UNIVERSITY OF PIRAEUS
SCHOOL OF ECONOMICS, BUSINESS AND INTERNATIONAL STUDIES
DEPARTMENT OF ECONOMICS

Evaluating Investment Strategies among the International Financial Markets:

Three essays on Investment Decisions.

Ph.D. Thesis

Mamais Konstantinos

A DISSERTATION SUBMITTED
TO THE DEPARTMENT OF ECONOMICS
OF UNIVERSITY OF PIRAEUS
IN PARTIAL FULLFILLMENT OF THE REQUIREMENTS
FOR THE DEGREE OF DOCTOR OF PHILOSOPHY

Piraeus, 2021

ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΑ
ΣΧΟΛΗ ΟΙΚΟΝΟΜΙΚΩΝ, ΕΠΙΧΕΙΡΗΜΑΤΙΚΩΝ ΚΑΙ ΔΙΕΘΝΩΝ ΣΠΟΥΔΩΝ
ΤΜΗΜΑ ΟΙΚΟΝΟΜΙΚΗΣ ΕΠΙΣΤΗΜΗΣ

Αποτίμηση Επενδυτικών Στρατηγικών στο πλαίσιο των Διεθνών Χρηματαγορών.

Τρία Δοκίμια βασισμένα στη λήψη Επενδυτικών αποφάσεων.

Διδακτορική Διατριβή

Μαμάης Κωνσταντίνος

Η ΔΙΑΤΡΙΒΗ ΥΠΟΒΑΛΛΕΤΑΙ
ΣΤΟ ΤΜΗΜΑ ΟΙΚΟΝΟΜΙΚΗΣ ΕΠΙΣΤΗΜΗΣ
ΤΟΥ ΠΑΝΕΠΙΣΤΗΜΙΟΥ ΠΕΙΡΑΙΩΣ
ΣΕ ΜΕΡΙΚΗ ΕΚΠΛΗΡΩΣΗ ΤΩΝ ΥΠΟΧΡΕΩΣΕΩΝ ΓΙΑ ΤΗΝ
ΑΠΟΚΤΗΣΗ ΔΙΔΑΚΤΟΡΙΚΟΥ ΔΙΠΛΩΜΑΤΟΣ

Πειραιάς, 2021

UNIVERSITY OF PIRAEUS

SCHOOL OF ECONOMICS, BUSINESS AND INTERNATIONAL STUDIES

DEPARTMENT OF ECONOMICS

Evaluating Investment Strategies among the International Financial Markets:

Three essays on Investment Decisions.

Ph.D. Thesis

Mamais Konstantinos

Supervisor: Vlamis Prodromos

Assistant Professor of Economics

Piraeus, 2021

UNIVERSITY OF PIRAEUS

SCHOOL OF ECONOMICS, BUSINESS AND INTERNATIONAL STUDIES

DEPARTMENT OF ECONOMICS

Evaluating Investment Strategies among the International Financial Markets:

Three essays on Investment Decisions.

Ph.D. Thesis

Mamais Konstantinos

Defense Committee

Assistant Professor Vlamis Prodromos

Professor Manolis Tsiritakis

Professor Dimitrios Thomakos

Professor Maria Psillaki

Professor Nikolaos Mylonas

Associate Timotheos Angelidis

Associate Georgios Papanastasopoulos

Piraeus, 2021

I would like to dedicate this thesis to my family…

Acknowledgements

First and foremost, I would like to express my sincerely gratitude to my research supervisor Assistant Professor Prodromos Vlamis, who believed in me and trusted me. He filled me with inspiration, strength, faith, loving research and gave me this unique opportunity for such a magical journey in the field of financial economics and econometric. His invaluable guidance throughout my Ph.D research motivate and filling me with optimism and passion to continue even during tough times. It was a great privilege and honor to collaborate with him, making my Ph.D experience productive and stimulating.

I would like to thank Professor Emmanuel Tsiritakis for his timeless support, the trust he showed me throughout my doctoral study, as well as the encouragement to deal with the research field as his postgraduate student. I was inspired by his stimulus discussions, useful comments, and great assistance. It was a great privilege and honor to collaborate with him.

This thesis would not been possible without the help and support of Professor Dimitrios Thomakos who believed in my capabilities and dreams from the undergraduate level until today. I would like to thank him for his timeless support and invaluable guidance, which push me to constantly evolve throughout my Ph.D research.

For this dissertation I would like to thank my reading committee members for their time, constructive comments and productive questions during my oral defense committee.

Last but not least, I would like to thank my parents and mainly my father for supporting my dreams and inspire me to try being better and better and not to give up no matter what; Matina for her supportiveness and unlimited patient during this period of my life and to my early mathematician, Eudoxia Kaplani, who first inspired me and structure my personality and the way I behave today, awakening first the need for in-depth knowledge and research, by making me surpass myself.

ABSTRACT

This dissertation consists of four chapters, each one of which studies investment strategies, covering the European (Germany) and the US market, and ends with documenting a careful and detailed analysis on the Chinese market. Also, I present three different approaches to investment strategies that contribute to the perception and understanding of investment activities.

Chapter 1 is an extensive literature review analysis on investment strategies, focusing mainly on momentum and its versions. Momentum is one of the most commonly accepted investment class among investors and academics across all investment strategies. In Chapter 1, I introduce the power and importance of momentum for investors, its difference with cross-sectional momentum, the lead-lag effects, the profitability and portfolio performance in momentum strategies. Also, I analyze the risk adjusted time series momentum and finally, there is a discussion about the power of momentum as one profitable investment strategy.

Chapter 2 consists the first research study of this dissertation, with title “Feeling Good, as a Guide to Performance: The Impact of Economic Sentiment in financial market Performance for Germany”. This Chapter illustrates the power of economic sentiment on German market as a guide for timing it, and how an investor could win the basic buy and hold strategy by taking advantage of sentiment as a strategy for various sub-periods from 1990 to 2017. Also, the economic sentiment influences the return and valuation of assets, the volatility and the bond yield spread, as it combines economic judgments, expectations, and attitudes of all economic agents.

Chapter 3 bases on momentum performance and portfolio beta changes across time and sectors, with title "Driven by portfolio beta changes and sectoral power in US stock market. Explaining momentum across time and sectors". This Chapter documents a careful and detailed analysis of the components of the NASDAQ index, that seeks to assess the role and what drives momentum portfolio performance in an appropriately and timely selection. I follow a three well-structure approaches. I examine the role of momentum portfolio performance, beta and Sharpe ratio across different economic sub-periods from January of 1985 to December of 2017 that are identified by clear exogenous events. Second, I study the time-varying sectoral characteristics of the components of the index and discuss the post-2007/2008 increase of healthcare companies’ participation in the index. Third, I perform a careful post-portfolio construction performance attribution to examine the impact of various characteristics of the portfolios themselves and the underlying fundamentals of the portfolios to explain the excess returns of momentum. Our findings align with the recent literature of asset management and momentum strategies and emerge for first time the highest sectoral percentage of momentum

portfolio participation and how these findings are linked in the beta variation and portfolio expected returns across periods.

Chapter 4 comprises the last section of my Ph.D thesis, with title “The Evolution of the Chinese Stock Market: A Review and a Historical Comparison”, which deals with an innovative subject matter: the characteristics of the Chinese stock market and its relationship with other financial markets. The innovation does not stand with the subject matter itself, but rather with the approach used to do the cross-comparisons with other market indexes. First, I provide a very detailed literature review on the historical evolution and characteristics of the Chinese stock market in general. The review covers every aspect of the Chinese market that has appear hitherto in the literature and provides a foundational framework for the rest of the analysis. This literature covers the Intraday Chinese trade, the intraday momentum, the role of the circuit breakers in the Chinese stock market, the co-moves among international markets and the Chinese investment sentiment. To understand the similarities and differences between the Chinese and other markets I collect data on a number of the most popular indices: US (S&P500 and RUSSELL 1000), France (CAC), Germany (DAX), and China covering Hong Kong and Shanghai (HIS, SSE50, CSI300, CSI500, and SSE) and I compute the returns, the realized risk and correlation measures. Importantly, I add in the analysis the dollar evolution of two major cryptocurrencies, the Bitcoin and the Ethereum, as alternative investments. The whole analysis is based on a very detailed historical sample split counting on the critical dates of the US, China, and Covid-19 period.

This dissertation aims to illustrate the importance of investment strategies and decisions across different financial markets, market characteristics and investor’s behaviors. This is achieved by bringing famous and timeless investment strategies, such as the economic sentiment and momentum. Finally, it offers a well structure approach in the field of investment decision providing economic solutions and justifications about the evolution of the international markets and which market offers the best risk reward trade of.

Περίληψη

Η παρούσα Διατριβή αποτελείται από 4 κεφάλαια, καθένα από τα οποία μελετά τις επενδυτικές στρατηγικές καλύπτοντας την Ευρωπαϊκή (Γερμανική) και την Αμερικάνικη αγορά, καταλήγοντας με σχολαστική διερεύνηση και ανάλυση στην Κινέζικη αγορά. Επίσης, παρουσιάζω τρεις διαφορετικές προσεγγίσεις των επενδυτικών στρατηγικών που συμβάλλουν στην αντίληψη και την κατανόηση των επενδυτικών δραστηριοτήτων.

Το Κεφάλαιο 1 αποτελεί μια εκτεταμένη βιβλιογραφική ανασκόπηση βασισμένη στις επενδυτικές στρατηγικές, εστιάζοντας κυρίως στο ίδιο το momentum και στις εκφάνσεις του. Το Momentum αποτελεί μια από τις κοινώς αποδεκτές κατηγορίες επενδύσεων μεταξύ όλων των επενδυτικών στρατηγικών έχοντας λάβει υπόψη επενδυτές και ακαδημαϊκούς. Στο Κεφάλαιο 1 παρουσιάζω τη δυναμική και τη σημαντικότητα του momentum για τους επενδυτές, τη διαφορά του με το cross-sectional momentum, τις επιδράσεις υστέρησης, την κερδοφορία και την απόδοση του χαρτοφυλακίου στις στρατηγικές momentum. Επίσης, αναλύω τις χρονολογικές σειρές του momentum προσαρμοσμένες στον κίνδυνο και τέλος, υπάρχει μια συζήτηση για τη δυναμική του momentum ως μία κερδοφόρα επενδυτική στρατηγική.

Το Κεφάλαιο 2 αποτελεί την πρώτη ερευνητική μελέτη αυτής της διατριβής, με τίτλο «Αισθάνοντας ασφαλείς με οδηγό την απόδοση: Ο αντίκτυπος του δείκτη Οικονομικής Ευαισθησίας στην απόδοση της Γερμανικής χρηματαγοράς». Αυτό το Κεφάλαιο παραθέτει την δυναμική του δείκτη οικονομικής ευαισθησίας για την Γερμανία ως κανόνα για να την καθοδήγηση του επενδυτή, και για το πώς ένας επενδυτής θα μπορούσε να ξεπεράσει σε απόδοση στην απλή βασική επενδυτική στρατηγική του αγοράζω και κρατάω, εκμεταλλευόμενος την στρατηγική της Ευαισθησίας για ένα πλήθος από υποπεριόδους από το 1990 έως το 2017. Επίσης, ο δείκτης Οικονομικής Ευαισθησίας επηρεάζει την απόδοση, την αποτίμηση των περιουσιακών στοιχείων, την διακύμανση και την απόδοση των ομολόγων, καθώς συνδυάζει οικονομικές κρίσεις, προσδοκίες και συμπεριφορές όλων των οικονομικών παραγόντων.

Το Κεφάλαιο 3 βασίζεται στην απόδοση του momentum και στις αλλαγές των β του χαρτοφυλακίου μέσα στο χρόνο και στους κλάδους εταιρειών, με τίτλο «Καθοδηγούμενοι από τις αλλαγές των β του χαρτοφυλακίου και της δυναμικής των κλάδων των εταιρειών στην Αμερικανική χρηματαγορά. Εξηγώντας το momentum μέσα στο χρόνο και στους κλάδους εταιρειών». Αυτό το κεφάλαιο τεκμηριώνει μια προσεκτική και λεπτομερή ανάλυση των στοιχείων του δείκτη NASDAQ, που επιδιώκει να αξιολογήσει το ρόλο και τι οδηγεί την απόδοση του momentum χαρτοφυλακίου σε μια κατάλληλη και έγκαιρη επιλογή. Για το λόγο αυτό ακολουθώ μια τριπλή προσέγγιση. Εξετάζω τον ρόλο της απόδοσης του momentum χαρτοφυλακίου, του δείκτη β και του Sharpe σε διάφορες οικονομικές υποπεριόδους από τον Ιανουάριο του 1985 έως τον Δεκέμβριο του 2017, τα οποία αναγνωρίζονται από σαφή εξωγενή

συμβάντα. Δεύτερον, μελετώ τα χρονικά μεταβαλλόμενα χαρακτηριστικά κλάδων εταιρειών των συνιστωσών του δείκτη και συζητώ την αύξηση της συμμετοχής των εταιρειών Υγειονομικής Περίθαλψης μετά το 2007/2008 στο δείκτη. Τρίτον, μελετώ προσεχτικά τον αντίκτυπο πολλαπλών χαρακτηριστικών των ίδιων των χαρτοφυλακίων και των θεμελιωδών μεγεθών τους, για να εξηγήσω την υπερβάλλουσα απόδοση του momentum. Τα ευρήματα επιβεβαιώνουν την πρόσφατη βιβλιογραφία για τη διαχείριση περιουσιακών στοιχείων και τις στρατηγικές momentum αναδύοντας για πρώτη φορά το υψηλότερο ποσοστό συμμετοχής των κλάδων στο momentum χαρτοφυλάκιο και το πώς όλα αυτά τα ευρήματα συνδέονται με την παραλλαγή των β και τις αναμενόμενες αποδόσεις του χαρτοφυλακίου σε όλες τις περιόδους.

Το Κεφάλαιο 4 περιλαμβάνει την τελευταία ενότητα της διδακτορικής διατριβής μου με τίτλο «Η Εξέλιξη του Κινέζικου Χρηματιστηρίου: Μια Ανασκόπηση και μια Ιστορική Σύγκριση», που ασχολείται με ένα καινοτόμο θέμα: τα χαρακτηριστικά του Κινέζικου χρηματιστηρίου και τη σχέση του με άλλες χρηματοοικονομικές αγορές. Η καινοτομία δεν έγκειται στο ίδιο καθαυτού το αντικείμενο έρευνας αλλά στην προσέγγιση, που χρησιμοποιείται στις συγκρίσεις με άλλους δείκτες της αγοράς. Πρώτον, παρέχω μια λεπτομερέστατη ανασκόπηση της βιβλιογραφίας για την ιστορική εξέλιξη και τα χαρακτηριστικά του Κινέζικου χρηματιστηρίου εν γένει. Η ανασκόπηση καλύπτει κάθε πτυχή της Κινέζικης αγοράς που έχει εμφανιστεί μέχρι τώρα στη βιβλιογραφία και παρέχει ένα θεμελιώδες πλαίσιο για την υπόλοιπη ανάλυση. Αυτή η βιβλιογραφία καλύπτει την ενδοημερήσια Κινέζικη συναλλαγή, το ενδοημερήσιο momentum, τον ρόλο των circuit breakers στην Κινέζικη χρηματιστηριακή αγορά, τις από κοινού κινήσεις μεταξύ των διεθνών αγορών και τον Κινέζικο δείκτη ευαισθησίας. Για την κατανόηση των ομοιοτήτων και διαφορών μεταξύ των Κινέζικων κι άλλων αγορών, συνέλλεξα δεδομένα για έναν αριθμό από τους πιο δημοφιλείς δείκτες: ΗΠΑ (S & P500 και RUSSELL 1000), Γαλλία (CAC), Γερμανία (DAX) και Κίνα καλύπτοντας το Χονγκ Κονγκ και τη Σαγκάη (HIS, SSE50, CSI300, CSI500 και SSE) και υπολογίζοντας τις αποδόσεις, τον πραγματικό κίνδυνο και τη συσχέτιση. Είναι σημαντικό το γεγονός ότι συμπεριέλαβα στην ανάλυση την εξέλιξη του δολαρίου και των δύο σημαντικότερων κρυπτονομισμάτων του Bitcoin και του Ethereum ως εναλλακτικές επενδύσεις. Η όλη ανάλυση βασίζεται σε ένα πολύ λεπτομερές ιστορικό διαχωρισμό δείγματος που στηρίζεται στις κρίσιμες ημερομηνίες των ΗΠΑ, της Κίνας και της περιόδου Covid-19.

Αυτή η διατριβή στοχεύει να αναδείξει τη σημασία των επενδυτικών στρατηγικών και αποφάσεων σε διάφορες χρηματοοικονομικές αγορές, τα χαρακτηριστικά των αγορών και τις συμπεριφορές των επενδυτών. Αυτό επιτυγχάνεται φέρνοντας διάσημες και διαχρονικές επενδυτικές στρατηγικές, όπως τον δείκτη Οικονομικής Ευαισθησίας και το momentum. Τέλος, αποδίδετε μία πλήρες δομημένη προσέγγιση στον τομέα των επενδυτικών αποφάσεων παρέχοντας λύσεις και αιτιολογίες για την εξέλιξη των διεθνών αγορών καθώς και ποια αγορά παρέχει την καλύτερη σχέση απόδοσης κινδύνου.

Contents

List of Figures

List of Tables

Chapter 1

Literature on investment strategies

1.1 Introducing Momentum

While fundamental analysts study a company's underlying indicators of profit such as earnings, dividends, new products and R&D, the technical analysts focus mainly on price and return but unwittingly also consider psychological aspects in the demand for a company's stock. Traders and portfolio managers use technical analysis that forecast stock price movements using historical prices to formulate buy and sell decisions. Momentum is one of the most commonly accepted investment class among investors and academics across all investment strategies and asset management industry. Momentum, according to rational and behavioral asset pricing theories underlines the idea of buying winners and selling losers, based on its average past realized returns. Momentum is an unexhausted active research topic and important studies include Moskowitz and Grinblatt (2003), Choria and Shivakumar (2006), Sadka (2006), Hou, et al., (2011), Fama and French (2012), Moskowitz et al., (2012), Bajgrowicz and Sxaillet (2012) and Menkhoff, et al. (2012).

The first academic paper which highlight the importance of profitability of momentum as an investment strategy was by Jegadeesch and Titman (1993). They focused on the performance of equally weighted portfolios of stocks chosen according to their performance over several combinations of periods and held for a variety of holding periods. Their results supported that the stocks with best past performance (top 10%) outperformed those stocks with the worst past performance (bottom 10%). Also, Jegadeesh and Titman (1993) examined several momentum strategies and documented that strategies which bought stocks with high returns over the previous 3 to 12-months and sold stocks with poor returns during the same period earned profits of about 1% per month for the following year. Additionally, they observed that over an intermediate horizon of 3 to 12-months, past winners on average continued to outperform past losers and as a result there was "momentum" in stock prices. Investment strategies that exploit such momentum, by buying past winners and selling past losers, attracts the attention of many professional investors. Although, a part of literature argues that from such strategies, results provide strong evidence of "market inefficiency", the other part argue that the returns are either compensation for risk, or product of data mining. Using a sample period from 1990 to 1998, Jegadeesh and Titman (1993) showed that momentum strategies continued to be profitable and that past winners outperformed past losers by about the same magnitude as in the earlier period. Conrad and Kaul (1998) argued that the profitability of momentum strategies could be entirely due to cross-sectional variation in expected returns rather than to any predictable time-series variations in stock returns. Conrad and Kaul (1998) hypothesis that momentum strategies yield positive returns on average even if the expected returns on stocks are constant over time. Many practitioners and academics in the pre-market-efficiency era believed that predictable patterns in stock returns could lead to “abnormal” profits to trading strategies. The main reason for the existence of abnormal profits were because of market inefficiencies in time series pattern returns. Also, Conrad and Kaul (1998) analyzed two strategies, the contrarian strategy that relies on price reversals and the momentum strategy based on price continuations (or “momentum” in asset prices). A contrarian investment strategy is followed from investors who prefer to go against the prevailing market tendency based on a simple strategy of buying when the investors sell and via versa. Initially, there was relatively more emphasis on contrarian strategies, but there were growing evidence that price continuations resulted in consistent “abnormal” profits to momentum strategies.

Conrad and Kaul (1998) stated that stock prices were inextricably linked and followed random walks with drifts, and the unconditional drifts vary across stocks. Differences in unconditional drifts across stocks explained momentum profits as any predictability under the hypothesis of differences in unconditional drifts and not about the random component of price changes in any particular period. They also implied that the profits from a momentum strategy should be the same in any postranking period. In other words, that hypothesis predicts that the stocks on the long term of the momentum portfolio should continue to outperform stocks on the short one by the same level at any postranking period. The behavioral models imply that the holding period abnormal returns arise due to a delayed overreaction to information that pushes the prices of winners (losers) above (below) their long-term values. Higher returns of winners in the holding period represented their unconditional expected rates of return and thus predicted that the returns of the momentum portfolio would be positive on average in any postranking period. However, positive momentum returns are sometimes associated with postholding period reversals and others not, indicating that the behavioral models can not justify the momentum anomaly. An incentive for behavioral literature is the fact that there is evidence of postholding period returns which are probably negative. Such an example comes from Jegadeesh and Titman (1993), who presented some evidence that in the postholding period the average return of their momentum portfolio became negative. DeBondt and Thaler (1985) came to reinforce these facts, by providing stronger evidence of longer-term overreaction.

As already mentioned, momentum is the most actively used strategy class in the asset management industry. The main idea was to use the power of past performance into the future by buying "winners and selling losers". The drawback of a typical mom0entum strategy is that it uses trading signals that are based on averages of past realized returns and therefore completely ignores the noise that is introduced into these signals by the fluctuating stochastic volatility. This might be inefficient because averaging past realizations of highly heteroskedastic returns may produce a very noisy estimate of the true expected return. Dudler et al., (2014) posed that removing heteroskedasticity from the trading signals via a simple risk-adjustment procedure significantly improved the strategies' performance. Normalizing past returns by realized volatility removes a part of their variation that is driven purely by changing volatility and not by changing fundamentals and as a result leads to much more stable trading signals.

Momentum is one of the strongest and most puzzling asset pricing anomalies. Momentum is puzzling because it suggests that prices are not even weak form efficient. For it to be rational, risk would have to increase after positive returns, contrary to the intuition that risk should actually decline. Empirically Jegadeesh and Titman (2001) found that risk adjustment tended to accentuate rather than explained momentum. Lewellen (2002) argued that investors either underreact or overreact late to firm-specific news. Lewellen (2002), extended its research by using the size, B/M[1], and double-sorted size-B/M portfolios (5, 10, or 15 size and B/M portfolios; 9, 16, or 25 double-sorted portfolios). Momentum in these portfolios was as strong, and in some cases stronger, than momentum in individual stocks or industries. He also focused on the autocorrelation patterns in returns. It was well known that momentum was not the same as positive autocorrelation. Lo and MacKinlay (1990) tried to give explanations about the reason of existence of momentum. Momentum is possibly caused due to the autocorrelation in returns, the lead-lag relations in stocks meaning cross-serial correlation, or cross-sectional dispersion in unconditional means. Generally, a stock that outperformed other stocks in the past usually has the tendency to outperform in the future too. This evidence existed for three reasons. Firstly, the stock return was positively autocorrelated, so its own past return predicts high future returns. Secondly, the stock return was negatively correlated with the lagged returns on other stocks, so their poor performance predicts high future returns. Thirdly, the stock simply had a high unconditional mean relative to other stocks. Empirically, lead-lag relations among stocks played an important role.

Momentum profits were created from the difference of power that the volume of lead-lag effects tended to surpass that of autocorrelations. Observing together momentum with negative autocorrelation, the investors underreacted to portfolio specific news but overreacted to macroeconomic events. Second, excess covariance among stocks could produce a similar result, where "excess covariance" means, loosely, prices covary more strongly than dividends. Lewellen (2002) argued, however, that portfolio-specific underreaction did not explain size and B/M momentum because investors seemed to overreact to market news and underreact to size or B/M related news. What is more, the lead-lag relations among large and small stocks are too

[1] B/M stands for book equity/market equity ratio.

large to be explained by market reversals. Based on Lewellen (2002) size and B/M portfolios, momentum was strong as that in individual stocks and industries. That finding suggested that momentum was a pervasive feature of returns. Moreover, he implied that momentum could not be attributed simply to firm-specific returns. The size and B/M portfolios are quite well diversified, so their returns reflected systematic risks. Macroeconomic factors took responsibility for size and B/M momentum, and not particularly firm-specific returns. In principle, size and B/M momentum might be explained by investor underreaction. Empirically the returns on industry, size, and B/M portfolios are negatively autocorrelated and cross-serially correlated. However, it was potentially consistent with portfolio-specific underreaction, along with macroeconomic reversals, but that story also had difficulty in explaining the evidence. Firstly, large stocks were weakly negatively autocorrelated, and they predicted other portfolios quite strongly (the cross-serial correlations were stronger than the underreaction story predicts). Secondly, market returns predicted portfolio-specific returns on many size, B/M, and industry portfolios and the Fama and French (1993) three-factor model largely absorbed the serial correlation patterns in size and B/M portfolios. Theoretically the underreaction story was unappealing because investors reacted differently to portfolio-specific and market-wide news. No behavioral model predicted that result. Perhaps more critically, news about size and B/M portfolios cannot reasonably be described as idiosyncratic. These observations could be important for investment decisions, testing asset pricing models, and evaluating the performance of mutual funds.

1.2 Time series vs cross-sectional Momentum

Cross-sectional and TSMOM consists two of the most favorable and popular among investors investment strategies, where the time series is consisted to be more profitable and latest. One of the most perplexing aspects of this literature is that these two diametrically opposed strategies, time series and cross-sectional momentum (CSMOM), appear to “work” simultaneously, albeit for different investment horizons. Specifically, contrarian strategies are apparently profitable for the short-term (weekly, monthly) and long-term (3 to 5 year, or longer) intervals, while the momentum strategy was profitable for medium-term (3 to 12-month) holding periods. Profits from trading strategies based on securities’ past performance contain two components. First component was for time-series predictability in security returns and second was for cross-sectional variation in the mean returns of the securities comprising the portfolio. The actual profits to the trading strategies implemented based on past performance and contain a cross-sectional component that would arise even if stock prices were completely unpredictable and did follow random walks. As long as, there were some cross-sectional dispersion in mean returns of the securities universe, a momentum strategy would be profitable. Conversely, a contrarian strategy would be unprofitable on average even in a world where stock prices follow random walks. In their research, Conrad and Kaul (1998) suggested that the momentum strategy usually gets positive, and frequently statistically significant, profits at medium horizons, except during the 1926–1947 sub-period, while a contrarian strategy is successful at long horizons, although the profits to these strategies were statistically significant only during the 1926–1947 sub-period.

The cross-sectional dispersion in mean returns appears responsible for the paucity of statistically profitable contrarian strategies. Although they consistently observed statistically significant price reversals at virtually all horizons, the profits emanating from these reversals were typically neutralized by the losses due to the large cross-sectional variance in mean returns. Even the most conservative estimates suggested that the cross-sectional variation in mean returns was a nontrivial determinant of the profitability of trading strategies. Traders may view the cross-sectional variation in mean returns as a source of "abnormal" profits.

The unconditional probabilities of success of momentum and contrarian strategies were approximately equal. From 55 statistically profitable strategies, 30 are momentum, while 25 are contrarian strategies. This finding was noteworthy given that momentum and contrarian strategies were diametrically opposed in philosophy. More importantly, based on Conrad and Kaul (1998), all 11 of the momentum strategies that yield statistically significant profits were medium-horizon strategies. The contrarian strategy was statistically profitable only twice in the three postwar sub-periods. This evidence was also consistent with the results of Fama and French (1988) and Kim, Nelson, and Startz (1991), who found that long-term mean reversion in the prices of portfolios of securities were peculiar to the prewar period. Recent research showed that the profitability of short-term strategies may be spurious because it was generated by market microstructure biases.

The profitability of momentum strategies at medium horizons might not be due to price continuations, potentially induced by market inefficiencies. Moreover, the lack of statistically profitable contrarian strategies might be because these strategies lost the cross-sectional dispersion in means, with this loss being particularly severe at long horizons. Conrad and Kaul (1998) found that an important determinant of the profitability of trading strategies was the estimated cross-sectional dispersion in the mean returns of individual securities comprising the portfolios used to implement these strategies. They suggested that cross-sectional differences in mean returns played a nontrivial role in determining the profitability of momentum strategies. These again appear to have no relation to time-series patterns in security returns that form the basis of trading strategies; they occurred because a contrarian strategy on average involves the purchase of low-mean securities from the proceeds of the sale of high-mean securities.

1.3 Momentum in investor's reactions

Barberis et al. (1998) presented a model that combines the conservatism bias with what Tversky and Kahneman (1974) explained as a "representative heuristic", in order to explain the shorter-term momentum and the long-term overreaction. As representative heuristic, Tversky and Kahneman (1974), stated the ability of people to determine how to sides or variables are connected. Generally, the representativeness drives to an underweighting, while conservatism bias overweighting relative to the sample evidence. In their model they stated the tendency of traders for identifying the "representative heuristic". Additionally, Barberis et al. (1998) stated that the representative heuristic about stock prices usually drove investors to believe that the current enormous earnings and growth continued to the future. That conclusion of course is out of the box. That behavioral tendency in conjunction with the representative heuristic lead to long horizon negative returns for stocks with consistently high returns in the past.

Lee and Swaminathan (2000) suggested that stock prices typically oscillated around their fair value. Under these circumstances, the key to success at any momentum strategy would be based on it. The success is attributed to the fact that implementation rules are in harmony with the periodicity of the pricing and mispricing cycles. The gap of delay in identifying winner and loser securities is drawn from the fact that the momentum trading signals counts on recent pricing movements. Jegadeesh and Titman (2001) stated in their post-holding period that the momentum profits arise from investors' underreaction to the relevant period information. However, such evidence lasts for a while since the information was gradually incorporated during the holding period into stock prices. An extensive reference is made by Barberis et al. (1998), who analyzed how a "conservatism bias" made investors to underreact to information. Edwards (1968), who first gave the attribution of conservatism bias, suggested that individual's underweight new information in updating their priors. However, when the information is incorporated into prices, then stock returns become unpredictable.

What is more, Daniel et al. (1998) analyzed that when traders are fully informed, they suffered from a "self-attribution" bias, as in their model, the part of investors with positive signals, are the ones with high performance after the signal is captured. Taking into account the cognitive biases, the full informed investors considered the stock selection skills played a key role about performance of ex post winners and bad luck about performance to ex post losers. As a result, such investors become overconfident about their ability to pick up winners and thereby overestimate the signals for these stocks. Their confidence leads them to increase the prices of the winners above their fundamental values. Hong and Stein (1999), considered two groups of investors who trade according to different sets of information. The first group is mention to the "news watchers", who are actually the informed traders. This very group obtain signals about future cash flows but on the other hand they ignore information about the past history of prices. In their model, the informed investors obtained the information with a delay. So, it is partially incorporated in the prices when first revealed to the market and such part of model add to underreaction leading to momentum profits. Following Hong and Stein (1999), the other part of investors counts on a limited history of prices and, in addition, do not observe fundamental information. Both groups of investors in that model act rationally in updating their expectations conditional, but as far their return predictability, traders in each group uses only partial information in order to update their expectation. Evidence of underreaction over intermediate horizons suggests that a stock with low past returns will on average experience low subsequent returns. It might be argued that a contrarian overreaction story would instead predict high subsequent returns for such a stock. The common element was the market's tendency to stick enough on past trends. Investors discount new information that is at odds with their mindsets and change their perceptions gradually. Given that, when disappointing news arrives, investors initially discount the information and this result to downward drift in prices.

One of the simplest and most widely used trading strategies based on technical analysis is the Moving Average (MA) rule. It is an objective rule-based trading strategy in which buy and sell signals are determined by the relative magnitudes of short and long-term MAs. Hong and Satchell (2015) found that there were two reasons why the MA rule is popular. Firstly, the MA rule could identify the price momentum, which confirmed the results of the previous momentum literatures. Secondly, the MA rule was a simple way of tracing and exploiting the price autocorrelation structure without knowing its structure. The MA rule provided a simple and clear methodology that could take advantage of the price autocorrelation structure. If a conservatism bias existed in a market, the MA rule would be profitable. A conservatism bias indicates that investors are too slow (too conservative) in updating their beliefs in response to recent evidence. This means that they might initially underreact to news about a firm, meaning that prices will fully reflect new information only gradually. Such a bias would give rise to momentum (price autocorrelation) in the stock market.

Hong and Satchell (2015) stated that it was not just about buying past losers or winners but was also about price trends and the autocorrelation structure. Momentum trading strategy was well known for its advantage of trend within the times series data and because it strengthens the autocorrelation. That shows a TSMOM trading strategy as a common way of conditioning on past price information. Brock, Lakonishock and LeBaron (1992), posed that “According to the MA trading rule, buy and sell signals are generated by two MAs of the level of the index – a long-period average and a short-period average”. That strategy urged traders buying (or selling) when the long-term MA was below (above) from a rise in short-period MA. Such a trend is considered to be initiated. They also suggested the importance of logic behind the MA bull rule, when a price penetrated the MA from below, the bull trend is believed to be established and the trader exploited that expectation for further upward movements in prices.

The MA bear rule known to practitioners as short-term price reversal. When the trader expects a price reduction (enough to penetrate the MA from above) due to market overreaction, then the trader took long position expecting that the price would return immediately back. Fong and Yong (2005) stated the connection of MA rule and price momentum. Generally, an upward (bullish) movement occurred when prices tended to rose above its MA, and a downward (bearish) trend occurred from a price reduction below its MA. Another approach of bullish and bearish trend is determined from the relation between sensitivity of the expected price ratio with today's price. The positive sensitivity indicated bullish momentum and the negative bearish momentum.

