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Black Monday, globalization and trading behavior of stock investors

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Non-technical summary

Research question:
The paper tests whether systematic trading behaviors on stock markets have changed over the long-term. In doing so, the two different trading strategies, momentum and contrarian, serve as the systematic trading strategies. For the empirical part, the daily returns of two sets of stock market data (Deutscher Aktienindex and Dow Jones Index) since 1959 are used. The focus of the analysis is on the distributional property of increases and decreases in returns, especially sequences of the sign. The empirical probability of sequences of the sign is tested by the theoretical distribution resulting from the assumption of the martingale process of return series implying absence of systematic trading strategies.

Contribution:
The paper provides a further evidence for the systematic trading strategy of the stock investors in the literature. The novel sign test proposed in the paper and the empirical results are the main contribution of the paper.

Results:
The empirical results show that the probabilities of sequences of the same sign (both positive and negative) before Black Monday are significantly higher than those of the theoretical distribution. This means that the investors preferred the momentum strategy. After Black Monday, however, the probabilities of sequences of the same sign are significantly lower than those of theoretical distribution. This means that the investors are tending to trade according to the contrarian strategy.

Nichttechnische Zusammenfassung

Fragestellung:
Das Papier behandelt die Frage, ob sich das Ausmaß systematischen Handelsverhaltens an den Aktienmärkten in langfristiger Perspektive verändert hat. Als Ausdruck systematischen Handelsverhaltens werden dabei die zwei unterschiedlichen Handelsstrategien "Momentum Trading" und "Contrarian Trading" betrachtet. Für die empirische Analyse nutzt das Papier aggregierte Marktdaten (Deutscher Aktienindex, DAX und Dow Jones Index, DJ) über tägliche Renditen seit 1959. Im Kern geht es um die Häufigkeit täglicher Kurszuwächse bzw. Kursrückgänge, wobei Sequenzen gleichgerichteter Kursbewegungen untersucht werden. Der empirische Befund wird dabei mit den theoretisch erwarteten Ergebnissen verglichen, die sich aus der Annahme des Martingal-Prozesses (morgiger Preis im Erwartungswert = heutiger Preis) ergeben, welche eine Abwesenheit systematischen Verhaltens bedeutet.

Beitrag:
Das Papier liefert somit eine plausible Ergänzung der bisherigen Untersuchungen zum Nachweis spekulativer Verhaltensweisen an den Aktienmärkten. Der Beitrag der Studie besteht dabei zum einen in der Technik des vorgestellten Vorzeichentests, zum anderen in den empirischen Ergebnissen.

Ergebnisse:
Die empirischen Ergebnisse zeigen für verschiedene Sequenzlängen mit Blick auf den DAX und den DJ, dass vor dem "Schwarzen Montag" die empirischen Wahrscheinlichkeiten gleichgerichteter Sequenzen (sowohl positiver als auch negativer Vorzeichen) signifikant höher sind als die theoretischen Wahrscheinlichkeiten. Dies deutet auf eine Tendenz zu Momentum-Handelsverhalten hin. Nach dem "Schwarzen Montag" sind die empirischen Wahrscheinlichkeiten gleichgerichteter Sequenzen dagegen niedriger als die theoretischen Wahrscheinlichkeiten. Dies deutet auf eine Tendenz zu einer Contrarian-Strategie hin.[1]

[1] Diese nichttechnische Zusammenfassung hat Teile des ausgezeichneten Gutachtens übernommen.

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Black Monday, globalization and trading behavior of stock investors[†]

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Abstract

Using a simple sign test, we report new empirical evidence, taken from both the US and the German stock markets, showing that trading behavior substantially changed around Black Monday in 1987. It turned out that before Black Monday investors behaved more as in the momentum strategy; and after Black Monday more as in the contrarian strategy. We argue that crashes, in general, themselves are merely a manifestation of uncertainty on stock markets and the high uncertainty due to globalization is mainly responsible for this change.

Keywords: Trading behavior, Momentum, Contrarian, Black Monday, Globalization, Uncertainty.

JEL classification: C12, G02, G11.

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1 Introduction

The economy is largely shaped by certain behavioral patterns of agents. The economic behavior of agents is presumably influenced, in turn, by the given economic circumstances. This reciprocal relationship can also often be observed in speculative markets. It is, therefore, of interest to examine which economic and financial circumstances can influence the behavioral patterns of agents.

