	1.551	0.199	4.064	6.614**
THB	−0.036	1.658	0.255	2.953	1.344
∅	0.068	2.026	0.232	4.641	14.904***
(C) MEA					
TRY	0.770	3.881	0.861	6.331	72.062***
ZAR	0.517	4.704	0.413	4.605	16.699***
∅	0.644	4.293	0.637	5.468	39.535***
(D) LATAM					
BRL	0.346	4.750	0.510	4.248	13.314***
MXN	0.395	3.575	0.977	6.236	73.235***
∅	0.371	4.163	0.744	5.242	37.109***

Note: This table provides the sample statistics for each currency using monthly exchange rates per USD from May 1, 2007, to August 1, 2017, with a sample size of 123. All series are in logarithmic first differences and expressed as a percentage on a monthly basis. J-B test matches the skewness and kurtosis to the normal distribution. Stars indicate significance as follows: *10%, **5%, ***1%.

In general, differences in returns mainly occur in and between the applied subgroups. Thereby, return distribution is relevant to investors' behavior. The currency universe varies between carry trade strategies and offers different investment possibilities due to diverse portfolio compositions. For arbitrage opportunities, currencies with negative (positive) returns should be used as funding (investment) currencies. As provided in Table 3.2, most carry trade strategies exhibit negative returns on average in our sample. Only the GCI portfolio has a positive return of 0.35% on a monthly basis. This carry strategy is the only

portfolio that incorporates a broad range of currencies and benefits from positive returns arising from traded currencies in MEA as well as LATAM. The rate of return for commodities is in contrast positive due to a high value of 0.517% for gold. Simultaneously, the return distribution of gold is normally distributed. As discussed earlier, gold serves as a safe haven and the underlying price rises during market downturns. Oil prices have been falling since 2014 and returns disclose a high volatility with a t-value from the J-B test of 37.749***. Returns for futures indicate opposed trends with respect to the economic area. Positive values correspond to the US, G-9, and Asia in contrast to negative values for MEA and LATAM. The smallest (largest) mean is observed for LATAM (the US) with a value of -0.444 (0.410). As expected, all return distributions are skewed and leptokurtotic relative to the normal distribution. The J-B test discloses values between 15.751*** and 43.140*** for MEA and the US, respectively. With these outcomes in mind, it is important to examine correlations in order to obtain significant results for our further analysis in a global setting.

Table 3.2: Descriptive statistics of investment strategies

	Mean	St.Dev.	Skewness	Kurtosis	J-B
(A) Carry trade strategies					
DBH	−0.101	3.181	−0.753	5.723	49.624***
ICI	−0.329	3.780	−0.592	3.912	11.447***
TTRI	−0.033	4.255	−0.354	3.934	7.040**
GCI	0.350	1.713	0.506	4.552	17.593***
∅	−0.028	3.232	−0.298	4.530	21.426***
(B) Commodities					
Gold	0.517	5.634	−0.368	3.295	3.222
Oil	−0.220	10.218	−0.846	5.122	37.749***
∅	0.149	7.926	−0.607	4.209	20.486***
(C) Futures					
US	0.410	5.240	−0.914	5.253	43.140***
G-9	0.103	6.200	−0.780	5.386	41.649***
Asia	0.305	6.550	−0.467	4.947	23.899***
MEA	−0.188	8.688	−0.356	4.602	15.751***
LATAM	−0.444	8.851	−0.589	5.170	31.245***
∅	0.037	7.106	−0.621	5.072	31.137***

Note: This table illustrates the sample statistics for carry trade strategies, commodities, and futures using returns from May 1, 2007, to August 1, 2017, with a sample size of 123. All series are in logarithmic first differences and expressed as a percentage on a monthly basis. J-B test matches the skewness and kurtosis to the normal distribution. Stars indicate significance as follows: *10%, **5%, ***1%.

Table 3.3 presents the Pearson correlation coefficients for returns of selected carry trade strategies, commodities, and futures contracts grouped according to economic regions. First of all, most correlations are highly significant positive on a 1% level and imply a strong dependency between return types and a global interconnectedness. Carry trade strategies depend differently between each other with values ranging from 0.207^{**} to 0.700^{***} for ICI with GCI and TTRI, respectively. We infer that returns of both ICI and TTRI behave similarly during the observed period. This fact results from the underlying currency portfolio and the individual weighting scheme. The interaction with futures returns on an cross-area basis is not less interesting. Not surprisingly, returns of G-9 are more significantly positive correlated with returns of DBH (0.789^{***}), ICI (0.703^{***}), and TTRI (0.482^{***}) than for all other futures subsamples because these portfolios only contain G-10 currencies. When considering the GCI portfolio, the highest value of 0.472^{***} is estimated for futures contracts of MEA. In general, the dependency diminishes according to the applied carry trade strategy – the same transitive relation exists for all futures subgroups. Given a particular subgroup, the correlation coefficient for returns is larger for DBH than for ICI. Simultaneously, the coefficient is greater for ICI than for TTRI and is smaller for GCI than for TTRI. We identify that returns of futures contracts are highly correlated due to global interconnectedness. The smallest (largest) value is 0.736^{***} (0.903^{***}) for MEA and the US (G-9 and Asia). In addition, we consider dependencies with and among commodities as global indicators. Gold is significantly positive correlated with oil on a 1% level (0.259^{***}). Oil always exhibits higher correlations than gold when considering futures. Values range from 0.492^{***} (0.042) to 0.646^{***} (0.324^{***}) for oil (gold). As with futures, the same finding holds for carry trade strategies and an insignificant correlation of 0.042 is found for GCI with respect to gold. For the carry trade portfolios, gold (oil) correlates most strongly with ICI (DBH) with a value of 0.318^{***} (0.609^{***}). The choice for an appropriate currency carry trade strategy is not easy due to the large diversity. However, all mentioned findings suggest to use DBH as the representative strategy in the further analysis.[17]

3.5 Model Framework and Specification

We disclose interdependencies within a global interconnectedness between carry trade strategies, futures, exchange rates, and commodities by offering various statistics for the applied GVAR model in the following. First, we give a brief overview of the GVAR modeling framework and outline individual models. An

[17] Tse and Zhao (2012), Cheung et al. (2012), Fung et al. (2013), or Lee and Chang (2013) employ the same carry trade strategy.

Table 3.3: Correlation matrix for returns

	DBH	ICI	TTRI	GCI	US	G-9	Asia	MEA	LATAM	Gold	Oil
DBH	1										
ICI	0.673***	1									
TTRI	0.354***	0.700***	1								
GCI	0.426***	0.207**	0.230**	1							
US	0.759***	0.566***	0.339***	0.279***	1						
G-9	0.789***	0.703***	0.482***	0.352***	0.901***	1					
Asia	0.738***	0.631***	0.442***	0.394***	0.818***	0.903***	1				
MEA	0.712***	0.630***	0.473***	0.472***	0.736***	0.827***	0.864***	1			
LATAM	0.760***	0.671***	0.465***	0.447***	0.784***	0.870***	0.880***	0.810***	1		
Gold	0.152*	0.318***	0.156*	0.042	0.042	0.187**	0.254***	0.227**	0.324***	1	
Oil	0.609***	0.543***	0.312***	0.278***	0.526***	0.646***	0.560***	0.492***	0.590***	0.259***	1

Note: This table contains returns of currency carry strategies, commodities, and futures contracts for stock price indices. Returns of futures are equally weighted within an economic area. Stars indicate significance as follows: *10%, **5%, ***1%.

examination on the part of weights, unit root tests, cointegration rank statistics, lag orders, contemporaneous effects, and eigenvalues follows afterwards.

Individual country VECMs with core domestic variables are grouped according to the introduced five economic areas and the US is considered as the numeraire region with $i = 0$. Thereby, all region-specific models include the following variables:

$$\begin{aligned} q_{i,t} &= ln(F_{i,t}), \quad e_{i,t} = ln(E_{i,t}), \\ p_t^o &= ln(P_t^o), \quad p_t^g = ln(P_t^g), \quad p_t^c = ln(P_t^c), \end{aligned} \tag{3.12}$$

where

$$\begin{aligned} F_{i,t} &= \text{Futures price index of region } i \text{ at time } t \text{ in USD}, \\ E_{i,t} &= \text{Exchange rate of region } i \text{ at time } t \text{ in USD}, \\ P_t^o &= \text{Price of oil at time } t \text{ in USD}, \\ P_t^g &= \text{Price of gold at time } t \text{ in USD, and} \\ P_t^c &= \text{Price of carry trade strategy at time } t \text{ in USD}. \end{aligned}$$

$q_{i,t}$ and $e_{i,t}$ are considered as domestic and $p_{i,t}^g$, $p_{i,t}^o$, and $p_{i,t}^c$ as global variables.[18] Foreign variables $x_{i,t}^* = (q_{i,t}^*, e_{i,t}^*)^T$ are constructed as weighted averages according to Eq. (3.8) with $k_i^* = 5$ for all regions i.

Table 3.4 presents the region-specific weighting matrix and controls for foreign-specific variables. As it can be seen, the degree to which one economic area depends on the remaining areas is relatively diverse – weights vary from 0.7% to 74.6%. G-9 is much more integrated with the rest of the world than Asia, MEA, or LATAM. The US, Asia, and MEA have similar shares ranging between 54.1% and 59.5% with respect to G-9. For a given economic area, the largest two regions (measured by trade volume) account for more than three-quarters of the total trade. Hence, transmissions of shocks play a key role through second-round effects and via all remaining markets.

The Augmented Dickey-Fuller (ADF) test is implemented to test the stationarity of variables for log-levels, first as well as second differences. Thereby, a variable can either contain a unit root (null hypothesis) or is generated by a stationary process (alternative hypothesis). Table 3.5 reports that all variables included in the region-specific models are $I(1)$ with respect to domestic, foreign, and

[18]Note that $e_{0,t}$ is not defined for the base region because we use exchange rates in USD. Furthermore, we allow for lagged feedback with the inclusion of feedback variables in the GVAR model. To be more precise, $q_{i,t-1}$ and $e_{i,t-1}$ have a time-delayed impact on p_t^g, p_t^o, and p_t^c.

global differentiation. Therefore, we can distinguish between short- and long-run relations.

Table 3.4: Weighting matrix

	US	G-9	Asia	MEA	LATAM
US	0	0.583	0.342	0.167	0.746
G-9	0.541	0	0.566	0.595	0.154
Asia	0.170	0.294	0	0.203	0.093
MEA	0.014	0.060	0.036	0	0.007
LATAM	0.275	0.063	0.056	0.035	0

Note: Weights are based on trade shares of exports as well as imports and displayed in columns by economic areas, whereby every column sums up to one. The underlying fixed year is 2017.

Table 3.5: ADF unit root statistics

Variables	US	G-9	Asia	MEA	LATAM	Variables	Global
q	-3.099	-2.848	-3.380	-2.637	-2.609	p^o	-2.775
$\triangle q$	-4.153^{***}	-7.186^{***}	-5.160^{***}	-7.865^{***}	-7.104^{***}	$\triangle p^o$	-6.049^{***}
$\triangle^2 q$	-12.567^{***}	-10.828^{***}	-10.805^{***}	-9.047^{***}	-11.093^{***}	$\triangle^2 p^o$	-9.265^{***}
e		-2.571	-2.094	-2.451	-2.247	p^g	-1.973
$\triangle e$		-4.327^{***}	-5.637^{***}	-8.388^{***}	-6.644^{***}	$\triangle p^g$	-8.452^{***}
$\triangle^2 e$		-10.439^{***}	-8.784^{***}	-8.687^{***}	-7.683^{***}	$\triangle^2 p^g$	-10.334^{***}
q^*	-2.776	-3.390	-3.437	-3.478^{**}	-3.241	p^c	-2.976
$\triangle q^*$	-7.181^{***}	-4.268^{***}	-7.553^{***}	-7.383^{***}	-4.172^{***}	$\triangle p^c$	-6.823^{***}
$\triangle^2 q^*$	-10.932	-11.738	-11.352	-11.064	-12.077	$\triangle^2 p^c$	-9.395^{***}
e^*	-2.021	-2.132	-2.554	-2.498	-2.443		
$\triangle e^*$	-6.930^{***}	-5.468^{***}	-4.504^{***}	-4.507^{***}	-4.982^{***}		
$\triangle^2 e^*$	-7.598^{***}	-9.419^{***}	-10.152^{***}	-10.291^{***}	-7.776^{***}		

Note: ADF unit root statistics include a linear trend and are obtained on the basis of univariate AR(p) models in levels with $p \leq 5$. The difference operator is denoted by $\triangle$. Stars indicate significance as follows: *10%, **5%, ***1%.

Many choices exist when dealing with individual region-specific models concerning lag orders, number of cointegrating relationships, and possible long- as well as short-run restrictions. When fixing the lag orders p_i and q_i, we would theoretically consider 16 GVAR models due to uncertainty regarding the number of cointegration.[19] If we only assume uncertainty with respect to p_i and q_i with $p \max_i = q \max_i \leq 2$, we end up with $2^5 = 32$ models. An even larger number of models would result for uncertainty in both specifications. Hence, we provide cointegration rank statistics and lag orders of p_i and q_i according to AIC in Table 3.6 and Table 3.7, respectively, to overcome this issue.

The cointegration relation is based on Johansen (1995) with a restricted intercept for the estimation of the maximum eigenvalues and trace statistics in

[19]The calculation is based on $k_i = 2$ ($k_i = 1$) endogenous variables for $i > 1$ ($i = 0$) with $N + 1 = 5$ – obtaining $\prod_{i=0}^{N} k_i$ different GVAR models.

panel (A) and (B), respectively.[20] Here, level series are used for endogenous as well as weakly exogenous variables. Both tests suggest unambiguously one cointegration relation for Asia. We infer that only short-run relations tend to exist among domestic variables and/or between domestic and foreign variables. Therefore, we can neglect overidentifying restrictions on cointegration relations.