1.4 The lead-lag effects

Another important issue was the lead-lag effects on contrarian and momentum strategies. The issue of stock returns in short-term predictability and its implications on the profitability of contrarian and momentum strategies had attracted significant attention in the literature (Conrad and Kaul (1988), Jegadeesh (1990), Lehmann (1990), Jegadeesh and Titman (1993), Levich and Thomas (1993), Lo and MacKinlay (1990), Asness (1994)). Jegadeesh (1990) and Lehmann (1990) found evidence that reinforced the short-term contrarian strategies (as opposed to momentum) since, individual stock returns exhibited negative serial correlation. These short-term contrarian profits were initially regarded as evidence that stock prices tended to overreact to information (Poterba and Summers (1988)).

Lo and MacKinlay (1990) gave a different explanation about the profitability of contrarian strategies. They attributed these profits to a systematic lead-lag relation among returns of size-sorted portfolios and not as usual to market overreaction. Using weekly US stock market data for five equally-weighted size-sorted portfolios, they found evidence of positive cross-autocorrelation between lagged returns of portfolios of large capitalization stocks (large-firm portfolios) and the returns of portfolios of small capitalization stocks (small-firm portfolios). That indicated large portfolio returns led small-portfolio returns. Portfolios with large-capitalisation stocks showed positively cross-autocorrelated with lagged in contrast to small-capitalisation stocks. This relation indicated that the transmission of information between large and small firms was such a complex mechanism that had repercussions on their portfolio returns (see Merton (1987), Badrinath, Kale and Noe (1995)). Specifically, Lo and MacKinlay (1990) argued that this relation may be since information shocks are transmitted first to large firms and then becomes known to the small ones. That's the reason why there are evidence of a lagged adjustment of small-firm portfolio prices. Lo and MacKinlay (1990) stated that such pattern provided a channel through which contrarian strategies were profitable. They concluded that the lead-lag effect between large and small firms was very important in explaining contrarian profits, indicating a complex process of information transmission between small and large firms.

Kanas (2004) study the lead-lag effects in the mean and variance of returns of size sorted equity portfolio in UK and the implication on contrarian and momentum strategies by constructing three sets of portfolios. Namely, the first was a size-sorted equally-weighted portfolios builded up of different capitalization size, the second was a set of size-sorted value-weighted portfolios but with different capitalization size, and a third set of portfolios of the same capitalization size. Evidence in the mean and variance of lead effect for both sets of portfolios with different capitalization size and all size firm portfolios. As such result was independent from weighting scheme of constructing portfolios, it indicated that strategies on large firm portfolios were profitable. Unfortunately, for portfolios of equal capitalization size there were no evidence to state in lead-lag effect neither in the mean nor in the variance. The lead-lag effect was due to the difference in the capitalization size among portfolios. Kanas (2004) applied the CCF (Cross-Correlation Function) test in order not only to capture the unique trading strategy that indicated more profits but also to find the cross-portfolio effects. The signs of all statistically significant CCF test statistics were positive, suggesting that contrarian strategies were profitable. As in Lo and MacKinlay (1990), there were no evidence that returns on small-firm portfolios affect returns on large-firm portfolios. For portfolios of equal capitalization size, however, the lead-lag effect disappeared or was much weaker. With regard to the lead-lag effect in variance, they found that such an effect arises among size-sorted portfolios and did not appear among equal-size portfolios. The existence of lead-lag effects in mean and variance was therefore driven by the capitalization size difference of the portfolios used. These results were robust for the pre and post October 1987 sub-period. These results were of interest to technical analysts and institutional investors, who seek to identify profitable strategies on the basis of past returns, and the predictability of asset returns respectively, as well as to producers asset-pricing models, who seek to identify relevant variables in explaining asset returns. The capitalization size of portfolios influences the results of the tests for lead-lag effects. That finding echoes the results of Fama and French (1992) who found that size was an important variable in explaining asset returns. The economic significance of these results is discussed on the basis of economic factors which explained these lead-lag effects. Such factors include the level of institutional ownership, and the information set-up cost. Badrinath et al. (1995) argued that institutional investors place significant emphasis on firm size in addition to the usual risk and return criteria.

Information set-up costs was a second economic factor which was consistent with the existence of lagged information transmission between large and small-capitalization firms. Merton (1987) argued that there was a receiver or set-up cost associated with information processing. An investor was to incur this fixed cost only whether the value-added by adding the stock to portfolio was sufficiently large. Institutional investors, who undertook systematic investigations, tended to concentrate their investment on stocks for which the volume of available information was large relative to the information set-up cost. Merton (1987) showed that, on average, these tend to be large-capitalization firms. Ross (1989) posed that the variance of returns was related directly to the rate of flow of information. Thus, examining the predictability of variances of returns of small and large firm portfolios would help better understand the mechanism by which information is assimilated across firms of different market value. Kanas (2004) concluded that no lead-lag effect found for portfolios of equal capitalization size and suggest that contrarian, as opposed to momentum, trading strategies on UK large-firm portfolios are profitable.

An important implication that emerged from Lo and MacKinlay's (1990) findings referred to the utility, that investors achieved from information that small firms acquired and contributed to short-run predictability of portfolio returns. Namely, using the portfolio returns from large firms, an investor reliably predicts the returns in the short-run in small-firm portfolios. Kanas and Kouretas (2005) developed a formal framework illustrating how the lead-lag effect in returns is related with cointegration at price of the small-firm portfolio and the lagged price of the large-firm portfolio. This rule of lead-lag effect in returns defined as evidence of a long-run lead-lag relation among prices of size-sorted portfolios and not the cointegration between the contemporaneous price of small-firm portfolio price and the lagged large-firm portfolio. Evidence of cointegration between contemporaneous small-firm portfolio prices and lagged large-firm portfolio prices found only for size-sorted portfolios and not for equal-size portfolios, thereby indicating the importance of size in driving a long-run lead-lag effect. That result echoes the findings of Banz (1981) and Fama and French (1992) regarding the role of size in explaining asset returns. For size-sorted portfolios, the large-firm portfolio price appears to be the 'long-run forcing variable' for the explanation of the small-firm portfolio prices. It is important to note that, small-firm portfolio prices cannot be treated as 'long-run forcing variables' for the explanation of large-firm portfolio prices. Lo and MacKinlay (1990) ended up that the conclusion of lead-lag effect came from the prices of large market value securities as first incorporated the information and then followed the prices of small market value securities.

1.5 Profitability and portfolio performance in Momentum strategies

Many portfolio managers and stock analysts subscribe to the view that momentum strategies yield significant profits. TSMOM assigns more stocks to the winner than to the loser portfolio when markets are strong, with the opposite being during periods when markets had been experiencing weak performance. In contrast, CSMOM always assigns the same number of stocks to each portfolio irrespective of how the market is performing. Hence, there is a timing element in the selection of stocks embedded in time-series momentum which does not exist in CSMOM. Cooper et al. (2004) showed that the performance of cross-sectional analysis conditioned by the performance of the market, as in down markets very large deterioration happened in the performance of the winner portfolios. When markets were falling, the winner portfolio of CSMOM showed stocks experienced poor performance. As a result, CSMOM must dig much deeper to find winner stocks during down markets and this contributes to the relatively poor performance of the winner portfolios. The pervasiveness of the empirical findings on momentum has stimulated numerous studies seeking an explanation for its apparent continued profitability. These studies can broadly be split into two camps. One group that proposes more traditional explanations aimed at establishing that the findings are due to methodological flaws in research design (e.g. failure to control risk and transaction costs). A second group argues that the momentum profits are attributable to irrational behavior of investors that results in stocks prices both under- and over-reacting to information signals.

Jegadeesh and Titman (1993) found an astonishing seasonality[2] in momentum profits. They documented that the winners outperformed losers in all months except January, but in January the losers significantly outperform the winners. Jegadeesh and Titman (2001) stated that due to the fact that small industries had more volatile returns, both winners and losers tended to be smaller firms than the average stock in the sample. So smaller firms are more likely to appear in the extreme return sorted portfolios. For the winner's portfolio the average size rank exceeded to the one portfolio that consisted of losers' stocks. Furthermore, they indicated that the losers are riskier than the winners because these were more sensitive to all three Fama-French factors, since the loser portfolios were more sensitive to the Fama and French size and book-to-market factors.

Latane and Jones (1979), Bernard and Thomas (1989), and Bernard, Thomas, and Wahlen (1995), among others, found that firms reporting unexpectedly high earnings outperform firms with unexpectedly poor earnings. The superior performance persists over a period of about 6-months after earnings announcements. Accordingly, one possibility is that the profitability of momentum strategies is entirely due to the component of medium horizon returns that is related to these earnings related news. If this explanation is true, then momentum strategies will not be profitable after accounting earnings for past innovations and forecasts. Another possibility is that the profitability of momentum strategies stemmed from overreaction induced by positive feedback trading strategies. This possibility is discussed by DeLong et al.

2 This seasonality could potentially be a statistical fluke; January is one of twelve calendar months and it is possible that in any one calendar month momentum profits are negative.

(1990). This explanation implies that "trend-chasers" reinforce movements in stock prices even in the absence of fundamental information, so that the returns for past winners and losers are temporary in nature. Under this explanation, it is expected that past winners and losers will subsequently experience reversals in their stock prices. A momentum strategy about earnings may benefit from underreaction to information related to short-term earnings, while a price momentum strategy may benefit from the market's slow response to a broader set of information, including longer-term profitability.

Foster, Olsen, and Shevlin (1984) found that residual returns close to the announcement date had no predictable power while standardized unexpected earnings contributed to prediction of future returns. Klein (1990) also found that investors tended to be optimistic in their forecasts especially for poor stock performance firms. This optimistic attitude may come from the fact that the analyst's best interest is to avoid being the first messenger with bad news, as this might antagonize management. Analyst's tendency is to remain optimistic and wait with a view to confirm evidence of poor earnings and then to slowly modifying their estimates. Since there is a large correlation between the analysts' incomes on the amount of business and the type of news they are expecting, this fact drives them to become less willing to disseminate unfavorable news (see Lakonishok and Smidt (1986)).

All in all, the momentum in stock prices partially depicts the market's slow adjustment to the information in earnings because of the high association between prior returns, prior earnings news and the sluggishness in the market's response to past earnings surprises. The delay of market to slowly incorporate the information and to react on time, create drifts in future stock returns. These drifts can be forecasted using abnormal announcement return. Surprisingly, however, Foster, Olsen, and Shevlin (1984) found that future returns are associated with past standardized unexpected earnings, but this not happened with past abnormal announcement returns. The general trend about stock price performance discloses the market's slowly adjustment to earnings surprises. It is important to state that the market is still surprised with the type of news that characterizes the standardized unexpected earnings of stocks at the next announcement date of earnings. Sorting stocks on the basis of past returns and on past earnings, it yields large differences in subsequent returns and spread in the future. The spreads in returns associated with the earnings momentum strategies, however, tend to be smaller and last for shorter length periods when it is compared to the results of the price momentum strategy.

Moskowitz and Grinblatt (1999) suggested that industry momentum investment strategies (bought stocks from past winning industries and sold stocks from past losing industries) were highly profitable compared with the momentum investment strategies. That observation happened even when momentum controls the size, book-to-market equity, individual stock momentum, the cross-sectional dispersion in mean returns, and potential microstructure influences. That suggestion is reinforced since the industries momentum strategies were robust to various specifications and methodologies, and were profitable especially in the largest, most liquid stocks. As far as the industry strategies over intermediate horizons, the profitability was pre-dominantly driven by the long positions. However, the profitability of individual stock momentum strategies is characterized by selling past losers, specifically among the less liquid stocks. On contrary to individual stock momentum, industry momentum was strongest in the short-term (at the one-month horizon) and like individual stock momentum it tended to dissipate after 12-months, eventually reversing at long horizons. The signs of short-term period performance of these two stock momentum strategies were totally opposed, whereas these signs were identical for performance at intermediate and long-term.

Another contribution of Moskowitz and Grinblatt (1999), was to show that momentum strategies were not very well diversified. This was due to the fact that industry momentum derived by individual stock momentum, and industry "stocks" had higher correlation than stocks across industries. In other words, momentum was far from an arbitrage. Rational investors, who might realize momentum as an "arbitrage" opportunity, could make profit from their irrational counterparts at low risk with taking positions in large numbers of stocks only in case the bulk of investors intensely and irrationally underreacted to information that was uncorrelated across firms. Prior literature showed minimum impact of industries on asset prices both in domestically and in international markets. On contrary, corporate finance literature recognized the importance of industries in explaining hot and cold IPO, merger and acquisition activity, SEO markets, and other investment and financial policy decisions. What is more, they found an extremely strong industry influence when they condition returns on the information in past prices. Recent rational and behavioral theories about momentum reinforced the importance of industries in conditional asset pricing.

Bird, et al., (2016) suggested that the role of stock selection is crucial for the notability of specifying the prior period[3] over and to measure stock returns with later the cut-off rule[4], that identifies stocks as being either winners or losers. Moreover, they highlighted the importance of portfolio construction decisions which are the holding period, the portfolio rebalancing and the determination of the weights assigned to stocks. Jegadeesh and Titman (1993) considered the strategies of buy and hold strategy where the portfolio is rebalanced at the end of each holding period (BHAR) and rebalanced every month irrespective of the holding period for the stocks (CAR) and found monthly rebalancing to be superior. Bird, et al., (2016) also presented the difference between the returns on these two strategies and found that under the best implementation the time-series momentum outperforms CSMOM in all 24 markets.

[3] The importance of this decision is to set the formation period long enough to identify the establishment of true trends in markets but not too long so as to leave the identification of the trend until too late in the cycle.

[4] Specifying the cut-off rule that identifies stocks as being either winners or losers. The use of this cut-off would suggest that past performance provides a good signal of future performance across the whole range of performance outcomes.

This outperformance was significant in 13 of the markets and the average difference across all markets was slightly less than 0.7% per month or an annualized 8.2%. The purpose of the formation period is to allow sufficient time to identify trending stocks with a balance to be made between setting the period too short and taking into consideration a number of false signals and setting the period too long so leads "too much money is left on the table". They finally found that the best implementation typically involves a relatively long formation period of either 9 or 12-months, with this being the case in 16 of the 24 markets.

Moskowitz et al. (2012) empirically investigated TSMOM and found strong positive predictability of a security's own past returns. They used a method to distinguish all stocks. Stocks that realized a positive past return were the winners and those that realized a negative return were the losers. They also examined how to optimally explore TSMOM in financial markets. Using monthly returns from S&P 500 index they exhibited the optimal performance of their strategy by using the portfolio wealth and Sharpe ratio. In that way they measured the performance of various trading strategies based on the pure momentum and pure mean-reversion models. Such optimal strategies outperform the market, TSMOM and passive holding strategies in the empirical literature. He, et al., (2015) suggested that the optimal strategy took into account not only the trading signal based on momentum and fundamentals but also the size of position, which is associated with market volatility, in contrast to a TSMOM strategy based on trend only. Except from price trend, position size was another very important variable for momentum. Moskowitz et al. (2012) showed that TSMOM exhibited strong positive predictability as far as securities past returns. Moskowitz et al. (2012) posed that using excess returns over the past 12-months on TSMOM found persistent for between 1 and 12-months for a majority of futures and forward contracts. So, it is partially reversed over longer horizons. They also stated that positive auto-covariance is the main driving force for TSMOM and CSMOM effects, while the contribution of serial cross-correlations and variation in mean returns was small. He, et al., (2015) developed an asset price model by taking both mean reversion and TSMOM and demonstrated the explanatory power of the model through the outperformance of the optimal strategy. Asness, et al., (2012) suggested the dynamic utility, that both had value and momentum than examining each separately. Huang, et al., (2013) highlighted that not only mean reversion but momentum could exist the same time in the S&P 500 index. He et al., (2015) showed theoretically that a combined TSMOM and reversal strategy was optimal. They construct portfolios using excess return on monthly base with window lag 1-month and conclude that this strategy performed the best in contrast to all the momentum strategies with look-back and holding periods varying between 1 and 48-months.

He et al., (2015) took fixed long/short positions and construct simple buy-and-hold momentum strategies over a large range of look-back and holding periods by showing that the TSMOM strategy of Moskowitz et al., (2012) could be optimal when the mean reversion was not significant in financial markets. On the other hand, this provides a theoretical justification for the TSMOM strategy when market volatilities are constant, and returns are not mean-reverting. However, the optimal portfolio also depends on volatility and as a result this explains the dependence of momentum profitability on market conditions and volatility in empirical studies.

In addition, the optimal portfolio defines the optimal wealth fraction invested in the risky asset. Moskowitz et al., (2012) showed that the TSMOM strategy based on a 12-month horizon better predicted the next month's return than other time horizons and TSMOM strategy delivered its highest profits during the most extreme market episodes. In many studies, such as Jegadeesh and Titman (2011), showed that momentum strategies performed poorly after the subprime crisis in 2008. It is clear, that the optimal strategy still outperformed the market over the sub-periods, in particular, during the Financial crisis around 2009 by taking large short positions in the optimal portfolios. Considering the optimal portfolio as a combination of market portfolio with risk-free asset, the optimal portfolio should be located on the capital market line and hence should have the same Sharpe ratio as the market.

He et al., (2015) also implemented the out-of-sample tests for the pure momentum and pure mean-reversion models and found that they cannot outperform the market in most out-of-sample tests (last 10, 20 and 71 years), but did outperform the market for out-of-sample tests over the last five years (2007 – 2012). They also implemented the estimations for different length of 25, 30 and 50 years and found that the estimated parameters were insensitive to the size of rolling window and the performance of strategies was similar to the case of 20 year rolling length estimation. With respect to the market trend and market volatility, the optimal portfolios outperformed the market on average for time horizons from 6 to 20-months.

The CSMOM literature showed that momentum profitability could be affected by market states, investor sentiment and market volatility. For example, Cooper, et al., (2004) found that short-run, like 6-months, momentum strategies made profits in an up market and loose in a down market, but the up-market momentum profits reversed in the long run (13 to 60-months). Hou, et al., (2009) found momentum strategies with a short time horizon 1 year not profitable in the down market but in the up market. Similar profitability results were also reported in Chordia and Shivakumar (2002), that common macroeconomic variables related to the business cycle could explain positive returns to momentum strategies during expansionary periods and negative returns during recessions. Baker and Wurgler (2006, 2007) found that investor's sentiment affects the cross-sectional stock returns and the aggregate stock market. Wang and Xu (2012) found that market volatility had significant power to forecast momentum profitability. For TSMOM, however, Moskowitz et al. (2012) found that there was no significant relationship of TSMOM profitability to either market volatility or investor sentiment. He et al., (2015) found that investor sentiment had no predictive power on portfolio returns. Also, no predictive power on portfolio returns had market volatility according to the time series analysis of regressing the excess portfolio return on past month's volatility or volatility conditional on up and down-market state. No influence also had the investor sentiment and market volatility on optimal strategies.

They also compared the performance of the optimal strategy to that of Moskowitz et al. (2012) about TSMOM strategy. In an effort to investigate the excess return of buy-and-hold strategies, the position is determined by the sign of the optimal portfolio strategies with different combinations of time horizons τ and holding periods h, and showed that the TSMOM strategy underperforms the market while the MMR[5] strategy outperforms it. The optimal strategy also significantly outperforms all the momentum, mean-reversion and TSMOM strategies. Note that the only difference between the optimal strategy and the MMR strategy was that the former considered the size of the portfolio position, which was inversely proportional to the variance, while the latter always took one unit of long/short position. In addition, the size of the position was another very important factor for investment profitability. Comparing the performance of the two momentum strategies, He et al., (2015) found that the TSMOM strategy, based on momentum and reversal trading signal, was more profitable than the pure momentum strategy of Moskowitz et al. (2012). The importance of the impact of time horizon on investment profitability also is posed by De Bondt and Thaler (1985) and Jegadeesh and Titman (1993).

Volatility and frictions play a key role in real-world portfolio construction. Many recent empirical asset pricing studies examined effects of risk weighting or volatility scaling and associated portfolio turnover on portfolio performance. Such studies are Moskowitz, et al., (2012) and Baltas and Kosowski (2013) who studied TSMOM strategies and Barroso and Santa-Clara (2014) and Daniel and Moskowitz (2016) who studied the effect of volatility scaling on the performance of CSMOM strategies. The effect of risk-weighting and the choice of volatility estimator on the performance of time-series momentum strategies has received increased attention after provided impressive diversification benefits during the recent Financial crisis in 2008 as in previous business cycle downturns. Baltas and Kosowski (2013) showed that the choice of volatility estimator had a relatively small impact on portfolio turnover, but the choice of trading signal could reduce turnover and associated transaction costs by two thirds. That had an economically and statistically significant effect on the Sharpe ratio net of transaction costs. Baltas and Kosowski (2013) posed that TSMOM referred to the results of trading strategy from the aggregation of a number of univariate momentum strategies on a volatility-adjusted basis. The univariate TSMOM strategy relies heavily on the serial correlation and predictability of the asset's return series, in contrast to the CSMOM strategy,

[5] Xue-Zhong He et all (2015), referred momentum and mean-reversion as an abbreviation MMR.

which is constructed as a long-short zero-cost portfolio of securities with the best and worst relative performance during the lookback period. They also, studied the effect of the volatility estimator and momentum signal choice on portfolio turnover and the profitability of time-series momentum strategies.

The traditional daily volatility estimators, like the standard deviation of daily past returns, provided relatively noisy volatility estimates, and worsen the turnover of the time-series momentum portfolio. In their analysis, Yang and Zhang (2000) estimator dominates the remaining estimators because in Baltas and Kosowski (2013) study, it was theoretically the most efficient range estimator, as it exhibited the smallest bias when compared to the ex-post realized variance. Finally, it generated the lowest turnover, and minimizing the costs of rebalancing the momentum portfolio. What is more, they focused on the information content of traditional momentum trading signals and then devised new signals that captured a price trend, in an effort to maximize the out-of-sample performance and to minimize the transaction costs incurred by the portfolio rebalancing. In their results, they claimed that the sign of past returns in the traditional form of momentum, impelled excessive trading following a pricing trend. Moskowitz et al. (2012), Baltas and Kosowski (2013), posed that the above suggestion created a cost as there was a dramatically increasing in transaction costs. For that purpose, they introduced another methodology that focused on the trend behavior of the price path. They introduced the idea of sparse trading that only instructs taking a position when there exists a statistically significant trend. Momentum strategies with indications of such trend signals had not only insignificantly different Sharpe ratio, but also lower volume of trading by two thirds, in contrast to the origin strategy.

Lo and Wang (2009) reported that when the idiosyncratic volatile of a stock was high then the turnover for such stock was also high. The positive correlation between turnover and volatility across stocks was distinct from the well-known temporal relation between trading activity and volatility (see Karpoff 1987). In a theoretical study of Dorn and Huberman (2009), it is presented a model in which traders used the power of volatility for risk purposes so as to hold and trade stocks. Baltas and Kosowski (2013) suggested that the smoother the transition between different states of volatility, the lower the turnover of a strategy. They hypothesis that more efficient volatility estimator could significantly reduce the turnover of a constant-volatility strategy or TSMOM strategy and hence improved the performance of the strategies after accounting for transaction costs. Finally, they showed that the time-series momentum strategy had the attractive feature of generating higher performance in recessions rather than in booms. The time-series momentum strategy tends to be on average shorter in recessions than in booms independent of the trading signal used.

Hutchinson and O’Brien (2015) found evidence that the strategy returns are connected to the business cycle. Returns are positive in both recessions and expansions, but profitability is especially high in expansions. In order to help investors understand the drivers of profitability, Hutchinson and O'Brien (2015) explicitly test the connection between TSMOM strategies and the business cycle. Firstly, TSMOM portfolio returns exhibited statistically significant differences across the business cycle. Being positive in both, typically the performance of the portfolio was higher in economic expansions than recessions. So, the TSMOM generated higher returns in periods when economic uncertainty was lower. Secondly, they showed that though a linear macroeconomic factor model it had little explanatory power, a model which allowed the coefficients to vary through time, resulted in several of the macroeconomic factors having a statistically significant relationship with TSMOM. Finally, they showed that when TSMOM portfolios are formed on either factor-related or asset-specific portions of financial futures returns, they generated statistically significant excess returns in both cases, with about 40% of returns coming from the factor-related portion.

The literature on TSMOM is typically focused on the performance of different variations of these strategies for particular markets in specific periods (see for example Erb and Harvey (2006), Miffre and Rallis (2007) and Fuertes et al. (2010) for commodities, and Okunev and White (2003) and Menkhoff et al. (2012) for currencies). The evidence of these studies was generally positive on the performance of TSMOM, with positive Sharpe ratios and little correlation with traditional asset classes. In a comprehensive study of Moskowitz et al. (2012), the TSMOM related to market movements, sentiment, and positions of speculators. Such finding evidence reinforced by behavioral explanation for TSMOM profitability. Hutchinson and O'Brien (2015) focused on macroeconomic factors which been important for hedge funds and traditional portfolios, tried to employ methodologies which directly incorporated time variation in factor exposures, and provided evidence that rational asset pricing might also be important in explaining returns. According to their analysis, macroeconomy showed that following each of the six largest Financial crises in the last hundred years, there was an extended period where TSMOM performance was below average. They suggested several explanations why the performance of the strategy might differ in different economic conditions, but they provided no empirical evidence connecting the strategy to the business cycle. Hutchinson and O'Brien (2015) addressed the gap by identifying the link between the business cycle and their findings, that TSMOM tends to perform below average following periods of Financial crisis. Using a new methodology, they documented that uncertainty around changes in macroeconomic factors was the transmission mechanism, linking the below average returns following large global Financial crisis and business cycle.

Chordia and Shivakumar (2002) argued with Conrad and Kaul (1998) about the intense interaction between macroeconomic factors and returns on CSMOM and added that the profits came from the differences in cross-sectional expected returns. Illustrating this, Chordia and Shivakumar (2002) demonstrated that when the returns of the underlying equities are divided into macroeconomic factor-related and asset-specific components, the majority of CSMOM profitability comes from the portion of equity returns explained by macroeconomic factors. Based on the hedge fund literature, Bali et al. (2014) stated that in order to explain cross-sectional deviation in the hedge performance, it was necessary to understand the sensitivity of hedge funds to the uncertainty about economy. Hutchinson and O’Brien (2015) applied that methodological approach of Bali et al. (2014), to TSMOM by revealing that in periods where economic uncertainty was lower, the returns of TSMOM were indeed higher. They divided the sample into two sub-periods with a view to assess performance in different long-term interest rate cycles. According to the peak of the great inflation, these periods were January 1950 to December 1979 and January 1980 to September 2014. The first period is characterized by high inflation and increasing interest rates, whereas from 1980 inflation fell quickly and remained in a range of 2% to 5% for most of that period. In second sub-period interest rates fell steadily, from a high of 15.5% in 1981 to a low of 1.7% in 2012. Returns of the CSMOM strategy are shown to be primarily due to the component of individual equity returns explained by macroeconomic factors (Chordia and Shivakumar (2002)). That was important as it showed that the returns to CSMOM were in large part exposure to macroeconomic risk. Under that construction, whether TSMOM returns were entirely due to exposure to macroeconomic risk, then only the portfolios formed on factor-related returns should yield positive payoffs. By measuring the business cycle using NBER, GDP data or interest rate spreads as proxies for short and long-term fluctuations, their results were consistent. Returns were statistically significantly higher around 5% and 8% in expansions.

These findings dispelled the notion that high returns to TSMOM were specific to equity market states. Hutchinson and O'Brien (2015) results indicated that about 40% of the returns of TSMOM were due to time varying exposure to macroeconomic variables, which were related to the business cycle. These findings were consistent with the conclusions of Chordia and Shivakumar (2002) for CSMOM, that a portion of the profitability of momentum strategies represents compensation for bearing time varying risk, consistent with rational asset pricing theories. The performance of TSMOM improves when economic uncertainty is diminished so, TSMOM tends to perform less well than average following periods of Financial crisis, and changes in the business cycle.

1.6 The Risk-adjusted time series momentum

Dudler et al., (2014) made a breakthrough in investment strategies. They introduced a new class of momentum strategies, the risk-adjusted time series momentum (RAMOM) strategies, which are based on averages of past futures returns, normalized by their volatility.

The difference between RAMON and the TSMOM strategy of Moskowitz, et al., (2012) was that, instead of using averages of past realized returns as trading signals, they constructed trading signals from averages of past risk-adjusted returns.

They showed that RAMOM strategies outperformed the TSMOM strategies of Moskowitz, et al., (2012) for almost all combinations of holding and look-back periods. For almost all 64 futures contracts, independent from asset classes, realized futures volatility was simultaneously negatively related to market (MKT), value (HML), and momentum (UMD) factors of the Fama and French (1987). As a result, TSMOM returns underperformed the RAMOM returns, which built-in exposure to the MKT, UMD, and HML factors when factors deliver good returns. The difference between RAMOM and TSMOM returns could potentially be used as a hedge against drops in the UMD returns. Dudleret al., (2014) studied two types of momentum volatilities: aggregate momentum volatility, defined as the realized volatility of momentum returns pooled across all 64 instruments, and class specific momentum volatility, defined as the realized volatility of momentum returns pooled within a given asset class. Surprisingly, using aggregate momentum volatility, it led to a significantly higher realized Sharpe ratio than using class-specific momentum volatilities. For equity index futures, the regression coefficient for the aggregate momentum (class-specific) volatility was negative (positive), which explained why aggregate momentum volatility was better than class-specific volatility in terms of managing the momentum risk-return profile. What is more, investors who used RAMON had been exposed to Fama and French factors independently the tradable volume stock.

Another important result in their analysis was the reduction of trading cost. Dudleret al., (2014) showed that there was a drastic reduction in trading cost when RAMON is used as a strategy. Namely, the dollar turnover of RAMOM strategies was about lower than that of TSMOM by 40%. What is more, they found that momentum risk management significantly increased Sharpe ratios, but at the same time might lead to more pronounced negative skewness and tail risk. Compare the kurtosis of RAMOM returns adjusted by the two types of momentum volatilities, they found that adjusting by the aggregated volatility increased negative kurtosis in most cases. In contrast, using class-specific momentum leads to a significant reduction in negative kurtosis. Finally, they found that RAMOM returns adjusted by the aggregate momentum volatility had much lower exposure to market, value, and momentum factors. As a result, risk-managed momentum returns offered significantly better diversification benefits than standard momentum returns. Through risk management, momentum had the advantage of lower exposure to value, market, and factors of momentum in contrast to the "naked" momentum. This result means that the returns of risk-managed momentum had higher diversification benefits in relation to standard momentum. That result implied that the level of volatility determines risk management.

Barroso (2014) investigated the bottom-up beta of CSMOM, estimated from the betas of individual stocks, and showed that it exhibited significant variations over time, increasing in bull markets and decreasing in bear markets. He showed that the conditional betas could explain a large part of variations in momentum-specific risk. Dudler et al., (2014) did not focus at the dynamics of betas, but at momentum betas with respect to the four Fama-French factors (market, size, value, and CSMOM). All of these betas were significant and positive, with the exception only of short-term RAMOM and TSMOM returns that had a negative market beta. Furthermore, betas were larger for RAMOM returns because of a significant negative relationship between futures volatilities and Fama-French risk factors. Several interesting patterns emerged for very short-term and very long-term momentum. Firstly, short-term momentum returns had a negative market beta and could therefore potentially be used as a hedge against market downturns. Secondly, long-term (two years) momentum returns had a negative beta with respect to the SMB and HML factors.

Barroso and Santa-Clara (2012) showed a surprising and important property of the CSMOM strategy: Momentum-specific risk (measured as the realized volatility of momentum returns) was highly predictable and forecasted momentum returns. Specifically, high momentum volatility indicated both high expected future volatility and low expected returns. Therefore, normalizing momentum position by momentum volatility significantly improved the performance of the CSMOM strategy.

1.7 Is momentum really momentum?

According to Novy-Marx (2011), stocks that rose the most over the past 6-months and simultaneously performed poorly during the first half of the former year, remarkable underperform those stocks that fell the most over the past 6-months but performed strongly over the first half of the preceding year. However, intermediate horizon past performance, measured over the period from 7 to 12-months prior, better predict average returns than did past performance. Taking that fact into account, it was hard to reconcile using the traditional view of momentum, that rising stocks tended to be kept rising, while falling stocks tended to be kept falling, i.e., a short-run autocorrelation in prices.

Performances of intermediate horizon had more predicting power than other past performances. Fama-MacBeth (1973) used regressions with stock returns and showed that the coefficient on intermediate past performance was significantly higher than that on recent past performance. Momentum trading strategies based on intermediate past performance generated larger, more significant returns than those current past performance and according to Fama-French four-factor model had also significant alphas, while the same did not happen for strategies based on recent past performance. The predictive power for intermediate horizons returns had been more profitable over the last 40 years and greater than the recent returns. Such intense difference in performance was triggered by an increased correlation on the strategies' returns. Profits from strategies were at peak based on cpast performances in 1950 and 1960 but indeed did not perform at the same level yet. Such supremacy for intermediate horizon past performances continued for the Sharpe ratio too. Particularly, the Sharpe ratio for the intermediate horizon was more than twice as large as the Sharpe ratios of the strategies based on recent past performance. Also, another advantage of intermediate horizons was the recognition that the abnormal returns of buying winners and selling losers derived mainly from that horizon, while strategies on recent past performance never generated significant abnormal returns. Such fact was more realistic for most liquid, largest stocks as it showed more momentum from other stock.

Novy-Marx (2011) showed that the value-weighted strategy, restricted to large[6] stocks which bought (sold) the top (bottom) quintile of 7 to 12-months period before the portfolio formation, and performed average returns of almost 10% per year from January 1927 through December 2010. The fact that Fortune 500 companies exhibited strong momentum, suggested that the profits from designed momentum strategies were undervalue by the estimations of Korajczyk and Sadka (2004) and the trading cost critique of Lesmonda, Schill, and Zhou (2004) was significantly overstated. Either, the behavioral (e.g., Barberis, Shleifer and Vishny, (1998); Hong and Stein, (1999)) or the rational (e.g., Johnson, (2002); Sagi and Seasholes, (2007)) delivered the observed term-structure of momentum information, which exhibited significant information in past performance at horizons of such duration.