Shiller (1987) reports his survey results on investors' behavior around Black Monday in 1987. One of the findings of his empirical survey is that *many investors thought that they could predict the market*. This result refers to the time of the crash, but it can be also interpreted to mean that investors thought that they *could* predict the market for the entire duration prior to Black Monday. This belief of alleged predictability can be interpreted to mean that investors regarded stock returns as a stationary process (with a significant autocorrelation coefficient). Consequently, the sign of returns yesterday seemed to continue today unless the error term (shocks in fundamentals) dominates the autocorrelation from yesterday. This promotes a tendency to co-movement between stock prices and fundamentals, and produces less volatility in stock price dynamics. After Black Monday, investors were more acutely aware of the high uncertainty and risks on the stock markets that were intensified by the globalization of financial markets that has been accelerating significantly since the mid/late 1980s. After the experience of Black Monday, investors seemed to regard stock prices as a random walk process. The belief in the random walk property (i.e. zero autocorrelation of returns between yesterday and today) produces higher uncertainty expressed in terms of higher volatility and, hence, more bubbles and crashes, which is shown analytically in Branch and Evans (2013) who defined this relationship as a self-fulfilling process. To the extend that crashes can be regarded as a financial occurrence which reminds investors of the higher uncertainty and the larger risks on the globalized stock markets.

In this paper, our main concern is whether and how Black Monday in 1987 changed trading behavior on the stock markets. In order to interpret our empirical evidence in terms of economic hypotheses, we apply two concepts of trading behavior; the momentum and the contrarian strategies. The main finding of this paper is that before Black Monday investors behaved more as in the momentum strategy; and after Black Monday more as in the contrarian strategy. This empirical evidence can be observed in both the US and the German stock markets.

The rest of the paper is structured as follows. In Section 2, we propose some test statistics to quantify trading behavior on the stock markets. Section 3 presents some stylized facts found in the two sets of stock price data – the daily Dow Jones index (DJ) and the daily German stock index (Deutscher Aktien Index, DAX) – which show a substantial change in trading behavior before and after Black Monday. Based on these empirical findings, we discuss and hypothesize in Section 4 that the higher uncertainty due to globalization on the stock markets is mainly responsible for this change. Section 5 gives some concluding remarks.

2 Quantification of trading behavior

In order to establish a link between our empirical findings and economic hypotheses, we introduce two concepts of trading behavior; a day-to-day momentum and a day-to-day contrarian trading behavior. The concepts of momentum and contrarian trading behavior were popularized by Jegadeesh (1990) and Jegadeesh and Titman (1993). In order to apply one of these strategies, investors have to identify winners and losers among the stocks. This identification is based on a certain length of time in the past. In the literature, the duration of this time length is usually few weeks, months or years. Some authors also consider rather very short time horizons. Goetzmann and Massimo (2002), for example, analyze the trading behavior of index fund investors based on the daily momentum and contrarian concepts. In a similar way to the definitions in Goetzmann and Massimo (2002), we also formulate definitions of the momentum and contrarian trading behavior by means of the reaction to previous daily returns as follows.

Definition 1 (Day-to-day momentum and contrarian trading behavior)
Day-to-day momentum trading behavior is defined as buying (selling) today when the return yesterday was positive (negative). Day-to-day contrarian trading behavior is defined as buying (selling) today when the return yesterday was negative (positive).

In our empirical analysis, we also extend Definition 1 by taking into consideration trading behavior based on sequences (more than one day) of the same sign. Consequently, a higher probability for sequences of the same sign in the return processes (higher than statistically expected under the assumption of no systematic behavior) will be regarded as a tendency of momentum trading behavior; and a lower probability for sequences of the same sign in the return processes (lower than statistically expected under the assumption of no systematic behavior) will be regarded as a tendency to contrarian trading behavior. As will be shown, the momentum trading behavior can indeed be observed more frequently in stable phases, while contrarian trading behavior becomes more prominent when market volatility is high, as also identified in Goetzmann and Massimo (2002).

Let r_t be a stock return in time $t = 1, \ldots, T$. Furthermore, let $\theta^{(p)}$ and $\theta^{(n)}$ ratios of the number of positive (plus zero) and negative returns be

$$\theta^{(p)} := \sum_{t=1}^{T} \mathrm{I}_{[0,\infty)}(r_t)/T \tag{1}$$

and

$$\theta^{(n)} := \sum_{t=1}^{T} \mathrm{I}_{(-\infty,0)}(r_t)/T, \tag{2}$$

where $\mathrm{I}_{\{\mathcal{A}\}}(a)$ is a usual indicator function, 1 when $a \in \mathcal{A}$ and 0 otherwise. Due to the inclusion of zero returns[1] in positive returns, the sum of the two ratios is one, i.e. $\theta^{(p)} + \theta^{(n)} = 1$.