Table 3.6: Cointegration rank statistics

H_0	H_1	US	G-9	Asia	MEA	LATAM
(A) Maximum eigenvalues						
$r = 0$	$r = 1$	**24.842**	**30.767**	39.304	**25.721**	**23.899**
$r < 1$	$r = 2$		13.844	**15.982**	13.774	16.263
(B) Trace						
$r = 0$	$r > 1$	**24.842**	**44.611**	55.286	**39.494**	**40.162**
$r < 1$	$r \geq 2$		13.844	**15.982**	13.774	16.263

Note: The cointegration rank statistic compares r cointegration vectors (null hypothesis) against (at most) $r + 1$ vectors (alternative hypothesis). Unrestricted intercepts and restricted trend coefficients with $I(1)$ endogenous as well as exogenous variables are included in the model. Critical values are obtained from MacKinnon et al. (1999) and statistics in bold represent acceptance of the null hypothesis at the 95% confidence level.

We select VARX orders according to the AIC with the objective to include sufficient lags in the model. Otherwise, a misspecification would either lead to a loss on the part of degrees of freedom (df) or cause autocorrelation in the residuals while employing too many or too few lags, respectively. As shown in Table 3.7, for most regions a VARX(1,1) specification seems to be satisfactory. However, a VARX(2,1) and VARX(2,2) are favored by the AIC for the US and Asia, respectively.

All examined statistical test results so far allow for consistent estimations of comovements among domestic and foreign variables. Hence, we investigate contemporaneous effects of foreign variables on domestic counterparts, where the estimations can be interpreted as impact elasticities between domestic and foreign variables.[21] As it can be seen in Table 3.8, all elasticities are significant even

[20] It should be noted that the trace statistic has better power properties than the maximum eigenvalues statistic for small samples. Cheung and Lai (1993) or Ho and Sorensen (1996) demonstrate less robust deviations from normal errors by applying Monte Carlo simulations.

[21] Consistent estimations are achieved at least for variables where the residual serial correlation test is not significant. Following Godfrey (1978a,b), we perform the F-version of the familiar Lagrange multiplier (LM) statistic to detect residual serial correlation in region-specific VARX models. Not provided calculations support that most regressions pass the test at the 95% level.

Table 3.7: VARX order

p_i	q_i	US	G-9	Asia	MEA	LATAM
1	1	295.462	**661.381**	669.284	**525.160**	**528.256**
1	2	293.659	658.035	670.532	519.402	524.018
2	1	**296.550**	665.674	686.452	523.680	525.412
2	2	293.722	654.985	**670.857**	517.597	523.672

Note: AIC is used to select the lag orders p_i and q_i for domestic and foreign variables, respectively. The model with the highest value (in bold) is chosen with respect to the economic area.

at the 1% level and have a positive sign. To be more precise, a 1% change of the corresponding foreign-specific variable q^* leads to an increase between 0.87% and 1.106% on q. As expected and consistent with former studies, equity markets show a high degree of contemporaneous interdependence due to the international linkage.

Table 3.8: Contemporaneous effects of foreign variables on domestic-specific counterparts

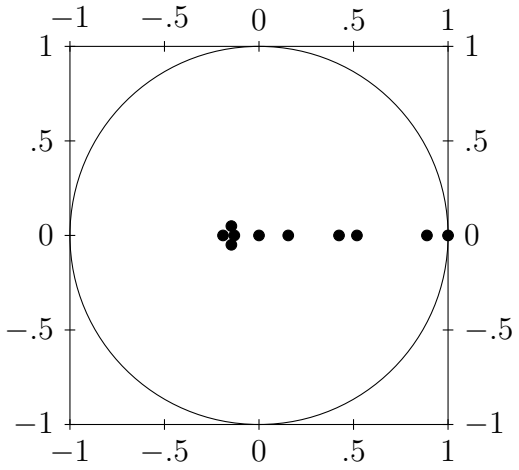
Economic area	q
US	0.870***
	(0.089)
G-9	0.970***
	(0.043)
Asia	1.027***
	(0.074)
MEA	1.106***
	(0.089)
LATAM	1.034***
	(0.090)

Note: Stars indicate significance as follows: *10%, **5%, ***1%. In parentheses: Newey-West heteroskedasticity and autocorrelation consistent standard errors.

Stability of the applied GVAR model is investigated by the moduli of the eigenvalues. According to Hamilton (1994) and Lütkepohl (2005), the system is stable if all values lie either on or inside the unit circle. Figure 3.1 confirms that the model is stationary because most complex eigenvalues $r + c$i are well inside the

unit circle and all roots have an absolute value less or equal than one. As a result, most values converge with a reasonable rate to the former long-run equilibrium after sudden shocks. However, some shocks will have permanent effects on the level of the endogenous variables due to the unit eigenvalues of the system. We estimate the magnitude, direction, and time path of the stable GVAR model in the next section by exploring interrelationships among variables with GIRFs.

Figure 3.1: Eigenvalues



Note: The graph illustrates visually the unit circle and all complex eigenvalues $r + ci$ lie either on or inside the circle. Corresponding moduli of the eigenvalues from the estimated GVAR model are computed as $mod(\lambda_{eig}) = \sqrt{r^2 + c^2}$ and satisfy the eigenvalue stability condition.

3.6 Empirical Results

Following Koop et al. (1996) and further developed by Pesaran and Shin (1998), we make use of GIRFs for VECMs as an alternative approach in contrast to Sims (1980), who introduces orthogonalized impulse response functions (OIRFs). Unlike the OIRF, the GIRF uses the observed distribution of all shocks to integrate out effects of other shocks by considering individual errors without any orthogonalization. The ordering of regions and variables is invariant in addition.[22] Therefore, we assume an absence of strong a priori beliefs and focus on the dynamics of the transmission of shocks with respect to changes in stock price movements, exchange rates, currency carry trading, and commodity prices for gold as well as oil by applying GIRFs. The standard deviation of the reduced form residuals of the respective shock variable depicts the magnitude of the shock. The underlying time horizon comprises the first three years (36 periods) following the shock in order to detect convergence properties. We base the analysis rather

[22] A suitable ordering of OIRFs to the GVAR model is not directly obvious because it is not clear how to order regions even by the use of economic theory and general a priori reasoning.

on bootstrap median estimates and 90% bootstrap confidence bands with 1000 replications than on point estimations due to possible error variance changes.[23]

3.6.1 GIRFs

GIRFs are presented in Figures C.1 - C.5 with respect to the original shock. We first consider a positive one standard error (1 s.e.) shock to equity prices in each economic area. In general, equity prices have no significant effect on gold prices, oil prices, and DBH. However, the positive shock has an effect on stock prices and exchange rates as illustrated in Figure C.1. In contrast to Tse and Zhao (2012), the shock results in positive as well as negative stock price changes and depends on the initial region. In general, we determine a positive response in stock prices from the initial economic area to itself. There is an immediate impact during all periods and the reaction is more pronounced for MEA as well as LATAM. This overreaction reflects a higher volatility in these equity markets. A shock in Asia has a significant negative effect on stock prices in the US and G-9, but the impact dissipates after four months. The same finding holds for the US with respect to MEA. Furthermore, we detect positive one-sided and two-sided responses. To be more precise, the US has an impact on G-9, G-9 on Asia, and LATAM on MEA. A two-sided effect is observed between LATAM (MEA) and Asia with a larger magnitude. This can be explained by the fact that second-round effects intensify the prior shock.

Some exchange rates experience a significant appreciation during the first months, especially from a shock in their origin economic area. The value of currencies with higher (lower) interest rates is positively (negatively) affected by equity prices according to Katechos (2011). We find that currencies with higher interest rates appreciate more often than currencies with lower rates due to speculative dynamics on the market. Consistent with the forward premium puzzle, investors require a higher risk premium in the form of larger interest differentials. For example, G9 has a lower interest rate on average in contrast to LATAM. An unexpected shock in foreign regions results in a significant appreciation of the exchange rate in LATAM, whereas the exchange rate in G9 is only influenced by domestic equity price changes.

Given Figure C.2 and Figure C.3, prices of futures contracts are positively and significantly affected, especially during the first months apart from the US (Asia

[23]The calculation is performed from estimated residuals of the region-specific models by adopting the sample covariance matrix $\widehat{\sum}_u$. A positive definite matrix is required because the applied bootstrap orthogonalizes the estimated residuals $\hat{\boldsymbol{u}}_t$ with the inverse of the Cholesky factor. Bailey et al. (2019) recommend a shrinkage approach in order to obtain an unchanged size of the shock and a reliable estimation when computing error bands.

and MEA) after a positive 1 s.e. shock on gold (oil). As Bénassy-Quéré et al. (2007) discuss, strong economic growth, proxied by equity prices, is influenced by oil prices in emerging markets. Basher and Sadorsky (2006) argue that the relationship depends on the data frequency and is not symmetrical with positive and negative impacts on stock market returns.[24] In contrast to Basher et al. (2012), we find no significant depression of emerging market futures prices after a positive shock to oil. This finding is in line with a fast growing demand for oil. Emerging economies become large players in global financial markets and consume an increasing share of the world's oil. Hence, a sudden shock does not disrupt their strong economic growth opportunities. Futures prices in the US benefit due to the global economic expansion and are less susceptible because the US energy market is nowadays more diversified with renewables and (natural) gas. Kilian and Park (2009) confirm persistent positive effects on cumulative stock returns because an expansion outweighs the drag on the economy arising from higher oil prices. Increased oil prices generate a higher level of activity in the oil producing economy due to an immediate transfer of wealth from oil importers to oil exporters. The US is becoming the world's largest oil exporter while reducing the total oil consumption stemming from imports. Therefore, we can neglect negative trade effects.

The analysis illustrates that fluctuations in oil (gold) prices are largely dependent on oil (gold) itself and gold price fluctuations have a positive impact on oil prices in period two.[25] Furthermore, the significantly positive impulse response effect on DBH lasts a maximum of five months after a shock on oil and gold. One possible reason is the following. Global trade of oil and gold is the biggest creator of USD in the financial market. Increased commodity prices, especially gold prices, act as a signal for inflation. This in turn leads to a loss in value of the USD. Therefore, currency carry trading as an alternative investment source is used by investors to store value and to improve performance in line with Das et al. (2013).

Sujit and Kumar (2011) state that the currency of oil exporting (importing) countries rise (fall) in value after sudden oil price increases. We find no significant transmission after a 1 s.e. shock to oil according to Figure C.2. One possible explanation for this outcome is due to the grouping of the economic areas. Given G-9 for example, Japan relies on oil imports and Canada can be seen as one of the largest oil exporting nations. Therefore, the decrease and increase in value

[24] Oil price increases tend to have a greater influence on the macroeconomic aggregates in absolute terms according to Park and Ratti (2008).

[25] Floating exchange rates are a major source of price instability in the gold market after the dissolution of the Bretton Woods international monetary system. Therefore, only gold prices denominated in USD have an impact on oil prices in contrast to gold prices in EUR according to Sujit and Kumar (2011).

result in a missing cumulative effect on exchange rates. On the contrary, gold has a persisting negative impact on exchange rates as shown in Figure C.3. This explanatory power is more peculiar to gold than to commodities in general as stated by Dooley et al. (1995). Under the assumption that gold can be seen as a safe haven without belonging to a specific region, we argue that prices of gold depend on changing preferences in a particular region.[26] Therefore, the effect on exchange rates illustrates a coterminous relationship with events which change preferences for holding claims on different countries.

Figure C.4 provides GIRFs of a positive 1 s.e. shock to DBH. First of all, we identify significant spillovers from DBH to prices of futures contracts in all economic regions in line with Fung et al. (2013) or Lee and Chang (2013). As we know from Tse and Zhao (2012), market risk sentiment justifies the violation of the UIP hypothesis with respect to currency carry trading and spillovers are associated with the extent of sentiment according to Diebold and Yilmaz (2012). Therefore, currency carry trade returns have an impact on market returns due to a positive correlation with market risk sentiment.

Oil prices seem to be affected more severely. The stimulation takes place in the first four months after the impact and then winds down slowly in a persistent fashion. Commodity price fluctuations seem to be more sensitive to short-term imbalances according to Chen et al. (2010). The USD tends to depreciate against other major currencies in our sample period due to multiple rounds of quantitative easing and the ultra-loose monetary policy resulting from the financial crisis. It is well known that the price of oil tends to rise when the USD weakens as the currency can be seen as the benchmark pricing mechanism for most commodities. Therefore, the shock to DBH unwinds the carry trade and results in higher oil prices.

We identify a significant and positive effect on gold during the first months after the shock. This finding can be explained by the following facts. First, real interest rate expectations are the primary forces for the response profile. Second, diversified currency carry trades tend to be beneficial because the return volatility falls dramatically as Clarida et al. (2009) state. Therefore, it can be assumed that both DBH and gold have similar safe haven properties.

The volatility of actively traded currencies depends on carry trading.[27] Brunnermeier et al. (2008) suggest that currency carry trading affects exchange rate movements and Spronk et al. (2013) show that exchange rates are pushed downward to a larger extent when increasing the effect size of carry trades. In our

[26] Sujit and Kumar (2011) state budget, inflation, government policies, economic conditions, and political conditions as possible reasons.

[27] Gochoco-Bautista et al. (2014) identify that the effect is larger for carry trade than for commodity prices.

case, we exhibit a significant appreciation for all exchange rates, especially for MEA and LATAM. Investors demand a larger risk premium due to interest differentials arising for holding risky interest rate currencies. Thereby, currency appreciations increase the compensation and can be used in part to explain the forward premium puzzle.

A positive 1 s.e. shock to exchange rates has opposite spillover effects compared to DBH as Figure C.5 shows. Futures prices fall significantly in most regions by following the same persistent profile and prices in Asia are always affected.[28] The reason for a price decrease is lower profit due to a direct change in costs and revenues according to Sujit and Kumar (2011). However, the US futures market does not respond to exchange rate movements because of return chasing motives. Albuquerque et al. (2007) highlight that US investors buy foreign shares from local investors when foreign stock prices increase. Therefore, other regions tend to be more open and more strongly affected after shocks than the US as Ehrmann et al. (2011) justify.