Novy-Marx (2011) supported that the results were the same for momentum strategies that traded other asset classes, including industries, investment styles, international equity indices, commodities, and currencies. One aspect that not considered to be tested in that literature was the length of period that test should end up before portfolio formation. Probably, the gap reflected the presumption that the returns of buying winners and selling losers was due to momentum, short-run autocorrelation in stock returns, and that the power of past returns to predicted future returns, therefore, decays monotonically over time. The reason why intermediate horizons contributed more to the profitability of momentum strategies than did past performance at recent horizons was due to the substantially stronger relation between intermediate past performance and expected returns than between recent past performance and expected returns. The relation between intermediate horizon past performance and average

[6] Largest quintile by market equity using New York Stock Exchange break points, made up of roughly three hundred largest firms in the economy.

returns was strong, and roughly linear, while the relation between recent past performance and average returns was both weaker and concentrated in the tails of the distribution.

The coefficient in intermediate horizon past performance was nearly twice that on recent past performance, and the difference was statistically significant. Grinblatt and Moskowitz (2004) argued that high past returns achieved with a series of steady positive months, generated larger expected returns than the same level of past returns achieved through a few extraordinary months. Watkins (2003) also found that firms that had positive (negative) returns every month for 6 straight months, significantly outperform (under-perform) the market over the following 6-months. Such outperformance (underperformance) disappeared after controlling momentum (UMD). A consistent winner, as defined by Grinblatt and Moskowitz (2004), is guaranteed to had at least 2 winning months over that period and is likely to had at least 4 winning months over that time. That consistent winner indicator conflates two effects. Stocks that won in 8 out of 11-months tended to be both big winners and consistent performers, i.e., stocks in the upper tail of the past performance distribution, and stocks that realized low return volatility over the same period.

Novy-Marx (2011) suggested that the consistency of performance result of Grinblatt and Moskowitz (2004) was essentially unrelated to the disparity in power between intermediate horizon and recent past performance for predicting returns. Namely, the consistent winner's indicator had significant power predicting expected returns, even after controlling for past performance. Big winners generated significantly higher expected returns, even after controlling for the level of past performance, suggesting a nonlinearity in the relation between past performance and expected returns. Higher realized volatility was also associated, even after controlling for past performance, with lower expected returns. That specification found a significant role for consistency of performance, as measured by realized volatility. In both cases the coefficient on intermediate horizon past performance was significantly higher than that on recent past performance.

Taking everything into account, on average recent winners that were intermediate horizon losers significantly under-perform recent losers that were intermediate horizon winners. That fact did not come up with the classic view of momentum, where rising stocks kept rising, and falling stocks kept falling. Popular behavioral explanations counted on biases, in the way, that investors interpreted information generated positive short-lag autocorrelations in prices. Ignoring recent performance, when selecting stocks significantly improved Sharpe ratios of momentum strategy. Performance was particularly enhanced in liquid and large cap stocks, which exhibited more momentum than was commonly recognized.

Chapter 2

Feeling Good, as a Guide to Performance: The Impact of Economic Sentiment in Financial Market Performance for Germany

2.1 Introduction

European financial markets have undergone several episodes of turbulence over the recent decades. The burst of the dotcom bubble in the early 2000s, the global Financial crisis in 2007-2008 and the recent European sovereign debt crisis[7] highlighted the need for further research in better understanding the main drivers of European markets. During the European crisis, Germany emerged as the main "exporter" of economic growth safety and stability in Europe, as indicated by the behavior of the country's economic sentiment indicator compared to that of other European countries. The Economic Sentiment Indicator (ESI) has recently received attention as an important driver of macroeconomic developments, both in the academic literature and in policy analysis. Indeed, the importance of this indicator for policy analysis has been highlighted in the recent European Commission's European Economic Forecasts for Spring-Summer 2019. The ESI is one of the indicators that can show the prospects of economic activity in Germany and depicts the year-on-year sentiment of anticipated economic performance. ESI is published monthly by the European Commission and contains five sub-indicators such as, the Industrial confidence indicator, the Consumer confidence, the Constructions confidence and Retail trade confidence indicator.[8]

In this Chapter, I seek to assess the role of the Economic Sentiment Indicator in driving the stock market of Germany. The focus on Germany is motivated by the strong resilience of this country during the recent European sovereign debt crisis, which is reflected in the behavior of its Economic Sentiment Indicator. I examine whether there is a causal relationship between

---

[7] The dates of the European sovereign crisis start with first MoU (Memorandum of Understanding), as the first instance of fiscal support to Greece in 2010 and end in 2018, when the Greek government was able to borrow again in open markets. During this period of time there was a set of countries that faced problems of fiscal nature, of various degrees, known as the PIIGS (Portugal, Italy, Ireland, Greece and Spain). For a detailed review of the historical evolution of the sovereign dept crisis, please see Lane (2012).

[8] For analytical details of the construction of the ESI, please see:
https://ec.europa.eu/eurostat/web/products-datasets/product?code=teibs010

DAX[9] the largest stock market index in Germany and the German ESI. If such a relationship is found, I seek to explore if the sentiment indicator can be used by investors as a leading indicator for designing profitable investment strategies.

The motivation for focusing on the Economic Sentiment Indicator is based on contributions documenting that investors' sentiment influences stock returns, volatility, and bond yield spreads (Fisher and Statman 2000; Brown and Cliff 2005; Baker and Wurgler 2006, 2007; Lemmon and Portniaguina 2006; Schmeling 2009), the volatility (Wang, Keswani, and Taylor 2006, Nayak 2010; Spyrou 2013; Baker and Wurgler 2012; Huang, Rossi, and Wang 2015). The economic sentiment is an indicator that combines economic judgements and expectations, as well as attitudes of all economic agents (producers and consumers). Such an indicator is made up of the components of business and consumer confidence indicators. It is expected that, when investors are bullish (bearish) about the economy, they are bullish (bearish) about the financial markets and vice versa (Qiu and Welch 2006).

The findings are summarised as follows: Firstly, there is a strong causal relationship between the economic sentiment indicator and the stock market in Germany, in line with the relevant literature. Second, using the economic sentiment indicator as a signal to invest in the German market, investors do outperform the simple buy-and-hold benchmark. Economic sentiment based excess returns can possibly be explained by Germany's economic performance[10] in the Post-Crisis years. The main message that emerges is that the economic sentiment is not only a significant determinant of the German stock market but also it can be used to design profitable stock trading strategies.

The rest of this Chapter is organized as follows. The next section briefly discusses relevant literature. Section III describes the data employed. In section IV, I present the empirical methodology and perform a careful sample-split analysis of both the characteristics of sentiment and financial market performance in various sub-periods from the 1990's until 2017. Section V discusses the empirical results drawing on implications for building investment economic sentiment-based strategies. Finally, Section VI reaches to a conclusion.

[9] DAX stands for Deutscher Aktien Index (in German). For details about the DAX Index please see the data section.

[10] In the 2010-2015 period, the average annual growth rate of real GDP of Germany was equal to 2.07%. This number clearly illustrate that, first, Germany's growth rate during this period was very high and certainly higher than the PIIGS countries and, second, that economic performance in Germany was used as a sensitivity gauge for other countries that were concerned about economic performance in Europe in general.

2.2 Literature review

De Long et al. (1990) formalized a role for investor sentiment in the US financial markets, specifying a model whereby trading on sentiment introduces a systematic risk, as a number of financial market anomalies can be explained by the idea of noise trader risk. The work of De Long, et al. (1990), stated that noise traders influence fundamental prices and as a result such investor changes in US sentiment are unpredictable.

In the literature there are stated various advantages for sentiment as a financial market influencer. Fisher and Statman (2000) investigated the relation between investor sentiment and future stock returns for 18 industrialized countries between 1985-1998 and found, that on average, across countries the sentiment is a considerable predictor of expected returns. Sentiment's predictive power is most applicable for short- and medium-term horizons of one to six months and washes out over longer horizons of twelve to twenty-four months. Moreover, they stated the importance of the impact of sentiment on returns is higher for countries that are culturally more prone to herd-like investment behavior as hypothesized later by Chui, Titman and Wei (2010). The same stands for countries that present less efficient regulatory institutions or less market integrity. Lee Jiang, and Indro (2002) showed that the US sentiment from 1973 up to 1995 is not only a significant factor in explaining equity excess returns and conditional volatility, but also a systematic risk that is actually priced. They suggested that excess returns are contemporaneously positively correlated with shifts in sentiment. Sentiment suffers changes based on the magnitude of bullish (bearish) trends, and such changes cause downward (upward) revisions in volatility and higher (lower) future excess returns. Barone-Adesi Mancini, and Shefrin (2012) examined the US sentiment impact during the August 2007 Crisis. They found that sentiment decreased dramatically as the systemic risk rose for the S&P 500 during the period of 2002-2009. The investor herd behavior and the increasing risk aversion render the investor sentiment as a powerful predictor of returns during crises and as a result, it rose a significant importance of sentiment impact for literature dramatically.

Bai (2014) studied eight main EU stock markets indices from 1994 to 2011 and hypothesized that after the crash, mispricing is even more likely to happen but less likely to be corrected by arbitrage; hence, investor sentiment plays a more important role in determining stock return and volatility. According to Bai (2014), sentiment variance has fairly diverse impacts on the conditional volatility of different markets. Keiber and Samyschew (2015), found that sentiment has significant explanatory power for some risk premia of macroeconomic risk factors, based on the G7[11] stock markets from 1999 to 2012. These risk premia came from the risk premium of industrial production and exchange rate. Another result is that the use of

[11] G7 group consist of Canada, France, Germany, Italy, Japan, UK and US.

sentiment as instrumental variable for the risk premia of global risk factors boost in explaining its time variation. Keiber and Samyschew (2016), show that sentiment indeed is a significant priced source of risk on the Euro area markets and that an investment from February 1999 to September 2015 would have been unattractive to the investors. Such studies report a negative relationship between sentiment and future returns. Smales (2017), focused on S&P 500 from 1990 to 2015 and found that investor sentiment has an influence on stock returns that is economically and statistically significant. Such influence is positive for contemporaneous returns and negative for future returns.

However, there is part of literature that weakens the influence of sentiment on financial markets. Solt and Statman (1988) and Brown and Cliff (2004) document an inverse relationship in that returns cause sentiment rather than vice versa for the US markets. Wang, Keswani, and Taylor (2006), examined the role of the US sentiment as a predicting tool from different scope from 1990 to 2001. They test the utility of sentiment to predict volatility and find that lagged returns cause volatility. They also stated that returns contain useful information for volatility forecasting purposes rather than sentiment. According to Baker et al. (2012), global sentiment has a contrarian predictable power from 1980 to 2005 on country-level returns. The US sentiment has also contrarian power of prediction on the time-series of cross-sectional returns within Japan, UK, US, Canada, France and Germany markets. Higher sentiment leads to low future returns and difficulties are emerged on arbitrage and valuation of stocks. Baker and Wurgler (2006) studied the US statement from 1962 to 2001 and predict that broad waves of US sentiment level up the degree of difficulty to arbitrage and value stocks, and these US stocks exhibit high “sentiment beta”. Baker and Wurgler (2012), found that a country’s higher total sentiment creates low future returns for its small, high return volatility, growth, and distressed stocks, based on six stock markets; Canada, France, Germany, Japan, UK and US from 1980 to 2005.

Bai (2014) explored the role of sentiment at developed and emerging EU stock market from 1994 to 2011. These regional sentiments have significant impact on sample market excess returns and volatility. Investors’ confidence diminished during the crisis of August 2007, which has led to visible negative-sentiment spillover within Europe and to global equity markets (Bank for International Settlements, 2010). From September 2008, when the global crisis intensified significantly in depth and strength, Emerge EU stock markets built up huge losses. Fernandes et al. (2016), found that domestic and Euro area investors’ sentiment has a negative impact on future total return spreads for forecast horizons of 1 to 12 months, which, in general, is consistent with the theoretical considerations of the impact of the noise trader behavior.

2.3 Data

We use the German economic sentiment indicator (ESI) which is released on a monthly basis, the monthly closing prices of the DAX index, and the 10-Year Germany Government Bond Yields with the aim of comparing them with the ESI. The DAX index is a stock index for Germany calculated through Xetra, which was created in 1988, and represents the 30 largest German companies that trade on the Frankfurt Exchange. I collected monthly data for the DAX from Datastream, as I did for the German Government Bond Yields. The Economic sentiment indicator of Germany is published monthly by the European Commission since 1985, and represents a composite indicator constructed from sub-indicators for manufacturing, services, consumptions, construction and retail trade. The monthly data of ESI have been extracted from Eurostat. The 10-Year Government Bond Yield of Germany represents the cost of government borrowing in the long-term and it also represents the health condition of Germany's federal government. The German bonds have played an essential role during the sovereign debt crisis as depositories of wealth from nations and wealthy individuals and when interest rates reach the zero lower bound these bonds exhibited negative yields: people were willing to pay for "parking" their money to German bonds.

Our sample period starts in January 1990 and ends to December of 2017. These data were segmented for further analysis to the following sub-periods. Initially, from 1990 to 1999 as the Pre-Euro unification period, when Germany is still in the process of re-industrialization. From 2000 to 2007, the Post-Euro or Pre-Crisis period, which is characterized as the period of accession in Europe until the beginning of the crisis. The crisis period starting from November of 2007 up to the end of 2009 and finally, the Post-Crisis period from 2010 up to 2017 in which Germany has overcome the crisis.

The relationship between DAX and ESI for Germany is presented via graphical illustrations. Figure 2.1 has a scatter plot between DAX levels and ESI levels for each and every sub-period I studied, from 1990 to 2017 and concludes that especially for the period 2012-2017 the trend for both ESI and DAX levels is almost identical. Similarly, I point out that such an observation also holds for the period of 2012-2017 in Figure 2.2. In Figures 2.1 and 2.2, I present the correlations of ESI and DAX in levels that are extremely high and linear during the Post-Crisis period. The same cannot be told for the other sub-periods.

In Figure 2.3 and 2.4, the returns (percentage changes month-to-month) of ESI and DAX are illustrated through scatter plots for all the sub-periods under examination. I see that their correlation appears quite low, and for the 2007-2009 period the correlation becomes clearly positive and larger than the other periods. For those two Figures of scatter plots, the bigger slope for the period 2007-2009 is due to economic situation and the trend that DAX levels and ESI levels share.

Figure 4.1: Scatter plot of ESI levels vs. DAX levels in the 6 sub-periods from 1990 to 2017.

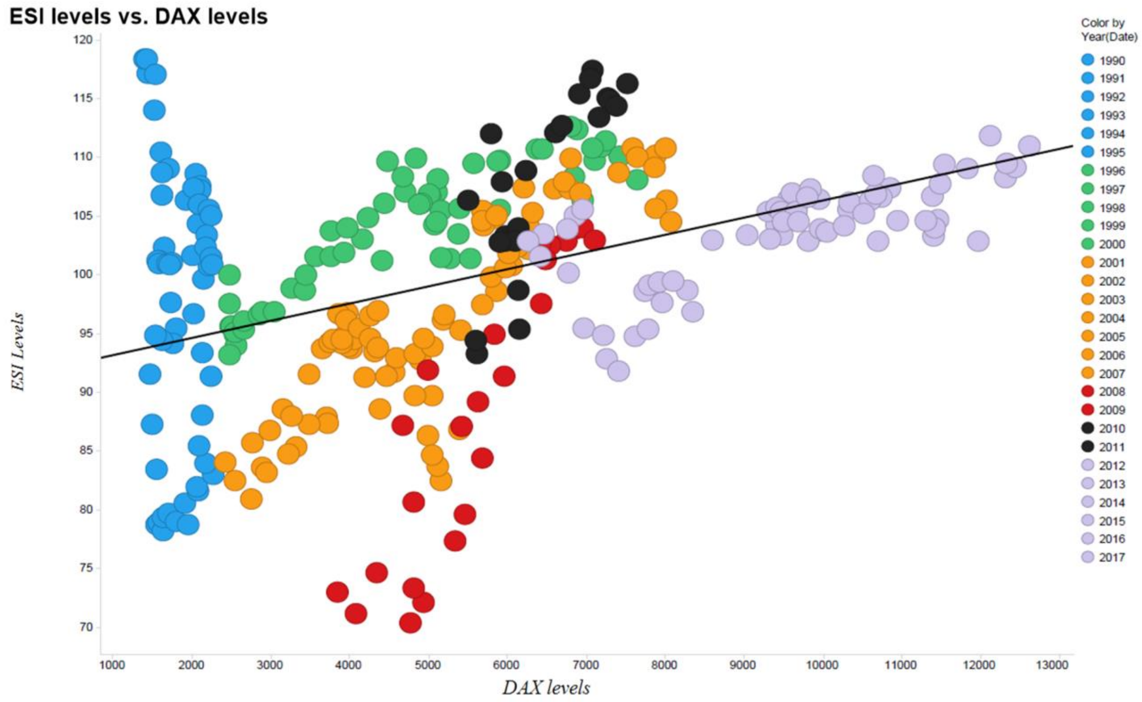


Figure 2.2: Scatter plot of ESI levels vs. DAX levels from 2012 to 2017.

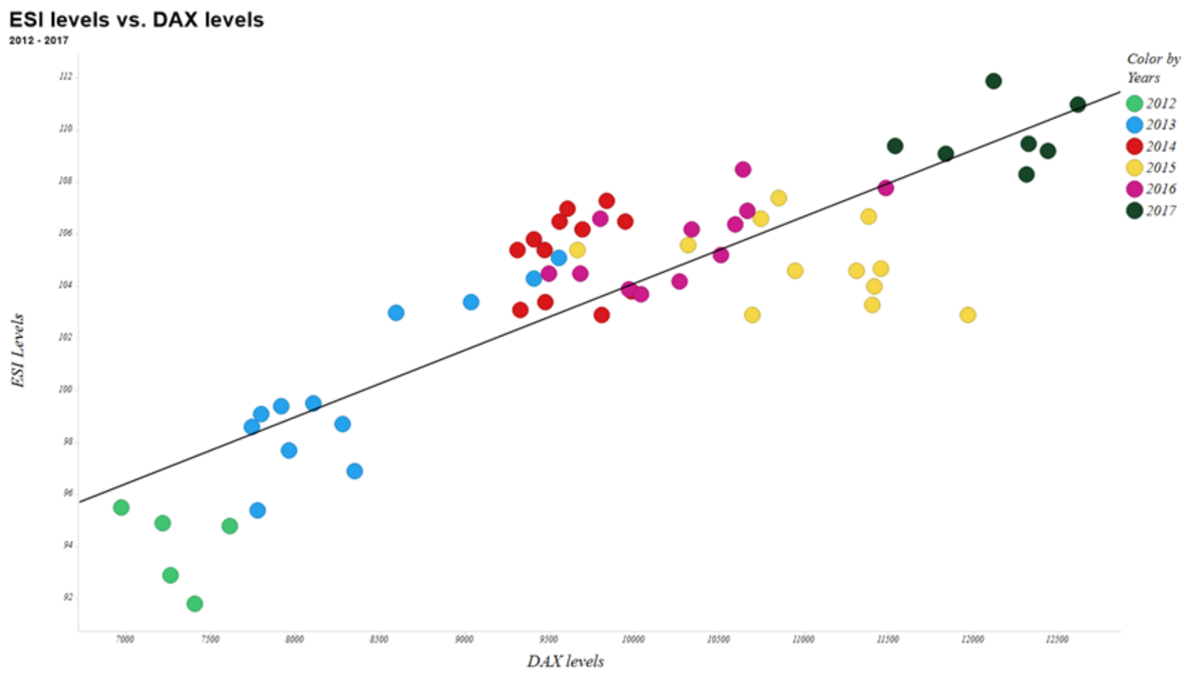


Figure 4.13: Scatter plot of DAX returns vs ESI returns from 1990 to 2017.

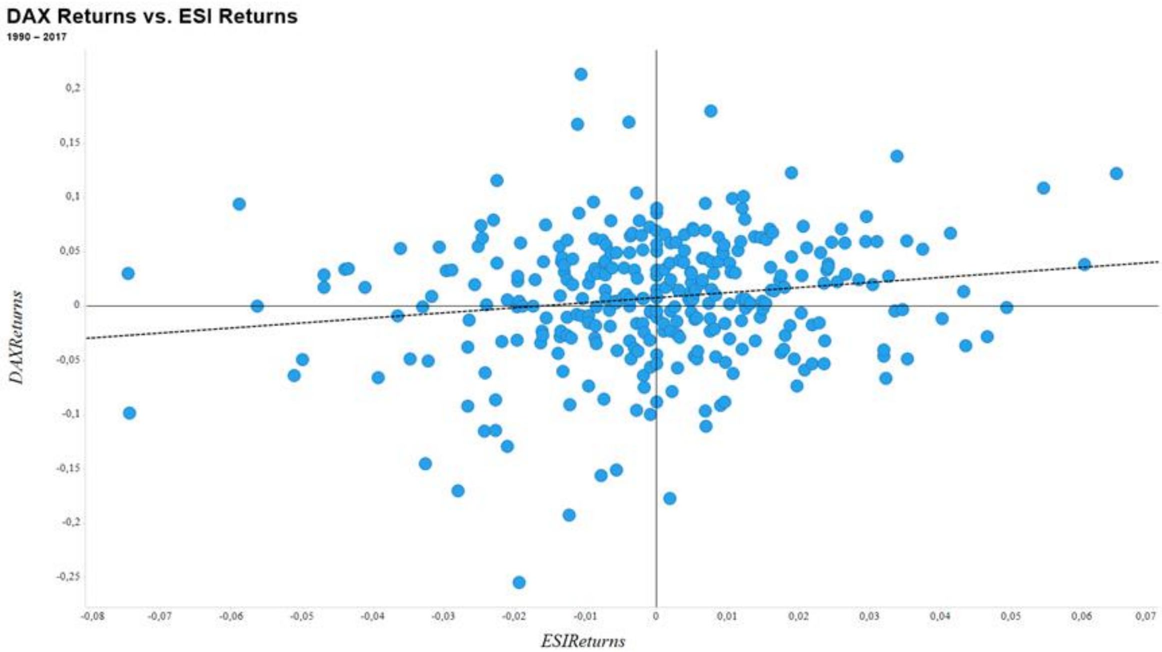
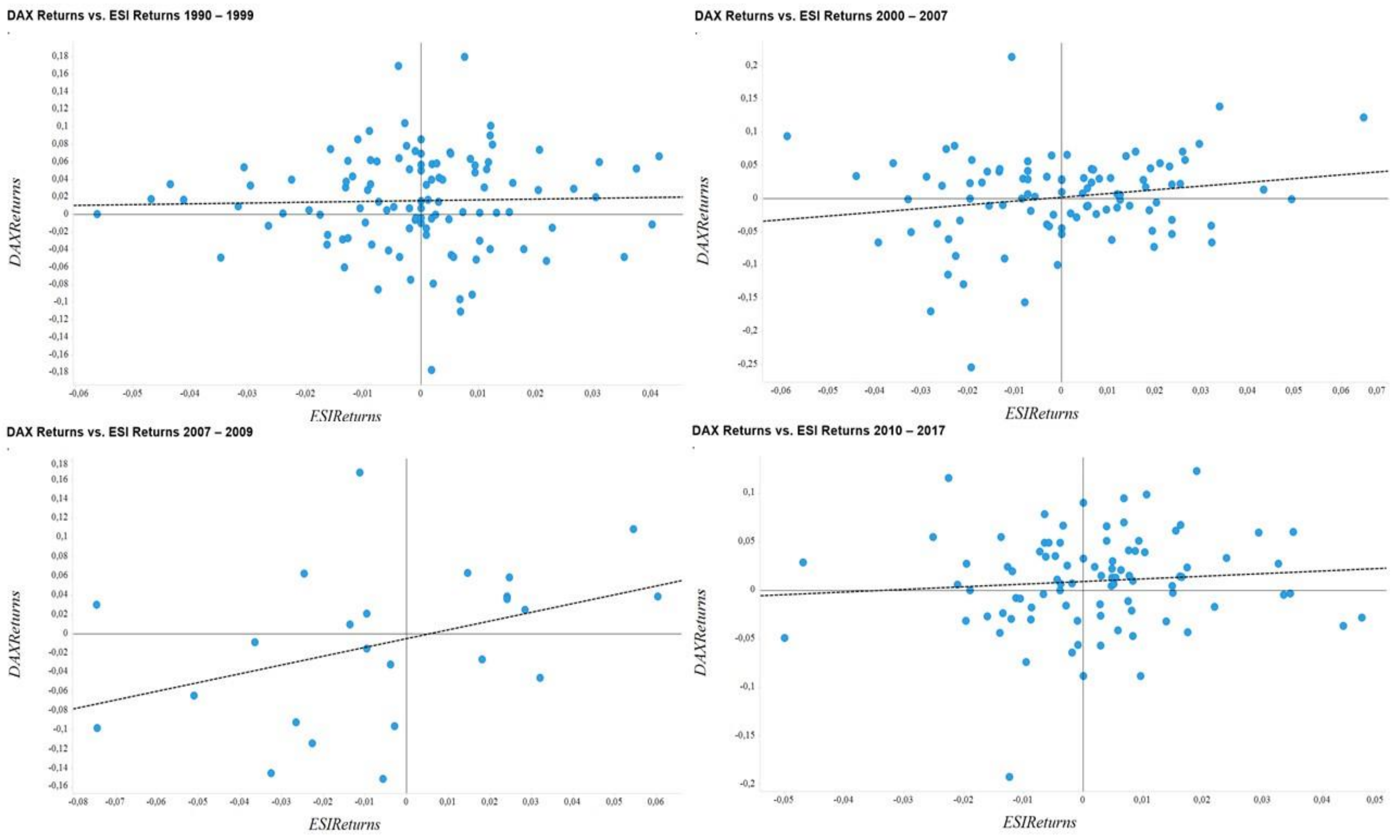


Figure 4.14: Scatter plot of DAX returns vs ESI returns for four sub-periods from 1990 to 2017.



To examine the impact of economic sentiment in financial market performance for Germany, I considered different look-back periods for the analysis. The discussion on returns of DAX and ESI changes, begins by providing descriptive statistics and correlations for all the variables and all sub-periods plus a battery of Granger Causality tests, for lags 1, 2, 3, 6 and 12, in order to examine the hypothesis of causality among the variables in the dataset.

Table 2.1 presents a summary of descriptive statistics on returns of ESI, DAX and 10-Year Government Bond for each sub-period under examination from 1990 to 2017. These are the average, the total return, the min and max, the annualized standard deviation as a measure of risk, the Sharpe ratio as a credit of reward to risk and last the skewness and kurtosis. The financial type statistics (i.e. the Sharpe ratio which measures the risk-return reward for a tradable asset) for the ESI are clearly not meaningful outside the context of trading and I provide them for consistency with the other variables in Table 2.1. I split the whole sample 1990-2017 into sub-periods, considering the economic circumstances over the years, as I analyzed previously, in order to capture the evolution through time of ESI, DAX and 10-Year Government bond of Germany. Some interesting results emerge very clearly on the average, the annualized standard deviation, and the Sharpe ratio. Firstly, the average ESI returns were negative and experienced a constant decrease, with an increase in the annualized standard deviation and negative Sharpe ratio, from Pre-Euro until the end of 2009 crisis sub-period. The ESI returns performed higher from crisis to Post-Crisis sub-period, with the average return stood an increase 152%, the annualized standard deviation halved from 12.10% to 5.70%, and the Sharpe ratio rose 210.51% and became positive. Secondly, from the Pre-Euro to Euro sub-period, the average DAX returns and Sharpe ratio indicated positive values with a significant decrease, while the annualized standard deviation increased.

As the DAX represents the financial market of Germany and is influenced by Europe's economic situation, the crisis period deep reduced the performances of average return and Sharpe ratio about 553.08% and 475.48% respectively, and as a result the risk rose by 20.67%. The DAX returns rose again from the crisis to the Post-Crisis sub-period, with the average returns and the Sharpe ratio reaching a new high from -13.67% to 11.90% and from -0.49 to 0.70 respectively. The annualized standard deviation almost halved for DAX returns from 27.38% in the crisis period to 16.92% in the Post-Crisis. On contrary, Germany's 10-Year Government Bond followed a reverse trend from the other indices, noted historic high for the average return and Sharpe Ratio during the crisis sub-period, due to Germany's better performance against the rest Europe. From the Pre-Euro to the Post-Crisis sub-period, the returns for Germany's 10-Year Government Bond showed a significant rise for risk and a decrease for the average and Sharpe ratio, with the Pre-Euro and Euro sub-periods performances indicated very closely results.

Table 2.1: Descriptive statistics on returns of ESI, DAX and 10-Year Government Bond of Germany for four sub-periods.

ESI returns	**1990 - 1999**	**2000 - 2007**	**2007 - 2009**	**2010 - 2017**
Average	-0.51%	-0.02%	-4.72%	2.46%
Annualized Std Dev	5.82%	7.41%	12.10%	5.70%
Sharpe Ratio	-0.0870	-0.0024	-0.3900	0.4310
Min	-5.63%	-5.89%	-7.45%	-5.00%
Max	4.14%	6.48%	6.03%	4.66%
Skewness	-0.3933	0.1016	-0.2649	-0.0424
Kurtosis	1.4054	0.3510	-0.1475	1.5519
Total Return	-6.47%	-2.22%	-10.72%	18.54%

DAX returns	**1990 - 1999**	**2000 - 2007**	**2007 - 2009**	**2010 - 2017**
Average	18.88%	3.02%	-13.67%	11.90%
Annualized Std Dev	18.98%	22.69%	27.38%	16.92%
Sharpe Ratio	0.9950	0.1330	-0.4994	0.7030
Min	-17.71%	-25.42%	-15.07%	-19.19%
Max	18.01%	21.38%	16.76%	12.32%
Skewness	-0.2251	-0.6473	0.0870	-0.6457
Kurtosis	1.3015	2.9680	-0.2466	2.4419
Total Return	374.30%	2.96%	-30.48%	116.46%

10Y Gov Bond returns	**1990 - 1999**	**2000 - 2007**	**2007 - 2009**	**2010 - 2017**
Average	-2.84%	-3.00%	1.18%	-25.39%
Annualized Std Dev	3.64%	4.14%	3.42%	15.99%
Sharpe Ratio	-0.7803	-0.7237	0.3436	-1.5883
Min	-4.17%	-6.31%	-1.48%	-29.91%
Max	3.42%	3.41%	3.90%	10.34%
Skewness	-0.4522	-1.8334	2.4505	-3.6014
Kurtosis	2.9567	9.0623	9.2541	18.3895
Total Return	-25.08%	-21.28%	2.36%	-86.67%

Table 2.2 below summarizes the correlation among variables in levels and among variables in first differences for every sub-period. There are three notable observations. Firstly, the relationship between DAX levels and ESI levels become stronger from 1990-1999 to 2000-2007 by 133.7%, while it reaches its peak at 0.8914 in 2007-2009, before it finally falls to 0.1814 in 2010-2017 Post-Crisis period. This relationship, as shown later, is non-linear because of the threshold effects in trading the DAX based on ESI. Secondly, the same happens for ESI changes and DAX returns too. During 2007-2009, the higher correlation is observed for the returns compared with the other sub-periods.

The following Table reports the correlation between the three tested variables (i.e. ESI, DAX and 10-Year Government Bond of Germany) for both their returns and levels, so as to show the degree of their relation. It should be noted that I calculate the returns of DAX and ESI counting on their indices, as a division of the difference between two consecutive months and the value of the smaller month of such difference. In this way, I observe the performance during the performing sub-periods.

Table 2.2: Correlation between ESI, DAX and 10-Year Government Bond of Germany for four sub-periods and full sample.

1990-2017

	Bond Yields Levels	DAX Levels	ESI Levels	Bond Yields Returns	DAX Returns	ESI Returns
Bond Levels	1					
DAX Levels	-0.9229	1				
ESI Levels	-0.2653	0.4256	1			
Bond Yields Returns	0.3146	-0.3409	-0.1183	1		
DAX Returns	0.0229	0.0319	-0.0072	-0.0698	1	
ESI Returns	-0.0740	0.0840	0.0795	-0.0933	0.1561	1

1990-1999

	Bond Yields Levels	DAX Levels	ESI Levels	Bond Yields Returns	DAX Returns	ESI Returns
Bond Levels	1					
DAX Levels	-0.9073	1				
ESI Levels	-0.4673	0.3759	1			
Bond Yields Returns	0.3652	-0.4380	0.2841	1		
DAX Returns	-0.1184	0.1879	-0.0147	-0.0742	1	
ESI Returns	-0.2193	0.1997	0.0383	-0.1137	0.0215	1

2000-2007

	Bond Yields Levels	DAX Levels	ESI Levels	Bond Yields Returns	DAX Returns	ESI Returns
Bond Levels	1					
DAX Levels	-0.5713	1				
ESI Levels	-0.5540	0.8785	1			
Bond Yields Returns	0.1569	0.0448	-0.0133	1		
DAX Returns	-0.1951	0.0792	0.0254	-0.1708	1	
ESI Returns	-0.1033	-0.0198	0.0921	-0.1090	0.1886	1

2007-2009

	Bond Yields Levels	DAX Levels	ESI Levels	Bond Yields Returns	DAX Returns	ESI Returns
Bond Levels	1					
DAX Levels	-0.8842	1				
ESI Levels	-0.9132	0.8914	1			
Bond Yields Returns	0.1219	0.0015	0.1523	1		
DAX Returns	0.2173	-0.0049	-0.3101	-0.2224	1	
ESI Returns	-0.1191	0.2536	-0.0010	-0.3539	0.3759	1

2010-2017

	Bond Yields Levels	DAX Levels	ESI Levels	Bond Yields Returns	DAX Returns	ESI Returns
Bond Levels	1					
DAX Levels	-0.9222	1				
ESI Levels	-0.0203	0.1814	1			
Bond Yields Returns	0.3652	-0.3002	-0.1065	1		
DAX Returns	0.0183	0.0662	-0.1333	-0.0522	1	
ESI Returns	0.0466	0.0439	0.1118	-0.0715	0.0912	1

Min Negative Correlation   Max Positive Correlation

The correlation degree is indicated with color from red for the lowest, to green for the highest. Over time, both levels and returns of ESI and DAX show more positive correlation. The P-values of Granger Causality test implemented for lags 1, 2, 3, 6, 12 in all sub-periods are presented in the Table 2.3. I cover every possible pairwise match between the examined variables. I tested for each returns and levels the following hypothesis: if DAX returns Granger causes ESI returns and levels, as well as 10-Year Government Bond returns, if ESI returns Granger causes DAX returns and 10-Year Government Bond returns, if ESI levels Granger causes DAX returns and finally, if 10-Year Government Bond Granger causes DAX and ESI returns.