[1] The empirical probabilities of $r_t = 0$ in our empirical data are indeed negligibly small, namely 1.16% and 0.78% for the DJ and the DAX for the whole sample. Even if the probabilities of $r_t = 0$ are included in negative returns, both our statistical arguments and our main empirical results remain unchanged.

Furthermore, we define a statistic for the sequences of a positive sign as

$$\theta_j^{(p)} := \sum_{t=j}^{T} \prod_{i=0}^{j-1} \mathrm{I}_{[0,\infty)}(r_{t-i})/(T-j+1) \quad j=1,2,\ldots,J. \tag{3}$$

The subindex j means the length of a sequence of the same sign. When $j=1$, the statistic in (3) reduces to that in (1), i.e. $\theta_1^{(p)} = \theta^{(p)}$.

Analogously, for the negative sign

$$\theta_j^{(n)} := \sum_{t=j}^{T} \prod_{i=0}^{j-1} \mathrm{I}_{(-\infty,0)}(r_{t-i})/(T-j+1) \quad j=1,2,\ldots,J. \tag{4}$$

Again, when $j=1$, the statistic in (4) reduces to that in (2), i.e. $\theta_1^{(n)} = \theta^{(n)}$.

Under the martingale assumption of the return process, i.e. uncorrelated distributed random process, the two statistics in (3) and (4) have a binomial distribution (see Mood et al., 1974, Theorem 3, p. 89) as

$$\theta_j^{(p)} \sim BN(0.5^j, 0.5^j(1-0.5^j)/T) \tag{5}$$

and

$$\theta_j^{(n)} \sim BN(0.5^j, 0.5^j(1-0.5^j)/T). \tag{6}$$

The martingale assumption ensures the detection of such trading behavior, where the departure from the randomness of the sign of returns is systematic. This is because the martingale hypothesis states that *the expected change of stock price is zero, conditioned on the stock price history, and, hence, the stock price is just as likely to rise as it is to fall* (Campbell et al., 1997, p. 30).

The significant number of more positive observations is, however, one of the usual empirically stylized factors of speculative price changes[2], mostly because of the asymmetric behavior and/or the risk aversion of investors in general, as expressed by the counter-cyclical stock market volatility in Mele (2007). This empirical evidence can also be explained by the leverage effect described in Black (1976), which refers to a negative correlation between asset returns and their changes in volatility and, hence, is responsible for the left-skewness of empirical distributions of stock returns. Therefore, there are (relatively) many (relatively) small steps in increasing phases, but (relatively) few (relatively) large steps in decreasing phases, so that the probability of the positive sign is not equal to that of the negative sign. As a result, we need some other measurements of the probability of the positive (and negative) sign which take such stylized factors in dynamics of stock prices into account, and, hence ensure that the momentum and/or contrarian trading behavior is measured appropriately. When measuring the momentum and/or contrarian trading behavior, the sequence of signs is of relevance, not the general tendency to the positive (and negative) sign. Consequently, the equal probability of the sign in (5) and (6) is replaced by the empirical probability of the positive (and negative)

[2]Considering the full period of the DJ with 14,298 returns, the number of positive returns is 7,337 (51.31%), of negative returns 6,795 (47.52%), and of zero returns 166 (1.16%). For the DAX, among 14,001 returns, the number of positive returns is 7,224 (51.60%), of negative returns 6,668 (47.63%), and of zero returns 109 (0.78%).

sign given in (1) and (2). This substitution now adjusts the deviation from 0.5 observed in the empirical data to

$$\theta_j^{(p)} \sim BN([\theta^{(p)}]^j, [\theta^{(p)}]^j(1 - [\theta^{(p)}]^j)/T) \tag{7}$$

and

$$\theta_j^{(n)} \sim BN([\theta^{(n)}]^j, [\theta^{(n)}]^j(1 - [\theta^{(n)}]^j)/T). \tag{8}$$

To ensure an adequate number of observations in our empirical application, it seems appropriate to set the highest number of the same sign sequences, J, to 7, meaning that the stock price has increased (decreased) for six consecutive trading days after a positive (negative) return. The number of observations longer than the seven-day sequence decreases by nature rapidly and is not large enough for a reliable statistical evaluation.[3] The empirical numbers of all sequences are given in Table 1.