We notice a significant depreciation for all exchange rates after a domestic as well as foreign shock. Evidence suggests that persistent spillovers exist across regions because the volatility is not contained in one market. Engle et al. (1990) denote this effect as a "meteor shower". Thereby, exchange rate changes occur due to heterogeneous traders with private information even for immediate market adjustments.[29] Resolving heterogeneous expectations leads to second-round effects as exchange rates in other economic regions respond to the initial shock. Another explanation stems from the fact that policy coordination among economic areas can result in spillovers. Ito et al. (1992) find a meteor shower with increased uncertainty in a foreign country after a change in fiscal policy in a domestic country.

3.6.2 Outlook

The applied GVAR model neglects any form of time-varying weights and thus does not affect the computation of prospective foreign variables over time. Both moving averages as well as current weights could be used for the construction of the region-specific weighting matrix. Dees et al. (2007) adopt three year moving averages and compare foreign variables $x^{*}_{i,t}$ (based on fixed weights) with $x^{**}_{i,t}$ (based on time-varying weights). They conclude that both measures are very highly correlated for levels as well as first differences with correlation coefficients

[28] Pan et al. (2007) find a causal relation from exchange rates to stock markets for most Asian countries in particular during an economic turmoil.

[29] Exchange rate effects are higher the greater the difference in expectations is according to Hogan Jr and Melvin (1994).

being close to unity. Furthermore, other key data should be involved besides trading volume to identify particular shares. Both the volume of contracts traded as well as the open interest for a given futures contract in a particular country illustrate the amount of bought or sold futures and the amount of not closed, expired, or exercised futures contracts, respectively.

The estimation window is dedicated to the availability of carry trade strategies. To avoid a small sample size, further research could examine interactions by adopting daily data in the model. The use of even smaller time-based delimitations provides deeper insights into mutual effects. However, Christiansen et al. (2011) highlight difficulties due to the limited availability of high quality data, especially on short-term interest rates.

Other domestic and global variables are certainly desirable to consider in the model. The CBOE Volatility Index (VIX) is used by Brunnermeier et al. (2008) in order to identify currency crashes. Thereby, the VIX can help to resolve the UIP violation because higher predicted returns automatically reduce the FX return predictability of interest rates. Basher et al. (2012) argue that monetary and fiscal policy affect global financial markets. The inclusion of interest rates as a variable can disclose further impacts because inflation erodes the real value of investments. Investors' behavior may change during inflationary times so that they prefer other assets. Building on this, global shocks can be implemented as a weighted average of all variable shocks – arising from the world economy as a whole. However, one needs to be cautious about the explanatory power and the growing number of possible GVAR model combinations as indicated in section 3.5. The number of long-run relationships is imposed by cointegration. Zero cointegrating restrictions reflect full uncertainty, whereat economic theory suggests overidentifying restrictions for theoretical long-run relations. Garratt et al. (2003) theoretically disclose coherent foundations while studying dynamic properties. However, a detailed long-run structural analysis with all mentioned extensions is beyond the scope of the present chapter.

It becomes clear that the analysis is far more complex and is not just about interest rate differentials. Thus, future research should examine how carry trade affects other assets in different markets during changing volatility states.

3.7 Conclusion

Currency carry trading, often referred to as the forward premium puzzle, presents a widespread trading strategy. Investors borrow low-yielding currencies with the

aim to invest in high-yielding ones in order to benefit from arbitrage opportunities. This in turn justifies the violation of the UIP hypothesis, which predicts a one-to-one relationship between interest rate differentials and expected changes in exchange rates. On this basis, we explore the interaction between currency carry trading, futures, exchange rates, and commodities through structural shocks. GIRFs are used to describe how the variables react over time to exogenous impulses by applying a GVAR model.

A shock to equity prices results in positive as well as negative stock price changes and depends on the initial region. We differentiate between one-sided and two-sided spillovers. In contrast to the UIP prediction, currencies with higher interest rates appreciate more often than currencies with lower rates due to speculative dynamics on the market. Prices of futures contracts are positively affected apart from the US (Asia and MEA) after a shock on gold (oil). A sudden oil price shock does not disrupt strong economic growth opportunities of emerging markets. Prices in the US benefit due to the diversified energy market. An expansion of oil outweighs the drag on the economy arising from higher oil prices. We show that fluctuations in oil (gold) prices depend on oil (gold) and have an impact on DBH. Increased commodity prices tend to act as a signal for inflation and investors consider currency carry trading as an alternative investment source. Gold has a positive (negative) impact on oil (exchange rates). The effect on exchange rates illustrates that investors change their preferences for holding claims on different countries because gold can be seen as a safe haven without belonging to a specific country. DBH influences all variables in our model. Currency carry trading is correlated with market risk sentiment and investors desire a higher risk premium for interest differentials. Therefore, spillovers to prices of futures contracts and an appreciation of exchange rates are in line with the violation of the UIP hypothesis. Commodity prices seem to be affected because of the ultra-loose monetary policy and real interest rate expectations. Futures prices fall after a shock to exchange rates because a direct change in costs and revenue suppresses profits. We argue that return chasing motives explain why investors in the US are less affected. They buy foreign shares from local investors when foreign stock prices increase. All exchange rates depreciate after a domestic as well as foreign shock to exchange rates. Heterogeneous investors with private information exist even for immediate market adjustments. Hence, persistent spillovers spread out as meteor showers across regions.

Conclusion

This dissertation shows that trading decisions change due to dynamic interactions and market conditions. The integration of capital market theory with behavioral finance offers meaningful conclusions and provides explanations for irrational financial decisions. Furthermore, interactions are important to global risk management and asset pricing in order to find advantageous investment opportunities as well as to understand mutual effects arising from trading decisions. Naturally, institutional and private investors will always look for yield pick-ups and alternatives.

Chapter 1 focuses on trading decisions and the Brexit referendum serves as a suitable event in order to depict investors' behavior under distress. Our research verifies that serial correlation exists for index returns by capturing global market movements without to specify an explicit measure of volatility. Market conditions have an effect on investors' behavior. As a direct consequence, domestic traders invest less in stocks while the volatility is rising. Furthermore, asset classes have a mutual relationship among each other when considering absolute and relative returns. Both the return type and the particular state affect the dependency. Thus, investors should consider the whole asset spectrum and incorporate Bitcoin as a new specific asset class for diversification purposes. Given expected durations in a particular volatility state, we argue that Bitcoin can be grouped as in between a safe haven and a risky investment. Even the market crash has no negative impact on returns of Bitcoin. For further research, hedging capabilities against portfolios and asset classes should be investigated for different market conditions.

Chapter 2 extends previous studies on feedback trading by decomposing the overall return premium and introducing the global feedback trading model. The global feedback trading model assumes an interconnectedness between multiple countries and captures spillovers. Empirical results illustrate two important findings. First, feedback trading strategies differ across markets when distinguishing between day and night returns. A decline in trading volume overnight causes positive feedback trading to occur more often for day than night returns because

investors need to be compensated for bearing higher risk. Feedback traders in Germany and the UK behave different during a full trading day in contrast to traders in Japan as well as Hong Kong. We find no feedback trading in Germany during trading hours. Second, feedback trading patterns change when considering an interaction of specific markets. Day returns from Germany have an impact on trend chasing investors in the UK, whereas investors' behavior in Germany is not influenced by all other countries. When considering night returns, one-sided spillovers are present from Germany to the UK. Therefore, rather negative feedback trading tends to occur in this particular country in contrast to the literature. Future work should include more renowned sentiment measures and a broader range of investor groups to understand behavioral preferences. In addition, the employment of intraday data can capture spillover effects during contemporaneous stock exchange openings.

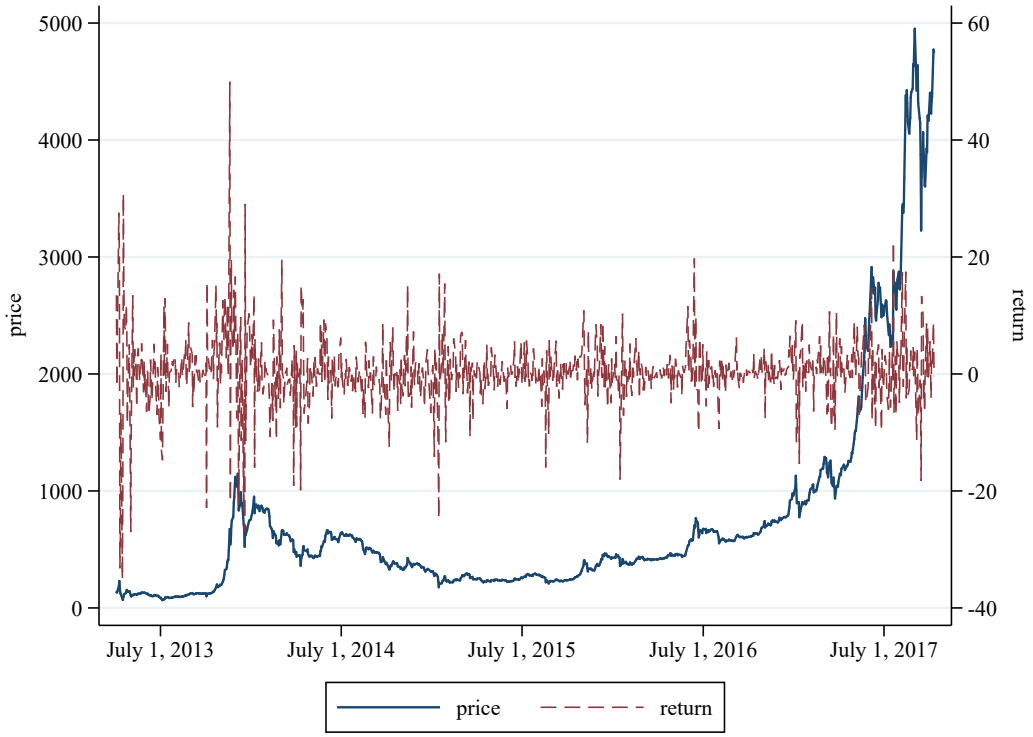
The interaction between currency carry trading, futures, exchange rates, and commodities through structural shocks is explored in chapter 3. Investors desire a higher risk premium after unanticipated shocks due to an increase in the volatility, which in turn spills over to other asset classes and markets. In line with the forward premium puzzle, we disclose an appreciation of exchange rates and spillovers to prices of futures contracts. On the one hand, future prices fall after a positive shock to exchange rates. On the other hand, the direction of futures prices depends on the initial region of the equity shock. Findings support that currencies with lower interest rates appreciate less often than currencies with higher rates. Furthermore, commodity prices and currency carry trading have a mutual impact due to monetary policy implications as well as real interest rate expectations. Currency carry trading depends on oil and gold prices because increased commodity prices tend to act as a signal for inflation. Time-varying weights and other asset classes are desirable to consider in future research in order to obtain a better understanding of dynamic interactions.

Appendix A

Appendix to Chapter 1

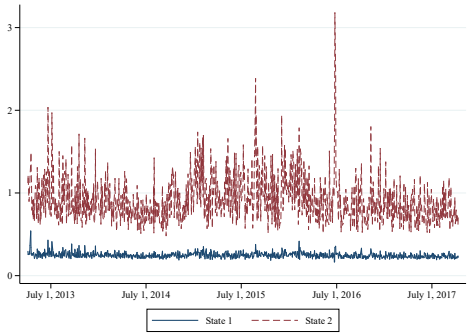
A.1 Figures for Chapter 1

Figure A.1: Closing prices and daily returns of Bitcoin

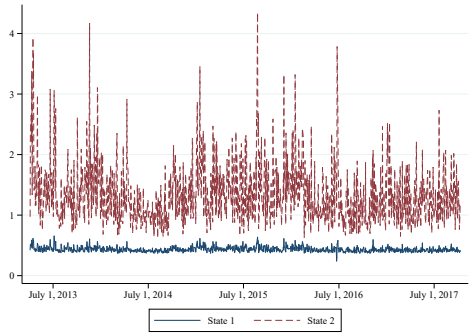


Note: This figure provides closing prices and daily returns of Bitcoin on a daily basis from April 3, 2013 to October 10, 2017. All returns are in logarithmic first differences and expressed as a percentage. Prices are indicated in USD as a common currency basis.

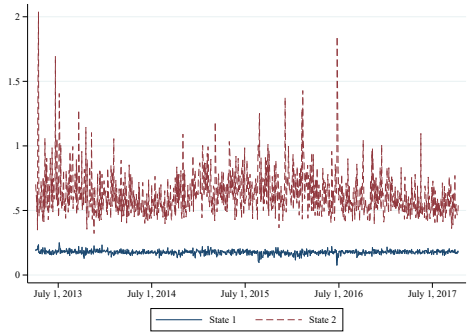
Figure A.2: State-specific predictions of absolute returns



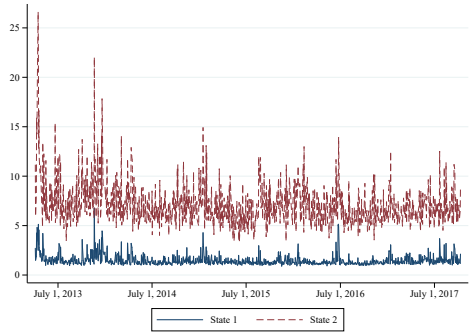
(a) Equity



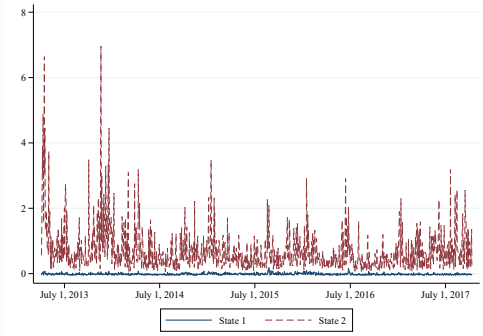
(b) Gold



(c) Currency



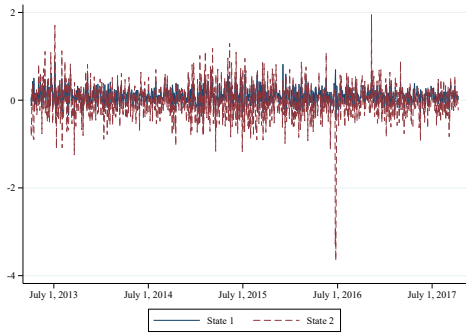
(d) Bitcoin



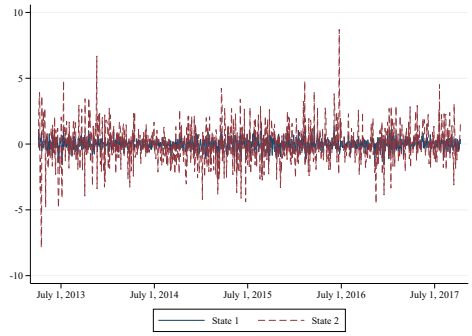
(e) Bond

Note: State-specific one-step predictions of absolute returns are presented on a daily basis from April 3, 2013 to October 10, 2017. All predicted returns are higher in state 2 than in state 1.