Table 2.3: Causality between ESI, DAX and 10-Year Government Bond of Germany for several sub-periods.

H_0	Lag	P-value 1990 - 1999	2000 - 2007	2007 - 2009	2010 - 2017	1990 - 2009	2000 - 2009	1990 - 2017
DAX Returns does not Granger cause ESI Returns	1	0.5542	0.4049	0.3851	0.0543	0.1805	0.1731	0.0437**
	2	0.7087	0.4239	0.0369**	0.1326	0.0267**	0.0504	0.0069***
	3	0.0207**	0.4708	0.0434**	0.1619	0.0056***	0.0618	0.0015***
	6	0.1602	0.0261**	0.1245	0.5882	0.0163**	0.0164**	0.0040***
	12	0.3971	0.0014***	-	0.1338	0.0016***	0.0017***	0.0003***
DAX Returns does not Granger cause ESI Levels	1	0.6788	0.0985	0.0261**	0.2733	0.0038***	0.0042***	0.0019***
	2	0.0171**	0.2095	0.0350**	0.6926	0.0040***	0.0464**	0.0027***
	3	0.0343**	0.0055***	0.0452**	0.5946	0.0047***	0.0050***	0.0055***
	6	0.1808	0.0363**	0.8811	0.9492	0.0733	0.0209**	0.0545
	12	0.4330	0.0297**	-	0.5165	0.0170**	0.0697	0.0076***
ESI Returns does not Granger cause DAX Returns	1	0.1267	0.1940	0.1965	0.6544	0.0079***	0.0427**	0.0050***
	2	0.1509	0.3600	0.2147	0.6247	0.0324**	0.0624	0.0151**
	3	0.1789	0.3776	0.0129**	0.7395	0.0171**	0.0332**	0.0113**
	6	0.3441	0.4787	0.0001***	0.7170	0.0120**	0.0629	0.0042***
	12	0.3131	0.4529	-	0.5946	0.0147**	0.1664	0.0042***
ESI Levels does not Granger cause DAX Returns	1	0.7721	0.0773	0.0976	0.4401	0.0104**	0.0065***	0.0049***
	2	0.2258	0.0893	0.0107**	0.3312	0.0056***	0.0034***	0.0014***
	3	0.2230	0.2512	0.0129**	0.3566	0.0113**	0.0182**	0.0028***
	6	0.3402	0.1180	0.0001***	0.4120	0.0018***	0.0072***	0.0003***
	12	0.4055	0.1777	-	0.5898	0.0039***	0.0111**	0.0008***
ESI Returns does not Granger cause Bond Returns	1	0.8389	0.0990	0.0543	0.2024	0.0208**	0.0133**	0.9989
	2	0.8899	0.2523	0.1506	0.2857	0.0952	0.0493**	0.6627
	3	0.8622	0.1353	0.2855	0.4940	0.1626	0.0348**	0.6184
	6	0.7368	0.0900	0.6127	0.6888	0.2502	0.0499**	0.5394
	12	0.8241	0.0328**	-	0.2690	0.0038***	0.0187**	0.6552
DAX Returns does not Granger cause Bond Returns	1	0.2669	0.7146	0.2125	0.6128	0.8179	0.3320	0.7071
	2	0.5249	0.2513	0.3935	0.6263	0.1490	0.1316	0.3115
	3	0.5536	0.1337	0.4067	0.7733	0.0772	0.0482**	0.3969
	6	0.6487	0.3368	0.9589	0.5837	0.1245	0.2212	0.5363
	12	0.9176	0.1317	-	0.9777	0.3189	0.5487	0.8146
Bond Returns does not Granger cause DAX Returns	1	0.7855	0.8003	0.6149	0.5160	0.6755	0.6150	0.5069
	2	0.9529	0.9510	0.6559	0.8184	0.8212	0.6955	0.7884
	3	0.1552	0.3701	0.8945	0.8867	0.0802	0.4315	0.8310
	6	0.0771	0.5224	0.6485	0.9784	0.1830	0.3561	0.9301
	12	0.0134**	0.7506	-	0.9047	0.4555	0.2362	0.9581
Bond Returns does not Granger cause ESI Returns	1	0.0525	0.9767	0.4615	0.7281	0.1889	0.6472	0.3233
	2	0.1142	0.0688	0.8049	0.8107	0.0088***	0.0584	0.3682
	3	0.2672	0.1168	0.3211	0.8164	0.0157**	0.0767	0.4821
	6	0.7368	0.2622	0.1821	0.7459	0.0754	0.0753	0.7989
	12	0.9662	0.5713	-	0.1974	0.0773	0.2135	0.4028

The results in the Table 2.3 show that ESI returns Granger causes DAX returns during 2007-2009, 1990-2009 and 2000-2009, and also for the full sample of 1990-2017. During 2007-2009, the DAX returns causes ESI returns at 2 and 3 lags, and ESI returns causes DAX returns at 3 and 6 lags. Thus, for both tests that the DAX returns Granger causes the ESI returns and vice versa, in 2007-2009, there is a feedback at lag 3. During 1990-2009 and 1990-2017, there is a full feedback, as the null hypotheses are rejected at all lags. For 2000-2009 the returns of ESI causes DAX returns at 1 and 3 lags, and the DAX returns causes ESI returns at 6 and 12. This observation suggests that ESI is a very important tool for investors to track the tendency of and take position on DAX even during crisis and uncertainty periods. The justification of the latter contention is related to the very essence of ESI. ESI is a survey-based indicator of future business conditions. Anticipation of a crisis or increased uncertainty is captured in the respondent managers' views which in turn are reflected in ESI. As the stock market is a mechanism of discounting future events, including crises and periods of increased uncertainty, any ESI change should have an impact on the stock market index, hence the causality line identified above. My results are interpreted as evidence of predictability of and information revelation for DAX by ESI.

2.4 Trading the ESI

If ESI is indeed a leading market indicator, then I should be able to derive (abnormal) positive excess returns for the DAX. For each sub-period, I apply simple investment strategies between DAX and ESI, so as to gauge whether these strategies beat the buy-and-hold strategy. The comparative performance of the ESI based on investment strategies is examined using the NAV (Net Asset Value) of €1, the annualized average return, the annualized standard deviation and the Sharpe ratio.

To implement the strategies, I let x_t to be the monthly percentage change of Germany's ESI and y_t be the monthly percentage change (return) of DAX. Define the signal variable be the

(1) $$s_t(k) = \left[\prod_{J=t-k+1}^{T-1}(1 + x_{\bar{J}})\right] - 1$$

k-period cumulative percentage of ESI. Then the DAX trading strategy is $t_{t+1}(k) = y_{t+1}$ if $s_t(k) \geq c$ where c is a threshold defined in increments from -0.05 to -0.01, and $t_{t+1}(k) = 0$ if $s_t(k) < c$ when c takes prices of -0,01, -0,02 , -0,03 , -0.04 , and -0,05. I evaluate the strategy over T periods and then have $\{T_{t+1}(k)\}_{t=0}^{T-1}$ observations over which I compute the evaluations statistics. These statistics were the annualized average return,

(2) $$\bar{t}_{T-1}(k) = [\tfrac{1}{T-1}\textstyle\sum_{t=0}^{T-1} t_{(t+1)|t(k)}] * 12$$

the annualized standard deviation,

(3) $$\mathrm{t}_{\mathrm{T-1}}^{\mathrm{S}}(k) = \sqrt{\tfrac{1}{T-1} * \textstyle\sum_{t=0}^{T-1} [\![\{t]\!]_{(T+1)/T}(k) - \bar{t}_{T-1}(k)\}^2} * \sqrt{12}$$

the annualized Sharpe ratio,

$$t_{T-1}^{SR} = \frac{\bar{t}_{T-1}(k)}{t_{T-1}^{s}(k)} \tag{4}$$

and the total trading NAV

$$t_{T-1}^{NAV} = \prod_{t=0}^{T-1}[1 + t_{(t+1)|t(k)}] \tag{5}$$

The investment strategies I implemented follow the ESI changes as a sign for investing on DAX as presented in the following Table.

Table 2.4: Investing on DAX following the ESI.

The first column comes for the descriptive statistics, the second stands for the simple buy-and-hold strategy and the rest are the alternative strategies with their limits that are applied to beat the simple buy-and-hold on DAX. I highlight the best investment strategies performance for the total return value of 1 Euro across sub-periods.

DAX returns	**Buy-and-hold strategy**	**if ESI returns > -5%**	**> -4%**	**> -3%**	**> -2%**	**> -1%**	**> 0%**	**> 1%**	**> 2%**	**> 3%**	**> 4%**	**> 5%**
1990-1999												
Total Return Value of €1	4.4327	4.5369	4.4697	4.0188	3.6230	3.0571	2.5140	2.1973	2.3186	1.3610	1.2341	0.9584
Annualized Wtd Average	18.61%	18.75%	18.58%	17.35%	16.07%	14.01%	11.68%	10.01%	10.14%	3.85%	2.72%	-0.34%
Annualized Std Dev	19.04%	18.40%	18.41%	18.25%	17.68%	16.95%	16.20%	15.29%	12.00%	9.08%	8.71%	5.21%
Sharpe Ratio	0.9775	1.0192	1.0096	0.9502	0.9087	0.8265	0.7208	0.6548	0.8455	0.4241	0.3120	-0.0651
2000-2007												
Total Return Value of €1	1.1070	1.1386	1.1508	1.1855	2.1107	1.8180	1.7845	1.2080	1.2206	0.9691	0.8171	0.8651
Annualized Wtd Average	4.07%	4.06%	4.20%	4.33%	11.30%	9.25%	8.79%	3.22%	3.06%	-0.08%	-2.49%	-1.75%
Annualized Std Dev	22.99%	21.32%	21.32%	20.00%	16.31%	16.03%	14.67%	11.76%	8.98%	8.29%	6.22%	5.94%
Sharpe Ratio	0.1770	0.1904	0.1971	0.2166	0.6929	0.5771	0.5992	0.2738	0.3402	-0.0098	-0.4007	-0.2951
2007-2009												
Total Return Value of €1	0.8583	1.1156	1.1156	1.1156	1.1256	1.0876	1.0876	1.1664	1.1664	1.1664	1.0519	1.0519
Annualized Wtd Average	-4.77%	7.02%	7.02%	7.02%	7.50%	5.51%	5.51%	9.04%	9.04%	9.04%	3.10%	3.10%
Annualized Std Dev	27.14%	14.78%	14.78%	14.78%	14.74%	13.88%	13.88%	11.52%	11.52%	11.52%	8.44%	8.44%
Sharpe Ratio	-0.1758	0.4752	0.4752	0.4752	0.5091	0.3970	0.3970	0.7849	0.7849	0.7849	0.3676	0.3676
2010-2017												
Total Return Value of €1	2.0318	1.7840	1.7840	1.4819	1.6276	1.7099	1.6609	1.5484	1.5784	1.4615	1.4615	1.1992
Annualized Wtd Average	11.36%	9.44%	9.44%	6.76%	7.69%	8.35%	7.70%	6.51%	6.57%	5.42%	5.42%	2.59%
Annualized Std Dev	16.82%	16.23%	16.23%	15.73%	13.37%	13.07%	11.08%	8.99%	6.10%	4.92%	4.92%	3.25%
Sharpe Ratio	0.6752	0.5814	0.5814	0.4295	0.5754	0.6385	0.6947	0.7247	1.0759	1.1014	1.1014	0.7950
1990-2009												
Total Return Value of €1	3.1729	4.3419	4.3234	4.7873	8.0052	5.6219	4.5380	2.8793	3.0700	1.4307	1.0289	0.8670
Annualized Wtd Average	8.58%	9.80%	9.77%	10.12%	12.52%	10.52%	9.23%	6.55%	6.55%	2.30%	0.44%	-0.59%
Annualized Std Dev	21.75%	19.55%	19.55%	18.53%	16.65%	16.10%	15.17%	13.44%	10.74%	8.99%	7.67%	5.81%
Sharpe Ratio	0.3944	0.5009	0.4998	0.5462	0.7517	0.6537	0.6083	0.4875	0.6098	0.2561	0.0570	-0.1017
2000-2009												
Total Return Value of €1	0.7697	1.0290	1.0400	1.2808	2.3758	1.9773	1.9409	1.4090	1.4237	1.1303	0.8595	0.9100
Annualized Wtd Average	0.21%	2.46%	2.57%	4.40%	10.28%	8.30%	7.93%	4.25%	4.12%	1.67%	-1.36%	-0.78%
Annualized Std Dev	23.98%	20.54%	20.53%	18.81%	15.76%	15.38%	14.28%	11.53%	9.38%	8.90%	6.62%	6.40%
Sharpe Ratio	0.0089	0.1198	0.1252	0.2341	0.6526	0.5394	0.5557	0.3686	0.4395	0.1872	-0.2052	-0.1215
1990-2017												
Total Return Value of €1	6.8679	8.2521	8.2170	7.5578	13.8806	10.2411	8.0298	4.7496	5.1624	2.2276	1.6019	1.1076
Annualized Wtd Average	9.52%	9.86%	9.85%	9.36%	11.34%	10.09%	8.98%	6.74%	6.75%	3.40%	2.06%	0.55%
Annualized Std Dev	20.47%	18.68%	18.68%	17.80%	15.84%	15.35%	14.21%	12.45%	9.82%	8.28%	7.29%	5.59%
Sharpe Ratio	0.4649	0.5281	0.5273	0.5261	0.7156	0.6572	0.6322	0.5413	0.6875	0.4103	0.2826	0.0978

2.5 Results

Having documented the previously documented causal effect from ESI to the stock market, I show that investors can outperform the buy-and-hold strategy, by considering the ESI as an indicator of timing their positioning on the DAX. This is true for every sub-period examined. Table 2.4 reveals three important findings. Firstly, the four sub-periods, the Pre-Euro in 1990-1999, the Post-Euro or Pre-Crisis in 2000-2007, the 2007-2009 crisis, and the Post-Crisis period in 2010-2017, have characteristics of potential non-linearity, possibly because of varying causality from DAX to ESI and the presence of threshold effect in the out-off point that defines the moves of ESI. The investors' threshold increases as I move on from the Pre-Euro period towards the crisis periods and becomes positive after the crisis. Namely, I observe that the threshold moves from -5% at the Pre-Euro period, then to -2% at the Post-Euro period and ended up to 1% and 2% at the crisis and the Post-Crisis periods respectively. In the first three sub-periods I see that as the threshold increases, there is a rising performance and during the Post-Crisis period the ESI improves the risk reward characteristics. I also observe at the 2010-2017 period the buy-and-hold strategy has higher return, but my strategy risk reward is stronger, if the ESI returns are between 2% and 5%.

More specifically, during the 1990-1999, the Pre-Euro unification period, Germany was in the process of re-industrialization and the ESI was not the driving force for investors, as the result of DAX returns in the buy-and-hold strategy seemed to be relatively high in the said period, except the total return of 1 Euro, when the threshold of ESI changes was greater than -5% and -4%. Over the Post-Euro and Pre-Crisis period in 2000-2007, sentiment became a stronger driving force for investors. My results are much stronger, not only compared to the previous period, but also compared with the buy-and-hold benchmark for period 2000-2007, when ESI returns were greater than -2%, there was an increase in total return of up to 90.66%, in annualized average up to 177.64%, in the Sharpe ratio up to 291.46% and a significant decrease of risk about 29%. During the period of the 2007-2009 crisis, when the wave of economic uncertainty and crisis hit the European “door” from the US financial markets, the returns of the sentiment index became stronger than ever and the driving investors’ decisions reaching very high, historical profits. Namely, for the crisis period in 2007-2009, the total return of 1 Euro increased by 35.90%, the risk decreased as the standard deviation was lower to 57.56%, and the Sharpe ratio became 4 times better, compared to the buy-and-hold benchmark. In the Post-Crisis period of 2010-2017, was naturally and not unexpectedly different for German financial markets, as the crisis was over. An investor could not count on the sentiment index now according to the ESI returns because the buy-and-hold performs better as market return to normality. This is a period of monetary and growth exhaustion caused by the problems created by zero or negative interest rates.

Performing the same strategies for the 1990-2009 and 2000-2009 sub-periods, I found similar results, highlighting the dynamic of the strategy for investing in the ESI when its returns are higher than -2%, with the total return value of 1 Euro yielding 152.30% and 208.67% respectively, and with the Sharpe ratio improving significantly for both sub-periods. The same trend holds for the risk, which is reduced by 23.45% and 34.28% for the two periods.

In combining the results so far, there is a combination of time-varying causality from ESI to DAX, a threshold effect on the change of ESI to DAX returns and a macro outlook that is reflected in the performance of my approach during different time periods in Germany's recent history. I showed the importance of the ESI dynamics and the opportunities that arise from investors who can take advantage of ESI swings, even during the crisis. I confirm the validity of the result on the related literature of Fisher and Statman 2000; Brown and Cliff 2005, Baker and Wurgler 2006, 2007 who stated that the ESI influences the return and valuation of assets, the volatility and the bond yield spreads, as it combines economic judgments, expectations and attitudes of all economic agents. These results also support the Baker and Wurgler (2012) who claim that when a country's total sentiment is high future returns are relatively low, the volatility is high, there is a growth, and distressed stocks. These strategies decreased the risk as Barone et al. (2012), but also exhibit increased returns during the great economic crisis and emerge the sentiment to be the leader guide for investors on DAX.

2.6 Concluding Remarks

The main contribution of this Chapter was to explore whether economic sentiment of a "safe heaven" country such as Germany, can influence stock returns and decrease risk. There is ample literature that warrants investigation of this connection and, moreover, the historical events of the sovereign debt crisis with Germany acting as such a "safe heaven" country, suggested that such connection between sentiment and performance would be present as well.

I used a two-pronged approach to explore my hypothesis, causality testing and a simple trading strategy. In the causality testing I examined whether sentiment causes DAX returns and whether there is feedback between the ESI and the DAX, while in the trading experiment I illustrated not only the impact that ESI had on DAX returns, but also the non-linear and time-varying nature of this impact. The results suggested that DAX responded in different magnitudes of ESI changes differently in different periods; that is, the trading threshold of ESI changes that was providing the best trading performance, was different in different periods I examined. This is further evidence on the importance of sentiment as a predictor of future returns, as it suggests that investors could have differential responses in changing economic conditions.

Extrapolating from my results I claim that in periods of higher economic uncertainty, sentiment becomes a crucial representative of economic conditions and thus a market driver. This is not an unreasonable proposition, given that other countries during the same period faced problems, i.e. Greece, had a decrease in both their financial market performance and also in their sentiment indicators, as well. Therefore, more work on the impact of economic sentiment on market performance might reveal also other results that I have not covered in my work.

Future research along the lines of this study can include the examination of a variety of countries during the same period using the same methodology (e.g. Germany vs. the PIIGS countries), a more extensive examination on the presence of non-linear effects of sentiment on market returns, a formal forecasting comparison of economic sentiment as a (statistical and economic) predictor of market returns and also a comparison of all these for Europe (or Eurozone) countries and the USA. I currently pursue some of these issues.

Chapter 3

Driven by portfolio beta changes and sectoral power in US stock market: Explaining momentum across time and sectors.

3.1 Introduction

Momentum is one of the most commonly accepted investment approaches among investors and academics across all investment strategies in the asset management industry. Momentum, according to rational and behavioral asset pricing theories underlines the idea of buying winners and selling losers, based on their average past realized returns. Moskowitz and Grinblatt (1999) noted the importance of industry momentum where industry factors have on individual stock momentum strategies in terms of profits. The strategies of buying stocks from past industry winners and selling stocks from past industry losers creates significant profits. They also show that the significant returns to industry momentum strategies came after the incorporation of size book-to-market, and micro-structure effects. After the 2008 crisis, I follow up the Daniel et al. (2016) analysis of where I stand now on the efficacy of momentum. They explained that strong positive average returns and Sharpe ratio about the momentum strategies are from circumstantial crashes that occurs during market stress.

Following the initial approach of Jegadeesh and Titman (1993) for the cross-sectional momentum and then the approach of Moscowitz et al. (2012) about time series momentum, I consider a very detailed class of momentum analysis using 9 sub-periods of different economic characteristics and 5 different look-back periods with a holding period of 1 month. The look-back period states the horizon of past returns that constitute trading signals, the holding period refers to the interval that the realized past returns are for future position and finally sub-periods are used to capture the main characteristics of each economic condition I am to examine.

Our study is a careful reexamination of the NASDAQ components, as in Chan, et al. (1996), Jegadeesh and Titman (2001), Hong, et al. (2000), Avramov, et al. (2007). In such study, to the best of my knowledge, I focus on a different perspective than the literature: I seek to assess the role of momentum portfolio performance, beta and Sharpe ratio across different economic sub-period from January of 1985 to December of 2017 and the degree of their change in relation to sectoral participation and the related fundamentals. I focus on the factors that affect the momentum portfolio beta and how these factors are driven at different look-back periods and different economic periods. I also test for possible relationship between each sector's participation in momentum portfolios and the change of momentum portfolio beta trend. All in all, I generated 50 portfolios based on different momentum look-back periods and economic situations, considering the top 10% of NASDAQ firms that exhibit the highest momentum across all stocks on each specific period. I analyze the portfolio performance by looking at standard attribution measures, careful factor regressions that include dummies for the 2008 crisis (taking prices 1 for pre-crisis of 2008 and 0 for the post crisis period) and also regressions using sectoral fundamentals. My findings align with those of Jegadeesh and Titman (2011) and Baltas and Kosowski (2013). The portfolio betas are statistically significant across all evaluating models and affect the expected returns and Sharpe ratio of momentum portfolios. Beta differentials seems to be driven mainly by sectoral participation.

The rest is organized as follows. The next section briefly discusses the relevant literature, in a non-exhaustive manner. Section III describes the data employed and the empirical methodology I used, performing a carefully sample-split analysis based on NBER data, VIX and Monetary policy announcements in various sub-periods for NASDAQ from January 1985 until December 2017. Section IV discusses the empirical results and findings. Section VI offers some concluding remarks.

3.2 Literature Review

Jegadeesch and Titman (1993) were the first that illustrated the profitability of momentum as an investment strategy. They found that the performance of equally weighted portfolios of stocks with the best top 10% past performance outperformed those stocks with the worst bottom 10% past performance, and that over an intermediate horizon of three to twelve months, past winners on average continue to outperform past losers, experience profits of about one percent per month for the following year. They considered the strategies of buy and hold where the portfolio is rebalanced at the end of every month holding period and every month irrespective of the holding period for the stocks and found monthly rebalancing to be superior. Latane and Jones (1979) and Bernard and Thomas (1989), among others, found that firms reporting unexpectedly high earnings outperform firms reporting unexpectedly poor earnings. The superior performance persists over a period of about six months after earnings announcements.

In follow-up work, Jegadeesh and Titman (2001) found that when small firms seem to have more volatile returns, both winners and losers tend to be smaller firms than the average firm in the sample, and smaller firms are more likely to appear in the extreme return sorted portfolios. Lo and MacKinlay (1990) also documented a lead-lag relation between weekly returns of size-sorted portfolios for the US market. They found that portfolio returns are higher for those portfolios which consist of large-capitalization stocks and as a result these portfolios lead the ones consisting of small-capitalization stocks. Using the portfolio returns from large firms, an investor can reliably predict the returns in the short-run in small-firm portfolios. Moskowitz and Grinblatt (1999) suggested that industry-based momentum investment strategies are more profitable compared with the momentum investment strategies when momentum controls for size, book-to-market equity, individual stock momentum, the cross-sectional dispersion in mean returns, and potential microstructure influences. This is reinforced since the industry-based momentum strategies are robust to various specifications and methodologies, and are profitable especially in the largest, most liquid stocks. Barberis et al. (1998), Daniel et al. (1998) and Hong and Stein (1999), Pan Liano and Huang (2004), found that own autocorrelation in industry portfolio returns is the driving force for the industry momentum and yields significant profits when it is positive and statistically significant. Mulvey and Kim (2008) found that a segmentation scheme on each industry yields improved investment performance. This happens because firms cannot change their industry status while their size, growth and fame vary across different economic periods. Such advantage helps investors to track each of the segmentation easily and increase the performance on active funds as they will count on the type and style of stocks that are in their portfolio.

The momentum in stock prices partially depicts the market's slow adjustment to the information in earnings because of the high association between prior returns, prior earnings news and the sluggishness in the market's response to past earnings surprises. The delay of the market to slowly incorporate the information and to react on time, creates drifts in future stock returns. These drifts can be forecasted using abnormal announcement return. Studies showing the difference in price drifting patterns caused by bad and good news include Hong et al. (2000) and Chan (2003) that found it in equity markets, Andersen et al. (2007) that found such asymmetry in the FX market, and Beber and Brandt (2009) that found it in US bond markets.

Behavioral models imply that the holding period of abnormal returns arise due to a delayed overreaction to information that pushes the prices of winners (losers) above (below) their long-term values. Conrad and Kaul (1998) suggest, that the higher returns of winners in the holding period represent their unconditional expected rates of return and thus predict that the returns of the momentum portfolio will be positive on average and that the stocks on the long term of the momentum portfolio should continue to outperform stocks on the short one by the same level in any postranking period.

Cooper et al. (2004), and Hou et al (2009), argued that short-run (six months) momentum strategies make profits in an up market and lose in a down market, but the up-market momentum profits reverse in the long run (13–60 months). Wang and Xu (2012) found that market volatility has significant power to forecast momentum profitability. For time series momentum, however, Moskowitz et al. (2012) found that there is no significant relationship of time series momentum profitability to either market volatility or investor sentiment. Volatility and frictions play a key role in real-world portfolio construction. Empirical asset pricing studies examine effects of risk weighting or volatility scaling and associated portfolio turnover on portfolio performance. Such studies include Moskowitz et al. (2012) and Baltas and Kosowski (2013) who studied time series momentum strategies and Barroso and Santa-Clara (2013) and Daniel and Moskowitz (2016) who studied the effect of volatility scaling on the performance of cross-sectional momentum strategies. Lo and Wang (2009) reported that when the idiosyncratic volatility of a stock is high then the turnover for such stock is also high. The positive correlation between turnover and volatility across stocks is distinct from the well-known temporal relation between trading activity and volatility. Moskowitz, et al (2012) empirically investigated time series momentum (TSM) which characterizes strong positive predictability of a security's own past returns where stocks that realize a positive past return are the winners and those that realize a negative return are the losers. They showed that the TSM strategy based on a 12-month horizon better predicts the next month's return than other time horizons and TSM strategy delivers its highest profits during the most extreme market episodes.

In many studies, such as in Jegadeesh and Titman (2011), it is shown that momentum strategies perform poorly after the subprime crisis of 2008. Baltas and Kosowski (2013) show that the time-series momentum strategy has the attractive feature of generating higher performance in recessions rather than in booms. The time-series momentum strategy tends to be on average shorter in recessions than in booms independent of the trading signal used. Hutchinson and O'Brien (2015) following on Bali et al. (2016), showed that in periods where economic uncertainty is lower, the returns of time series momentum are indeed higher. They indicate that about 40 percent of the returns of time series momentum are due to time varying exposure to macroeconomic variables, which are related to the business cycle. These findings are consistent with the conclusions of Chordia and Shivakumar (2002) for cross sectional momentum, that stated that a portion of the profitability of momentum strategies represents compensation for bearing time varying risk, consistent with rational asset pricing theories. The performance of time series momentum improves when economic uncertainty is diminished so, time series momentum tends to perform less well than average following periods of Financial crisis, and changes in the business cycle.

Grundy and Martin (2001) suggested that during the bear markets, the momentum gets significant negative beta, but with the contribution of hedging to market exposure to instability, the momentum returns become stable. According to the literature, the momentum has not time constant market betas because winners are low beta stocks and losers accordingly have high betas after bear markets. On the contrary, Daniel and Moskowitz (2016) disagree because by using these betas in real time, the crashes of the strategy still appear. Barroso and Santa-Clara

(2014) found that the risk of momentum is predictable and highly variable over time. Controlling and managing momentum risk, investors eliminate the crashes and almost double the Sharpe ratio by this strategy. Dudler et al. (2014) first introduced the risk-adjusted time series momentum, a strategy which outperform the time series momentum strategies of Moskowitz et al. (2012) for almost all combinations of holding and look-back periods they performed. They also studied two types of momentum volatilities, the aggregate momentum volatility, and the class specific momentum volatility where the use of aggregate momentum volatility leads to a significantly higher realized Sharpe ratio than using class-specific momentum volatilities. They found that risk-adjusted time series momentum returns (RAMOM) adjusted by the aggregate momentum volatility and have a much lower exposure to market, value, and momentum factors. As a result, risk-managed momentum returns offer significantly better diversification benefits than standard momentum returns. Barroso (2013) investigates the bottom-up beta of cross-sectional momentum, estimated from the betas of individual stocks, and showed that it exhibits significant variations over time, increasing in bull markets and decreasing in bear markets. He showed that the conditional betas can explain a large part of variations in momentum-specific risk. They also consider the momentum betas with respect to the four Fama-French factors (market, size, value, and cross-sectional momentum). All these betas are significant and positive, with the exception only of short-term RAMOM and TSM returns that have a negative market beta. Furthermore, betas are larger for RAMOM returns because of a significant negative relationship between futures volatilities and Fama-French risk factors. Several interesting patterns emerge for very short-term and very long-term momentum. First, short-term momentum returns have a negative market beta and can therefore potentially be used as a hedge against market downturns. Second, very long-term (two years) momentum returns have a negative beta with respect to the SMB and HML factors.

He et al. (2015), suggested that the optimal TSM strategy should take into account not only the trading signal based on momentum and fundamentals but also the size of position, which is associated with market volatility, in contrast to a TSM strategy based on the trend only. Except from price trend, position size is another very important variable for momentum. Huang, et al. (2014) highlighted that not only mean reversion but momentum can exist the same time in the S&P 500 index. He et al. (2015) showed theoretically that a combined TSM and reversal strategy is optimal. They constructed portfolios using excess return on monthly base with a window of one-month lag and concluded that this strategy performs the best in contrast to all the momentum strategies with look-back and holding periods varying between one month to 48 months. They found that the TSM strategy based on momentum and reversal trading signal is more profitable than the pure momentum strategy of Moskowitz et al. (2012). Bird et al. (2016) highlighted that the importance in the portfolio construction decisions are the holding period, the portfolio rebalancing and the determination of the weights assigned to stocks.

3.3 Data and Methodology

We extract all the NASDAQ stocks listed in Datastream, subject to specific selection criteria. First, I exclude listed firms with less than 5 years, and priced below 5$ at the beginning of the holding period, as in Jegadeesh and Titman (2001). This prevents results from suffering from low priced and very illiquid stocks. I collect data monthly from 1985 until the end of 2017 on the NASDAQ index and its components, for a universe of 2467 firms. The data are on stock prices, dividend yield, market to book value ratio, earnings per share ratio, total assets, market capitalization and operating profit margin for both the NASDAQ index and its components.

In order to take full advantage of the sample I split it into eight critical sub-periods. This separation was based on NBER data, on VIX and Monetary policy announcements, all taken from the FRED database, to capture the growth and recession periods, and important economic events. These sub-periods are as follows:

1. the Gulf War I 1985-1991,
2. the Expansion I 1992-2001(August),
3. the 2001 WTC Attack 2001(September)-2002,
4. the Expansion II 2003-2007(June),
5. the Early Credit Crisis 2007(July)-2008(August),
6. the Lehman Collapse and Recession 2008(September)-2009,
7. the Fiscal Policy Battle of currency crisis and sovereign debt crisis 2010-2013(October),
8. and the US Recovery period 2013(November)-2017(December),

and I also study an imputed sub-period about Financial Crisis and Recession about 2007(July)-2009(December).

For each one of the above sub-periods, I calculate the descriptive statistics for the index and all components of NASDAQ based on their log returns. Then I estimate the momentum on the NASDAQ components for 1, 3, 6, 9 and 12-months using a 1-month holding period for each sub-period. Momentum strategies are constructed using various lengths of look-back and holding periods. In this way, I created 50 portfolios (eight sub-periods with five momentum look-back lengths for each one of these) with the top 250 firms per portfolio, or almost 10% of the index composition which exhibit highest momentum. Each portfolio return is calculated as the equally weighted average return of the corresponding 250 stocks. I also perform a sectoral analysis, estimated the percentage of participation of each sector per momentum portfolio and computed the average return, volatility, market capitalization and earnings per share across momentum portfolios for each sector. For performance analysis I use a variety of evaluating regressions to compliment the basic performance statistics. I analyzed the link between the expected returns, the Sharpe ratio and risk for each portfolio with the rest of the descriptive measures for the sub-periods of 1985-2017, 1985-2007 and 2007-2017 before and after crisis. I also use additional regressions with both fundamentals and descriptive measures as explanatory variables. The analysis is always both for the total and the sectoral portfolios.

The basic evaluating regression model is nested within the following specification:

Basic Model: $y_{it} = a_i + D_t + \beta'_1 x_{it} + \beta'_2 z_{it} + \gamma'_1 x_{it} + \gamma'_2 z_{it} + \varepsilon_{it}$

where y_{it} is either R_t (momentum portfolio return) or y_{it} is Shr_t (momentum portfolio Sharpe ratio) or y_{it} is Sd_t (momentum portfolio standard deviation) and where x_{it} contains the variables associated with performance statistics and z_{it} contains the variables associated with the fundamentals. The x_{it} can contain any or all of R_t, $Beta_t$, Sd_t, D_t, Shr_t,$Skew_t$ and $Kurt_t$, and z_{it} can contain any or all MV_t, DY_t, EpS_t and D_t is a dummy variable that takes the values of 1 and 0 for the pre and post 2008 crisis period respectively. I take advantage of the natural ordering of the different economic periods and use these ordering as "time" variable t while the look-back period of each momentum portfolio is used as the corresponding cross-section i. I use Fixed effects for the estimation of parameters as well as Dynamic GMM to account for all possible sources of potential endogeneity. All variable abbreviations for the associated models appear in Table 3.1 that follows. I finally test the influence that Sd_t, MV_t, DY_t, EpS_t and $MTBV_t$ have on each sectoral performance of momentum with the following model.