Table 1. Empirical numbers of the same sign sequences

			Length of the same sign sequences															
Data	Regime[a]	Sign	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
DJ	before	+	3652	2048	1117	597	323	170	88	48	25	13	7	3	1	0	0	0
		−	3441	1837	961	504	256	124	58	28	16	10	5	1	0	0	0	0
	after	+	3851	2004	1024	513	238	115	54	24	9	4	1	0	0	0	0	0
		−	3354	1507	668	285	109	39	10	4	0	0	0	0	0	0	0	0
DAX	before	+	3586	2070	1154	622	331	171	85	42	19	10	6	4	3	2	1	0
		−	3428	1911	1008	521	274	150	82	44	25	15	9	5	3	1	0	0
	after	+	3747	1991	1044	571	302	150	78	44	25	16	10	5	1	0	0	0
		−	3240	1484	659	281	121	53	22	10	5	2	1	0	0	0	0	0

[a]before and after Black Monday

3 An empirical application

3.1 Data

In this section, we apply our measurements for the empirical data, namely the DJ and the DAX. The sample covers the entire history of the DAX, namely between October 01, 1959 and April 30, 2015. In order to improve comparability, we also use the same period for the DJ. There are daily data with 13,866 observations for the DJ and 13,570 for the DAX. Our main concern is to analyze whether and how the trading behavior on the two stock markets differs between the two regimes, namely before and after Black Monday in 1987. More precisely, the first regime covers the period from October 01, 1959 to October 18, 1987 and the second regime covers the period from October 19, 1987 to April 30, 2015. The reason for this division is that these two regimes have one basic distinction regarding economic and financial circumstances: the degree of globalization and liberalization supported by technical development, especially in computer technology

[3]The longest sequence of the same sign was a positive thirteen-day sequence in the DJ and a positive fifteen-day sequence in the DAX.

and telecommunications. Globalization and liberalization, which have accelerated since the late 1980s and the early 1990s, make it increasingly possible for financial markets across the globe to work as a single national market. Many empirical papers corroborate this view. For example, Hale (2011) documented that foreign capital raised by firms has increased substantially since the early 1990s in terms of equity as well as debt.

Figure 1 and 2 show our two sets of empirical data, namely the DJ (upper panel) and the DAX (lower panel), and their returns.

Figure 1: Daily DJ and DAX October 01, 1959 – April 30, 2015

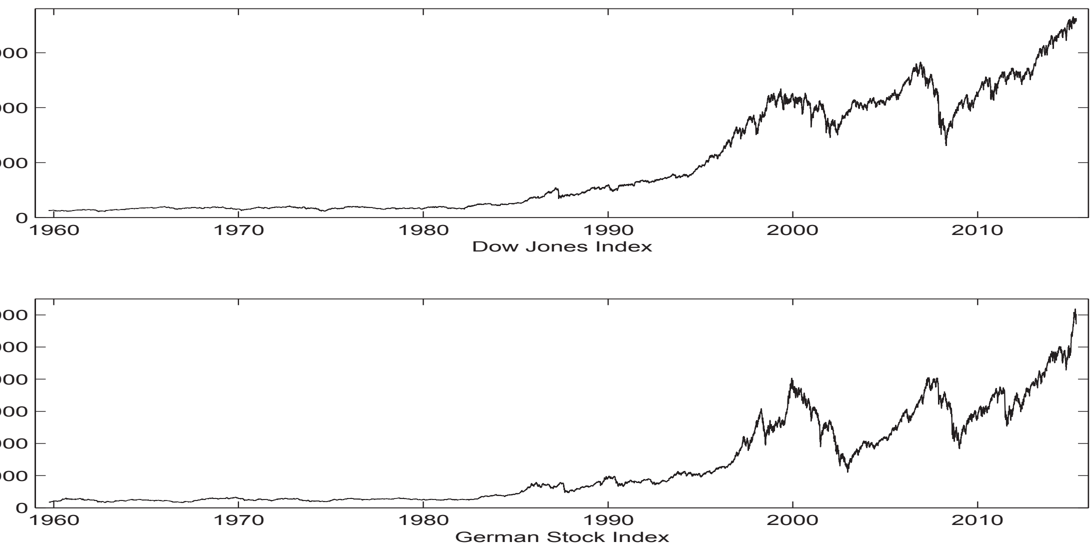
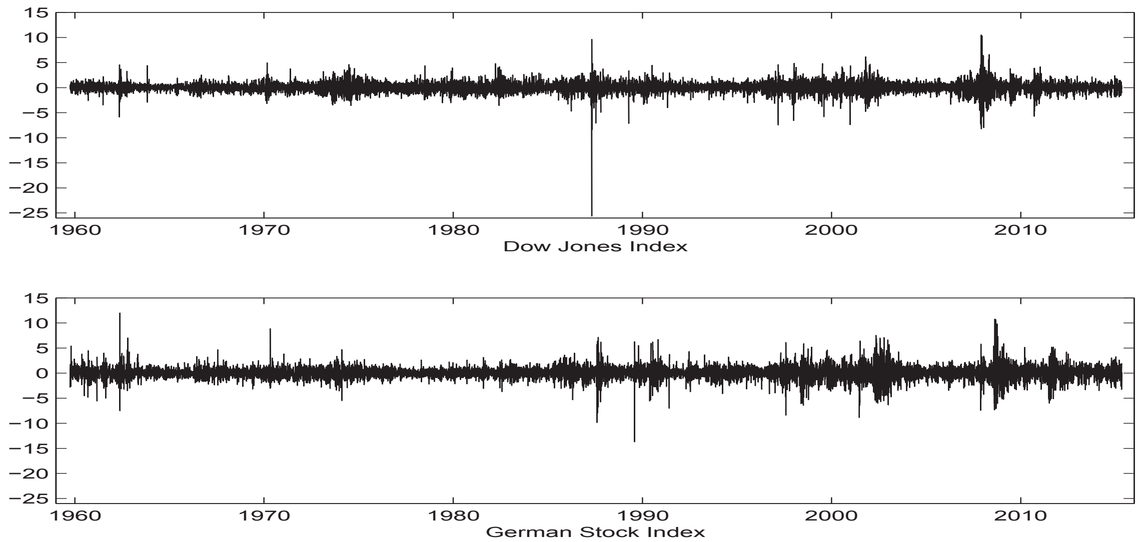