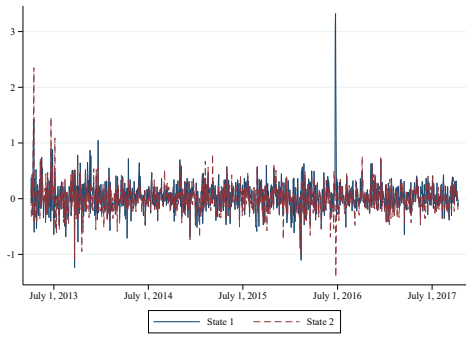
Figure A.3: State-specific predictions of relative returns



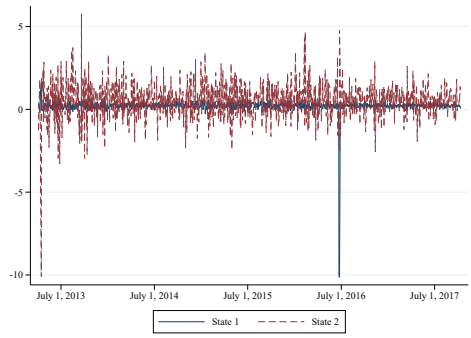
(a) Equity



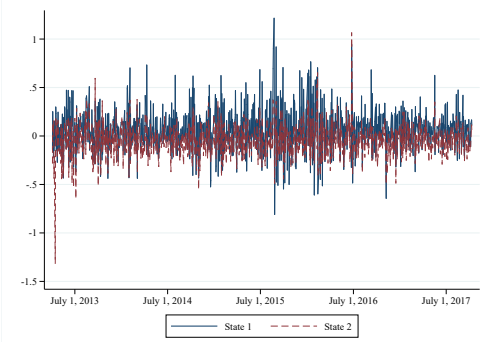
(b) Gold



(c) Currency



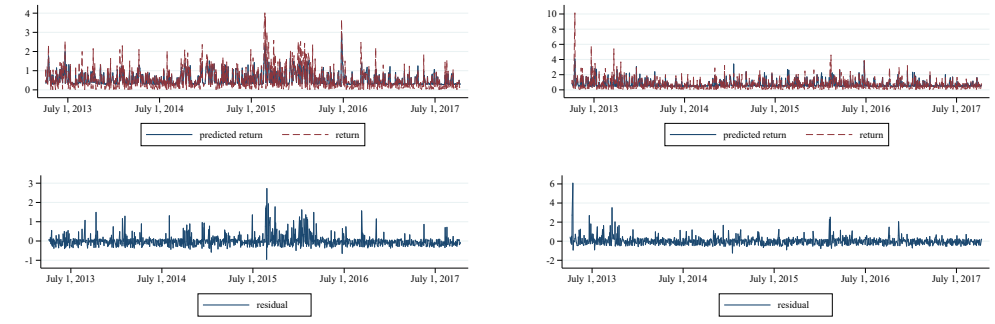
(d) Bitcoin



(e) Bond

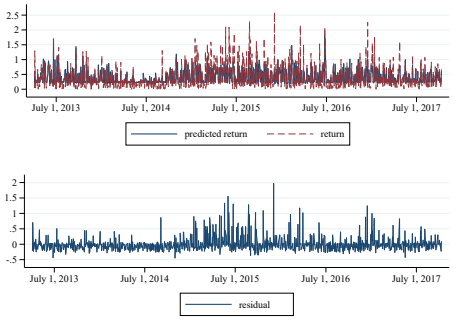
Note: State-specific one-step predictions of relative returns are presented on a daily basis from April 3, 2013 to October 10, 2017. In general, predicted returns are higher in state 2 than in state 1.

Figure A.4: Model fit for absolute returns

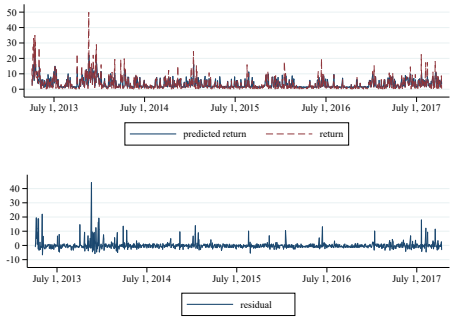


(a) Equity

(b) Gold



(c) Currency

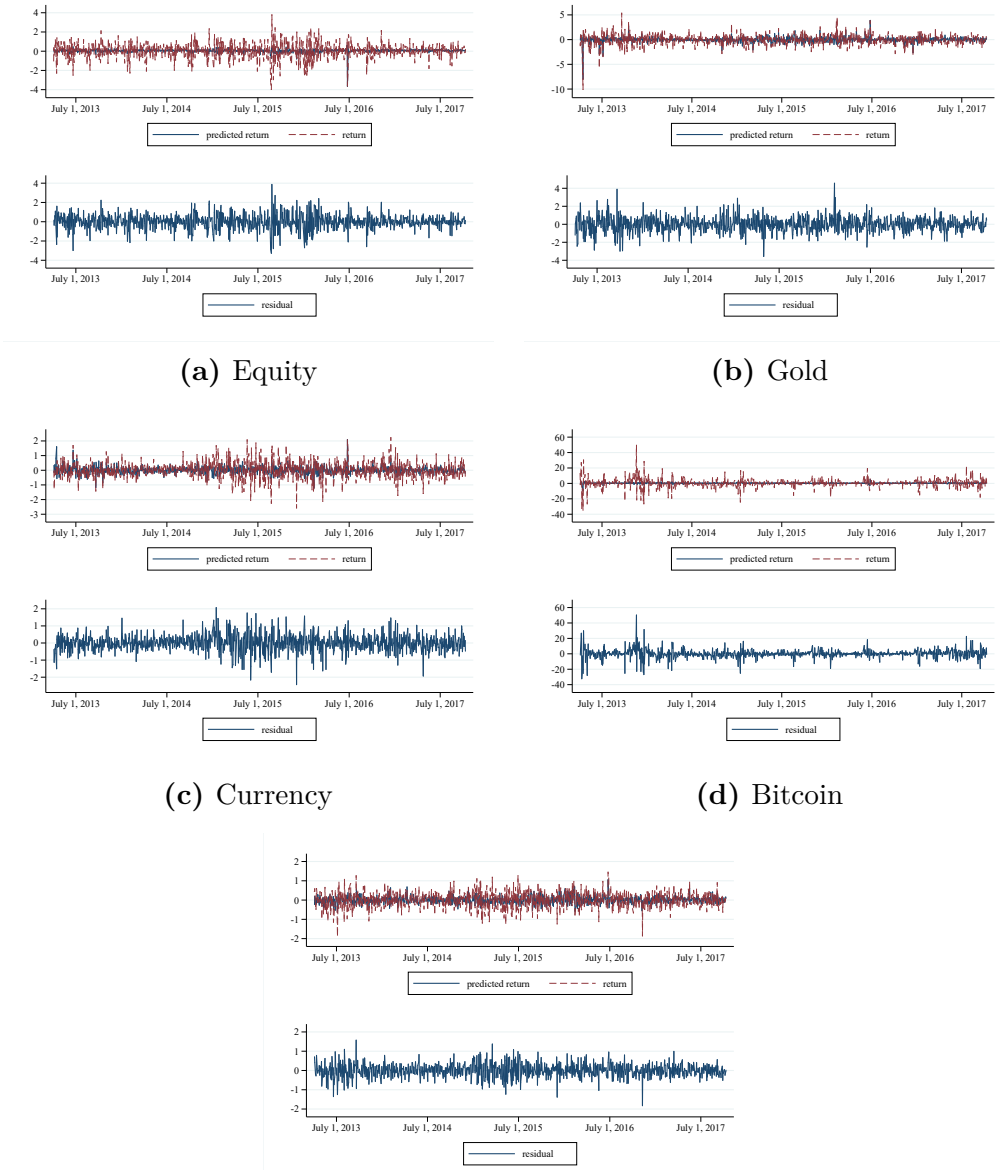


(d) Bitcoin

(e) Bond

Note: This figure illustrates the model fit for absolute returns on a daily basis from April 3, 2013 to October 10, 2017. Fitted values are obtained by using smoothed probabilities given all sample information. Residuals are computed as the difference between predicted and realized returns.

Figure A.5: Model fit for relative returns



(a) Equity

(b) Gold

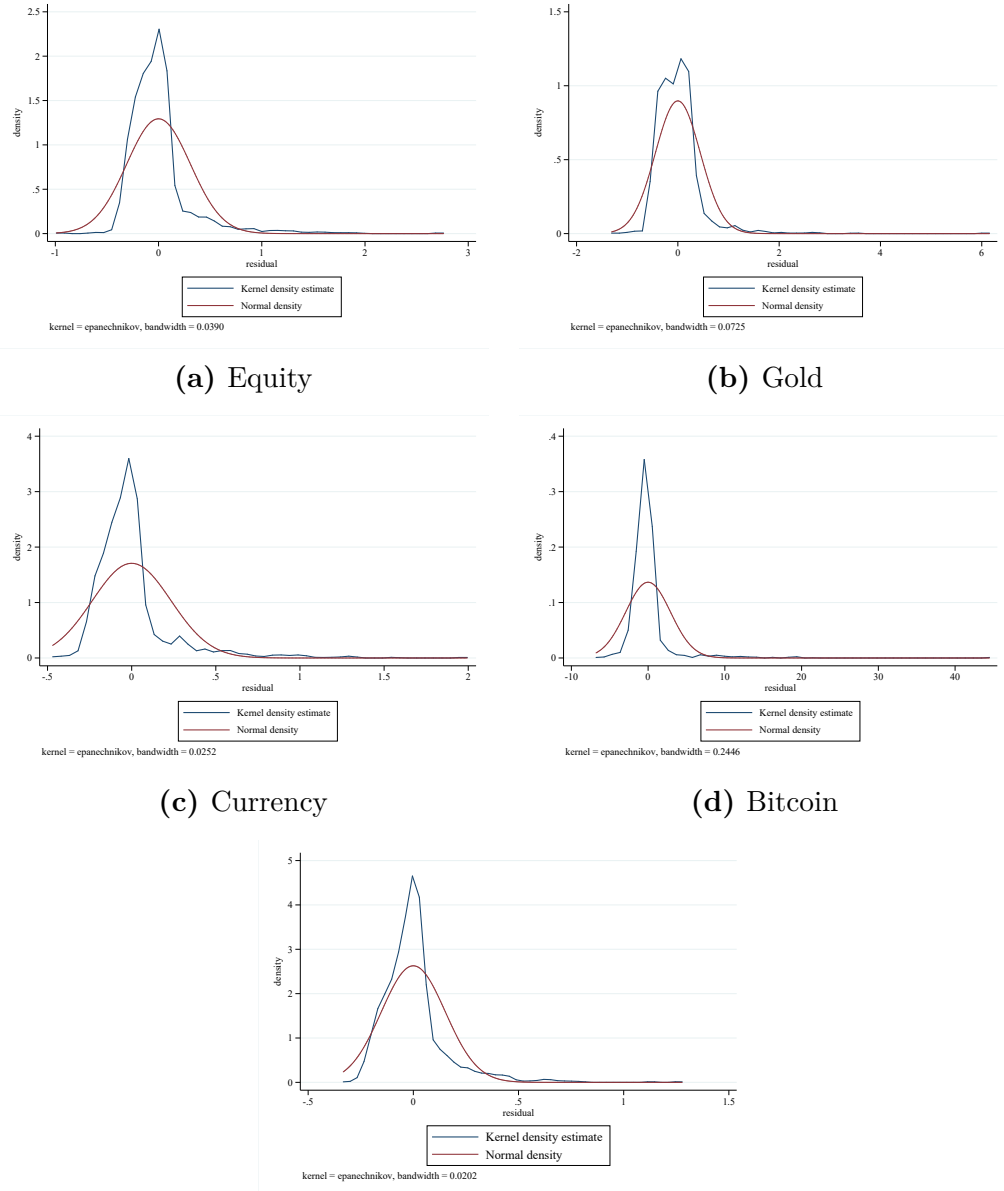
(c) Currency

(d) Bitcoin

(e) Bond

Note: This figure illustrates the model fit for relative returns on a daily basis from April 3, 2013 to October 10, 2017. Fitted values are obtained by using smoothed probabilities given all sample information. Residuals are computed as the difference between predicted and realized returns.