Sectoral Model: SEC_{it}=$\omega_i + \delta'_1 Sd_{it} + \delta'_2 MV_{it} + \delta'_3 DY_{it} + \delta'_4 EpS_{it} + \delta'_5 MTBV_{it} + \varepsilon_{it}$

Table 3.1: Variable Explanation.

Abbreviation	**Variable Explanation**
R_t	Equally Weighted Expected Returns of Momentum portfolio.
$Beta_t$	Momentum portfolio Beta.
D_t	Dummy variable; 1 for pre-crisis and 0 for post-crisis of 2008.
Shr_t	Momentum portfolio Sharpe ratio.
Sd_t	Momentum portfolio Standard deviation.
$Skew_t$	Momentum portfolio Skewness.
$Kurt_t$	Momentum portfolio Kurtosois.
MV_t	Momentum portfolio Market Value.
DY_t	Momentum portfolio Dividend Yield.
EpS_t	Momentum portfolio Earnings per Share.

All variable abbreviations that I use in my model are presented in this Table with its explanations. The variable D_t denotes a dummy variable, which gives 1 for periods before crisis from 1985 to June 2007, and 0 for periods after crisis from July 2007 to December 2017.

We next present a short discussion on about momentum portfolios both for the fundamentals and for the percentage of participation within each sector across all sub-periods. In Table 3.2, I have the average momentum of the fundamentals for each of the six momentum NASDAQ portfolios per each sub-period and the full sample. These are the dividend yield (DY), the earnings per share (EpS), the market value (MV), and the market to book value (MTBV) on monthly basis, while yearly I have the total assets (TA), the market capitalization (MC) and the operating profit margin (OPM).

Starting with the DY I can see that for the full sample the highest average DY momentum is given by the 12-month portfolio, and the same holds for all sub-periods that correspond to the post 2008 recovery. I note that the highest average DY is for the 2007-2009 sub-period at 12-month and also 12-month momentum high exists for 2010-2017 sub-periods but with negative in sign and almost zero in magnitude. Among the other portfolios across sub-periods, I observe that the highest average DY momentum appears on 3 and 9-month portfolios. Specifically, the 3-month portfolios gives the highest average DY momentum in sub-periods of the 2001 WTC Attacks, Expansion II, Early Credit Crisis, Lehman collapse, that collectively correspond to the continued rise of the stock market after the dot-com collapse and the 2001 WTC Attacks, up to and just before the 2008 crisis. On the other hand, the 9-month portfolio gives the highest average DY momentum in sub-periods of 1985-2001 and 1992-2001. Thus, I observe that the average DY momentum varies per economic period I examined and see that shorter periods as 3-months give the highest average DY momentum only for the “crisis-free” period of 2001-2007, while longer periods of 9 and 12-months give highest average DY momentum in other sub-periods that contain crisis and recovery from a crisis.

Another variable I use is the EpS, as a per share version of how companies do in terms of their profits, which are allocated to each outstanding share of each common stock. The results for the average EpS momentum show that the 12-month portfolio is highest across the full sample and all sub-periods except the pre- and crisis periods of the Early Credit Crisis and the Lehman collapse up to 2009. Thus, it appears that the slowdown on the average EpS momentum look-back period from 12 to 9-months is possibly associated with an early warning of the 2008 crisis. A less sensitive trend is indicated for the MV, as for the full sample the highest average MV momentum is given by the 12-month portfolio, and the same stands for all sub-periods except from the Gulf War I, the 2001 WTC Attack, and the Early Credit Crisis, which has momentum high at 9-month portfolio. The highest average MV momentum is for 12-month portfolio at Lehman collapse, from September 2008 to the end of 2009, and is almost double at the 9-month portfolio for the same sub-period. This result is notable since MV usually are lower in bear markets that accompany recessions and increase at bull markets during economic expansions. The MTBV exhibit a consistent increase and continuous changes on momentum high across sub-periods after the Expansion I period until the end of October 2013, when it notes its highest peak at 7.123. Such peak at 12-month is 44 times stronger from the 12-month portfolio on the whole sample. As far as the TA, the MC, and the OPM, the results show many ups and downs and do not indicate a sufficient trend.

Table 3.3 has a sectoral analysis on each of the 50 portfolios I computed as a percentage of participation across the same sub-periods as in Table 3.2. The NASDAQ components are Basic Industries, Capital Goods, Consumer Durables and not Durables, Consumer Services, Energy, Finance, Health Care, Miscellaneous, Public Utilities, Technology and Transportation firms. I can immediately see two interesting results. First, for the pre-crisis period the index loads heavily on Technology and Finance stocks not surprisingly, and this probably corresponds to the early 1990's explosion of new computer technologies that were first adapted to hardware and software companies and those financial firms, large enough to afford an early transition to more automated and computer driven systems. Second, for the post-crisis period, the index loads heavily on Health Care stocks which shows the application of new technologies to biomedical engineering and new drug development that become possible only with the most recent advances in computational power, but also because of a shift in investment perspectives away from the traditional reliance of financial tech-based companies. What is more, in the full sample 1985-2017, the technology concentrates the highest percentage of sectoral participation in all portfolios around to 26%. The same results stand for the Expansion I from 1992 to August 2001, and for the Expansion II from 2003 to June 2007 period, with percentage of participation reaching around 36% and 24.5% respectively. The Gulf War I and the 2001 WTC Attack periods concentrates the highest percentage between 18.8% and 25% for Finance firms. Finally, during economic crisis periods of July 2007 to August 2008 and September 2008 to December 2009, the Health Care firms concentrates the highest stock participation.

Table 3.2: Fundamental Analysis.

		MONTHLY DATA					YEARLY DATA		
Economic Situation	**Periods**	**Momentum**	**Dividend Yield**	**Earnings per share**	**Market Value**	**Market to book value**	**Total Assets**	**Market Capitalization**	**Operating Profit Margin**
ALL SAMPLE	**1985 - 2017**	**1**	-0.001	-0.002	0.016	0.003	0.234	0.198	-0.054
		3	0.019	0.113	0.110	0.032			
		6	0.042	0.130	0.201	0.076			
		9	0.070	0.208	0.239	0.116			
		12	0.113	0.257	0.340	0.156			
GULF WAR I	**1985 - 1991**	**1**	-0.002	0.001	0.023	0.010	0.144	0.106	-0.042
		3	0.052	0.120	0.380	0.063			
		6	0.134	0.209	0.491	0.147			
		9	0.135	0.285	0.534	0.237			
		12	0.131	0.308	0.519	0.326			
EXPANSION I	**1992 - 2001(August)**	**1**	-0.003	0.000	0.031	0.006	0.246	0.088	-0.055
		3	0.009	0.135	0.132	0.036			
		6	0.026	0.335	0.352	0.060			
		9	0.039	0.515	0.617	-0.149			
		12	0.018	0.728	0.924	-0.231			
2001 WTC ATTACK	**2001(September) - 2002**	**1**	-0.018	-0.017	0.059	0.043	-0.003	-0.082	0.094
		3	-0.011	0.084	0.175	0.138			
		6	-0.062	0.047	0.460	0.322			
		9	-0.163	0.504	1.927	0.677			
		12	-0.232	0.820	1.176	0.700			
EXPANSION II	**2003 - 2007(June)**	**1**	-0.017	-0.003	0.063	0.284	0.133	0.150	0.065
		3	0.119	0.096	0.387	0.856			
		6	0.006	0.272	1.796	0.777			
		9	0.070	1.033	2.073	0.544			
		12	0.096	2.703	2.835	0.746			
EARLY CREDIT CRISIS	**2007(July) - 2008(August)**	**1**	-0.012	-0.011	0.065	0.040	0.144	-0.311	-0.130
		3	0.304	0.030	0.363	0.423			
		6	0.160	0.003	1.123	1.478			
		9	-0.048	0.827	5.419	0.660			
		12	-0.188	0.521	3.463	1.242			
LEHMAN COLLAPSE & RECESSION	**2008(September) - 2009**	**1**	-0.046	-0.007	0.066	0.060	0.041	-0.087	-0.004
		3	0.027	0.448	0.936	0.790			
		6	-0.145	1.243	0.779	0.743			
		9	-0.114	2.396	3.391	4.446			
		12	-0.087	0.484	6.238	-0.122			
FISCAL POLICY BATTLE - CURRENCY CRISIS - SOVEREIGN DEBT	**2010 - 2013 (October)**	**1**	-0.029	0.001	0.058	0.029	0.104	0.176	0.008
		3	-0.046	0.186	0.533	0.381			
		6	-0.135	0.391	2.231	1.335			
		9	-0.014	0.509	5.101	-0.688			
		12	-0.002	1.767	5.560	7.123			
US RECOVERY PERIOD	**2013(November) - 2017**	**1**	-0.018	-0.013	0.040	0.028	0.197	0.121	0.029
		3	-0.019	-0.016	0.041	0.027			
		6	-0.043	0.395	0.427	0.332			
		9	-0.072	0.424	0.759	0.495			
		12	-0.002	0.596	1.178	0.480			
FINANCIAL CRISIS AND RECESSION	**2007(June) - 2009**	**1**	-0.001	-0.019	0.034	0.021	0.104	-0.108	-0.133
		3	0.103	0.163	0.365	0.532			
		6	0.235	0.150	1.060	0.947			
		9	0.458	0.243	2.282	2.107			
		12	0.681	0.240	5.916	0.477			

Table 3.2 reports a fundamental analysis on 50 NASDAQ portfolios for 1, 3, 6, 9 and 12-month momentum in its sub-period, considering holding period 1 month The monthly fundamentals are the dividend yield, the Earnings per share, the Market value, and the market to book value, while on yearly base I perform the Total Assets, market capitalization and Operating profit margin. These estimations considering across all portfolios the average momentum of the top 10% firm's participation.

Table 3.3: Analysis on sectoral participation across sub-periods.

Economic Situation	Periods	Momentum	Basic Industries	Capital Goods	Consumer Durables	Consumer Non-Durables	Consumer Services	Energy	Finance	Health Care	Miscellaneous	Public Utilities	Technology	Transportation
ALL SAMPLE	1985 - 2017	1	2.00%	10.00%	6.00%	6.00%	16.00%	3.00%	13.00%	14.00%	0.00%	0.00%	26.00%	4.00%
		3	2.00%	9.00%	6.00%	6.00%	17.00%	3.00%	13.00%	16.00%	0.00%	0.00%	25.00%	3.00%
		6	2.00%	12.00%	5.00%	6.00%	17.00%	2.00%	13.00%	15.00%	0.00%	0.00%	25.00%	3.00%
		9	1.01%	10.10%	5.05%	6.06%	16.16%	2.02%	13.13%	16.16%	0.00%	0.00%	26.26%	4.04%
		12	1.01%	10.10%	5.05%	5.05%	17.17%	2.02%	13.13%	15.15%	0.00%	0.00%	26.26%	5.05%
GULF WAR I	1985 - 1991	1	2.08%	8.33%	7.29%	14.58%	8.33%	2.08%	18.75%	13.54%	0.00%	5.21%	16.67%	3.13%
		3	2.08%	7.29%	6.25%	15.63%	8.33%	2.08%	19.79%	13.54%	0.00%	5.21%	16.67%	3.13%
		6	2.08%	7.29%	6.25%	14.58%	9.38%	2.08%	21.88%	11.46%	0.00%	4.17%	16.67%	4.17%
		9	2.11%	7.37%	6.32%	14.74%	10.53%	2.11%	20.00%	11.58%	0.00%	4.21%	16.84%	4.21%
		12	2.11%	7.37%	6.32%	13.68%	10.53%	2.11%	21.05%	10.53%	0.00%	4.21%	17.89%	4.21%
EXPANSION I	1992 - 2001(August)	1	2.13%	11.70%	2.13%	2.13%	11.70%	2.13%	17.02%	7.45%	2.13%	1.06%	36.17%	4.26%
		3	2.11%	11.58%	3.16%	2.11%	12.63%	2.11%	14.74%	9.47%	2.11%	0.00%	35.79%	4.21%
		6	2.11%	11.58%	3.16%	2.11%	12.63%	2.11%	14.74%	9.47%	2.11%	0.00%	35.79%	4.21%
		9	2.11%	11.58%	3.16%	2.11%	12.63%	2.11%	14.74%	9.47%	2.11%	0.00%	35.79%	4.21%
		12	1.06%	12.77%	3.19%	2.13%	12.77%	1.06%	12.77%	12.77%	2.13%	1.06%	34.04%	4.26%
2001 WTC ATTACK	2001(September) - 2002	1	6.52%	6.52%	9.78%	2.17%	14.13%	2.17%	19.57%	7.61%	4.35%	1.09%	21.74%	4.35%
		3	8.70%	7.61%	9.78%	3.26%	13.04%	1.09%	25.00%	5.43%	3.26%	0.00%	18.48%	4.35%
		6	7.53%	8.60%	9.68%	5.38%	12.90%	0.00%	24.73%	8.60%	4.30%	0.00%	16.13%	2.15%
		9	8.70%	10.87%	9.78%	7.61%	16.30%	0.00%	20.65%	9.78%	3.26%	0.00%	9.78%	3.26%
		12	6.38%	10.64%	10.64%	7.45%	17.02%	0.00%	19.15%	12.77%	3.19%	0.00%	9.57%	3.19%
EXPANSION II	2003 - 2007(June)	1	8.25%	13.40%	4.12%	4.12%	7.22%	7.22%	7.22%	21.65%	4.12%	2.06%	19.59%	1.03%
		3	8.25%	13.40%	4.12%	3.09%	8.25%	6.19%	7.22%	22.68%	2.06%	1.03%	22.68%	1.03%
		6	7.45%	14.89%	1.06%	3.19%	10.64%	5.32%	8.51%	18.09%	4.26%	2.13%	23.40%	1.06%
		9	6.38%	13.83%	1.06%	2.13%	12.77%	8.51%	7.45%	17.02%	4.26%	1.06%	24.47%	1.06%
		12	7.45%	10.64%	1.06%	3.19%	11.70%	8.51%	8.51%	15.96%	4.26%	3.19%	24.47%	1.06%
EARLY CREDIT CRISIS	2007(July) - 2008(August)	1	5.49%	14.29%	6.59%	2.20%	6.59%	4.40%	2.20%	36.26%	3.30%	0.00%	16.48%	2.20%
		3	6.59%	15.38%	7.69%	1.10%	7.69%	5.49%	2.20%	29.67%	3.30%	0.00%	17.58%	3.30%
		6	7.61%	10.87%	6.52%	1.09%	9.78%	5.43%	1.09%	29.35%	5.43%	1.09%	18.48%	3.26%
		9	7.61%	14.13%	4.35%	1.09%	8.70%	4.35%	1.09%	31.52%	6.52%	1.09%	18.48%	1.09%
		12	6.59%	12.09%	3.30%	1.10%	8.79%	4.40%	1.10%	34.07%	6.59%	1.10%	19.78%	1.10%
LEHMAN COLLAPSE & RECESSION	2008(September) - 2009	1	5.38%	8.60%	6.45%	4.30%	16.13%	2.15%	4.30%	31.18%	6.45%	2.15%	11.83%	1.08%
		3	3.13%	7.29%	6.25%	5.21%	13.54%	3.13%	3.13%	29.17%	9.38%	2.08%	15.63%	2.08%
		6	4.30%	5.38%	3.23%	4.30%	10.75%	2.15%	7.53%	33.33%	8.60%	2.15%	16.13%	2.15%
		9	5.32%	3.19%	5.32%	4.26%	11.70%	3.19%	7.45%	34.04%	6.38%	1.06%	17.02%	1.06%
		12	7.53%	2.15%	5.38%	5.38%	13.98%	3.23%	11.83%	27.96%	5.38%	1.08%	13.98%	2.15%
FISCAL POLICY BATTLE - CURRENCY CRISIS - SOVEREIGN DEBT	2010 - 2013 (October)	1	3.13%	12.50%	6.25%	4.17%	14.58%	3.13%	10.42%	22.92%	5.21%	1.04%	16.67%	0.00%
		3	2.11%	12.63%	6.32%	4.21%	15.79%	3.16%	8.42%	25.26%	4.21%	0.00%	17.89%	0.00%
		6	2.13%	12.77%	5.32%	3.19%	13.83%	3.19%	8.51%	23.40%	4.26%	0.00%	23.40%	0.00%
		9	3.13%	14.58%	6.25%	3.13%	12.50%	3.13%	7.29%	22.92%	4.17%	0.00%	22.92%	0.00%
		12	4.17%	14.58%	5.21%	5.21%	11.46%	2.08%	5.21%	23.96%	3.13%	0.00%	25.00%	0.00%
US RECOVERY PERIOD	2013(November) - 2017	1	4.04%	13.13%	4.04%	5.05%	9.09%	0.00%	6.06%	28.28%	6.06%	0.00%	22.22%	2.02%
		3	2.02%	13.13%	4.04%	6.06%	8.08%	1.01%	5.05%	27.27%	6.06%	0.00%	25.25%	2.02%
		6	2.02%	10.10%	3.03%	6.06%	7.07%	1.01%	4.04%	31.31%	5.05%	2.02%	26.26%	2.02%
		9	2.04%	9.18%	3.06%	5.10%	7.14%	1.02%	4.08%	33.67%	5.10%	1.02%	27.55%	1.02%
		12	1.01%	8.08%	3.03%	4.04%	8.08%	1.01%	7.07%	33.33%	4.04%	1.01%	28.28%	1.01%
FINANCIAL CRISIS AND RECESSION	2007(June) - 2009	1	6.59%	8.79%	5.49%	4.40%	10.99%	3.30%	1.10%	24.18%	7.69%	2.20%	24.18%	1.10%
		3	6.38%	9.57%	5.32%	1.06%	11.70%	4.26%	1.06%	24.47%	7.45%	2.13%	25.53%	1.06%
		6	6.38%	6.38%	4.26%	2.13%	13.83%	3.19%	2.13%	28.72%	5.32%	2.13%	24.47%	1.06%
		9	4.21%	8.42%	4.21%	2.11%	16.84%	4.21%	1.05%	28.42%	5.26%	2.11%	22.11%	1.05%
		12	5.21%	7.29%	3.13%	2.08%	17.71%	4.17%	1.04%	28.13%	4.17%	3.13%	22.92%	1.04%

Table 3.3 reports the Sectoral participation of 50 NASDAQ portfolios for 1, 3, 6, 9 and 12-month momentum in its sub-period, considering holding period 1 month. The Sectors with zero percentage confirm the absence of participation in the specific portfolio of momentum and sub-period. I also highlight the highest percentages across sectors and momentum.

3.4 Empirical results

3.4.1 Performance Statistics

In Table 3.4 I have the performance statistics for own momentum portfolios across all sub-periods. Some interesting results emerge very clearly on expected returns, volatility, Sharpe ratio and beta. There is a progressive increase of all expected returns, volatility and Sharpe ratio measures as the look-back period of momentum goes from 1 to 12-months, with the 12-month look-back dominating performance everywhere. This result is of course highly consistent with the previous literature of Moskowitz et al. (2012), who showed that the TSM strategy based on a 12-month horizon better predicts the next month's return than other time horizons and TSM strategy delivers its highest profits during the most extreme market episodes.

Among the sub-periods I can observe that the highest expected returns, and Sharpe ratio are for the period of July 2007 to August 2008 of Early Credit Crisis at 12-month portfolio, while the volatility naturally increases at the Lehman collapse of September 2008 to December 2009 for the 6-month portfolio. Note that the difference between 12 with 9-month and 12 with 3-months Sharpe ratio values are 63.4% and 371.3% higher respectively and indicate that there was a progressive widening of their difference leading to the 2008 crisis. For example, the difference of 12 to 9-month Sharpe ratio values for the Expansion I period was only 19.3% higher, while for the Early Credit Crisis period went up 4 times the difference of the immediately previous period. Turning now to the estimated market betas, I see that the highest beta estimates correspond to look-back periods of less than 12-month, except only for the 2010-2013 period, although, I note that the beta of the 12-month portfolio is very close to that of 9-month portfolio for such period. For the rest of the periods, I observe that the highest betas that comes from the 6-month look-back are for the Gulf War I, the Lehman collapse, and the US Recovery sub-period and additionally, for 9-month look-back period are the 2001 WTC Attack and the Expansion II. The full sample estimates indicate that the highest beta is at 1-month look-back, closely to the rest portfolio values in this very period. It appears as though, the benefits of the 12-month look-back are to be reaped from the lower beta values that this portfolio has and from the increased diversification obtained by this portfolio. The beta momentum portfolios that noted value higher than 1 came for the sub-periods of the Expansion II, the Lehman collapse, the Fiscal Policy Battle at 3, 9 and 12-month momentum and for the US Recovery period at 6 and 9-month momentum. In such sub-periods the portfolios beta's values became theoretically more volatile than the US market.

Table 3.4: Portfolios performance statistics.

Economic Situation	Sub - Periods	Momentum	Expected Return	Standard Diviation	Skewness	Kurtosis	Modified Value at Risk	Sharpe Ratio	Treynor Ratio	Sortino Ratio	Downside Deviation	Beta
ALL SAMPLE	1985 - 2017	1	0.014	0.050	0.001	0.002	-0.068	-0.225	-0.031	0.294	0.033	0.689
		3	0.027	0.073	-0.001	0.002	-0.092	0.033	-0.015	0.442	0.048	0.674
		6	0.068	0.109	0.000	0.001	-0.112	0.393	0.039	0.852	0.065	0.614
		9	0.107	0.126	0.000	0.001	-0.100	0.653	0.104	1.293	0.068	0.541
		12	0.147	0.145	0.001	0.001	-0.092	0.840	0.173	1.548	0.077	0.512
GULF WAR I	1985 - 1991	1	0.019	0.059	0.002	0.002	-0.077	-0.097	-0.053	0.380	0.043	0.923
		3	0.038	0.094	0.001	0.001	-0.117	0.140	-0.032	0.518	0.066	0.958
		6	0.087	0.144	0.001	0.000	-0.150	0.428	0.016	0.948	0.085	0.979
		9	0.133	0.164	0.000	0.000	-0.136	0.659	0.059	1.508	0.081	0.974
		12	0.176	0.151	0.000	0.000	-0.072	1.003	0.113	2.454	0.066	0.861
EXPANSION I	1992 - 2001(August)	1	0.025	0.064	0.003	0.001	-0.079	0.004	-0.029	0.596	0.037	0.746
		3	0.025	0.064	0.003	0.001	-0.079	0.004	-0.059	0.596	0.037	0.371
		6	0.124	0.136	0.001	0.000	-0.101	0.723	0.108	1.710	0.066	0.638
		9	0.196	0.170	0.000	0.000	-0.084	1.005	0.215	2.324	0.076	0.623
		12	0.276	0.209	0.000	0.000	-0.068	1.199	0.315	2.437	0.102	0.650
2001 WTC ATTACK	2001(September) - 2002	1	0.054	0.065	0.005	0.000	-0.052	0.453	0.067	1.803	0.029	0.550
		3	0.101	0.090	0.003	0.000	-0.047	0.847	0.188	2.515	0.039	0.447
		6	0.247	0.142	0.003	0.000	0.013	1.563	0.569	2.865	0.085	0.400
		9	0.427	0.159	0.000	0.000	0.164	2.519	0.682	2.228	0.187	0.590
		12	0.574	0.181	-0.002	0.000	0.276	3.031	0.976	2.178	0.258	0.560
EXPANSION II	2003 - 2007(June)	1	0.054	0.063	0.011	0.002	-0.050	0.452	0.023	1.979	0.026	1.093
		3	0.107	0.094	0.008	0.001	-0.047	0.872	0.063	2.215	0.047	1.221
		6	0.251	0.175	0.005	0.000	-0.036	1.294	0.132	2.152	0.115	1.669
		9	0.381	0.242	0.004	0.000	-0.016	1.474	0.198	1.901	0.197	1.757
		12	0.500	0.275	0.003	0.000	0.048	1.728	0.310	1.776	0.275	1.494
EARLY CREDIT CRISIS	2007(July) - 2008(August)	1	0.052	0.058	0.003	0.000	-0.044	0.468	0.026	1.785	0.028	0.999
		3	0.106	0.086	0.002	0.000	-0.036	0.942	0.078	2.616	0.040	1.021
		6	0.286	0.122	-0.001	0.000	0.086	2.144	0.341	1.456	0.191	0.744
		9	0.454	0.158	-0.003	0.000	0.194	2.717	0.421	2.851	0.153	0.976
		12	0.628	0.136	-0.002	0.000	0.405	4.440	1.002	1.708	0.348	0.569
LEHMAN COLLAPSE & RECESSION	2008(September) - 2009	1	0.061	0.144	0.003	0.001	-0.176	0.252	0.050	0.679	0.087	1.168
		3	0.107	0.242	0.001	0.000	-0.291	0.340	0.076	0.709	0.147	1.371
		6	0.236	0.445	0.001	0.000	-0.495	0.475	0.150	1.217	0.183	1.481
		9	0.270	0.420	0.002	0.000	-0.420	0.584	0.203	1.937	0.127	1.212
		12	0.245	0.211	0.001	0.000	-0.102	1.043	0.299	2.463	0.085	0.699
FISCAL POLICY BATTLE - CURRENCY CRISIS - SOVEREIGN DEBT	2010 - 2013 (October)	1	0.046	0.065	0.007	0.001	-0.060	0.325	0.045	1.205	0.036	0.981
		3	0.091	0.096	0.004	0.001	-0.067	0.683	0.081	1.711	0.051	1.080
		6	0.224	0.168	0.002	0.000	-0.051	1.189	0.294	2.356	0.091	0.733
		9	0.356	0.216	0.003	0.000	0.000	1.530	0.208	2.418	0.141	1.653
		12	0.488	0.268	0.004	0.000	0.047	1.726	0.252	2.342	0.199	1.855
US RECOVERY PERIOD	2013(November) - 2017	1	0.034	0.044	0.003	0.000	-0.038	0.201	0.034	1.217	0.025	0.910
		3	0.071	0.062	0.003	0.000	-0.030	0.750	0.067	2.298	0.029	0.994
		6	0.174	0.091	0.002	0.000	0.023	1.627	0.137	2.613	0.063	1.199
		9	0.281	0.116	0.002	0.000	0.090	2.204	0.243	2.060	0.127	1.080
		12	0.275	0.118	0.001	0.000	0.081	2.122	0.399	1.458	0.177	0.646
FINANCIAL CRISIS AND RECESSION	2007(June) - 2009	1	0.026	0.098	0.002	0.001	-0.134	0.011	0.011	0.373	0.064	1.066
		3	0.050	0.144	0.000	0.000	-0.187	0.174	0.033	0.523	0.091	1.082
		6	0.126	0.232	-0.001	0.000	-0.256	0.436	0.108	0.939	0.130	1.021
		9	0.193	0.238	0.000	0.000	-0.198	0.708	0.198	1.749	0.107	0.882
		12	0.240	0.224	0.000	0.000	-0.129	0.958	0.297	2.644	0.086	0.729

Table 3.4 shows the performance statistics across the total portfolio in its momentum length and sub-period, retaining a holding period of 1 month. The descriptive statistics I estimated are the expected returns, the standard deviation, the skewness and kurtosis, the Modified value at risk, the Sharpe ratio, the Treynor and Sortino ratio, the Downside deviation, and the beta. Estimations considering the expected returns stood as the average momentum of the top 10% firm’s participation.

3.4.2 Sectoral Analysis

Tables 3.5-3.8 exhibits a detailed sectoral analysis for 50 portfolios for each of the six momentum NASDAQ portfolios per each sub-period and the full sample. Table 3.5 shows a sectoral portfolio analysis on expected returns, Table 3.6 concentrates on volatility, Table 3.7 examines the MC and finally Table 3.8 refers to the EpS.

The results of the whole sample 1985-2017 show that the Basic Industries exhibited a strong 12-month momentum high across all sectors for both expected returns and volatility. The Energy sector for the same period exhibited the higher EpS for 3, 6, 9 and 12-month momentum and the same was for volatility in the first three look-back periods of momentum. During the Gulf War I 1985-1991, the expected returns were higher for the 1 and 3-month momentum for Health Care and 6, 9, and 12-month momentum for Consumer Services. The EpS was also higher for the 3, 6 and 9-month momentum for the same period, while Basic Industries showed higher risk for 3, 6, 9 and 12-month momentum. The MC was higher for the Technology sector for all levels of momentum.

In 1992 the US economy met with growth and prosperity until August 2001, where the stocks of the Basic Industry sector constituted the best choice for investors, note the highest momentum in almost all levels for expected returns, risk, and EpS. For the same period, Technology had the best MC for all levels of momentum which started the beginning of a new era of breakthroughs on patents and innovations.

Following the next sub-period from September 2001 to December 2002, the US economy suffered a shock with the momentum performances being mixed. Namely, volatility increased for Energy, Miscellaneous and Technology at different momentum levels and the EpS momentum became high at Health Care, Consumer Durables, Energy and the Capital Goods sectors. However, the MC and the expected returns remained high for Basic Industry and the Health Care sector respectively.

As the US economy recovered from September 2003 to June 2007, it experienced a second wave of development, with the performance in returns varying on momentum between the Capital Goods, the Finance and the Consumer Durables sectors, and similarly for volatility. The MC increased more for the Transportation sector and the EpS yielded higher performance for the Energy and the Consumer Services sectors.

During the Early Credit Crisis from July 2007 to August 2008, the momentum levels been rather mixed and there was no trend at any sector for the total returns, the MC and the EpS. Besides, there was an increase in volatility for the Health Care sector at the 1, 3, 6 and 9-month momentum. The economic situation became even worse at the Lehman Collapse period from September 2008 to the end of 2009. The Capital Goods sector had the highest momentum in almost all levels for expected returns and the EpS. Volatility increased for the Transportation and the Capital Goods sector, while the MC showed strong momentum exclusively for the Transportation sector for the same sub-period.

For the next sub-period from January 2010 to October 2013, the Consumer Durables sector was the leader in terms of both returns performance and market risk. The MC reached highest momentum for the Basic Industries, Consumer Services and the Consumer Durables, sector without tracking any particular trend. For the EpS, the Capital Goods and the Consumer Durables had highest return performance for all momentum levels. Finally, during the last sub-period of the US Recovery from November 2013 to December 2017, the best performance came for the Energy and the Consumer Non-Durables sector, while volatility was different, and results scattered for each momentum levels across the different sectors.

To track the tendencies across sectoral momentum portfolios and how these evolve through look-back periods, I computed the sectoral mean, standard deviation, and coefficient of variance for each of the 50 portfolios. These estimations been applied both for Tables 3.5-3.8 about expected returns, volatility, the MC, and the EpS. The 12-month momentum exhibits highest sectoral expected return mean and standard deviation across all momentum portfolios, except from the US Recovery sub-period at 9-month momentum. The 12-month momentum continues to be highest for the sectoral risk mean and standard deviation for all momentum portfolios. The only exception was for the Early Credit Crisis and the Lehman collapse sub-periods. As far the sectoral MC, the results are mixed for the mean and the standard deviation, with the 1-month momentum been higher from 1985 to 2017. In the sectoral portfolio analysis, the mean and standard deviation of the EpS followed up the 12-month momentum high across all sub-periods, except for the 9-month momentum high of the Early Credit Crisis and the Lehman collapse. Moreover, the break of 12-month momentum continues for the US Recovery and Financial Crisis sub-period where the mean was higher at 9-month momentum and the standard deviation at 6-month momentum.

Considering Tables 3.3 and 3.5-3.8, there are sectors that exhibit relatively homogeneous behavior across their corresponding statistics. In the period from September 2001 to December 2002, the Technology sector participation and the expected returns of sectoral momentum had a high at 1-month momentum portfolio, respectively. Another interesting result comes for the risk of momentum portfolio and the Health Care sector, that had its highest values at the Early Credit Crisis for 1, 3, 6 and 9-month momentum. During the Expansion I sub-period, the Technology sector simultaneously concentrated the highest percentage sector participation and MC across all momentum portfolios. That can easily be justified as such period is noted for the burst of breakthroughs on patents and innovation. The same happened for the Health Care sector participation and MC at 6, 9 and 12-month momentum portfolios from June 2007 to December 2009. This is suggestive of the general trend that wants the high Health Care sector participation to be concentrated mainly at recession sub-periods.

Table 3.5: Sectoral portfolio analysis on Total Returns.