Figure 2: Daily returns of DJ and DAX



As will be shown more precisely in some descriptive statistics later on, Figure 1 and 2 show roughly the effects of globalization and liberalization. The effects are a higher mean value of the stock returns[4] (even after taking into account the visual impression regarding low and high level stock prices in the two regimes, namely before and after Black Monday) and, at the same time, a higher volatility of the stock returns. In comparison with the first regime, the second regime clearly shows both larger growth and, at the same time, higher volatility of the stock prices. In the first regime, there were no large crashes in the stock markets. (The last large crash on the US stock market on October 28, 1929 occurred almost 30 years ago prior to the start of our sample.) While, in the second regime, there were some crashes, such as the Asian crisis in the late 1990s, the New Economy bubble/crash in late 1999/early 2000 and the Lehman collapse in 2007 as well as the European sovereign debt crisis in July 2011, (of which the latter can be seen more clearly in the DAX). We will discuss the topic of globalization and volatility/uncertainty in more detail in Subsection 3.4.

3.2 Results

We first calculate the statistics in (1)-(2). The estimated statistics for the whole sample are 52.48% and 47.52% for the DJ, and 52.37% and 47.63% for the DAX. For the sub-samples, they are 51.49% and 48,51% for before Black Monday, and 53.45% and 46.55% after Black Monday for the DJ, and 51.13% and 48.87%, and 53,63% and 46.37%, respectively, for the DAX (see also Table 1). The ratios of positive and negative returns of the two stock indexes are very similar not only for the whole period, but also for the sub-sample periods. We then estimate the statistics in (3)-(4) and test them using the theoretical distributions given in (5)-(6). The results of our empirical application are summarized in Table 2.

[4]The stock price for the DJ (DAX) grew approximately 3.8 (4.0) times during the first regime of roughly 28 years before Black Monday, while it grew approximately 10.3 (7.9) times during the second regime of roughly 27.5 years after Black Monday.

Table 2. Estimated statistics for the empirical data[a]