Figure A.6: Kernel density estimation for residuals of fitted absolute returns



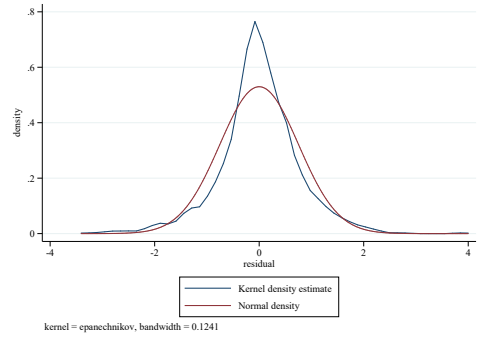
(a) Equity **(b)** Gold

(c) Currency **(d)** Bitcoin

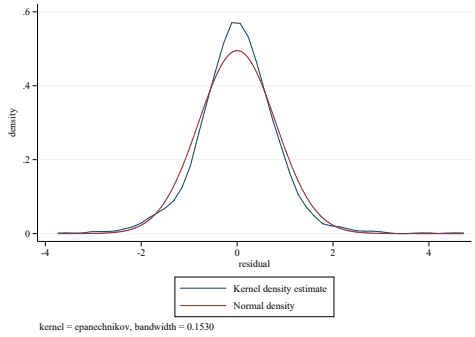
(e) Bond

Note: Kernel density estimations are provided for residuals of fitted absolute returns on a daily basis from April 3, 2013 to October 10, 2017.

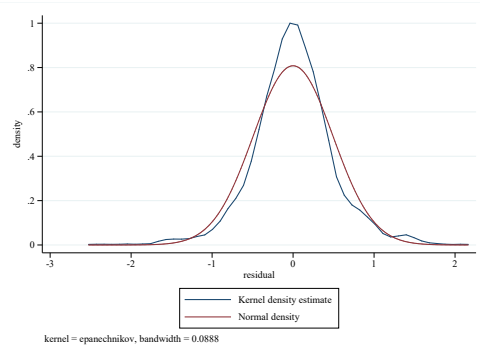
Figure A.7: Kernel density estimation for residuals of fitted relative returns



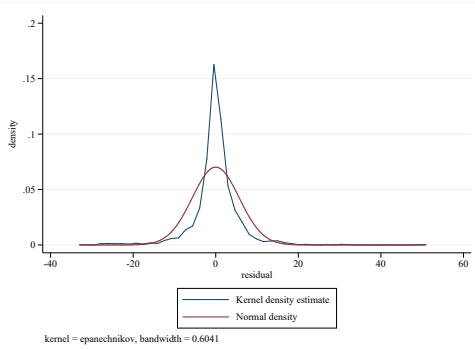
(a) Equity



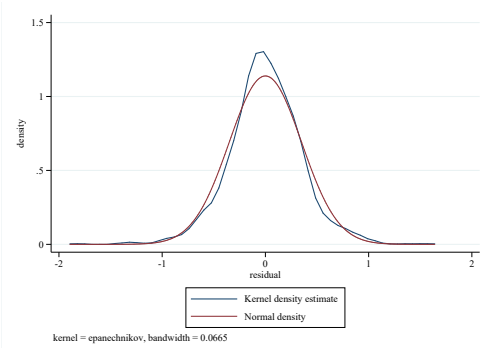
(b) Gold



(c) Currency



(d) Bitcoin



(e) Bond

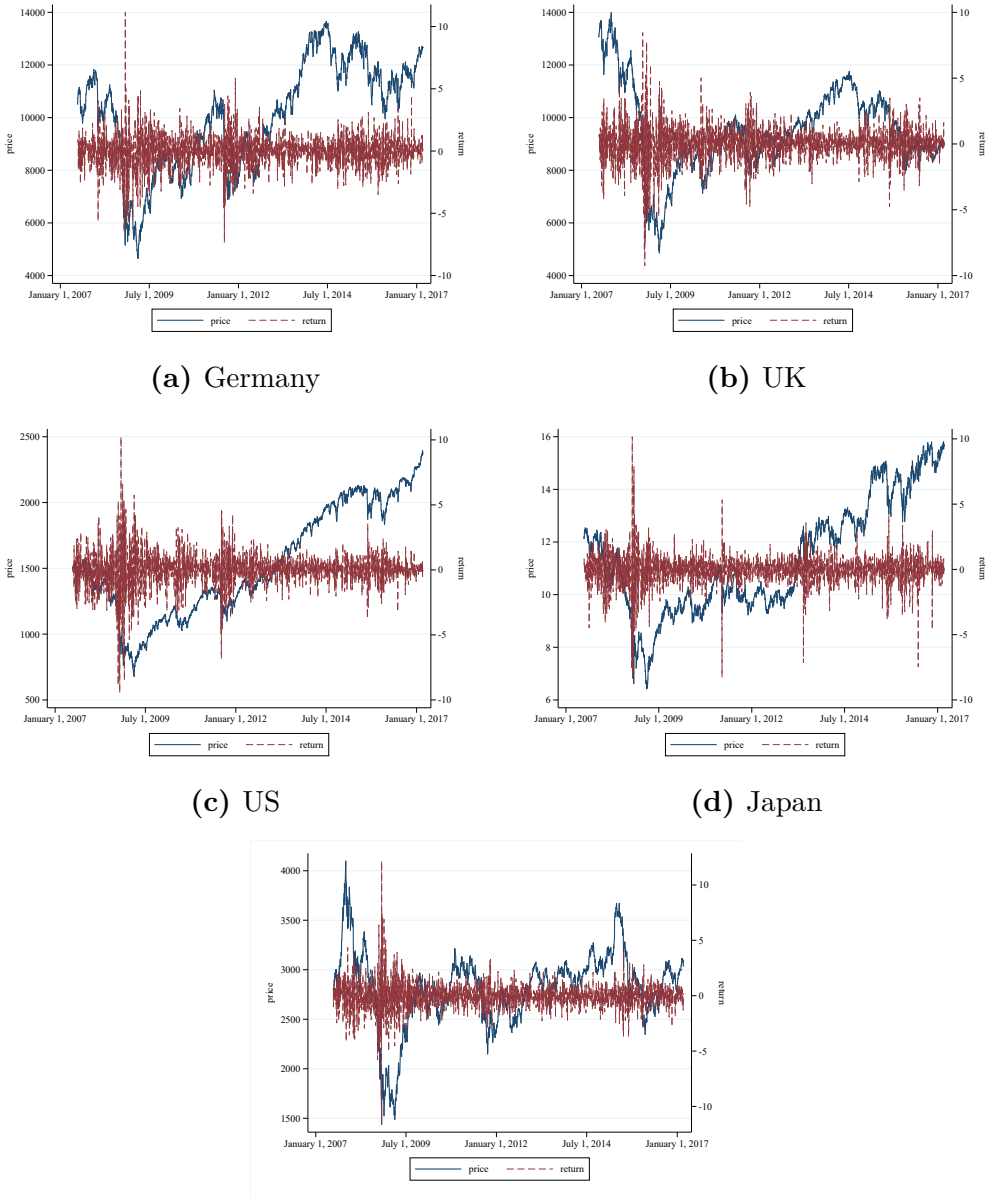
Note: Kernel density estimations are provided for residuals of fitted relative returns on a daily basis from April 3, 2013 to October 10, 2017.

Appendix B

Appendix to Chapter 2

B.1 Figures for Chapter 2

Figure B.1: Opening prices and day returns



(a) Germany

(b) UK

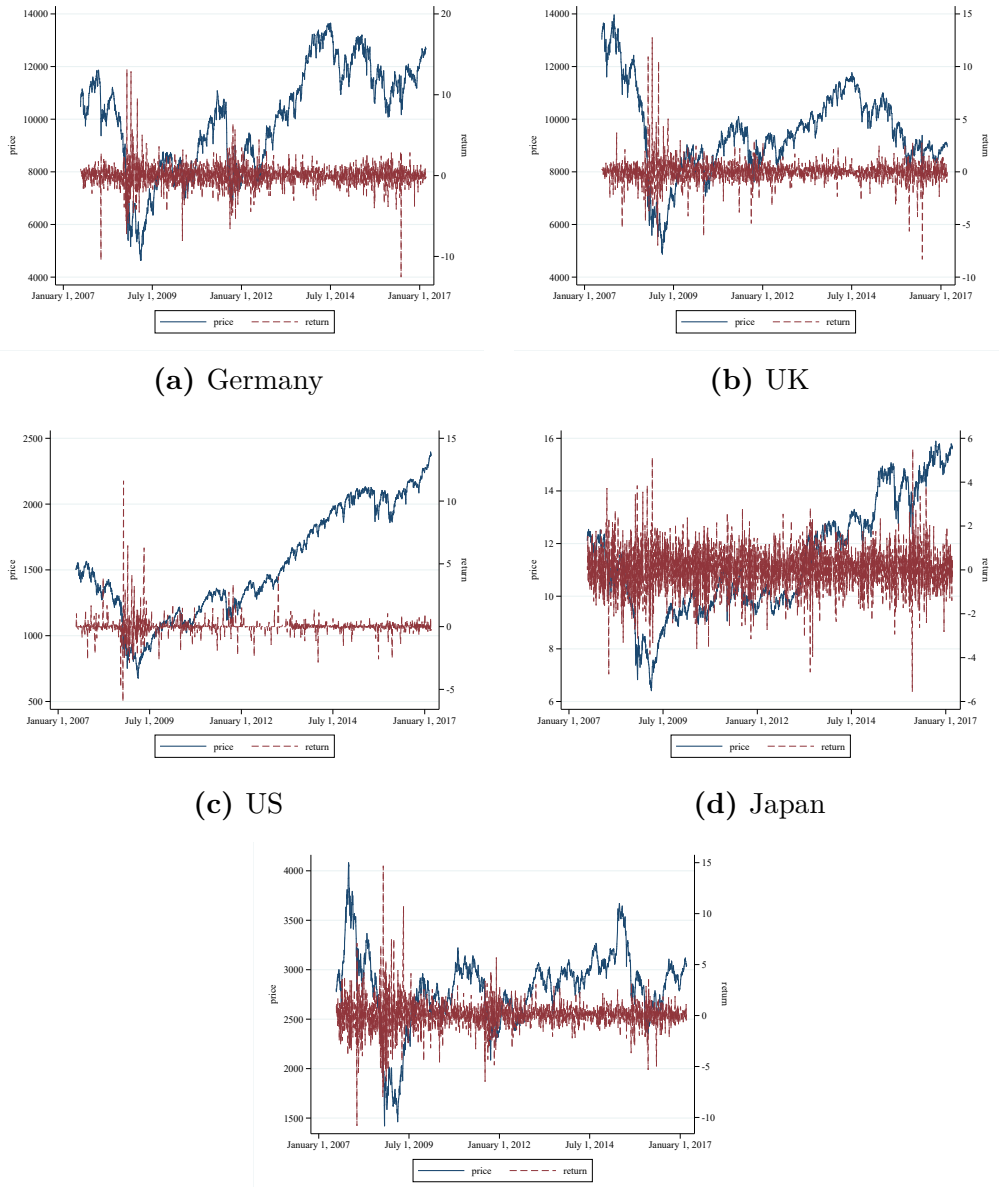
(c) US

(d) Japan

(e) Hong Kong

Note: This figure provides opening prices and day returns for each market on a daily basis from June 27, 2007 to March 7, 2017. All returns are in logarithmic first differences and expressed as a percentage. All foreign opening prices are indicated in USD as a common currency basis.

Figure B.2: Closing prices and night returns



(a) Germany

(b) UK

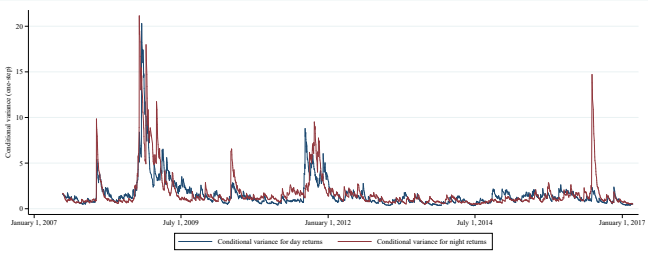
(c) US

(d) Japan

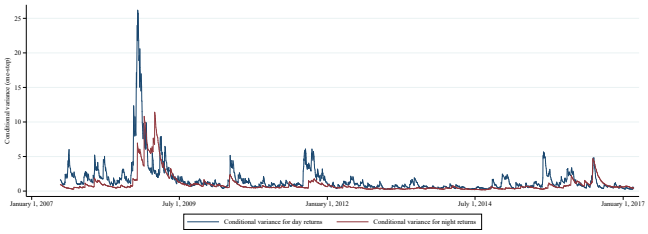
(e) Hong Kong

Note: This figure provides closing prices and night returns for each market on a daily basis from June 27, 2007 to March 7, 2017. All returns are in logarithmic first differences and expressed as a percentage. All foreign closing prices are indicated in USD as a common currency basis.