Economic Situation	Periods	Momentum	Basic Industries	Capital Goods	Consumer Durables	Consumer Non-Durables	Consumer Services	Energy	Finance	Health Care	Miscellaneous	Public Utilities	Technology	Transportation	Sectoral Mean	Sectoral Standard Deviation	Sectoral Coefficient of Variation
		1	0.0142	0.0133	0.0132	0.0146	0.0139	0.0110	0.0130	0.0146	0.0000	0.0000	0.0140	0.0134	0.0113	0.0053	0.4747
		3	0.0282	0.0270	0.0261	0.0290	0.0273	0.0221	0.0257	0.0282	0.0000	0.0000	0.0282	0.0284	0.0225	0.0107	0.4741
ALL SAMPLE	**1985 - 2017**	**6**	0.0695	0.0635	0.0658	0.0736	0.0680	0.0548	0.0635	0.0726	0.0000	0.0000	0.0698	0.0690	0.0558	0.0265	0.4754
		9	0.1365	0.1048	0.1058	0.0983	0.1090	0.0892	0.1006	0.1141	0.0000	0.0000	0.1098	0.1030	0.0893	0.0432	0.4837
		12	0.1894	0.1438	0.1444	0.1399	0.1473	0.1267	0.1371	0.1574	0.0000	0.0000	0.1499	0.1356	0.1226	0.0593	0.4838
		1	0.0219	0.0190	0.0159	0.0189	0.0206	0.0165	0.0174	0.0233	0.0000	0.0159	0.0211	0.0184	0.0174	0.0060	0.3431
		3	0.0418	0.0406	0.0329	0.0357	0.0414	0.0345	0.0346	0.0458	0.0000	0.0218	0.0419	0.0367	0.0340	0.0124	0.3636
GULF WAR I	**1985 - 1991**	**6**	0.0962	0.0947	0.0771	0.0879	0.0990	0.0738	0.0772	0.0951	0.0000	0.0666	0.0933	0.0799	0.0784	0.0268	0.3420
		9	0.1514	0.1421	0.1140	0.1249	0.1538	0.1111	0.1274	0.1433	0.0000	0.1004	0.1446	0.1250	0.1198	0.0413	0.3447
		12	0.1858	0.1817	0.1410	0.1814	0.2087	0.1338	0.1646	0.1928	0.0000	0.1218	0.1890	0.1738	0.1562	0.0556	0.3561
		1	0.0333	0.0253	0.0213	0.0239	0.0249	0.0215	0.0212	0.0246	0.0254	0.0000	0.0279	0.0263	0.0229	0.0080	0.3466
		3	0.0308	0.0253	0.0207	0.0235	0.0245	0.0222	0.0216	0.0235	0.0264	0.0000	0.0277	0.0269	0.0227	0.0077	0.3387
EXPANSION I	**1992 - 2001(August)**	**6**	0.1450	0.1237	0.1022	0.1152	0.1204	0.1089	0.1065	0.1143	0.1290	0.0000	0.1356	0.1300	0.1109	0.0371	0.3346
		9	0.2381	0.1964	0.1643	0.1854	0.1895	0.1729	0.1689	0.1825	0.2039	0.0000	0.2145	0.2043	0.1767	0.0594	0.3361
		12	0.2432	0.2644	0.2225	0.2548	0.2704	0.3780	0.2291	0.2668	0.2904	0.0181	0.3049	0.2849	0.2523	0.0843	0.3340
		1	0.0511	0.0495	0.0606	0.0512	0.0515	0.0433	0.0436	0.0613	0.0720	0.0329	0.0674	0.2349	0.0683	0.0536	0.7847
		3	0.0898	0.0931	0.1169	0.0843	0.1039	0.0370	0.0786	0.1470	0.1367	0.0000	0.1257	0.0785	0.0910	0.0414	0.4548
2001 WTC ATTACK	**2001(September) - 2002**	**6**	0.2726	0.2543	0.2790	0.2055	0.2563	0.0692	0.1936	0.3014	0.2382	0.0000	0.2787	0.2297	0.2149	0.0909	0.4232
		9	0.4551	0.4817	0.4669	0.3774	0.4230	0.0000	0.3448	0.5287	0.3910	0.0000	0.4402	0.3532	0.3552	0.1744	0.4911
		12	0.6159	0.6209	0.5783	0.5511	0.5825	0.0000	0.4763	0.6510	0.5561	0.0000	0.6398	0.4816	0.4795	0.2306	0.4810
		1	0.0422	0.0602	0.0446	0.0543	0.0593	0.0527	0.0536	0.0577	0.0450	0.0428	0.0484	0.0593	0.0517	0.0068	0.1320
		3	0.0843	0.1210	0.0867	0.1161	0.1136	0.1051	0.1111	0.1094	0.1093	0.0977	0.0958	0.1141	0.1054	0.0117	0.1114
EXPANSION II	**2003 - 2007(June)**	**6**	0.2413	0.2511	0.2059	0.2749	0.2589	0.2614	0.2842	0.2572	0.2657	0.2180	0.2347	0.2764	0.2525	0.0238	0.0941
		9	0.3663	0.3776	0.3036	0.4665	0.3778	0.3659	0.4103	0.4074	0.4389	0.3615	0.3557	0.4078	0.3866	0.0427	0.1104
		12	0.4742	0.5272	0.4097	0.5622	0.4677	0.5002	0.5257	0.5427	0.5919	0.4130	0.4669	0.5319	0.5011	0.0564	0.1126
		1	0.0406	0.0571	0.0499	0.0536	0.0400	0.0526	0.0000	0.0415	0.0518	0.0712	0.0603	0.0491	0.0473	0.0173	0.3662
		3	0.0863	0.1127	0.0917	0.1454	0.0755	0.0985	0.0000	0.0838	0.1117	0.1621	0.1172	0.0874	0.0977	0.0401	0.4109
EARLY CREDIT CRISIS	**2007(July) - 2008(August)**	**6**	0.2024	0.3639	0.2175	0.3437	0.1917	0.2583	0.1525	0.3741	0.2890	0.3310	0.3110	0.2554	0.2742	0.0728	0.2653
		9	0.3606	0.4070	0.3593	0.6336	0.3496	0.4042	0.2880	0.6837	0.4722	0.5861	0.4498	0.7242	0.4765	0.1448	0.3038
		12	0.5207	0.6134	0.5685	0.9022	0.5328	0.5155	0.4384	1.0680	0.5595	0.8164	0.7178	1.1683	0.7018	0.2367	0.3373
		1	0.0589	0.0939	0.0460	0.0482	0.0555	0.0397	0.0769	0.0685	0.0439	0.0463	0.0531	0.0547	0.0571	0.0157	0.2741
		3	0.1204	0.1326	0.0958	0.0798	0.1094	0.0741	0.0852	0.1263	0.0875	0.0993	0.0938	0.1011	0.1004	0.0185	0.1843
LEHMAN COLLAPSE & RECESSION	**2008(September) - 2009**	**6**	0.2673	0.2921	0.1929	0.2259	0.2774	0.2124	0.2469	0.2400	0.1856	0.1980	0.2470	0.1692	0.2296	0.0388	0.1690
		9	0.3568	0.3637	0.2426	0.2641	0.2354	0.2320	0.2457	0.2768	0.2486	0.3412	0.2577	0.2418	0.2755	0.0491	0.1781
		12	0.3294	0.2296	0.2531	0.1708	0.2209	0.2758	0.1700	0.2692	0.2117	0.3530	0.2569	0.1890	0.2441	0.0578	0.2366
		1	0.0508	0.0505	0.0650	0.0352	0.0427	0.0643	0.0390	0.0473	0.0416	0.0342	0.0433	0.0000	0.0428	0.0167	0.3905
		3	0.1174	0.0967	0.1304	0.0748	0.0807	0.1248	0.0773	0.0905	0.0810	0.0000	0.0881	0.0000	0.0801	0.0418	0.5219
FISCAL POLICY BATTLE - CURRENCY CRISIS - SOVEREIGN DEBT	**2010 - 2013 (October)**	**6**	0.2616	0.2254	0.3525	0.2239	0.2099	0.3066	0.2106	0.2189	0.2078	0.0000	0.2117	0.0000	0.2024	0.1046	0.5167
		9	0.3766	0.3384	0.5194	0.3949	0.3271	0.5092	0.3711	0.3242	0.3253	0.0000	0.3484	0.0000	0.3195	0.1632	0.5108
		12	0.4983	0.4726	0.6221	0.5184	0.4715	0.7384	0.5953	0.4621	0.5116	0.0000	0.4520	0.0000	0.4452	0.2237	0.5025
		1	0.0310	0.0300	0.0363	0.0397	0.0344	0.0341	0.0351	0.0323	0.0334	0.0320	0.0000	0.0000	0.0282	0.0134	0.4758
		3	0.0683	0.0589	0.0735	0.0756	0.0700	0.0948	0.0788	0.0630	0.0672	0.0648	0.0588	0.0000	0.0645	0.0226	0.3502
US RECOVERY PERIOD	**2013(November) - 2017**	**6**	0.1856	0.1466	0.2027	0.2115	0.1893	0.1911	0.1738	0.1472	0.1745	0.1597	0.1686	0.1333	0.1737	0.0239	0.1374
		9	0.2534	0.2368	0.3188	0.3979	0.3074	0.3044	0.2766	0.2354	0.2776	0.3069	0.3220	0.2207	0.2882	0.0491	0.1705
		12	0.2790	0.2346	0.3188	0.3589	0.2959	0.2653	0.2754	0.2387	0.2736	0.3069	0.3220	0.2207	0.2825	0.0404	0.1431
		1	0.0271	0.0271	0.0207	0.0177	0.0257	0.0256	0.0435	0.0294	0.0291	0.0233	0.0252	0.0174	0.0260	0.0068	0.2613
		3	0.0499	0.0539	0.0343	0.0504	0.0499	0.0431	0.0772	0.0549	0.0520	0.0519	0.0466	0.0416	0.0505	0.0103	0.2036
FINANCIAL CRISIS AND RECESSION	**2007(June) - 2009**	**6**	0.1069	0.1762	0.0921	0.1017	0.1173	0.1551	0.0563	0.1299	0.1453	0.1134	0.1285	0.0885	0.1176	0.0323	0.2750
		9	0.2017	0.2157	0.1483	0.1866	0.1856	0.1898	0.1526	0.1972	0.2118	0.1185	0.2059	0.1092	0.1769	0.0361	0.2040
		12	0.2395	0.2121	0.2043	0.2570	0.2114	0.2388	0.2003	0.2739	0.2914	0.1187	0.2423	0.0996	0.2158	0.0571	0.2648

Table 3.5 reports a sectoral analysis on the total returns for 50 NASDAQ portfolios about 1, 3, 6, 9 and 12-month momentum in its sub-period, considering holding period 1 month. The percentage of firm's participations for all momentum portfolios are about 10%. The sectors with zero percentage confirm the absence of participation in the specific portfolio of momentum and sub-period.

Table 3.6: Sectoral portfolio analysis on risk.

Economic Situation	Periods	Momentum	Basic Industries	Capital Goods	Consumer Durables	Consumer Non-Durables	Consumer Services	Energy	Finance	Health Care	Miscellaneous	Public Utilities	Technology	Transportation	Sectoral Mean	Sectoral Standard Deviation	Sectoral Coefficient of Variation
ALL SAMPLE	1985 - 2017	1	0.1428	0.1360	0.1108	0.1447	0.1103	0.1469	0.1137	0.1328	0.0000	0.0000	0.1340	0.0897	0.1262	0.0520	0.4122
		3	0.2086	0.1681	0.1551	0.2030	0.1592	0.2088	0.1587	0.1926	0.0000	0.0000	0.1854	0.1219	0.1761	0.0732	0.4156
		6	0.3541	0.2923	0.2416	0.3094	0.2424	0.3121	0.2505	0.2782	0.0000	0.0000	0.2921	0.1798	0.2753	0.1158	0.4207
		9	0.2860	0.3139	0.3978	0.3594	0.3346	0.3782	0.2651	0.3734	0.0000	0.0000	0.3183	0.2996	0.3326	0.1353	0.4069
		12	0.4196	0.4387	0.3793	0.3866	0.3353	0.4372	0.3673	0.3964	0.0000	0.0000	0.4111	0.2856	0.3857	0.1562	0.4049
GULF WAR I	1985 - 1991	1	0.1870	0.1628	0.1570	0.1296	0.1188	0.1891	0.0902	0.1688	0.0000	0.1734	0.1417	0.1073	0.1478	0.0529	0.3582
		3	0.2874	0.2211	0.2359	0.1861	0.1688	0.2664	0.1283	0.2370	0.0000	0.1860	0.2000	0.1606	0.2071	0.0750	0.3624
		6	0.4862	0.3407	0.2983	0.2906	0.2559	0.4341	0.1753	0.3312	0.0000	0.2895	0.3004	0.2407	0.3130	0.1223	0.3907
		9	0.6048	0.4204	0.3439	0.3585	0.3738	0.5158	0.2268	0.3863	0.0000	0.3614	0.3521	0.2886	0.3848	0.1480	0.3846
		12	0.7057	0.4709	0.3830	0.4166	0.4253	0.5508	0.2550	0.4321	0.0000	0.2716	0.3737	0.3286	0.4194	0.1716	0.4091
EXPANSION I	1992 - 2001(August)	1	0.1929	0.1821	0.1432	0.1502	0.1422	0.1845	0.0911	0.2295	0.1889	0.0000	0.1710	0.1453	0.1655	0.0591	0.3569
		3	0.1912	0.1858	0.1325	0.2264	0.1729	0.1005	0.1593	0.1448	0.1500	0.0000	0.1593	0.1745	0.1634	0.0567	0.3472
		6	0.4420	0.2943	0.2685	0.2499	0.4600	0.2969	0.3620	0.2710	0.2558	0.0000	0.3802	0.3930	0.3340	0.1208	0.3618
		9	0.9375	0.4805	0.3434	0.3226	0.3606	0.5370	0.3242	0.4912	0.5286	0.0000	0.4560	0.5801	0.4874	0.2184	0.4481
		12	1.1744	0.5703	0.4483	0.5076	0.4267	0.7512	0.3271	0.6327	0.6453	0.1786	0.5346	0.4823	0.5566	0.2460	0.4421
2001 WTC ATTACK	2001(September) - 2002	1	0.2760	0.1973	0.1577	0.1554	0.1602	0.7584	0.1175	0.2246	0.1947	0.1843	0.2749	0.2965	0.2498	0.1694	0.6782
		3	0.3137	0.2785	0.2307	0.1867	0.2318	0.1670	0.1554	0.2954	0.3409	0.0000	0.3816	0.1508	0.2484	0.1042	0.4195
		6	0.3708	0.3664	0.3283	0.3328	0.2891	0.2411	0.1836	0.4393	0.5035	0.0000	0.5814	0.2833	0.3563	0.1508	0.4232
		9	0.3432	0.4550	0.3945	0.3405	0.3387	0.0000	0.2300	0.5545	0.3956	0.0000	0.6102	0.2490	0.3556	0.1877	0.5279
		12	0.3513	0.5176	0.4520	0.3154	0.3251	0.0000	0.2380	0.5985	0.3936	0.0000	0.6610	0.2002	0.3684	0.2087	0.5663
EXPANSION II	2003 - 2007(June)	1	0.1968	0.2997	0.2459	0.1728	0.2377	0.1742	0.2462	0.3398	0.2696	0.1586	0.1987	0.1232	0.2219	0.0627	0.2826
		3	0.2316	0.3924	0.3601	0.2232	0.2973	0.2478	0.3473	0.4313	0.2905	0.2488	0.2701	0.1740	0.2929	0.0761	0.2600
		6	0.5521	0.5025	0.4420	0.3553	0.4474	0.4221	0.5425	0.6366	0.4026	0.3052	0.3992	0.3017	0.4424	0.1016	0.2296
		9	0.7052	0.6561	0.6164	0.5199	0.5440	0.5496	0.5680	0.7978	0.5354	0.4999	0.5383	0.4291	0.5800	0.0996	0.1717
		12	0.8177	0.7249	0.7007	0.5964	0.6082	0.6385	0.6541	0.9258	0.6484	0.5155	0.6149	0.5377	0.6652	0.1153	0.1734
EARLY CREDIT CRISIS	2007(July) - 2008(August)	1	0.1598	0.1866	0.1436	0.1452	0.1299	0.1749	0.0000	0.2679	0.1902	0.3030	0.1893	0.1718	0.1875	0.0740	0.3947
		3	0.2433	0.2589	0.1984	0.1340	0.1923	0.1974	0.0000	0.3623	0.2952	0.4481	0.2684	0.1989	0.2543	0.1121	0.4409
		6	0.3640	0.3501	0.2929	0.1601	0.2782	0.2135	0.1012	0.7188	0.4404	0.5855	0.3672	0.3624	0.3529	0.1719	0.4873
		9	0.3854	0.2817	0.3217	0.2059	0.3803	0.2629	0.1023	0.7933	0.5722	0.5604	0.3736	0.7246	0.4137	0.2088	0.5048
		12	0.3415	0.2754	0.2313	0.1924	0.3653	0.2197	0.1055	0.5477	0.0000	0.4985	0.3663	0.6022	0.3122	0.1789	0.5730
LEHMAN COLLAPSE & RECESSION	2008(September) - 2009	1	0.3070	0.4474	0.3734	0.3269	0.2638	0.2126	0.3609	0.4631	0.2679	0.2478	0.1906	0.5605	0.3352	0.1111	0.3316
		3	0.4378	0.5685	0.5450	0.3903	0.3978	0.3254	0.3314	0.5873	0.2942	0.3434	0.3203	0.5232	0.4221	0.1072	0.2540
		6	0.4617	0.8523	0.8163	0.7109	0.4624	0.5142	0.6839	0.6965	0.4130	0.3387	0.4974	0.9879	0.6196	0.2009	0.3243
		9	0.4759	0.9931	0.3904	0.4702	0.4408	0.5053	0.7052	0.6961	0.5368	0.5139	0.4684	0.2719	0.5390	0.1851	0.3435
		12	0.3335	0.8218	0.4017	0.4841	0.2202	0.4516	0.2966	0.5118	0.4067	0.5305	0.3588	0.2586	0.4230	0.1596	0.3772
FISCAL POLICY BATTLE - CURRENCY CRISIS - SOVEREIGN DEBT	2010 - 2013 (October)	1	0.1924	0.2216	0.3704	0.2422	0.1449	0.3208	0.1631	0.2069	0.2375	0.1550	0.1891	0.0000	0.2222	0.0923	0.4156
		3	0.3144	0.3139	0.5509	0.3155	0.1991	0.4978	0.2448	0.2850	0.3198	0.0000	0.2600	0.0000	0.3301	0.1626	0.4925
		6	0.4681	0.4826	0.9167	0.5028	0.2985	0.8089	0.3948	0.4395	0.6709	0.0000	0.3664	0.0000	0.5349	0.2759	0.5158
		9	0.5765	0.5696	1.0039	0.6651	0.4298	0.9775	0.5401	0.5332	0.8802	0.0000	0.4677	0.0000	0.6643	0.3217	0.4843
		12	0.5841	0.6486	0.8730	0.7129	0.4343	1.2792	0.7839	0.6530	1.3139	0.0000	0.4486	0.0000	0.7732	0.4095	0.5296
US RECOVERY PERIOD	2013(November) - 2017	1	0.2000	0.1201	0.1451	0.1328	0.1277	0.0973	0.1635	0.1288	0.1323	0.1270	0.0000	0.0000	0.1375	0.0591	0.4298
		3	0.2653	0.1903	0.2072	0.2253	0.1787	0.2614	0.2703	0.1845	0.1623	0.1780	0.4001	0.0000	0.2294	0.0930	0.4053
		6	0.3646	0.2721	0.2859	0.3464	0.2442	0.1826	0.3469	0.2714	0.2745	0.2775	0.7068	0.1971	0.3142	0.1355	0.4314
		9	0.3898	0.3096	0.3633	0.4456	0.3024	0.2066	0.4275	0.3526	0.3274	0.2866	1.0227	0.2201	0.3878	0.2128	0.5486
		12	0.2082	0.3344	0.3633	0.3349	0.2957	0.1820	0.4215	0.2792	0.3429	0.2866	1.0227	0.2201	0.3576	0.2205	0.6165
FINANCIAL CRISIS AND RECESSION	2007(June) - 2009	1	0.4828	0.2133	0.1859	0.3082	0.2382	0.2478	0.1562	0.2188	0.2049	0.3470	0.3192	0.1349	0.2548	0.0964	0.3783
		3	0.2561	0.4653	0.2404	0.1889	0.5060	0.3261	0.8793	0.3444	0.2841	0.2340	0.2796	0.3126	0.3597	0.1879	0.5222
		6	0.4228	0.9017	0.3433	0.3178	0.7056	0.4643	0.5400	0.4688	0.4448	0.3618	0.4681	0.4689	0.4923	0.1637	0.3324
		9	0.3281	0.9208	0.3819	0.4585	0.7501	0.4823	0.8225	0.5333	0.5389	0.4211	0.5309	0.5224	0.5576	0.1808	0.3243
		12	0.3164	0.9976	0.4362	0.5360	0.7838	0.4839	0.9577	0.5744	0.6044	0.3992	0.5052	0.3564	0.5793	0.2234	0.3856

Table 3.6 reports a sectoral analysis on the risk for 50 NASDAQ portfolios about 1, 3, 6, 9 and 12-month momentum in its sub-period, considering holding period 1 month. The percentage of firm's participations for all momentum portfolios are about 10%. The sectors with zero percentage confirm the absence of participation in the specific moment of momentum and sub-period.

Table 3.7: Sectoral portfolio analysis on Market Capitalization.

Economic Situation	Periods	Momentum	Basic Industries	Capital Goods	Consumer Durables	Consumer Non-Durables	Consumer Services	Energy	Finance	Health Care	Miscellaneous	Public Utilities	Technology	Transportation	Sectoral Mean	Sectoral Standard Deviation	Sectoral Coefficient of Variation
ALL SAMPLE	1985 - 2017	1	0.4295	0.2161	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.3228	0.1336	0.4140
		3	0.4295	0.2164	0.0918	0.0588	0.1655	0.2472	0.0839	0.2660	0.0000	0.0000	0.2164	0.4103	0.2186	0.1435	0.6565
		6	0.4295	0.2654	0.1028	0.0588	0.1655	0.3211	0.0839	0.2607	0.0000	0.0000	0.2105	0.4103	0.2309	0.1486	0.6438
		9	0.5760	0.2161	0.1425	0.0419	0.1597	0.3211	0.0839	0.2466	0.0000	0.0000	0.2072	0.3934	0.2388	0.1704	0.7134
		12	0.5760	0.2161	0.1425	0.0088	0.1732	0.3211	0.0839	0.2088	0.0000	0.0000	0.2030	0.3274	0.2261	0.1665	0.7366
GULF WAR I	1985 - 1991	1	0.0000	0.0000	0.1053	-0.1076	0.1352	0.0000	-0.3130	0.1335	0.0000	0.0000	0.4172	0.0000	0.0618	0.1704	2.7577
		3	0.0000	0.0000	0.1053	-0.1076	0.1352	0.0000	-0.3130	0.1335	0.0000	0.0000	0.4172	0.0000	0.0618	0.1704	2.7577
		6	0.0000	0.0000	0.1053	-0.1076	0.1352	0.0000	-0.1818	0.0282	0.0000	0.0000	0.3837	0.0000	0.0605	0.1385	2.2882
		9	0.0000	0.0000	0.1053	-0.1076	0.1352	0.0000	-0.1818	0.0282	0.0000	0.0000	0.3837	0.0000	0.0605	0.1385	2.2882
		12	0.0000	0.0000	0.1053	-0.1076	0.1352	0.0000	-0.1818	0.0282	0.0000	0.0388	0.5361	0.0000	0.0792	0.1753	2.2135
EXPANSION I	1992 - 2001(August)	1	0.0644	0.1065	0.0000	0.0000	-0.0915	0.0000	0.1961	-0.1558	0.0000	0.0000	0.1276	0.0978	0.0493	0.0965	1.9583
		3	0.0644	0.1065	0.0000	0.0000	-0.0915	0.0000	0.1961	-0.1558	0.0000	0.0000	0.1276	0.0978	0.0493	0.0965	1.9583
		6	0.0644	0.1065	0.0000	0.0000	-0.0915	0.0000	0.1961	-0.1558	0.0000	0.0000	0.1276	0.0978	0.0493	0.0965	1.9583
		9	0.0644	0.1065	0.0000	0.0000	-0.0915	0.0000	0.1961	-0.1558	0.0000	0.0000	0.1276	0.0978	0.0493	0.0965	1.9583
		12	0.0644	0.1065	0.0000	0.0000	-0.0685	0.0000	0.1608	-0.0411	0.0000	0.0000	0.1328	0.0978	0.0647	0.0725	1.1211
2001 WTC ATTACK	2001(September) - 2002	1	0.7663	0.2282	1.1647	0.0000	0.0738	0.2887	0.6349	-0.4169	-0.1593	0.0000	-0.2765	-0.8112	0.1493	0.5423	3.6336
		3	0.5143	0.3177	1.1647	0.0000	0.0795	0.0000	0.1128	-0.6763	-0.1593	0.0000	-0.2479	-0.8855	0.0220	0.5279	24.0001
		6	0.7200	0.3177	0.7637	0.4104	0.0517	0.0000	-0.0979	-0.3902	0.3583	0.0000	-0.4013	0.0000	0.1333	0.3784	2.8390
		9	0.7200	-0.0760	0.0144	0.3348	0.1489	0.0000	-0.3190	-0.3902	0.4772	0.0000	-0.6291	-0.9599	-0.0679	0.4690	-6.9095
		12	0.7200	0.0636	0.0447	0.3348	0.1890	0.0000	0.3794	-0.3545	0.4772	0.0000	-0.6625	-0.9599	0.0232	0.4791	20.6641
EXPANSION II	2003 - 2007(June)	1	0.4048	0.0567	0.2292	0.1360	0.1460	0.1983	0.1384	0.0432	0.0884	0.0000	0.2108	0.4875	0.1945	0.1441	0.7408
		3	0.4048	0.0567	0.2292	0.1360	0.2017	0.1924	0.1384	0.0559	0.1257	0.0000	0.2063	0.4875	0.2031	0.1408	0.6930
		6	0.0712	0.1288	0.3719	0.1360	0.2307	0.2244	0.1973	0.0771	0.2920	0.2334	0.2000	0.4875	0.2209	0.1202	0.5443
		9	0.0734	0.0947	0.3719	0.0745	0.1847	0.1733	0.1513	0.0352	0.2920	0.0000	0.2199	0.4875	0.1962	0.1445	0.7362
		12	0.4315	0.0911	0.3719	0.1486	0.1847	0.1733	0.1513	0.0352	0.2920	0.0254	0.2165	0.4875	0.2174	0.1497	0.6883
EARLY CREDIT CRISIS	2007(July) - 2008(August)	1	-0.1325	-0.2407	-0.1392	-0.3939	-0.7354	-0.1359	0.0000	-0.6243	-0.2052	-0.2487	-0.4518	-0.2710	-0.3253	0.2160	-0.6640
		3	-0.2506	-0.3462	-0.2475	0.0000	-0.6014	-0.1913	0.0000	-0.6243	-0.1144	-0.2487	-0.3734	-0.2138	-0.3212	0.1983	-0.6174
		6	-0.1968	-0.2916	-0.2922	0.0000	-0.3303	-0.1913	-0.2613	-0.6243	-0.1305	-0.1278	-0.3967	-0.2340	-0.2797	0.1565	-0.5595
		9	-0.1968	-0.5310	-0.2922	0.0000	-0.3223	-0.1913	-0.2613	-0.6243	-0.1537	-0.3340	-0.3189	-0.2406	-0.3151	0.1646	-0.5223
		12	-0.2953	-0.5062	-0.3026	0.0000	-0.5215	-0.3586	-0.2613	-0.6243	-0.2684	-0.6734	-0.3743	-0.2406	-0.4024	0.1869	-0.4645
LEHMAN COLLAPSE & RECESSION	2008(September) - 2009	1	-0.0114	-0.1176	-0.4407	-0.0330	0.0660	0.1329	-0.3000	-0.0520	-0.4088	0.2822	0.0295	0.0000	-0.0775	0.2155	-2.7804
		3	-0.0114	-0.0744	-0.2470	-0.3913	-0.1111	0.1329	-0.2720	-0.0580	-0.3444	0.2822	-0.0998	0.4789	-0.0596	0.2562	-4.2984
		6	0.0348	-0.1629	-0.7061	-0.2432	-0.2647	-0.2729	-0.2324	-0.0812	-0.2450	-0.8548	-0.0652	0.4789	-0.2179	0.3365	-1.5441
		9	-0.0416	-0.1629	-0.1881	-0.2257	-0.2676	-0.1441	-0.2324	-0.0530	-0.3869	0.0000	-0.0164	0.4789	-0.1127	0.2164	-1.9197
		12	-0.0093	0.0000	-0.1881	-0.1552	-0.2500	-0.1441	-0.1095	-0.1693	-0.3313	0.0000	-0.1383	-0.1601	-0.1655	0.0999	-0.6033
FISCAL POLICY BATTLE - CURRENCY CRISIS - SOVEREIGN DEBT	2010 - 2013 (October)	1	0.1986	0.1755	0.3840	0.1045	0.2641	-0.1101	0.0742	0.1922	0.1036	0.0000	0.1535	0.0000	0.1540	0.1313	0.8523
		3	0.1797	0.1755	0.3840	0.2069	0.2805	-0.1101	0.0829	0.1821	0.0199	0.0000	0.1516	0.0000	0.1553	0.1370	0.8824
		6	0.1797	0.1755	0.2777	0.1843	0.3060	-0.1101	0.0829	0.2128	0.0663	0.0000	0.1079	0.0000	0.1483	0.1224	0.8255
		9	0.5880	0.1822	0.2777	-0.1440	0.3106	-0.1101	0.1151	0.2358	0.0884	0.0000	0.0975	0.0000	0.1641	0.2016	1.2284
		12	0.4645	0.1558	0.3900	-0.0064	0.3588	-0.1160	0.1432	0.2686	0.1337	0.0000	0.1465	0.0000	0.1939	0.1792	0.9242
US RECOVERY PERIOD	2013(November) - 2017	1	0.1998	0.1614	-0.0029	-0.1655	0.1443	0.1588	0.1792	0.0511	0.1081	0.1172	0.0000	0.0000	0.0951	0.1062	1.1164
		3	0.1696	0.1433	-0.0029	-0.1897	0.1940	0.1045	0.1698	0.0462	0.1533	0.1172	-0.0163	0.0000	0.0808	0.1114	1.3783
		6	0.1696	0.1707	-0.0221	-0.1897	0.2474	0.1003	0.1443	0.0897	0.1472	0.1172	-0.0163	0.1632	0.0934	0.1176	1.2580
		9	0.1696	0.2144	-0.0221	-0.1938	0.2474	0.2776	0.1637	0.0897	0.1504	0.0761	-0.0163	0.3195	0.1230	0.1462	1.1883
		12	0.2829	0.1656	-0.0221	-0.1645	0.2531	0.1174	0.1539	0.0546	0.1499	0.0761	-0.0163	0.3195	0.1142	0.1394	1.2207
FINANCIAL CRISIS AND RECESSION	2007(June) - 2009	1	-0.2992	-0.1413	-0.0239	-0.0736	-0.0861	-0.4301	-0.4971	-0.0103	-0.2091	-0.1546	-0.1045	-0.1884	-0.1849	0.1535	-0.8303
		3	-0.2992	-0.2130	-0.0239	0.0000	-0.0511	-0.2582	-0.4971	0.0818	-0.2091	-0.1546	-0.1030	-0.1884	-0.1742	0.1556	-0.8935
		6	-0.2992	-0.2098	-0.0239	0.0000	-0.0384	-0.2582	-0.1593	0.0408	-0.2622	-0.1546	-0.0694	-0.1884	-0.1475	0.1140	-0.7726
		9	-0.2992	-0.1753	-0.0669	0.0000	0.0462	-0.2020	0.4424	0.0600	-0.2622	-0.1546	-0.0271	-0.1884	-0.0752	0.1998	-2.6566
		12	-0.3322	-0.1753	-0.0450	0.0000	0.0324	-0.2020	0.4424	0.1079	-0.3222	-0.1609	-0.0271	0.2249	-0.0416	0.2248	-5.4094

Table 3.7 reports a sectoral analysis on the market value for 50 NASDAQ portfolios about 1, 3, 6, 9 and 12-month momentum in its sub-period, considering holding period 1 month. The percentage of firm's participations for all momentum portfolios are about 10%. The sectors with zero percentage confirm the absence of participation in the specific moment of momentum and sub-period.

Table 3.8: Sectoral portfolios analysis on Earnings per Share.