Phase / Statistics	before Black Monday Oct. 01, 1959 – Oct. 19, 1987							after Black Monday Oct. 19, 1987 – Apr. 30, 2015						
	DJ													
$[\theta^{(p)}]^j$	51.49	26.51	13.65	7.03	3.62	1.86	0.96	53.45	28.57	15.27	8.16	4.36	2.33	1.25
$\hat{\theta}_j^{(p)}$	51.49	28.87	15.75	8.42	4.55	2.40	1.24	53.45	27.81	14.21	7.12	3.30	1.60	0.75
$F_{BN}(\hat{\theta}_j^{(p)})$	–	1.00	1.00	1.00	1.00	1.00	0.99	–	0.08	0.01	0.00	0.00	0.00	0.00
$[\theta^{(n)}]^j$	48.51	23.53	11.42	5.54	2.69	1.30	0.63	46.55	21.67	10.09	4.70	2.19	1.02	0.47
$\hat{\theta}_j^{(n)}$	48.51	25.90	13.55	7.11	3.61	1.75	0.82	46.55	20.92	9.27	3.96	1.51	0.54	0.14
$F_{BN}(\hat{\theta}_j^{(n)})$	–	1.00	1.00	1.00	1.00	1.00	0.98	–	0.06	0.01	0.00	0.00	0.00	0.00
	DAX													
$[\theta^{(p)}]^j$	51.13	26.14	13.36	6.83	3.49	1.79	0.91	53.63	28.76	15.42	8.27	4.44	2.38	1.28
$\hat{\theta}_j^{(p)}$	51.13	29.51	16.45	8.87	4.72	2.44	1.21	53.63	28.50	14.94	8.17	4.32	2.15	1.12
$F_{BN}(\hat{\theta}_j^{(p)})$	–	1.00	1.00	1.00	1.00	0.96	1.00	–	0.32	0.14	0.39	0.34	0.11	0.13
$[\theta^{(n)}]^j$	48.87	23.89	11.67	5.71	2.79	1.36	0.67	46.37	21.50	9.97	4.62	2.14	0.99	0.46
$\hat{\theta}_j^{(n)}$	48.87	27.25	14.37	7.43	3.91	2.14	1.17	46.37	21.24	9.43	4.02	1.73	0.76	0.31
$F_{BN}(\hat{\theta}_j^{(n)})$	–	1.00	1.00	1.00	1.00	1.00	1.00	–	0.30	0.07	0.01	0.01	0.02	0.04

[a]The numbers for $[\theta^{(p)}]^j$, $\hat{\theta}_j^{(p)}$, $[\theta^{(n)}]^j$ and $\hat{\theta}_j^{(n)}$ are percentage values. The numbers for $F_{BN}(\hat{\theta}_j^{(p)})$ and $F_{BN}(\hat{\theta}_j^{(n)})$ are quantiles of the corresponding binomial distributions.

Table 2 shows the following:

- Results for the DJ
  - Before Black Monday, the empirical probabilities of sequences of the same sign for both the positive and negative signs (as given in the second and fifth rows of the first block in the upper panel) are significantly higher than those of the theoretical values (as given in the first and fourth rows of the first block in the upper panel) for all six cases (i.e. two-day to seven-day sequences) for both the DJ and the DAX. The percentage values of the cumulative binomial distribution, evaluated at the number of the corresponding sequences, are equal to or higher than 99% except in one case, namely the seven-day negative sequence (98%).
  - After Black Monday, the empirical probabilities of sequences of the same sign for both the positive and negative signs (as given in the second and fifth rows of the second block in the upper panel) are significantly lower than those of the theoretical values (as given in the first and fourth rows of the first block in the upper panel) for all six cases (i.e. two-day to seven-day sequences). The percentage values of the cumulative binomial distribution, evaluated at the number of the corresponding sequences, are equal to or lower than 1% except in two cases, namely the one-day positive sequence (8%) and the one-day negative sequence (6%).
- Results for the DAX
  - Before Black Monday, the results for the DAX are almost the same as those of the DJ up to a small difference (no meaning to the main results) in the six-day positive sequence and seven-day negative sequence.
  - After Black Monday, the empirical numbers of sequences of the same sign for both the positive and negative signs (as given in the second and fifth rows of the second block in the lower panel) are smaller than those of the theoretical values (as given in the first and fourth rows of the first block in the lower panel). The empirical probabilities in terms of the p-values for the positive sign sequences are weaker than the DJ with a range of significance level from 11% to 39%. The negative sign sequences are still highly significant up to the one-day negative sequence (30%).

From these empirical results, we could draw the conclusion that Black Monday has changed trading behavior on stock markets. Before Black Monday, investors tended to buy when the stock return was positive and to sell when the stock return was negative (a day-to-day momentum strategy) while after Black Monday they tended to buy when the stock return was negative and to sell when the stock return was positive (a day-to-day contrarian strategy).[5]

[5]Because our empirical analysis is based on stock price indexes, our empirical results can, precisely speaking, be interpreted as the trading behavior of the investors who comprise an index fund and/or of an average investor who deals in stocks presented in the index.

3.3 Profitability evaluation of two trading strategies

Regarding the empirical findings, it is of interest to examine whether each of the trading strategies was profitable in the corresponding regime. In other words: before Black Monday was the momentum strategy more profitable than the contrarian one, and after Black Monday was the contrarian strategy more profitable than the momentum one? In the empirical literature as summarized in Park and Sabourian (2011), Jegadeesh (1990) showed the profitability of the contrarian strategy in the short term (weekly and monthly) while, based on the overreaction hypothesis, de Bondt and Thaler (1985) showed the profitability in the long term (three to five years). On the other hand, Jegadeesh and Titman (1993) also found profitability of the momentum strategy in the medium term (three to twelve-month holding periods). In order to examine whether these two strategies are profitable, the autocorrelation structures of return processes are usually used in the literature. We also analyze the autocorrelation structure of the daily return process of our empirical data.