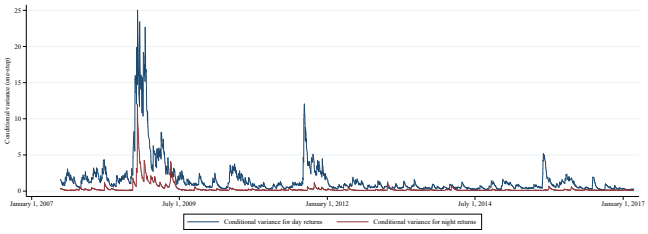
Figure B.3: Conditional variances of returns



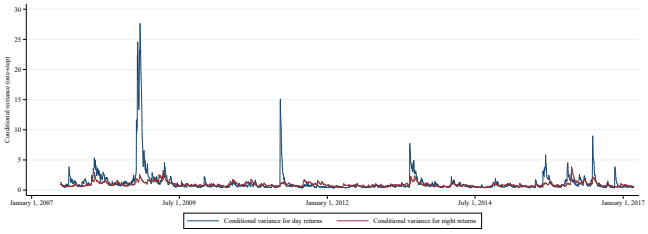
(a) Germany



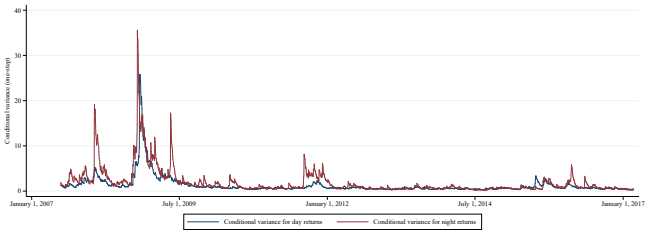
(b) UK



(c) US



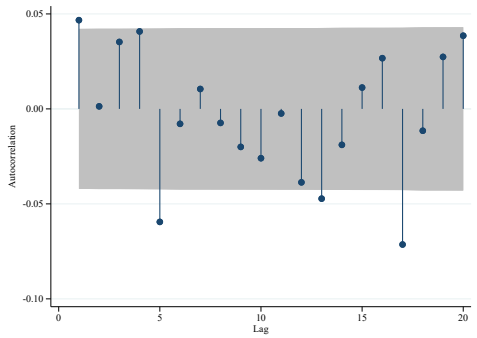
(d) Japan



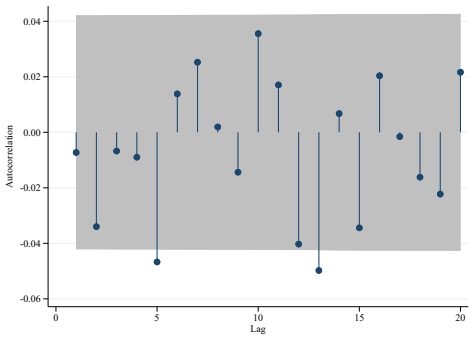
(e) Hong Kong

Note: Conditional variances of day and night returns are presented on a daily basis from June 27, 2007 to March 7, 2017. In general, variances of day returns exhibit larger magnitudes.

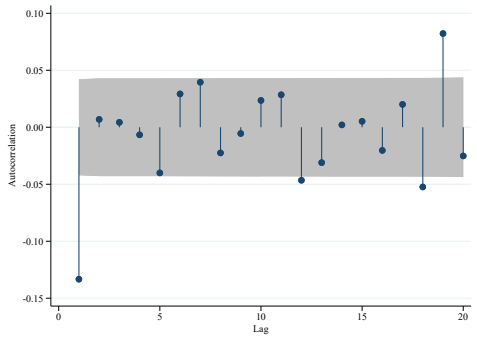
Figure B.4: Autocorrelations for day returns



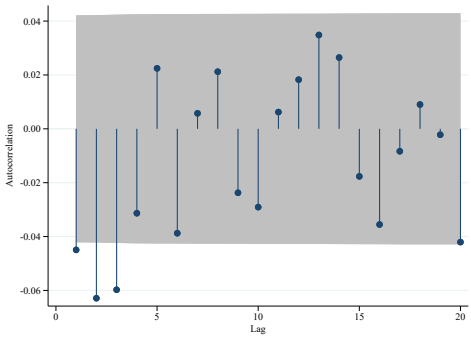
(a) Germany



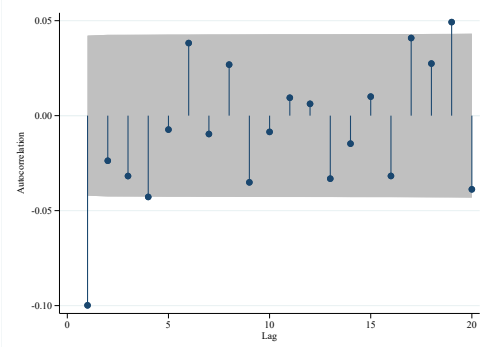
(b) UK



(c) US



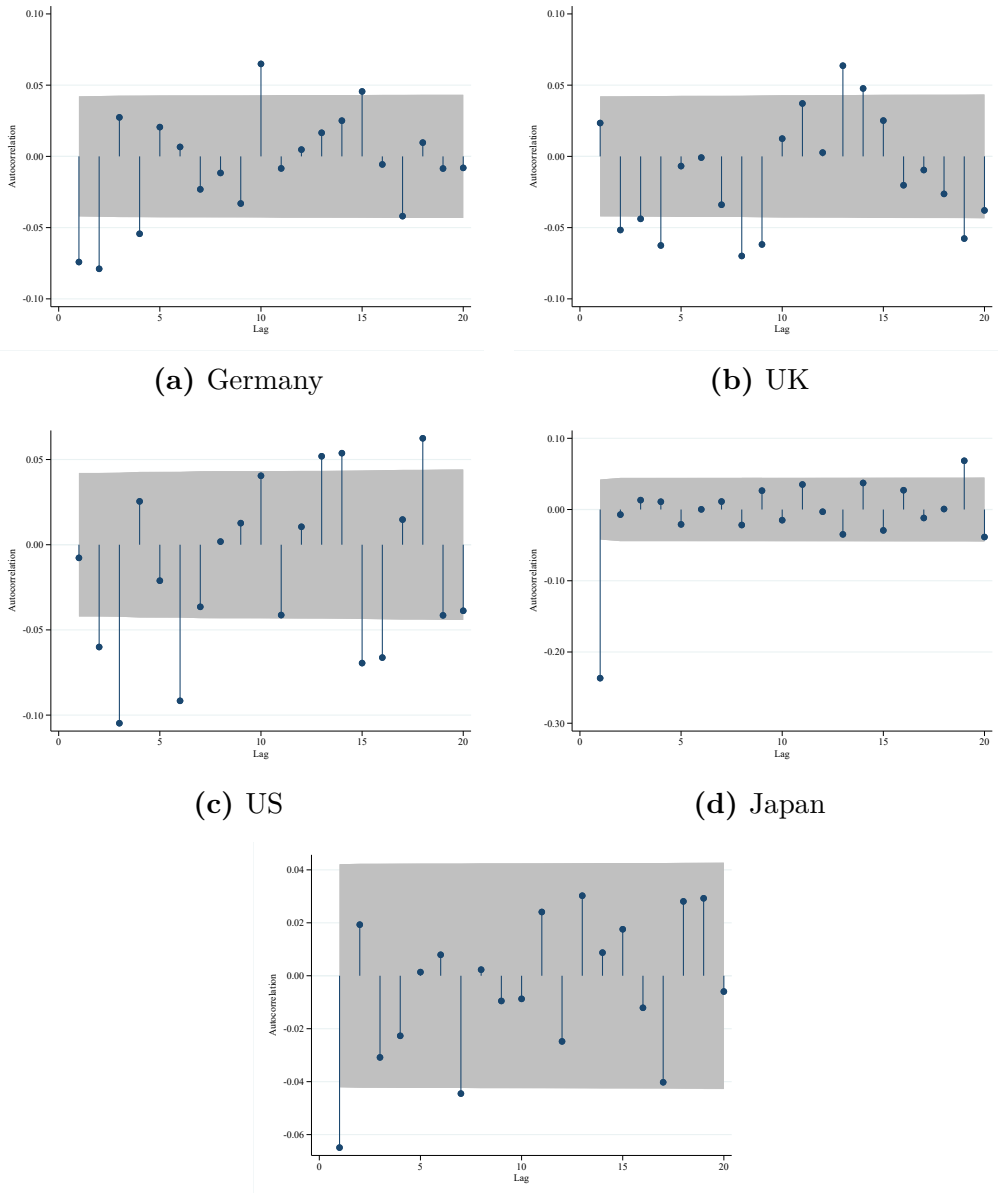
(d) Japan



(e) Hong Kong

Note: This figure provides autocorrelations of day returns up to 20 lags for each market. Confidence bands depict the variance at the 95% level according to Bartlett's formula. The EGARCH(1,1) model can be adopted since most autocorrelations are significant different from zero at least with a lag of one.

Figure B.5: Autocorrelations for night returns



(a) Germany

(b) UK

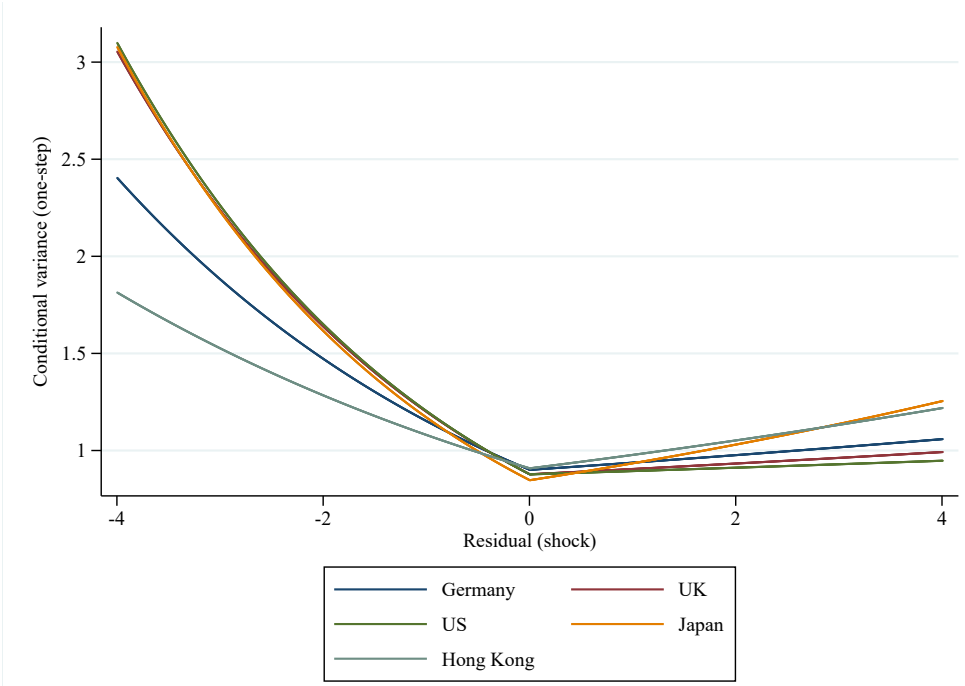
(c) US

(d) Japan

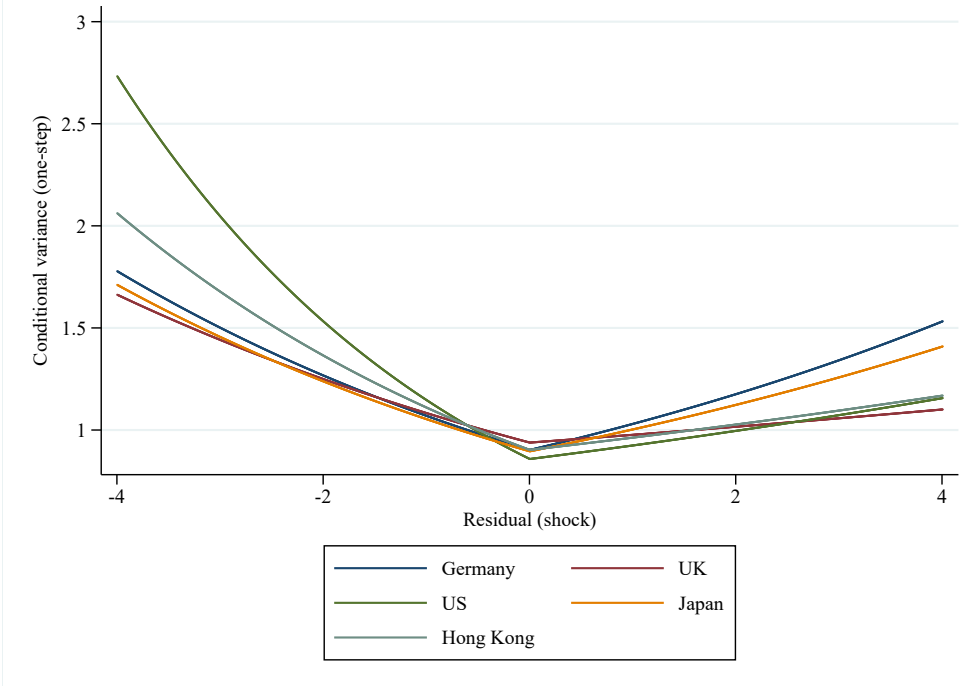
(e) Hong Kong

Note: This figure provides autocorrelations of night returns up to 20 lags for each market. Confidence bands depict the variance at the 95% level according to Bartlett's formula. The EGARCH(1,1) model can be adopted since most autocorrelations are significant different from zero at least with a lag of one.

Figure B.6: News response functions



(a) day returns



(b) night returns

Note: News response functions illustrate the impact of unanticipated shocks on the conditional variance for day and night returns. The conditional variance rises faster for negative residuals than for positive ones according to an asymmetric pattern and larger shocks have a greater impact on volatility.

B.2 Tables for Chapter 2

Table B.1: Log-likelihood

Coefficient	Germany	UK	US	Japan	Hong Kong
(A) Day returns with f_1 as the fundamental proxy					
GARCH	-3197.634	-3103.333	-2908.677	-2791.915	-2908.871
EGARCH	**-3168.477**	**-3066.954**	**-2878.993**	-2779.925	**-2899.521**
GJR	-3177.782	-3068.274	-2882.988	-2784.635	-2901.666
PARCH	-3193.760	-3102.101	-2908.674	-2791.284	-2906.895
NARCH	-3171.051	-3072.120	-2879.805	**-2777.907**	-2902.946
(B) Day returns with f_2 as the fundamental proxy					
GARCH	-3198.849	-3092.408	-2902.423	-2789.708	-2908.623
EGARCH	**-3168.725**	**-3062.940**	-2880.079	-2780.636	**-2897.983**
GJR	-3178.466	-3064.530	-2879.747	-2783.598	-2899.732
PARCH	-3194.892	-3091.271	-2902.404	-2789.489	-2906.431
NARCH	-3171.592	-3066.276	**-2878.547**	**-2777.383**	-2901.789
(C) Night returns with f_1 as the fundamental proxy					
GARCH	-3137.391	-2325.400		-2902.605	-3081.527
EGARCH	**-3124.226**	**-2313.100**		**-2898.319**	**-3064.398**
GJR	-3136.892	-2325.115		-2902.525	-3070.411
PARCH	-3124.500	-2316.438		-2899.168	-3076.035
NARCH	-3137.311	-2322.890		-2902.071	-3069.067
(D) Night returns with f_2 as the fundamental proxy					
GARCH	-3140.977	-2330.628		-2902.256	-3086.619
EGARCH	**-3127.728**	**-2317.743**		**-2897.535**	**-3068.330**
GJR	-3140.740	-2330.252		-2902.075	-3073.930
PARCH	-3128.634	-2321.855		-2898.400	-3082.091
NARCH	-3140.826	-2327.458		-2901.331	-3073.027

Note: This table reports log-likelihood values according to a selection of GARCH models with respect to day and night returns as well as both fundamental proxies (f_1 and f_2). Statistics in bold represent the best performing GARCH models.