Economic Situation	Periods	Momentum	Basic Industries	Capital Goods	Consumer Durables	Consumer Non-Durables	Consumer Services	Energy	Finance	Health Care	Miscellaneous	Public Utilities	Technology	Transportation	Sectoral Mean	Sectoral Standard Deviation	Sectoral Coefficient of Variation
		1	0.0044	-0.0012	-0.0008	0.0004	-0.0020	0.0177	0.0020	-0.0163	0.0000	0.0000	-0.0020	0.0020	0.0004	0.0075	18.7506
		3	0.1141	0.0582	0.0419	0.0303	0.1303	0.6284	0.0325	0.0475	0.0000	0.0000	0.0679	0.0123	0.1163	0.1722	1.4802
ALL SAMPLE	**1985 - 2017**	**6**	0.1815	0.0991	0.0385	0.0741	0.2020	0.2758	0.0618	0.1020	0.0000	0.0000	0.1673	0.0279	0.1230	0.0871	0.7084
		9	0.1616	0.2004	0.1124	0.1671	0.2691	0.6874	0.0838	0.1070	0.0000	0.0000	0.2982	0.0522	0.2139	0.1860	0.8695
		12	0.2092	0.3225	0.1335	0.1419	0.3026	1.0628	0.1040	0.1178	0.0000	0.0000	0.3387	0.0834	0.2816	0.2848	1.0112
		1	-0.0305	0.0008	0.0170	0.0097	0.0159	-0.0389	0.0029	-0.0156	0.0000	0.0112	-0.0044	0.0050	-0.0025	0.0177	-7.2140
		3	0.0367	0.1162	0.0740	0.1347	0.4427	0.0561	0.1585	0.0887	0.0000	0.0312	0.0365	0.0208	0.1087	0.1184	1.0887
GULF WAR I	**1985 - 1991**	**6**	0.1588	0.3942	0.1327	0.2303	0.7809	0.0665	0.1807	0.1792	0.0000	0.1445	0.0141	-0.0103	0.2065	0.2177	1.0542
		9	0.2402	0.4397	0.1825	0.2755	0.6320	0.1089	0.1134	0.2421	0.0000	0.1713	-0.0074	0.0272	0.2205	0.1866	0.8461
		12	0.8910	0.4848	0.2131	0.2420	0.5724	-0.1118	0.0911	0.3033	0.0000	0.1465	0.0397	0.0146	0.2624	0.2864	1.0913
		1	0.0184	0.0025	-0.0051	0.0144	-0.0007	-0.0229	0.0024	0.0103	-0.0011	0.0000	-0.0009	-0.0041	0.0012	0.0105	8.7854
		3	0.6941	0.1019	0.0594	0.0603	0.0587	0.0247	0.0147	0.5222	0.2062	0.0000	0.0817	0.0162	0.1673	0.2223	1.3288
EXPANSION I	**1992 - 2001(August)**	**6**	1.1995	0.2276	0.1153	0.1382	0.2302	0.0864	0.0298	1.3035	0.3231	0.0000	0.1821	0.0317	0.3516	0.4447	1.2649
		9	1.5072	0.3317	0.1119	0.2299	0.4358	0.1710	0.0467	2.3775	0.3452	0.0000	0.3036	0.0878	0.5408	0.7130	1.3185
		12	3.6704	0.4197	0.1099	0.3700	0.9405	0.4923	0.0876	2.8272	0.5592	0.0042	0.3552	0.1833	0.8350	1.1690	1.4000
		1	-0.0746	-0.1373	0.0218	0.0351	0.0272	0.0000	-0.0577	0.2662	-0.0013	0.0000	-0.0808	-0.2056	-0.0207	0.1153	-5.5736
		3	-0.0343	-0.0362	0.2705	0.0757	0.1011	0.1374	-0.0385	-0.0019	0.0610	0.0000	0.1874	0.0494	0.0702	0.0971	1.3836
2001 WTC ATTACK	**2001(September) - 2002**	**6**	0.0316	-0.0290	0.3493	0.1366	0.2163	0.6223	0.0205	-0.0847	0.1441	0.0000	-0.3041	0.2531	0.1233	0.2352	1.9075
		9	0.7760	1.8065	0.8048	0.1702	0.3808	0.0000	0.3350	0.1638	0.2372	0.0000	-0.1933	0.5072	0.4988	0.5312	1.0649
		12	1.3611	3.5750	1.7330	0.2389	0.5775	0.0000	0.1007	0.1742	0.3136	0.0000	-0.0998	0.6958	0.8670	1.0615	1.2244
		1	0.0061	0.0100	-0.0902	-0.0445	-0.0044	0.0228	-0.0189	-0.0003	0.0578	0.0182	-0.0035	-0.0044	-0.0043	0.0365	-8.5267
		3	0.0817	0.1665	0.0030	-0.0261	-0.0251	0.1993	0.0535	0.1929	0.0655	0.0000	0.0715	0.0221	0.0732	0.0806	1.1014
EXPANSION II	**2003 - 2007(June)**	**6**	0.2286	0.4933	0.0000	-0.0598	0.5256	0.4324	0.1754	0.2995	0.3059	-0.6383	0.2058	0.0464	0.1832	0.3148	1.7186
		9	-0.1099	0.7574	0.0000	-0.0867	3.3194	0.3578	0.4517	0.3748	0.5535	0.0000	0.2984	-0.0053	0.5911	0.9326	1.5777
		12	0.3119	1.0064	0.0000	-0.0778	4.5048	0.6552	0.7310	0.5126	0.7982	0.4565	0.3290	-0.0620	0.8333	1.2282	1.4739
		1	-0.0016	-0.0227	0.0503	-0.0734	-0.1141	0.0092	0.0000	0.0022	0.0253	0.0000	-0.0107	0.1007	-0.0035	0.0542	-15.5579
		3	0.1206	-0.0145	0.1214	-0.0993	-0.0946	0.0706	0.0000	0.0110	0.1071	0.0000	-0.0179	0.2094	0.0414	0.0928	2.2434
EARLY CREDIT CRISIS	**2007(July) - 2008(August)**	**6**	0.1371	-0.0834	0.1049	-0.3676	-0.1954	0.3421	-0.0806	0.0000	0.1203	-0.0174	-0.0453	-0.0202	-0.0096	0.1784	-18.5811
		9	0.2426	5.2226	0.1626	-0.5921	-0.0826	0.5297	-0.0729	0.0000	0.2423	-0.0845	0.2025	-0.0309	0.5217	1.5186	2.9106
		12	0.1601	0.0668	0.5942	-0.7127	0.0822	1.0675	-0.0532	0.0000	0.1988	-0.2354	1.4402	0.5741	0.2893	0.5795	2.0031
		1	-0.0506	0.0971	-0.0618	-0.0845	-0.0249	0.0000	-0.0268	0.0103	0.0653	0.0191	0.0486	-0.2126	-0.0201	0.0812	-4.0440
		3	0.1083	0.4472	-0.1037	0.0119	0.1011	-0.1386	-0.0023	0.4289	0.1996	0.1429	1.7162	-0.0998	0.2343	0.5039	2.1505
LEHMAN COLLAPSE & RECESSION	**2008(September) - 2009**	**6**	0.1178	2.3144	-0.4052	-0.2193	0.3123	0.1392	-0.1140	-0.0940	0.1798	-0.0686	1.5219	-0.2894	0.2829	0.8089	2.8591
		9	0.2582	4.3468	-0.1808	0.2637	0.1971	7.7447	-0.1201	0.0210	0.1617	0.9796	2.7817	0.1052	1.3799	2.4305	1.7614
		12	0.2500	1.6724	2.4658	0.1802	-0.0150	-0.7007	-0.0143	-0.1311	0.1183	0.7333	1.4580	0.0565	0.5061	0.9089	1.7959
		1	-0.0183	0.0254	-0.0070	0.0246	0.0087	0.0206	-0.0542	-0.0070	0.0298	-0.0005	-0.0056	0.0000	0.0015	0.0234	15.6612
		3	0.0862	0.5125	0.2369	0.0602	0.1474	0.1177	0.0426	0.1514	0.1366	0.0000	0.1296	0.0000	0.1621	0.1371	0.8454
FISCAL POLICY BATTLE - CURRENCY CRISIS - SOVEREIGN DEBT	**2010 - 2013 (October)**	**6**	0.1211	0.9485	0.4212	0.0210	0.3756	0.3094	0.0305	0.4143	0.1156	0.0000	0.3466	0.0000	0.3104	0.2751	0.8863
		9	0.6953	0.2465	1.0476	0.0554	0.7326	0.4789	0.1385	0.3588	0.1461	0.0000	0.8087	0.0000	0.4708	0.3550	0.7541
		12	0.9584	3.5166	1.3907	0.0565	0.5170	0.5337	0.0448	0.3899	0.0974	0.0000	1.2896	0.0000	0.8795	1.0070	1.1451
		1	0.0279	-0.0053	0.0108	-0.0282	-0.0086	-0.0064	0.0139	-0.1156	-0.0308	0.0009	0.0000	0.0000	-0.0141	0.0365	-2.5845
		3	0.0565	-0.0015	0.0108	-0.0763	0.0076	-0.0154	-0.0022	-0.1036	-0.0245	0.0009	0.0000	0.0000	-0.0148	0.0415	-2.8089
US RECOVERY PERIOD	**2013(November) - 2017**	**6**	2.3761	0.4404	0.6106	-0.0459	0.4555	0.2585	0.5262	0.3394	0.1107	0.0310	0.0000	0.0000	0.5103	0.6554	1.2844
		9	1.7405	0.5185	1.0527	0.0182	0.6544	1.0225	0.3777	0.8198	0.0817	0.0981	0.0000	0.0000	0.6384	0.5490	0.8599
		12	0.3141	0.8289	1.0968	0.1136	0.8215	0.7428	0.8072	1.2640	0.0855	0.1930	0.0000	0.0000	0.6267	0.4521	0.7214
		1	0.0102	0.0672	-0.0472	-0.0040	-0.0258	-0.1073	0.0000	-0.0414	-0.0017	0.0008	-0.0072	0.0069	-0.0136	0.0416	-3.0595
		3	0.0715	0.2605	-0.0058	0.0095	0.0255	1.7914	0.0000	0.2812	0.0314	0.1314	0.1115	0.0582	0.2515	0.5008	1.9912
FINANCIAL CRISIS AND RECESSION	**2007(June) - 2009**	**6**	0.0715	0.2605	0.0207	0.0080	0.0142	1.7914	0.0067	0.2226	0.0186	0.1314	0.0999	0.0582	0.2253	0.5004	2.2209
		9	0.2057	1.3957	0.1787	-0.1023	0.0729	1.0407	0.0000	0.2270	0.0707	0.9796	0.1379	-0.0167	0.3809	0.4948	1.2992
		12	0.2017	0.8055	0.4960	-0.1790	0.1847	0.5378	0.0000	0.3277	0.0583	0.2999	0.1963	-0.1246	0.2549	0.2845	1.1160

Table 3.8 reports a sectoral analysis on the earnings per share for 50 NASDAQ portfolios about 1, 3, 6, 9 and 12-month momentum in its sub-period, considering holding period 1 month. The percentage of firm's participations for all momentum portfolios are about 10%. The sectors with zero percentage confirm the absence of participation in the specific moment of momentum and sub-period.

The question that emerged through the section of performance statistics is about the break of 12-month momentum high, which better predicts the next month's return than other time horizons according to Moskowitz et al. (2012). That motivate us to explore the factors that influences the random beta results on each portfolio and to what extend the sectoral participation affected these changes.

3.4.3 Regression analysis

In this subsection, I investigate how the expected returns, the Sharpe ratio and the market risk (volatility), in each portfolio is associated with the other descriptive measures and fundamentals as control variables of stock characteristics, in a multivariate framework. Such analysis took place for the whole sample and two sub-periods of Pre-crisis from 1985 to June 2007 and post-crisis from July 2007 to December 2017. The choice of these two sub-periods is based on Jegadeesh and Titman (2011) who stated that momentum strategies perform poorly after the subprime crisis in 2008. Baltas and Kosowski (2013) also found that time series momentum strategy has the attractive feature of generating higher performance in recessions rather than in booms and Hutchinson et al. (2015) highlighted that in periods where economic uncertainty is lower, the returns of time series momentum are indeed higher.

In Tables 3.9-3.13, I report the regression analyses results. The *t*-statistics in parentheses are based on robust standard errors with *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. Table 3.9 reports the results with expected returns as the dependent variable for each sub-period, both for Fixed effects and Dynamic GMM. The results correspond to the model presented in the data and methodology section and include the impact of the dummy variable for the crisis. Overall, I find a strong relationship between the expected returns, the betas, and the Sharpe ratio, as the beta and the Sharpe ratio have positive coefficient and are statistically significant for Models (1), (2) and (3) during all sub-periods. I find a statistically significant α mainly in Model (3) for Fixed effects during the whole sample and the pre-crisis period. Models (2) and (3) incorporate the skewness and kurtosis, which are statistically significant mainly at the pre-crisis and whole sample period. For the Dynamic GMM the expected returns with lag(-1) yield positive statistical significant relation across all Models and sub-periods, except for the period of 1985-2017 in (1) and (2) Models, which did not contain the dummy variable contribution and at 1987-2007 period for Model (3). Adding the dummy variable to my specifications, the products of the dummy with the expected returns, betas and Sharpe ratio are statistically significant in Model (1), while in Models (2) and (3) the beta and the risk are also significant. Models (1) and (2) report higher adjusted R-squared values between 0.7103 and 0.8774 than Model (3). Higher R-squared values indicate a better understanding of portfolio's betas.

In Table 3.10, I replicate the analysis of Table 3.9, using the additional fundamentals of MV, DY and EpS from Table 3.1. I find results with a statistically significant α for all Models during the full sample. I note the negative coefficient for α in almost all versions of (4) and (5), and positive at (6) for the Fixed effects estimates. The product of Sharpe ratio with the dummy variable is statistically significant and shows a negative association with the expected returns in Models (4) and (5), both for Fixed effects and the Dynamic GMM. The beta contribution to the expected returns, using both types of estimation, is statistically significant and has positive coefficients while the product of beta with dummy variable yields negative estimates. The MV is statistically significant and positive both for Fixed effects and the Dynamic GMM for Model (5) and for Model (4) with the inclusion of the dummy variable and the corresponding products. The DY appears to not influence expected returns using Fixed effects on Models (4) and (5), but it is significant for the Dynamic GMM on Model (4). Moreover, for Models (4) and (5), the EpS and the product of expected returns with the dummy variable have positive effects on the dependent variable while the product of EpS with the dummy variable has negative association with expected returns. The adjusted R-square rose in relation to Models (1) and (2) of Table 3.9, taking prices between 0.8635 and 0.9516. The values of adjusted R-square at Model (6) remained at a low level, as for Model (3). It seems that the incorporation of risk (standard deviation) in Model (6) weaken the good fit and the statistical importance of the other control variables.

Table 3.11 reports a similar regression analysis as in Table 3.10 and 3.9, taking as the dependent variable the Sharpe ratio and the volatility, and for explanatory variables the beta, the expected returns, and their product with dummy variable for Models (7) and (8) respectively. The results show that Model (7) has a positive and statistically significant α for both Fixed effects and Dynamic GMM, except for the pre-crisis period of 1985-2007. The Sharpe ratio lag(-1) on Dynamic GMM effects is negative and statistically significant across all periods. The beta is statistically significant and negative along all regressions and sub-periods, with the only exception being at the pre-crisis period of 1985-2007 where beta has been positive. The product of beta with the dummy variable affects positively the Sharpe ratio. The expected returns and their product with the dummy variable have opposite impact on the dependent variable of Model (7), namely negative. The product of Sharpe ratio with the dummy variable is positive and significant, which shows that crisis events affect the average returns earned in excess of the risk-free rate positively. The fit in the models remains at a high level, as the adjusted R-square takes prices between 0.7217 and 0.8584. Model (8) has as its dependent variable the volatility, which is affected significantly and positively from beta, significantly and negatively from the product of beta with the dummy variable and positively from the product of standard deviation with the dummy variable only when I use the Dynamic GMM estimates. The expected returns are positive and significant except the 1985-2017 sub-period. Based on the adjusted R-square, Model (8) is weaker in relation to the others and closer to the results of (3) and (6) Model.

Table 3.9: Regression analysis on expected returns.

		FIXED EFFECTS				DYNAMIC EFFECTS (GMM)			
		1985-2017	1985-2017	1985-2007	2007-2017	1985-2017	1985-2017	1985-2007	2007-2017
Model 1	$\mathbf{R_t(-1)}$					0.3231	0.0808	0.5037	0.2647
						(0.0000)***	(0.1781)	(0.0000)***	(0.0002)***
	constant	−0.0921	−0.0052	−0.0243	−0.0459	−0.3518	−0.0762	0.0086	−0.1897
		(0.0527)*	(0.8646)	(0.4588)	(0.4672)	(0.0000)***	(0.0047)***	(0.2281)	(0.0101)**
	$\mathbf{Beta_t}$	0.1489	0.0857	0.0663	0.1302	0.2984	0.112696	−0.0299	0.212
		(0.0001)***	(0.0008)***	(0.0253)**	(0.0098)***	(0.0000)***	(0.0034)***	(0.0096)***	(0.0000)***
	$\mathbf{Shr_t}$	0.1222	0.1145	0.1617	0.1017	0.1368	0.1408	0.136	0.0811
		(0.0000)***	(0.0000)***	(0.0000)***	(0.0001)***	(4.39E-38)***	(0.0000)***	(0.0000)***	(0.0000)***
	$\mathbf{Beta_t * D_t}$	−0.1363				−0.3290			
		(0.0047)***				(0.0000)***			
	$\mathbf{Shr_t * D_t}$	−0.0939				−0.0749			
		(0.0536)*				(0.0000)***			
	$\mathbf{D_t}$	0.1153				0.3644			
		(0.0332)**				(0.0000)***			
	R-squared	0.8374	0.7214	0.8620	0.7103				
Model 2	$\mathbf{R_t(-1)}$					0.3653	0.2139	0.5235	−0.0172
						(0.0000)***	(0.1224)	(0.0000)***	(0.904)
	constant	−0.0555	−0.0038	−0.0416	−0.0114	−0.2804	−0.0149	0.007	−0.0549
		-0.2663	(0.9074)	(0.2882)	(0.8622)	(0.0000)***	(0.6507)	(0.257)	(0.5094)
	$\mathbf{Beta_t}$	0.1470	0.0921	0.171	0.07933	0.2497	0.0623	−0.0109	0.094
		(0.0003)***	(0.0017)***	(0.0000)***	(0.0066)***	(0.0000)***	(0.2805)	(0.1203)	(0.134)
	$\mathbf{Shr_t}$	0.10691	0.1133	14.3967	0.150756	0.1228	0.1204	0.1338	0.0529
		(0.0000)***	(0.0000)***	(0.6829)	(0.0061)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0002)***
	$\mathbf{Skew_t}$	−6.7745	−2.5590	0.08844	−19.4185	−8.3139	−6.1251	−7.9219	6.3642
		-0.4909	(0.6091)	(0.0305**)	(0.1703)	(0.262)	(0.178)	(0.0000)***	(0.003)***
	$\mathbf{Kurt_t}$	−17.4346	−2.1463	−6.6452	61.594	27.756	−2.7031	24.08	−309.53
		0.724	(0.9384)	(0.2732)**	(0.4197)	(0.4081)	(0.9103)	(0.0000)***	(0.003)***
	$\mathbf{Beta_t * D_t}$	−0.1555				−0.2584			
		(0.0056)***				(0.0000)***			
	$\mathbf{Shr_t * D_t}$	−0.0815				−0.0319			
		(0.1413)				(0.2312)			
	$\mathbf{Skew_t * D_t}$	10.1943				3.0056			
		(0.3893)				(0.633)			
	$\mathbf{Kurt_t * D_t}$	37.5677				−9.1684			
		(0.4499)				(0.7746)			
	$\mathbf{D_t}$	0.0666				0.2834			
		(0.2733)				(0.0000)***			
	R-squared	0.863	0.724	0.8774	0.7616				
Model 3	$\mathbf{R_t(-1)}$					0.9951	1.0307	0.1296	0.4171
						(0.0000)***	(0.0000)***	(0.7454)	(0.0051)***
	constant	0.1642	0.1464	0.1733	−0.0349	−0.0477	0.268	−0.0605	0.1382
		(0.0042)***	(0.0371)**	(0.0014)***	(0.8203)	(0.7587)	(0.059)*	(0.7414)	(0.0041)***
	$\mathbf{Beta_t}$	0.1276	0.1495	0.0643	−0.0633	0.2553	−0.0242	0.1366	0.0776
		(0.0451)**	(0.0615)*	(0.2588)	(0.5813)	(0.275)	(0.7532)	(0.3697)	-0.3843
	$\mathbf{Sd_t}$	−0.0735	−0.1085	−0.0475	2.1047	−0.8516	−0.8926	−0.1719	−0.1645
		(0.7032)	(0.6342)	(0.8591)	(0.1591)	(0.0946)*	(0.3727)	(0.4771)	-0.377
	$\mathbf{Skew_t}$	−44.1109	−48.2113	−4.16187	5.6956	−69.127	−10.2507	67.8588	−17.9835
		(0.0012)***	(0.0056)***	(0.6492)	(0.6741)	(0.0144)**	(0.447)	(0.0356)**	-0.2994
	$\mathbf{Kurt_t}$	126.454	182.647	−42.8985	−52.3430	148.53	−91.0751	−334.239	−40.0899
		(0.0989)*	(0.0668)*	(0.4035)	(0.5293)	(0.0787)*	(0.1114)	(0.0436)**	-0.2994
	$\mathbf{Skew_t * D_t}$	52.1497				66.186			
		(0.0012)***				(0.0082)***			
	$\mathbf{Kurt_t * D_t}$	−117.926				−190.56			
		(0.1649)				(0.0189)**			
	$\mathbf{Beta_t * D_t}$	−0.0800				−0.3342			
		(0.364)				(0.1911)			
	$\mathbf{Sd_t * D_t}$	−1.6097				−0.5262			
		(0.0345)**				(0.2338)			
	$\mathbf{D_t}$	0.0088				0.2590			
		(0.9207)				(0.2019)			
	R-squared	0.6921	0.5299	0.0412	0.2979				

Table 3.9 shows regression analysis on the Expected returns for Models (1), (2) and (3) with its coefficient and p-values, conducted both for Fixed and Dynamic GMM effects. The periods I studied where the full sample 1985-2017, and two sub-periods splitted on the break crisis June 2007. The column 1 and 5 explains the importance of control variables and its product with D as independent variable to Expected returns. The rest columns analyze a naked version of such Models without consideration of economic situation. The t-statistics in parentheses are based on robust standard errors with *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 3.10: Regression analysis on expected returns considering fundamentals.

		FIXED EFFECTS		DYNAMIC EFFECTS (GMM)	
		1985-2017		1985-2017	
Model 4	$R_t(-1)$			−0.1246	−0.4454
				(0.0014)***	(0.0012)***
	constant	−0.1245	−0.0059	−0.0097	0.0071
		(0.0012)***	(0.7941)	(0.1884)	(0.7489)
	Shr_t	0.1386	0.1195	0.1336	0.1503
		(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
	$Beta_t$	0.1006	0.0401	0.0827	0.0212
		(0.0004)***	(0.0639)*	(0.0124)***	(0.3798)
	MV_t	0.009	0.0026	0.0091	−0.0250
		(0.0007)***	(0.3496)	(0.0000)***	(0.7351)
	DY_t	−0.0327	−0.0944	−0.0863	0.1423
		(0.6305)	(0.2234)	(0.0152)**	(0.0000)***
	EpS_t	0.0791	0.0754	0.079	0.02
		(0.0000)***	(0.0000)***	(0.0000)***	(0.0503)*
	$Shr_t * D_t$	−0.1467		−0.1102	
		(0.008)***		(0.0000)***	
	$Beta_t * D_t$	−0.1243		−0.0522	
		(0.0076)***		(0.2809)	
	$DY_t * D_t$	0.1832		0.0829	
		(0.3382)		(0.1477)	
	$EpS_t * D_t$	−0.0967		-0.0605	
		(0.0433)**		(0.0002)***	
	$MV_t * D_t$	−0.0004		−0.0055	
		(0.9871)		(0.4266)	
	D_t	0.1213	0.8635	0.01819	
		(0.0041)***		(0.8024)	
	R-squared	0.9497	0.8635		

		FIXED EFFECTS		DYNAMIC EFFECTS (GMM)	
		1985-2017		1985-2017	
Model 5	$R_t(-1)$			0.165	−0.2651
				(0.3558)	(0.0000)***
	constant	−0.1158	−0.0104	−0.1648	−0.0037
		(0.0960)*	-0.6728	(0.0277)**	(0.8975)
	Shr_t	0.1333	0.1202	0.1164	0.151
		(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
	$Beta_t$	0.1055	0.0465	0.1721	0.0341
		(0.0268)**	(0.0513)*	(0.001)***	(0.2274)
	DY_t	−0.0173	−0.0885	0.0133	−0.0509
		(0.2896)	-0.2655	(0.7868)	(0.1696)
	EpS_t	0.0801	0.0767	0.0528	0.1172
		(0.0004)***	(0.0000)***	(0.0109)**	(0.0000)***
	MV_t	0.0089	0.0029	0.0062	0.0061
		(0.0000)***	-0.3073	(0.0824)*	(0.1025)
	$Skew_t$	−5.3585	−3.1995	−21.2227	−1.5140
		(0.1056)	-0.387	(0.004)***	(0.5977)
	$Kurt_t$	20.8492	12.1943	88.9146	−4.3380
		(0.2181)	-0.5582	(0.0081)***	(0.793)
	$Shr_t * D_t$	−0.1254		−0.0799	
		(0.0000)***		(0.029)**	
	$Beta_t * D_t$	−0.1273		−0.1892	
		(0.0161)**		(0.0016)***	
	$DY_t * D_t$	0.1597		0.035	
		(0.0116)**		(0.5081)	
	$EpS_t * D_t$	−0.0931		−0.0622	
		(0.0002)***		(0.0000)***	
	$MV_t * D_t$	0.0036		−0.0008	
		(0.5551)		(0.6814)	
	$Skew * D_t$	4.4791		19.4971	
		(0.2822)		(0.0059)***	
	$Kurt_t * D_t$	−11.6625		−77.6822	
		(0.5024)		(0.0063)***	
	D_t	0.1100		0.1677	
		(0.1171)		(0.0339)**	
	R-squared	0.9516	0.8674		

		FIXED EFFECTS		DYNAMIC EFFECTS (GMM)	
		1985-2017		1985-2017	
Model 6	$R_t(-1)$			−0.1508	0.349
				(0.3521)	(0.0242)**
	constant	0.1929	0.1981	−0.0498	0.1564
		(0.0006)***	(0.1981)***	(0.0285)**	(0.0134)**
	$Beta_t$	0.1138	0.1028	0.1248	0.08
		(0.0613)*	(0.1028)*	(0.0616)*	(0.178)
	DY_t	−0.0102	−0.5093	−0.2343	−0.3262
		(0.9545)	(−0.5093)***	(0.1964)	(0.1162)
	EpS_t	0.0681	0.0820	0.031	0.0787
		(0.1929)	(0.0820)*	(0.3073)	(0.1658)
	MV_t	−0.0002	−0.0016	−0.0064	−0.0073
		(0.9759)	(−0.0016)	(0.0336)**	(0.002)***
	$Skew_t$	−4.7243	−4.6407	−25.2231	−17.6069
		(0.0011)***	(−4.6407)	(0.0313)**	(0.1703)
	$Kurt_t$	1.5318	−5.453	117.005	−48.6827
		(0.0684)*	(−5.453)	(0.0265)**	(0.2005)
	Sd_t	−0.3538	−0.6829	−0.4423	−0.4071
		(0.2399)	(−0.6829)**	(0.0709)*	(0.0857)*
	$Beta_t * D_t$	0.0108		0.0814	
		(0.9317)		(0.0478)**	
	$DY_t * D_t$	−0.8052		−0.0693	
		(0.1776)		(0.7726)	
	$EpS_t * D_t$	0.0325		0.0887	
		(0.7289)		(0.0006)***	
	$MV_t * D_t$	−0.0056		−0.0019	
		(0.9353)		(0.8517)	
	$Skew * D_t$	5.5283		45.645	
		(0.001)***		(0.0000)***	
	$Kurt_t * D_t$	−1.979		−238.232	
		(0.0604)*		(0.0000)***	
	$Sd * D_t$	−0.9556		−2.99319	
		(0.2021)		(0.0000)***	
	D_t	0.0419		−0.0624	
		0.7337		(0.5274)	
	R-squared	0.767949	0.3899		

Table 3.10 reports regression analysis on the expected returns for Models (4), (5) and (6) with its coefficient and p-values, conducted both for Fixed and Dynamic GMM effects. Such Table is a replicate of previous one and provide additional insight using fundamentals. The periods I studied are the same as in Table 3.8. The column 1 and 5 states the significance of control variables and its product with D as independent variable to Expected returns. The rest columns analyze a naked version of such Models without consideration of economic situation. The t-statistics in parentheses are based on robust standard errors with *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 3.11: Regression analysis on Sharpe ratio and standard deviation.

		FIXED EFFECTS				DYNAMIC EFFECTS (GMM)			
		1985-2017	**1985-2017**	**1985-2007**	**2007-2017**	**1985-2017**	**1985-2017**	**1985-2007**	**2007-2017**
Model 7	$Shr_t(-1)$					−0.2302	−0.1007	−0.6340	−0.2743
						(0.0001)***	(0.0001)***	(0.0000)***	(0.0002)***
	constant	1.142	0.4540	0.2821	1.0219	1.5683	0.6216	−0.0885	1.5917
		(0.0003)***	(0.0362)**	(0.1188)	(0.0345)**	(0.0000)***	(0.0000)***	(0.3528)	(0.0001)***
	$Beta_t$	−1.1673	−0.6321	−0.3692	−1.2116	−1.2948	−0.5874	0.3397	−1.2009
		(0.0000)***	(0.0008)***	(0.0305)**	(0.0023)***	(0.0000)***	(0.0015)***	(0.0258)**	(0.0127)**
	R_t	6.2122	6.2156	5.3017	6.9588	6.1795	5.7606	6.7899	5.69
		(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0002)***	(0.0000)***
	$Beta_t * D_t$	1.1229				1.4989			
		(0.0008)***				(0.0000)***			
	$R_t * D_t$	−5.1510				−4.6369			
		(0.0037)***				(0.0000)***			
	D_t	−1.1990				−1.6627			
		(0.0011)***				(0.0000)***			
	R-squared	0.8478	0.7217	0.8584	0.7643				
Model 8	$Sd_t(-1)$					−0.2093	0.6568	−0.1572	−0.3982
						(0.1327)	(0.0406)**	(0.0287)**	(0.0045)***
	constant	−0.0108	0.0524	0.0794	0.0099	−0.0201	0.0014	0.0388	0.0643
		(0.8622)	(0.1527)	(0.0001)***	(0.917)	(0.8102)	(0.9616)	(0.2306)	-0.3164
	$Beta_t$	0.1663	0.0970	0.0449	0.1674	0.1573	0.0457	0.0935	0.0702
		(0.0015)***	(0.0025)***	(0.0026)***	(0.0321)**	(0.0016)***	(0.0073)***	(0)***	(0.0421)**
	R_t	−0.0157	0.0162	0.0960	−0.1145	0.2443	0.0836	0.2193	0.5646
		(0.9236)	(0.8922)	(0.0661)*	(0.6777)	(0.0162)**	(0.3951)	(0.002)***	(0.0071)***
	$Beta_t * D_t$	−0.1300				−0.1582			
		(0.062)*				(0.0016)***			
	$R_t * D_t$	0.0489				−0.2080			
		(0.8379)				(0.0468)**			
	D_t	0.0881				0.0412			
		(0.2322)				(0.5817)			
	R-squared	0.3552	0.2554	0.6191	0.3086				

Table 3.11 reports regression analysis on the Sharpe ratio and the standard deviation for Models (7) and (8) with its coefficient and p-values, conducted both for Fixed and Dynamic GMM effects. Such Table has the same philosophy as two previous Tables on the duration of studied periods and on column interpretation. The t-statistics in parentheses are based on robust standard errors with *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 3.12 is an extension of Table 3.11, integrating MV, DY and the EpS of the corresponding portfolios. The analysis is again both for Fixed effects and Dynamic GMM for Models (9) and (10). Model (9) is a well fitted model based on adjusted R-square performances, with high percentage of explanation in variation, as if, all the explanatory variables in the model affect the dependent variable. Also, in Model (9), the α, the expected returns and the product of the Sharpe ratio with the dummy variable are positive and significant for the dependent variable, the Sharpe ratio. Negative significance I have for the beta, EpS and MV, and positive for their products with the dummy variable, apart from the product of MV with D. Model (10) reports a regression analysis on volatility. As in the previous regression Models, which had as the dependent variable volatility, the results showed significance for the Dynamic GMM estimates. Namely, in Model (10), I observe positive and significant a, beta, EpS and MV, while the impact of the DY is negative.

Table 3.12: Regression analysis on Sharpe ratio and standard deviation considering fundamentals.

		FIXED EFFECTS		DYNAMIC EFFECTS (GMM)				FIXED EFFECTS		DYNAMIC EFFECTS (GMM)	
		1985-2017		1985-2017				1985-2017		1985-2017	
Model 9	$\mathbf{Shr_t(-1)}$			0.1969	0.1971	**Model 10**	$\mathbf{Sd_t(-1)}$			−0.0874	−0.0946
				(0.0000)***	(0.0000)***					(0.2349)	(0.1576)
	constant	1.0651	0.2695	0.5602	0.2297		**constant**	0.0379	0.0872	0.0468	0.0753
		(0.0000)***	(0.0413)**	(0.0000)***	(0.0236)**			(0.44)	(0.025)**	(0.3791)	(0.0023)***
	$\mathbf{Beta_t}$	−0.7128	−0.2462	−0.5524	−0.2613		$\mathbf{Beta_t}$	0.0554	0.0488	0.0649	0.0434
		(0.0002)***	(0.0768)*	(0.0000)***	(0.0052)***			(0.1876)	(0.0009)***	(0.0702)*	(0.0000)***
	$\mathbf{DY_t}$	0.1557	0.1084	0.0683	−0.0241		$\mathbf{DY_t}$	−0.1142	−0.1883	−0.1450	−0.2020
		(0.737)	-0.7781	(0.6731)	(0.9503)			(0.3424)	(0.1247)	(0.0974)*	(0.0058)***
	$\mathbf{EpS_t}$	−0.5672	−0.5977	−0.6465	−0.7022		$\mathbf{EpS_t}$	0.1316	0.0971	0.1245	0.1061
		(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***			(0.0000)***	(0.0241)**	(0.0000)***	(0.0000)***
	$\mathbf{MV_t}$	−0.0683	−0.0267	−0.0938	−0.0651		$\mathbf{MV_t}$	0.0051	0.0025	0.0042	0.005
		(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***			(0.1791)	(0.06)*	(0.0014)***	(0.0000)***
	$\mathbf{R_t}$	6.4228	6.8254	7.2926	6.7037		$\mathbf{R_t}$	−0.0722	−0.1644	−0.0607	−0.0619
		(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***			(0.5622)	(0.0951)*	(0.2722)	(0.2522)
	$\mathbf{Beta_t * D_t}$	1.02418		0.4742			$\mathbf{Beta_t * D_t}$	−0.0507		−0.0590	
		(0.0007)***		(0.0000)***				(0.4454)		(0.1481)	
	$\mathbf{R_t * D_t}$	−9.1635		−8.0359			$\mathbf{R_t * D_t}$	0.1856		0.0411	
		(0.0006)***		(0.0000)***				(0.5491)		(0.6057)	
	$\mathbf{DY_t * D_t}$	−2.2574		−0.5707			$\mathbf{DY_t * D_t}$	0.1536		0.0623	
		(0.0757)*		(0.0173)**				(0.6655)		(0.2964)	
	$\mathbf{EpS_t * D_t}$	0.8197		0.5868			$\mathbf{EpS_t * D_t}$	−0.1095		−0.1130	
		(0.0097)***		(0.0000)***				(0.0589)*		(0.0000)***	
	$\mathbf{MV_t * D_t}$	−0.0086		0.0681			$\mathbf{MV_t * D_t}$	−0.0237		−0.0128	
		(0.9629)		(0.0000)***				(0.6291)		(0.0395)**	
	$\mathbf{D_t}$	−0.9896		−0.5111			$\mathbf{D_t}$	−0.0365		−0.0535	
		(0.0003)***		(0.0000)***				(0.6411)		(0.3534)	
	R-squared	0.9571	0.8566				**R-squared**	0.7448	0.6523		

Table 3.12 shows regression analysis on the Sharpe ratio and the standard deviation for Models (9) and (10) with its coefficient and p-values, conducted both for Fixed and Dynamic GMM effects. Such Table has the same philosophy as three last Tables on the duration of studied periods and on column interpretation. Such Table take the analysis one step further, as Table 9, adding fundamentals for extra control variables.

Concentrating results from Table 3.9-3.12, I observe that for both Fixed effects and Dynamic GMM the models exhibit general higher statistical significance, mainly during the full sample period, with the incorporation of the fundamentals and their product with the dummy variable. Across the differences between Model pairs of 1-4, 2-5 and 7-9, there is an improvement of their initial version after the application of the fundamentals, retaining their coefficient and exhibiting stronger significance. This can easily be detected on the improvement of adjusted R-square, which prices are closer to 1. Second, the Sharpe ratio and the portfolio beta are always statistically significant across all significant Models, even when I study the volatility as dependent variable at Model 8, where the results are weakened. Third, using both Fixed effects and Dynamic GMM I show the robustness in the results, as the main results are identical.