Table 3. Autocorrelation structures in the empirical data[a]

Phase	before Black Monday						after Black Monday					
Lag / Data	1	2	3	4	5	6	1	2	3	4	5	6
DJ	**0.163**	-0.009	**0.023**	-0.015	0.001	-0.010	**-0.049**	**-0.036**	0.004	-0.006	**-0.038**	-0.002
DAX	**0.131**	**-0.074**	-0.015	**0.028**	-0.014	-0.008	-0.008	**-0.028**	**-0.022**	0.022	**-0.034**	-0.022

[a]According to the analysis by Bartlett (1946), we approximately calculate critical values for the 95% significance levels of $\pm 1.96/\sqrt{7093} \approx \pm 0.023$ and $\pm 1.96/\sqrt{7205} \approx \pm 0.023$ for the regime before and after Black Monday of the DJ, respectively; and of $\pm 1.96/\sqrt{7014} \approx \pm 0.023$ and $\pm 1.96/\sqrt{6987} \approx \pm 0.023$ of the DAX.

As is expected, Table 3 shows a clear difference between the two regimes. Before Black Monday, the first lag shows a highly significant positive correlation in both of the return processes, and other lags usually show a positive correlation when they are significant up to the second lag of the DAX return process. The opposite results can be seen in the regime after Black Monday. The first lag of the DJ returns process is highly negatively significant while that of the DAX returns process is negative, but not significant. All other lags (i.e. second to sixth lags) usually show a negative correlation when they are significant for both the DJ and the DAX. Based on the S&P500 stock return from April 1, 1928 to August 30, 1991, Ding et al. (1993) report a positively significant first lag (0.063) and a negatively significant second lag (-0.039) of the return process, where the critical value at the 95% significance level is ±0.015. Together with their finding, our results before Black Monday confirm the general view of the autocorrelation structures of stock return processes, namely a positively significant first lag and a negatively significant second lag. This earlier empirical stylized factor has been lost since Black Monday.[6] Our empirical results for the regime after Black Monday show that the opposite is true, i.e. the first lag is now highly negatively significant. Moreover, one more clear difference is

[6]The sample period in Ding et al. (1993) merely covers a short time span after Black Monday in comparison to the whole sample length. Therefore, the 'before-Black-Monday-effect', i.e. a significant positive first lag, is dominant throughout their sample period.

that various lags are positively significant before Black Monday, while being negatively significant after Black Monday.

To sum up, the positive (negative) sign for first lag of the two return series for the period before (after) Black Monday can be regarded as a result from the momentum (contrarian) trading behavior of the stock investors. This stylized factor manifests at the same time an empirical evidence of the profitability of the each trading strategy for the corresponding period.

3.4 Discussion: globalization and volatility

In this section, we try to give an explanation for our empirical findings. One possible scenario would be that in the first regime (before Black Monday), the stock market developed in step with the fundamentals, such as dividends and/or (national) macroeconomic data, while in the second regime (after Black Monday), the stock market became more volatile, owing to globalization and liberalization (i.e. more influential factors and, hence, more relevant information from the whole world), and, therefore, more uncertain and more speculative. In the literature, there seems to be a consensus on the advantages and disadvantages of globalization; see Tobin (1999), for example, on this topic. Stiglitz (2010) also argues that globalization is closely related to more uncertainty because of bankruptcy cascades and other financial contagions. For investors this means that if a stock indicator's development is based on the fundamentals it is itself a good indicator for making investment decisions, i.e., a positive return yesterday stimulates a positive investment today and *vice versa*. Therefore, investors would then follow the momentum strategy. When, however, uncertainty highly dominates in stock markets, investors would try to save a positive return yesterday (they behave like profit takers), i.e. a positive return stimulates a negative investment (sell) today and *vice versa*. Therefore, investors would then follow the contrarian strategy which produces more volatility in the dynamics of stock prices, as analytically shown by Park and Sabourian (2011). Kurz and Kurz-Kim (2013) also empirically test and conclude that high uncertainty on the stock market produces a stronger tendency to herding behavior among investors, and, hence, higher volatility. Table 4 and Figure 3 confirm the argument for the causal relationship between globalization and the increased volatility on the stock markets.