Table B.2: LR test

Coefficient	Germany	UK	US	Japan	Hong Kong
(A) Day returns with f_1 as the fundamental proxy					
EGARCH	58.314***	72.758***	59.368***	23.980***	18.700***
GJR	39.704***	70.118***	51.378***	14.560***	14.410***
PARCH	7.748***	2.464	0.006	1.262	3.952**
NARCH	53.166***	64.426***	57.744***	28.016***	11.850***
(B) Day returns with f_2 as the fundamental proxy					
EGARCH	60.248***	58.936***	44.688***	18.144***	21.280***
GJR	40.766***	55.756***	45.352***	12.220***	17.782***
PARCH	7.914***	2.274	0.038	0.438	4.564**
NARCH	54.514***	52.264***	47.752***	24.650***	13.668***
(C) Night returns with f_1 as the fundamental proxy					
EGARCH	26.330***	24.600***		8.572***	34.258***
GJR	0.998	0.570		0.160	22.232***
PARCH	25.782***	17.924***		6.874***	10.984***
NARCH	0.160	5.020**		1.068	24.920***
(D) Night returns with f_2 as the fundamental proxy					
EGARCH	26.498***	25.770***		9.442***	36.578***
GJR	0.474	0.752		0.362	25.378***
PARCH	24.686***	17.546***		7.712***	9.056***
NARCH	0.302	6.340**		1.850	27.184***

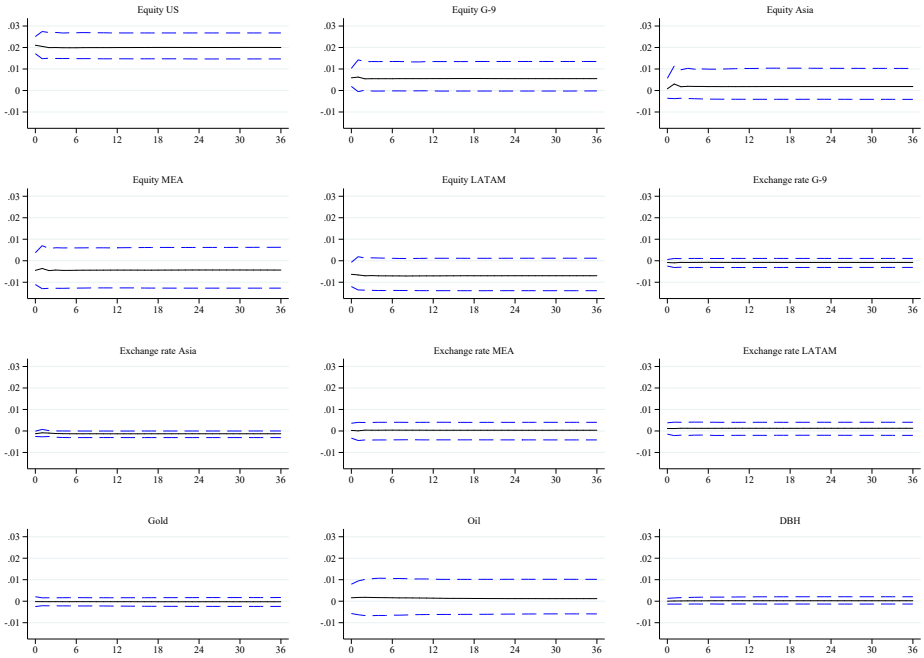
Note: This table illustrates the LR statistic in order to test the significance of the extended models (EGARCH, GJR, PARCH, and NARCH) to the nested model (GARCH) with respect to day and night returns as well as different fundamental proxies (f_1 and f_2). The LR statistic is calculated by LR$=-2*(L_0-L_1)$. Stars indicate significance as follows: *10%, **5%, ***1%.

Appendix C

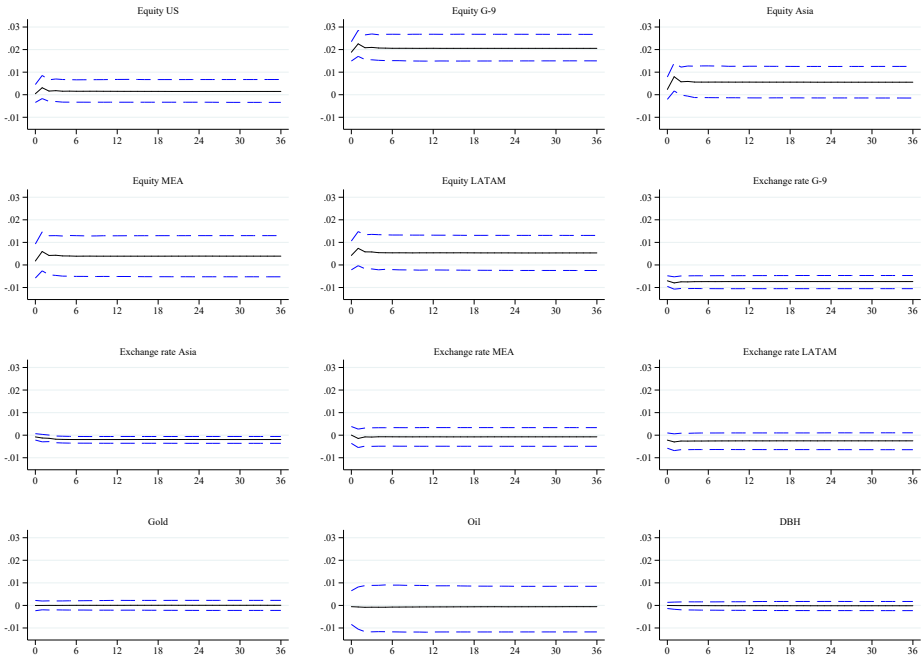
Appendix to Chapter 3

C.1 Figures for Chapter 3

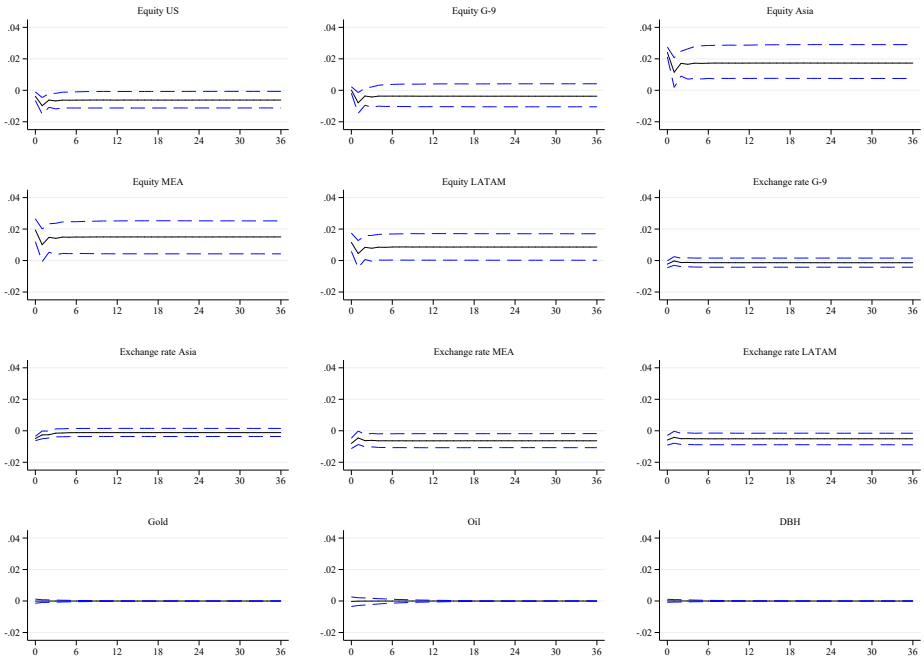
Figure C.1: GIRFs of a positive 1 s.e. shock to stock prices



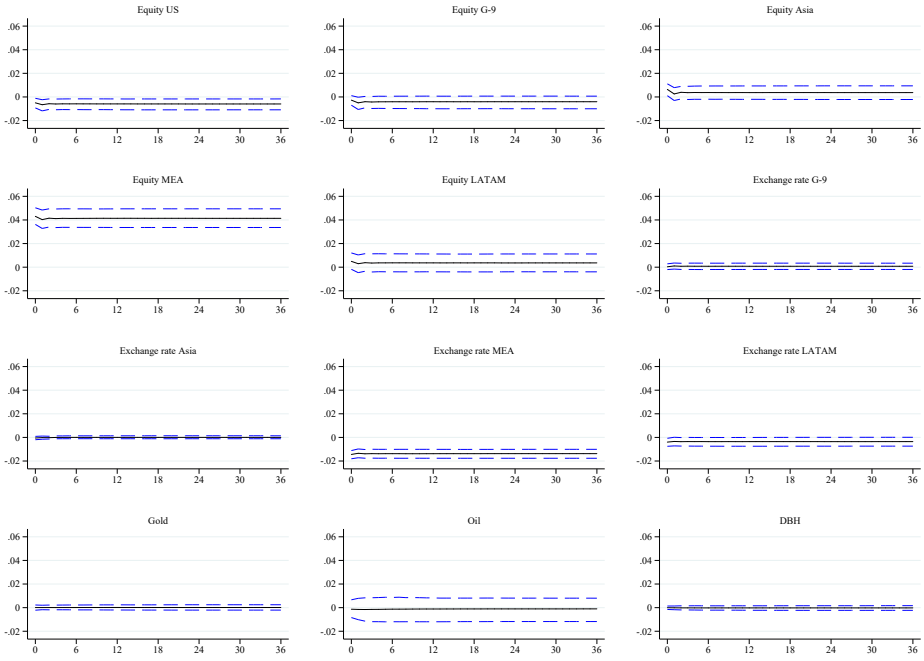
(a) in the US



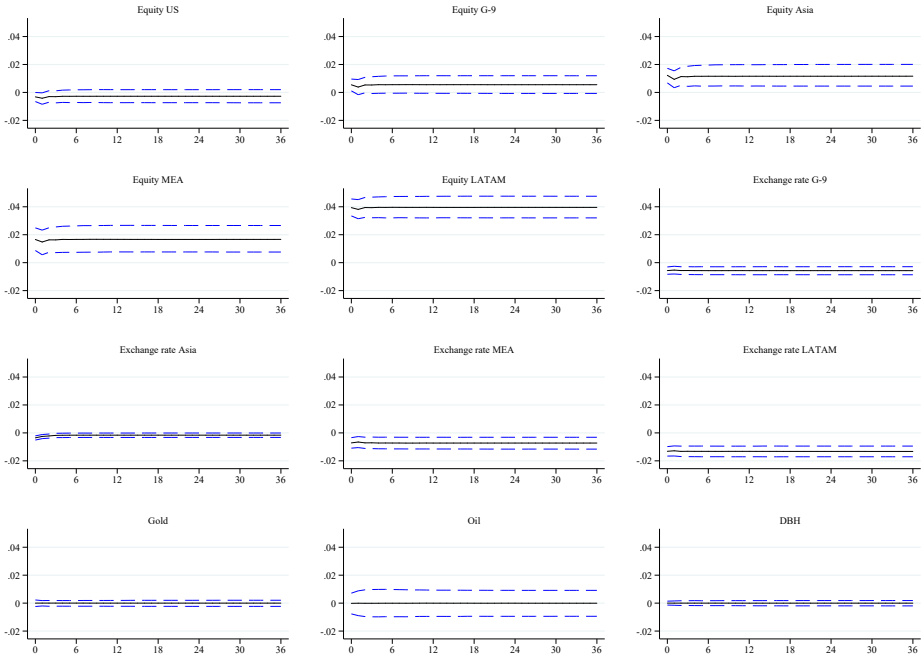
(b) in G-9



(c) in Asia



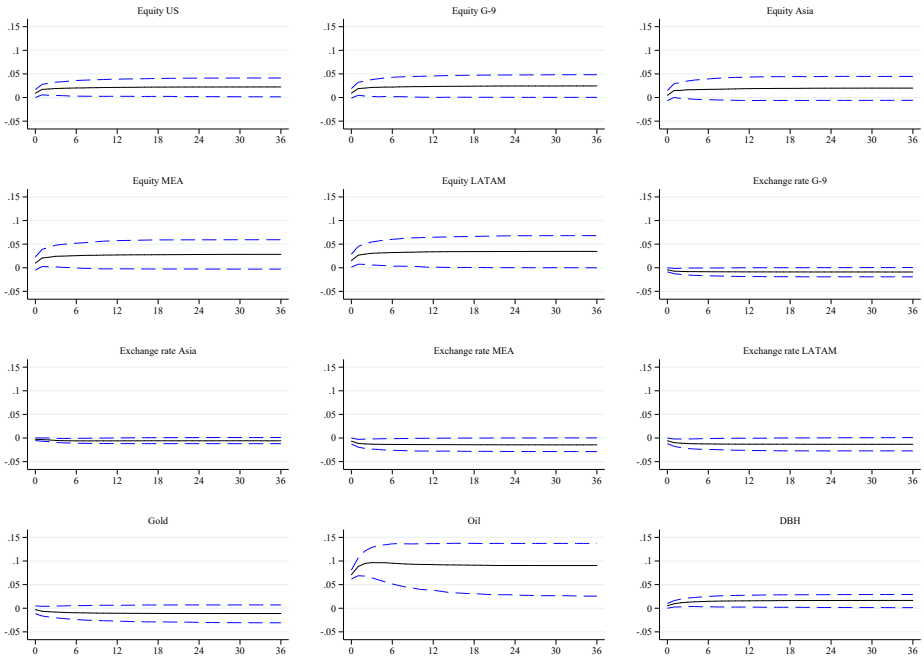
(d) in MEA



(e) in LATAM

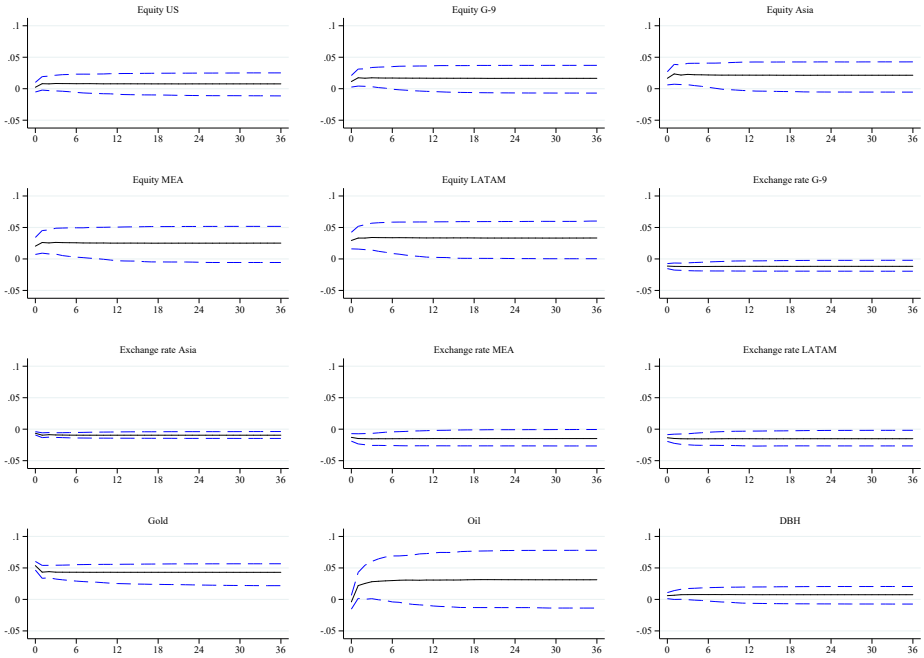
Note: This figure provides GIRFs of a positive 1 s.e. shock to stock prices in the respective economic area. Dashed lines indicate 90% bootstrap confidence intervals.

Figure C.2: GIRFs of a positive 1 s.e. shock to oil prices



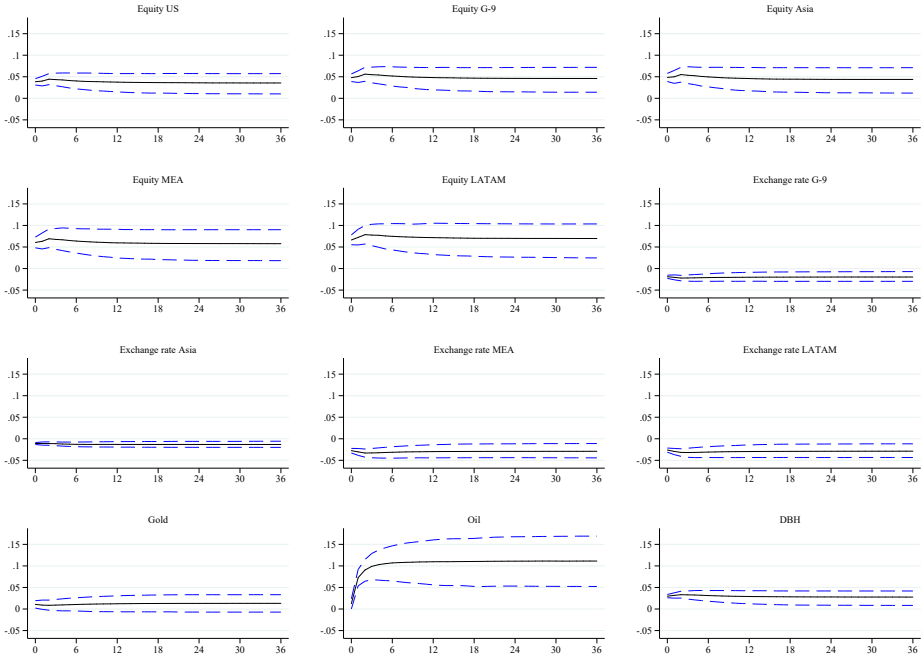
Note: This figure provides GIRFs of a positive 1 s.e. shock to oil prices. Dashed lines indicate 90% bootstrap confidence intervals.

Figure C.3: GIRFs of a positive 1 s.e. shock to gold prices



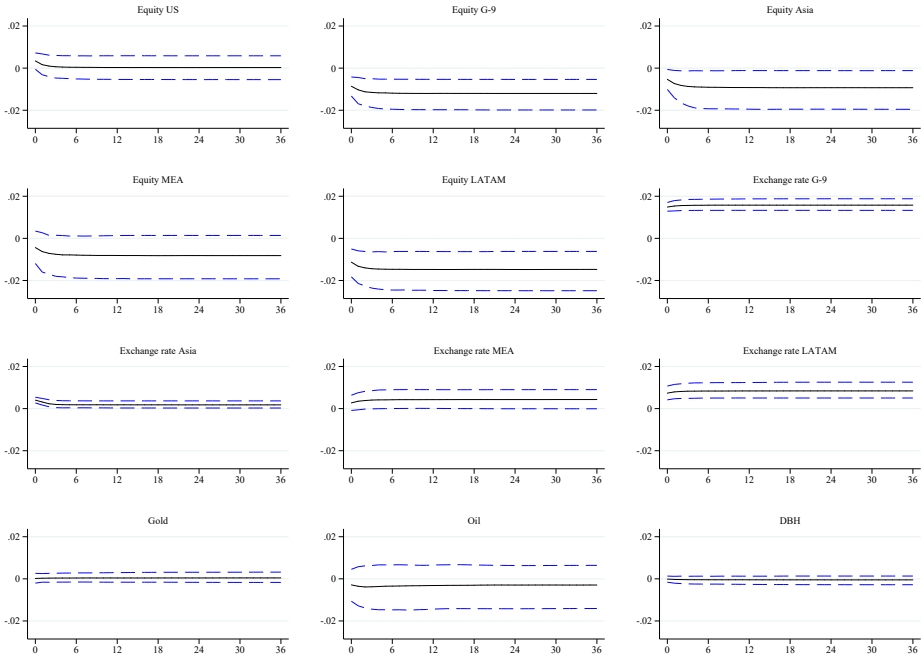
Note: This figure provides GIRFs of a positive 1 s.e. shock to gold prices. Dashed lines indicate 90% bootstrap confidence intervals.

Figure C.4: GIRFs of a positive 1 s.e. shock to DBH

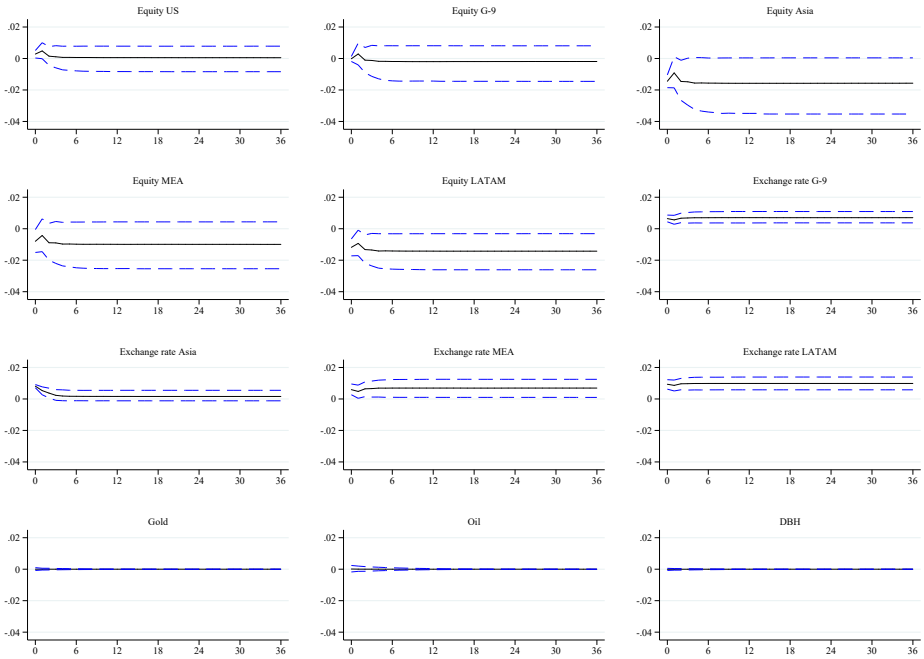


Note: This figure provides GIRFs of a positive 1 s.e. shock to DBH. Dashed lines indicate 90% bootstrap confidence intervals.

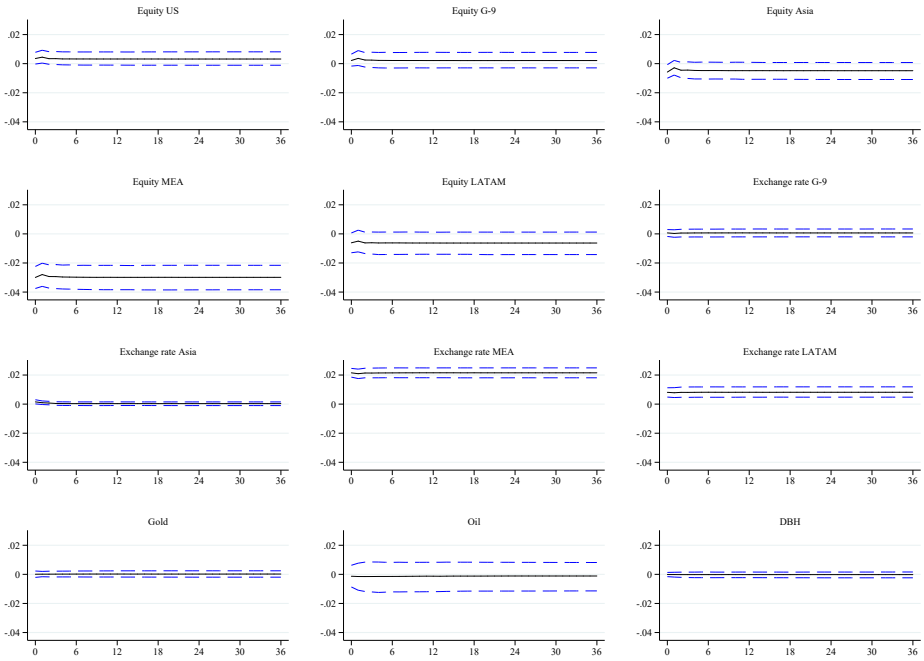
Figure C.5: GIRFs of a positive 1 s.e. shock to exchange rates



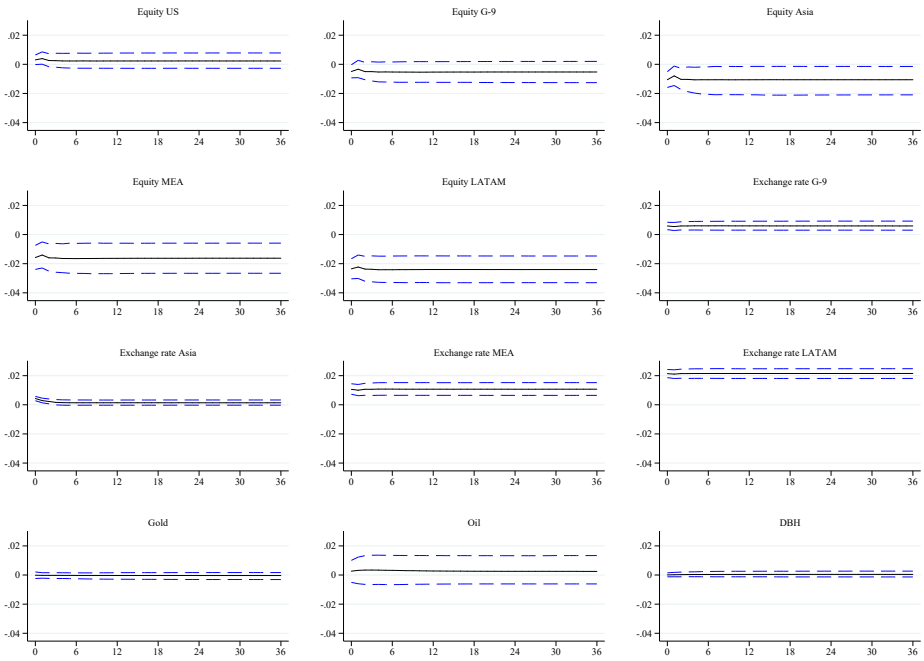
(a) in G-9



(b) in Asia



(c) in MEA



(d) in LATAM

Note: This figure provides GIRFs of a positive 1 s.e. shock to exchange rates in the respective economic area. Dashed lines indicate 90% bootstrap confidence intervals.

C.2 Tables for Chapter 3

Table C.1: Country coverage and economic areas

G-9	Asia	MEA	LATAM	US
Australia	Hog Kong	South Africa	Brazil	United States
Canada	India	Turkey	Mexico	
Germany	Malaysia			
Japan	Singapore			
New Zealand	South Korea			
Norway	Taiwan			
Sweden	Thailand			
Switzerland				
United Kingdom				

Note: Countries are grouped according to established classifications and economic areas. The US is excluded from G-10 and treated separately as an independent region.

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