Table 4. Realized volatilities in the empirical data (%)

	DJ	DAX
before Black Monday	0.8964	0.9585
after Black Monday	1.0909	1.4493

The ratio of the two variances are 1.22 and 1.51 for the DJ and the DAX, respectively. They are highly significant according to the usual F-test even if the fat-tail phenomenon of the empirical return distribution is taken into account. When the Student's t-distribution with degrees of freedom of 4 is assumed for the underlying data[7], the simulated critical values (from 10,000 replications with the empirical DJ sample size) for the 95%-significance

[7]The degrees of freedom of 4 fully take the tail thickness of the empirical data into account for the calculation of critical values. The (theoretical) number of the absolute returns larger than 2% for the

level is 1.15. Figure 2 shows the development of volatilities for the two stock indices, where the straight line in both the upper and lower panels shows recursively calculated volatilities with a starting sample size of ten years and the dashed line volatilities calculated using moving-windows with a window-size of ten years.

Figure 3: Volatility of DJ and DAX

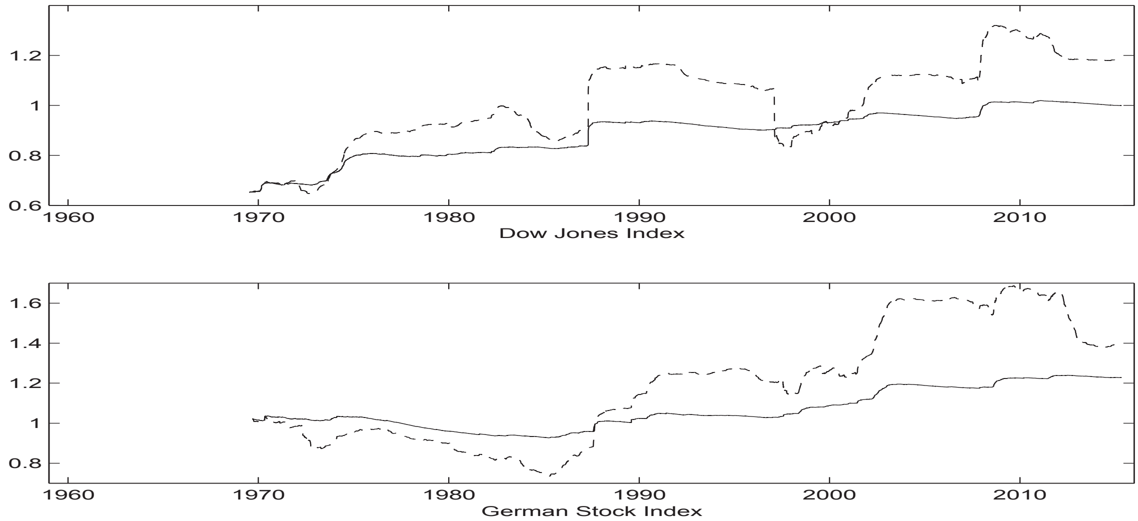


Figure 3 clearly shows a jump of volatility around Black Monday and, above all, a general increasing tendency of volatility despite some decreasing phases between the two crashes (the New Economy crash in 2000 and the financial crash in 2007) in both of the stock indexes.

4 Concluding remarks

The change in trading behavior in the stock markets, empirically found in this paper, can be interpreted as a long memory of the shock of Black Monday in 1987. But, a more plausible explanation for our empirical findings would be the change in the environments surrounding stock markets owing to globalization around and after the 1987 crash. Over the past few decades, globalization has meant more relevant information for investors, and more information leads to more volatility caused by higher uncertainty in the stock markets. That is, the crash in 1987 was a mark for a new time period, which stood for more uncertainty and in which fundamental-oriented forecasting became more difficult and more unreliable. Furthermore, we argue that the high uncertainty strengthens the belief in the random walk property of stock markets, which again promotes the tendency

Student-$t(4)$ is 11.61% higher than that of the empirical data of 4.60% for the DJ and of 8.09% for the DAX. The corresponding critical values for the F-statistic of the ratio of two variances will decrease as the degrees of freedom of the Student's t-distribution increase (i.e. tails of the distribution become thinner).

to a contrarian strategy such as profit taker and, at the same time, causes more volatilities, as analytically shown in Park and Sabourian (2011).

To sum up, our answer to the hypothesized question 'Did Black Monday, or generally, do crashes change trading behavior on stock markets?' is twofold. It should be 'yes', because crashes stoke uncertainty on stock markets identified in terms of volatility, and 'no', because crashes themselves are merely a manifestation of the uncertainty which has been driven by the globalization and liberalization of the financial markets.

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