In this study I confirm that the segmentation scheme of Mulvey and Kim (2008) on sectoral level attributes an improvement of investment performances, considering taking position on the profitable sectors that alternate stable per economic sub-period. I confirm the studies of Jegadeesh and Titman (2011) and Baltas and Kosowski (2013), as in the momentum portfolios expected returns, using time series momentum, it generates higher performances in recession rather than in booms. This evidence exists on Table 3.4 at the 2001 WTC Attack, the Early Credit Crisis, and the Fiscal Policy Battle at 12-month momentum. I find that the break of the beta momentum portfolio at 12-month momentum and the absence of tendency, do not share the same trend as the rest performance measures of portfolio momentum. Practically, such fact exists not only due to the fluctuations of the US market instability, but also because of different sectors that participate in the top 10% firm's momentum. I accept that the conditional betas can explain a large part of variations in momentum specific risk (Barroso (2013)), but I reject the absolute level that beta increase during bull markets and decrease during bear markets as there is variation in my results.

Table 3.13: Analysis across all sectors.

	Sectoral Analysis					
	Basic Industries	**Capital Goods**	**Consumer Durables**	**Consumer Non-Durables**	**Consumer Services**	**Miscellaneous**
constant	0.23	0.158	0.116	0.214	0.092	0.021
	(0.000)***	(0.000)***	(0.091)*	(0.001)***	(0.014)**	(0.000)***
Sd_t	−0.035	−0.320	0.142	0.090	−0.218	0.408
	0.538	(0.002)***	(0.490)	(0.570)	(0.043)**	(0.000)***
DY_t	−0.437	−0.082	−0.094	−0.006	−0.133	−1.139
	(0.0014)***	(0.253)	(0.268)	(0.869)	(0.268)	(0.000)***
EpS_t	−0.041	−0.007	0.088	−0.573	−0.002	0.168
	(0.0553)*	(0.096)*	(0.062)*	(0.000)***	(0.008)***	(0.0001)***
MV_t	0.009	0.281	−0.001	−0.013	0.388	0.007
	(0.0347)**	(0.000)***	(0.980)	(0.672)	(0.000)***	(0.006)***
$MTBV_t$	−0.043	0.057	0.013	0.010	0.042	−0.031
	(0.058)*	(0.432)	(0.883)	(0.883)	(0.024)**	(0.002)***
R square Adjusted	0.8217	0.7558	0.3997	0.7520	0.8676	0.6783
	Energy	**Finance**	**Health Care**	**Public Utilities**	**Technology**	**Transportation**
constant	0.219	0.134	0.018	0.003	0.062	0.023
	(0.000)***	(0.000)***	(0.493)	(0.730)	(0.078)*	(0.085)*
Sd_t	0.092	−0.120	0.407	0.116	0.178	0.115
	(0.528)	(0.222)	(0.000)***	(0.036)**	(0.051)*	(0.085)*
DY_t	−0.172	−0.101	−0.148	−0.116	−0.107	−0.004
	(0.709)	(0.354)	(0.276)	(0.162)	(0.241)	(0.670)
EpS_t	0.149	−0.157	−0.032	0.008	−0.023	0.172
	(0.299)	(0.164)	(0.045)**	(0.755)	(0.195)	(0.004)***
MV_t	0.370	0.264	−0.001	0.396	0.019	0.217
	(0.002)***	(0.027)**	(0.326)	(0.000)***	(0.372)	(0.002)***
$MTBV_t$	−0.673	−0.057	−0.003	0.03	0.230	0.196
	(0.023)**	(0.529)	(0.160)	(0.542)	(0.011)***	(0.013)**
R square Adjusted	0.8196	0.6566	0.7519	0.9808	0.7650	0.9746

Table 3.13 shows a sectoral analysis considering as dependent variable the performance of momentum of each sector and for control variables I use the risk, the dividend Yield, the Earnings per share, the Market Value, and the market to book value. The analysis is across all economic situations and all momentum.

Our final table is Table 3.13, which reports sectoral regression analysis where the dependent variable is the sectoral performance of momentum, considering estimations across all economic situations and all momentum look-back periods. I can easily see that the most important sectors, with a significant α are the Basic Industries, the Capital Goods, the Consumer non-Durables, the Energy, the Finance, the Consumer Services, and the Miscellaneous sectors. I see that volatility negatively affects the Basic Industries and the Consumer Services, while there is a positive impact for the Technology, Miscellaneous and Transportation sectors. The DY has a negative effect on the Basic Industries and the

Miscellaneous sectors while the EpS is also negative for the Basic Industries, the Consumer Goods, and the Consumer Services sectors; however, it has a positive contribution for the Consumer non-Durable, the Transportation and the Miscellaneous sectors. The MV affects positively and significantly almost all sectors, showing a strong influence across all of them.

3.5 Concluding Remarks

There is an immense literature that deals with the momentum approach in portfolio construction and, although academics must think that it has been exhausted, it is always of interest to try to explain it with a twist. This study tries to move one step forward combining the optimal portfolio construction using the time series momentum, the fundamentals, and the performance statistics changes over the last 33 years in conjunction with the sectoral participation. In this way, using a careful and detailed examination on two US economic expansions, a great Credit and Currency Crisis with sovereign debt, and an economic recovery, an investor acquires the knowledge of what drives momentum portfolios and in which sectors to invest in the future under similar economic conditions.

In this study I verify the fundamental literature of the improvement performance on investment strategies using the segmentation scheme, the higher performances in recession rather than in booms that exists in the momentum portfolios expected returns, and that the conditional betas can explain a large part of variations in momentum specific risk. It is worth to note that there is absence of tendency and break of the beta momentum portfolio at 12-month momentum. The beta highs do not follow the trend that share the rest performance measures of portfolio momentum. Additionally, I show that when I examine the expected returns of momentum portfolios, the betas are positively significant while when I study the Sharpe ratio the betas are negatively significant due to the incorporated risk. It is also remarkable that Technology sector exhibits the highest participation during the full sample and at bull US stock market, while Health Care sector dominates at recession sub-periods, considering the top momentum 10% NASDAQ components. The findings present new evidence and challenges for future research.

Chapter 4

The Evolution of the Chinese Stock Market: A Review and a Historical Comparison

4.1 Introduction

China is the second largest global economy and the world's largest emerging market. China possesses the second largest stock market as far market capitalization of the Shanghai and Shenzhen stock exchanges is concerned. Comparing China with other mature financial markets, the Chinese stock market is newer. China's financial markets support global economic growth and is always the subject of continued research. China comprises into two major security exchanges. The Shanghai Stock Exchange (SHSZ) and the Shenzhen Stock Exchange (SZSE). The Chinese market is a segmented market as the government applies limits on capital flows and gathers investors with different preferences that appear in other development markets. Chen et al., (2004) stated that the Chinese stock market is a separated market with domestic retail investors who are characterized by their behavioral and representativeness bias.

China’s stock market is full consisted of distinctive and unique characteristics. These are the T+1 trading mechanism, the high proportion of small and medium-sized investors, the high turnover and barriers on prices. It is also unique among International markets because of an awkward T+1 trading mechanism that started in January of 1995, when it stopped using the classical trading T+0 approach. The lack of supervision, the immature market conditions, and the excessive speculation in the old approach made the China Securities Regulatory Commission (CSRC) to replace the T+0 with the T+1 trading rule.

Zhang and Li (2014) examined the co-movement between the Chinese and US stock markets from 2000 to 2012 and found no long-term cointegration relationship within them. They stated that the US stock market has a strong impact mainly when the Chinese market experienced extreme movements. The correlation between the two markets was time-varying and had an upward trend in the 2008 Financial Crisis. Generally, the long co-movements within stock markets are triggered from fundamentals, while the market contagion affected the short-term co-movements.

In this study I explore the characteristics of the Chinese stock market and its relationship with other financial markets. The study encompasses cross-comparisons between Chinese Indices and other international indices. These Indices are from US (S&P500 and RUSSELL 1000), France (CAC), Germany (DAX), and China covering Hong Kong and Shanghai (HIS, SSE50, CSI300, CSI500, and SSE). I provide a very detailed literature review on the historical evolution and characteristics of the

Chinese stock market in general, in order to explain later the empirical analysis. The review covers every aspect of the Chinese market that has appeared hitherto in the literature and provides a foundational framework for the rest of the analysis. This literature covers the intraday Chinese trade, the intraday momentum, the role of the circuit breakers in Chinese stock market, the co-moves among international markets and the Chinese investment sentiment. In my analysis I add the dollar evolution of two major cryptocurrencies, the Bitcoin and Ethereum. These cryptocurrencies come as alternative investments that are recent and have redefined investments and global financing (e.g. see Trimborn, Li, Hardle (2020)). I use daily data to construct monthly returns, monthly realized volatilities and realized correlations and then I do the same calculations at the quarterly level. To the best of my knowledge this is the first time that these markets and cryptocurrencies are dealt with collectively and with realized risk and correlation measures. I consider a very detailed historical sample split counting on critical dates for the US, China, and Covid-19 period, presenting a very detailed discussion later. The discussion being focused on the comparison of averages for all measures which based on the nature of the risk and correlation measures. I organize the results on these averages and then aggregate at one more additional level to see the extremes (minima and maxima) of all the series across the sub-samples. Finally, I do a detailed comparison of these results with a focus on comparing the structure of these averages across time in my sub-samples and on comparing the other developed markets with the Chinese market.

The rest is organized as follows. The next section analyzes in-depth the Chinese market characteristics, peculiarities, and co-movements with other international markets in a non-exhaustive manner. Section three and four describes the data employed and the empirical methodology I used, based on a very detailed historical sample split counting on the critical dates of the US, China, and Covid-19 period. Section five discusses the empirical results and findings. Section VI offers some concluding remarks.

4.2 Literature Review: Evidence from Chinese stock market

4.2.1 Introducing the Chinese market

China constitutes the second largest global economy and the world's largest emerging market. China has the second largest stock market as far the market capitalization of the Shanghai and Shenzhen stock exchanges. China's financial markets contribute to the flourish of global economic growth and always attracts the attention for deeper examination about its stock market. China comprises of two major security exchanges. The Shanghai Stock Exchange (SHSZ) and the Shenzhen Stock Exchange (SZSE). These two exchanges are the same, except that SHSZ is larger than SZSE in terms of market capitalization. At the end of 2013, these exchanges had one of the highest total value of market capitalization. The market capitalization of SHSZ and SZSE is equivalent to 42% of China’s GDP in

2013. Common shares in the two exchanges are categorized as A-shares and B-shares, for local currency and foreign currencies (USD or Hong Kong dollar), respectively.

The Chinese market is a segmented market as the government applied limits on capital flows and gathers investors with different preferences that appear in other development markets. Chen et al., (2004) stated that China stock market is a separated market with domestic retail investors who characterized by their behavioral and representativeness bias. The Chinese market economy system reformed in 1990s, altered the old-fashioned economy to a brand-new global participator. The Chinese stock market has experienced rapid growth in 1990 and started to attract the international investors' attention since China joined WTO in 2001. The Hong Kong and the New York stock markets were of utmost importance for Chinese firms. The Chinese stocks started trading on the New York Stock Exchange in 1992, and later in 1993 the Chinese government gave its permission to many companies to entry on the Hong Kong market. The total capital increased by Chinese ADRs and H-shares and reached $5 billion and $20 billion until the beginning of 2003, respectively. China stock market submitted to three main reforms, to host new international investors and simultaneously to provide greater access to foreign assets to the already existed Chinese investors. The first reform was about the Qualified Foreign Institutional Investor (QFII) in 2003, which gave access to foreign investors to trade RMB-denominated A-shares. Another reform was on non-tradable shares on 2005 and last but not least, the Qualified Domestic Institutional Investor (QDII) reform in 2007 gave permission of domestic financial firms into foreign financial markets.

During the past twenty years the stock markets experienced several huge crashes. Such crashes brought unexpected slumps in the stock market that could not be explained by public market information and macroeconomic conditions. These implications resulted to unbalanced fluctuations on the Chinese stock market due to such short-term shocks. The East Asian Financial Crisis unleased a crash for Hang Seng index in 1997 with significant losses of 55.55%. The crash of the Taiwan stock market viewed losses of 64.53% between 2000 and 2001. The crash of the Nikkei index noted losses of 78.9% of its market value in 2003. The Internet Bubble crash of 2000 drove to total losses of 70.25% of its value in 2002. The Shanghai Composite index stated losses of 80.99% in 2008.

China's average annual GDP growth rate rise to 13% from 2000 to 2008 but shrunk to 6.9% in 2015. During the crisis period of 2008, the Chinese stock index noted a drop of 70%. The SHSZ Composite index lost over 32%, translated to more than 18 trillion Yuan in share value during June of 2015. The Shenzhen Stock Exchange Component index lost its 41% of high-tech firms and experienced one of its worst intraday loss 8.5% in just one day on 27 of July 2015. In the same period the liquidity of the Chinese market plunged due to crisis and contracted significantly after the downtrend. China's A-share market experienced a series of fluctuations. The Shanghai Composite index increased from 2100 in July 2014 to a peak of 5178 in June 2015 and followed up dramatically at 3500 in less than a month. That fact yielded obvious speculative opportunities. The growth rate of Chinese real economy was sinking, by the IMF landed its expectation about China's economic growth of 7% in 2015. Both the irrational behavior from the investors' perspective and economic fundamentals were responsible for the impact on market value of financial assets.

Taking a closer look, the Chinese economy viewed several crashes within eight years. During the first semester of 2007, extreme optimism created a new market era worldwide, including China's stock market. China had a stock market prosperity due to excessive liquidity in the capital market. The Chinese currency appreciation made international capital markets to have more money flowed into China. The SSECI and SZSECI benefited from rapid growth noted their highest point, but such fact triggered market reversals and unstable conditions. Moving on second semester of 2007, into the renowned Financial Crisis, the growth rate diminished instantaneously and the stock market in China experienced elimination of two-thirds of its market value. The best performing market in 2007 based on Reuters, was contained to the worst exchange markets in the world. Considering the Lehman Brothers blasting fuse of 2008 market crash, the global markets began their collapse into chaos, evaporating every real economy defense even the greatest stock markets. Statistically speaking the international markets were exposed to vast systemic risk after the Financial Crisis through various channels. The weakened US economy led to a sharp shrunk of imports mainly from its bigger partner, China, which was reflected to its stock market. The real economy of China felt considerable pressure and its liquidity was significantly reduced. The rose of international credit risk dried up the international Chinese market strength magnitude. The Chinese economy boosted up during the second quarter of 2009, the SSECI noted a yearly high in August, and the systemic risk decreased. The stimulus fiscal packages and expansionary monetary policies contributed to the reduction of systemic risk and to the Chinese market recovery.

After the crisis of 2008, the market conditions got better but a second huge bubble thrived until the 2015 Chinese market crash. The transaction volume and the stock index price doubled within a year, with the scale of margin trading skyrocketed at 2 trillion around June 2015. The bubble was created due to strong leverages, albeit the cut off corporate conditions and earnings. Inexperienced investors looked forward for easy fund to strangle the economic disasters and ended up getting into agreement with grey regulatory side to trade for unregulated margin loans. The mass liquidity and the higher leverage drove to a much more sensitive market. The first result was the establishment from CSRC of a very strong regulation that banned the shadow margin lending. The bubble wiped out at once all the liquidity.

China's stock market is also consisted of distinctive and unique characteristics. Some of these are the T+1 trading mechanism, high proportion of small and medium-sized investors, high turnover, barriers on prices, and only few delisting firms. The Chinese stock market is unique among international markets because of its T+1 trading mechanism in January of 1995, when it used the classical trading T+0. The lack of supervision, the immature market conditions, and the excessive speculation in such stock market made the China Securities Regulatory Commission (CSRC) to replace the T+0 with the T+1 trading rule. Since then, the T+0 mechanism proposed for reset after the 2015 Chinese stock market crash. Comparing China with other mature financial markets, the Chinese stock market is the newest.

Idiosyncratic phenomena, less transparency, weaken information environment about firms and markets, restrictions on foreign ownership, failure of circuit breaker, existence and prevalence of investor's herding behavior and the largest percentage of irrational individual investors are some of China market features.

Harvey (1995) stated that emerging markets were more prone to market frictions. The reason were the limited dissemination channels and high transaction cost. Over 200 million and upper 85% of the Chinese stock market were individual investors and traded with higher frequency than other investors behaved in other international markets. More than the half of the Chinese investors had low educational status and enough of them invested borrowed money. These factors altered the Chinese stock market full of irrational investment behaviors. Chen et al. (2007) stated that Chinese individual investors acquired inappropriate and irrational trading behaviors and decisions more than the institutional investors.

4.2.2 International Momentum power

Momentum as a common accepted investment strategy lay on the idea of buying winners and selling losers based on their average realized past returns. The momentum and contrarian effects, known for their market anomalies, analyze various market hypothesis. The two early versions of momentum, the cross-sectional momentum and contrarian effects, are two strategies studied exhausted across various asset classes, such as stocks, funds, currencies, and commodities, around global markets, and countries. Although vast of the studies are around the US market, there also reported plenty of examinations on momentum and contrarian strategies around the UK, Japan, Australia and China. The cross-sectional momentum are zero cost arbitrage portfolios that use the strategy of buying winners and selling losers. The versa exists for the investment strategy of contrarian. The latest investor and academic interest focused on time series momentum.

The performances either for the time series momentum or for contrarian strategies formed according to the firm-specific characteristics, look-back and holding periods. Momentum is an empirical feature of predicting and analyzing stock returns. Momentum induces positive autocorrelation of holding-period returns, while for certain holding-period affect dynamic portfolio choice. In that way momentum contributes to a strategic asset allocation. Momentum induces hedging demand and creates market-time opportunities.

Merton (1969) first attempted to study in continuous time finance and used quantitative methods to examine the optimal portfolio choice among different economic sub-periods. Through various studies, there were evidence that highlighted the predictable power of the asset returns, which later became common acceptable among financial economists, mainly over short horizons (momentum). Initially, Jegadeesch and Titman (1993) first illustrated the profitability of cross-sectional momentum as a strategy, where the past 6-month winners continued their uptrend move for at least the next 6-months. They also introduced for first time in US stock market the momentum anomaly returns where a zero-cost portfolio buys recent winners and sells recent losers. The momentum anomaly is examined across several other countries and other asset classes (e.g. Asness et al., (2013); Rouwenhorst, (1998)). Moskowitz, et al. (2012) first stated the time series momentum and its strong positive predictability of a security's own past returns.

Campbell (2004) stated that momentum which showed continuous inclination of stock prices for several months had previously experienced shock. He mentioned that return continuations of certain holding-period contributed to the configuration of the dynamic portfolio choice, using the strategic asset allocation. Through momentum, the return continuations created hedging demands and affected the market-time opportunities. Wu, Ma and Yue (2017) examined the momentum on strategic asset allocation. They stated that "momentum-adjusted" myopic demand and an intertemporal hedging demand comprised a linear combination of optimal portfolio demand about stocks. According to their results the intertemporal hedging demand contributed to lower levels of the portfolio demand for stocks. Investor's risk aversion coefficients exceed one when the levels of stock returns were positive or merely negative and simultaneously sharply increased the portfolio demand for stocks on negative stock returns Wu, Ma and Yue (2017) found that risk aversion stated important in determining portfolio choice and not the elasticity of intertemporal substitution. An influential paper by Goyal and Welch (2008) showed that some important fundamentals, such as the dividend yields and the dividend-price ratio, could explain future stock returns in-sample but that their out of-sample performance was worse than the benchmark of historical average. Wang et al (2018) stated that a good past forecasting performance is followed by a good future forecasting performance and that showed momentum of predictability. They used the dividend price ratio, the dividend yield, the earnings price ratio, the book to market ratio, the treasury bill rate and the long-term government yield to showed that the past forecasting performance of such macro-variables signals drove future business changes. That result constituted it an important sources of return predictability.

Lee, Li and Wang (2010) examined the daily relationship that institutional and individual investors had among stock returns and the trading of Shanghai Stock Exchange 180 stocks. Their results were consistent with the hypotheses of trend-chasing and attention-grabbing trading and found that the individual trading had better reaction on return shocks than that of institutional trading. Individuals characterized as net buyers and viewed more return shocks. They also highlighted that past individual trades (buys and sells) had predictive power, while the respective institutional had predictive power only about market returns in longer horizons. What is more, the individuals had larger average cumulative abnormal trading volume than that of institutions under the firms' earnings announcement. That constituted the individual investors, whose information is not enough, to be more influenced by firm-specific information disclosures and attention-grabbing events. Lee and Kuo (2010) found that the momentum effect variability existed exclusively on short horizon in bullish and bearish markets. Literature found that the asymmetric phenomenon appeared under different market states, while the evidence on different horizons were inconsistent. Lee et al. (2012) found that high-performing individual stocks created positive momentum effect while negative momentum stood for the low-performing individual stocks. The positive momentum effects stated to be stronger in bear markets. That result illustrated the ability of superior fundamental business performance to exceed in power in bullish markets. Both of these could triggered rose of prices. Lee et al. (2012) stated that the link between past turnover ratios and future returns were positively correlated, on condition of high-performing stocks, and negatively correlated for low-performing stocks.

Han and Li (2017) examined the Chinese A-share market and documented that the sentiment effects the emerging market of China. They supported that the investor sentiment consists a reliable momentum signal on monthly base, by refusing the prevailing knowledge that investor sentiment yields a contrarian predictor of market returns across all horizons. They found that local sentiment altered from a short-term momentum predictor into a contrarian predictor in the long run. These results implied that the investor sentiment triggered more of small-firm effects and that the positive time-series predictability existed mainly during longer horizons for small-cap stocks.

4.2.3 Intraday Momentum

Taking advantage of the speedy China's economic growth, the financial research and investors seeks to investigate the predictability of Chinese stock market. The special characteristic of China stock market is the 90-min break from 11:30 to 13:00 (Beijing Time) in which investors may acquire new signals and information and affect the intraday momentum. So, what makes the last half hour of trading so attractive and special to the investors herd? Most of the earnings and the signals of new information released before the opening of the market. The adjustment of stock prices to the new information takes around 30 minutes to be incorporated, since there is intense volatility and volume in the first half hour of trading and at last the market calms down at the last half hour, fully absorbed by the new signals.

Cushing and Madhavan (2000) and Foucault et al. (2005) suggested the need of institutional traders to study the closing stock prices, so as to calculate portfolio returns, to be placed on financial contracts and try of being exposure to overnight risk. In an intraday examination of Narayan et al., (2015) and Narayan and Sharma (2016), the S&P500 future returns predicted Chinese stock returns under specific trading frequency. Sun et al. (2016) and Renault (2017) suggested that the investor's high-frequency sentiment illustrated predictive power at the intraday stock return. Gao et al. (2018) stated that during an intraday momentum, the first half-hour returns yields positive prediction of the last half-hour return in the U.S. stock market. Intraday momentum acquires essential profitability, whether there are the right asset allocation and market timing conditions. The predictability got stronger during the most extreme volatile, recession and major macroeconomic announcement days. Bogousslavsky (2016) showed that intraday momentum is driven by investors inappropriate timely rebalancing of their portfolios. There are institutional investors that are affected on the one hand due to the slow movement across capital and various fundamental factors, which placed their portfolio rebalance in the first half hour, while others rebalanced in the last half hour. Tian, Wu and Wu (2018) studied the investors who were more active when the absolute value of market returns, or the daily range of market index prices surpassed 5% in the Chinese stock market. They found that institutional investors bought more when the magnitude of US equity market significantly rose. Also, China institutional investors bought more than individual investors under extreme market swings and mainly during downtrends. Institutional investors did not overreact under extreme market swings and drove the stock price away from their fundamental value on these conditions. These findings made the institutional investors appearance necessary in curbing stock market crashes across Financial markets.

Zhang et al. (2019) stated that the intraday momentum counts their findings on trading behavior of rare rebalancing, due to uninformed investors, and are familiar with the findings of a U-shaped volume pattern which happened on the first and seventh half-hour returns. They mentioned that in the Chinese stock market, the market returns that happened in the morning had predictable power on afternoon returns. In particular, the second-to-last half-hour return predict the last half-hour return than the first one. Elaut et al. (2018) and Zhang et al. (2019) stated a significant intraday momentum on Chinese stock market. Chu, Gu Zhou (2019) provided significant findings about the intraday momentum in the last-half-hour returns and on reversal effect in the second-half-hour. They found that the reversal effect has economic ramifications for investment and confirmed that noise trading led to intraday returns predictability. However, no evidence of strong momentum effect at intraday level revealed during the information announcement days. Besides, Zhang et al. (2019) highlighted that the intraday momentum is improved especially during median trading volume, high volatility, and low liquidity days. Zhang, Wang and Li (2020) verified previous findings of literature that the last half-hour return could be predicted by the first half-hour return and the second-to-last half-hour return. Their results showed that the predictability power of the last half-hour return affected from trading volume, volatility, as well as trade size and that the first half-hour return had predictive power on the last half-hour return when the first half-hour return was negative. The transaction costs put barriers to arbitrageur's intervention and these costs were the reason for the long-term predictability on intraday returns. Li et al (2020) documented the intraday time-series momentum in the Chinese stock index futures market. They performed analysis both for in-sample and out-of-sample and showed that there was positive relationship between the return of the first trading session and the return of the last trading session at 15, 30, and 60 min. The intraday momentum became stronger at 60 min returns and higher on days with greater volatility, volume, and investor attention.

Momentum and reversal trading strategies could generate robust and consistent returns over time; however, the intraday strategies could not generate sufficiently enough high excess returns able to cover the excessive costs due to the higher frequency of trading. Lower trading frequencies and longer holding periods momentum and reversal strategies could generate excess returns, but with higher maximum drawdown risk.

Shi and Zhou (2017) applied their study at SHCI, SZCI and CSI 300 indexes and found that on the short run there was a time series momentum effect and in long run there was contrarian effect in the Chinese stock market. They examined the time series momentum profitability and found significant relationship with firm-specific characteristics and industrial sectors in China. Parallel results came for the cross-sectional momentum effects in China too. Time series momentum exhibited higher profitability and became more statistically significant when both closing and adjusted prices of the selected securities had higher market value and lower trading volume. Yin and Wei (2020) found that the aggregate profit instability negatively affects the prediction on momentum returns, where the predictive power discreted in bull markets and diminish in bear markets. The predictability of momentum returns also aligns with the time-varying participation of speculators. They found significant source of positive momentum returns the negative risk price aggregate profit instability in the Chinese stock market. This result came against to the findings of Wang and Xu (2015), who suggested that bear markets exhibited highest significance of negative predictive power of market volatility about momentum returns.

4.2.4 Implications of T+1 stock mechanism

The daily trading mechanism (T+0) is the most common trading method across all international stock market and allows investors to buy and sell shares under the same day on spot. China stock market chose a unique method for its trading, the T+1 mechanism, which brought a mountain of implications and restrictions over the last 25 years. Investors who trading on T+1 China stock market are limited to the selling part, as the purchases of common equity shares are forbidden from being sold on the same day. The eminent investors must wait until the next trading day at 9.30 to make their selling movement. This rule constitutes barriers on the day trading and drives to artificial problems of short-term lockup. This procedure is well known among the Chinese investor herd and is repeated every trading day. The Chinese stock market is unique for its T+1 trading method, albeit the Chinese market used in the past the T+0 trading mechanism. The Chinese stock market suffer from lack of supervision, excessive speculation and obsolete market conditions, since China's Securities Regulatory Commission (CSRC) substitute the T+0 with the T+1 stock trading in the January of 1995.

During these 25 years, the emerged problems of the trading mechanism of T+1 contributed to the worsening of the crisis in 2015 and later followed multiple trading halts from the circuit breakers in 2016. The T+1 trading mechanism frozen the investors' choices for one night, driving overnight returns at lower levels. The paradox of inefficient T+1 mechanism is that stocks sold on a given day could be bought on the same day but not the versa stock trading. That constitutes the trading regulation unbalanced and asymmetric mainly in buying and selling demand of short-term traders, and this mismatch is not corrected until the next day in the A-share market. Investors who use short selling as a trading strategy suffer more from T+1 restrictions, as by default they already cannot borrow assets and sell them direct. These turbulences distort the normality between intraday returns and overnight returns. With a view to correcting the imbalances of the prior day, the pressure rose on the selling side and drove to overnight negative returns (Zhang (2020)). In Chinese stock market the clearing process pressure sellers to decrease their offers, so as to achieve a quicker transaction. This fact results to a steadily decreasing of price from the begging of the trading day, implying that the highest price occurs at 9.30 in the morning. The Chinese reveal its weakness mainly in contrast with other stock markets such as the US and with its closest related market of Hong Kong where both the overnight and intraday returns were positive. The T+1 trading method directs to long bearish and short bullish periods, worsening the effect of circuit breakers, embracing the stock speculation, and placing initial barriers to individual investors' decisions.

Literature on overnight and intraday return is very clear. Berkman et al. (2012) found positive returns during the overnight period taking into consideration the 3000 largest U.S. stocks of the NYSE market from 1996 to 2008, while the trend chasers' welfare got higher as T+1 trading rule reduced its total volume and price volatility (Guo et al.(2012)). Aretz et al. (2015) stated that the intraday returns exceeded almost double the overnight returns using a universe of 48,000 stock samples from 35 countries. Bian et al. (2017) stated that the T+1 mechanism limited and reduced the liquidity of stock market and led price at suffering lower discounts. Aboody et al., (2018) measured the firm-specific investor sentiment, by taking the China's overnight returns and analyzing the characteristics of sentiment. Lou et al. (2019) observed continuation in relationship between overnight and intraday firm-level return. The major problem of T+1 about the asymmetric conditions of buyers and sellers referred also from Qiao and Lammertjan (2019). They stated that investors subjected to additional risk, mainly when there was downward trend, due to their long positions. Investors are already informed about the prominent prices fall, fact that is unattractive from investment perspective, and forbids the anticipation for a rebound. Given trading conditions and restrictions, the Chinese stock market attracts many optimistic investors. Also, prices are unable to directly reflect their pessimistic sentiment side and as a result prices are overvalued and not efficient. T+1 trading mechanism generates negative overnight returns. Zhang (2020) stated that China stock market yielded strongly positive intraday return the last 15minutes. The T+1 trading method affected more the stocks that exhibited higher risk, gathered more individual investor, higher restrictions on arbitrage, and lower liquidity power.

4.2.5 The circuit breakers role in Chinese stock market

For Financial markets, the circuit breaker consists of the regulatory mechanism that at least merely impedes and interrupts, the trade on financial securities and simultaneously affected the price or volatility levels. The intervening force of the circuit breakers in curbing volatility, suppression and migration of liquidity, spillover and contagion of volatility had received much of the investors and academics attention. Circuit brakers are widely used within the financial regulators globally, in order to verify protection to the investors and to raise market stability.

Greenwald and Stein (1991) and Kodres and O'Brien (1994) stated that the presence of circuit breakers contributes to multiple benefits. They stated that noise trades influencing prices in shock and investors with knowledge of information tended to withdraw when there is price uncertainty. Fama (2012) stated that rational pricing did not automatic drove to lower volatility, and thus prices are not exclusively followed by higher volatility. To begin with, the US stock market did not suffer any turbulence due to halting trade, while the halting trade favor the circuit breakers who permitted a cool-down period for market participants to halt trading and to prevent panic selling and extreme changes in market prices. Circuit breakers reduced the market volatility extreme price movements, albeit in the Chinese stock market, the circuit breakers contributed to market crashes in early January 2016.

Based on several studies about the Chinese stock market, the price limits system forbids the trading, lower the effectiveness, and raises the stock price volatility during its trading days. Kim and Rhee (1997) found that the price limits system did not contributed to the reduction of stock market volatility of Tokyo and Taiwan. Besides, the price limit system brought unfavorable trading behavior, delaying the stock price processing and end up to volatility spillover effect. Following the literature, the circuit breakers contributes to market performance, efficiency on prices, great liquidity and when stock price reached its limit, it is created a “magnet effect”. Choi and Lee (2000) examined the Korean stock market and found speedy moves in pushing the price to its limits, which indeed created the magnetic effects. The magnetic effects accelerated the integration of the transaction and led to increase the price volatility. Circuit breakers always affected the investors’ decisions and the prices even in not clear circumstances.

Ackert, Church, and Jayaraman (2001) examined the likely impacts of circuit breakers on trade. They focused on the effects of NYSE-type market-wide circuit breakers and showed that agents are pushed to rapid tradings, as the price reached a trigger. Under these circumstances it is emerged the magnet effect. Goldstein and Kavajecz (2004) found that before the circuit breakers intervene, the market participants rose their ambition in demand for market sell orders instead of limit order. Kim et al. (2013) examined the Chinese stock market data and found neither magnet effect in terms of price limits, nor evidence for market-wide circuit breakers. Chen et al. (2018) found that a downside circuit breaker led to reduced stock prices but not the same for the volatility. When the volatility rose, the circuit breakers were closer in reaching the desirable price. Li, Hou and Zhang (2020) stated that circuit breakers affected the stock markets across countries varyingly. They mentioned that following the price-limiting mechanism the Chinese market had a magnet effect in the downward direction, and almost all stocks continued and fell after level of decline.

The existing literature imply that circuit breakers cause the “cooling effect”. That means that investors had more time to react, to digest new information and to improve their liquidity and on time prevent further market panics. Another part of the literature suggests that circuit breakers cause the socalled magnet effect, rather than the “cooling effect”. Hao (2016), Wong et al. (2016), and Yang and Jin (2017) conducted their studies around the market-wide circuit breakers in the Chinese markets. Besides, they expressed evidence for the magnet effect, they did not examine the magnet effect under market microstructure, liquidity, order imbalance and investor behaviors. Wang, Xu and Zhang (2019) examined the impacts of market-wide circuit breakers on market microstructure. They found that market-wide circuit breakers had no “cooling effect” at lower prices or returns or at the reduction of the market volatility. They also found that the market-wide circuit breakers induced significant magnet effects on stock returns, order and quote imbalances, and trades of different sizes.

4.2.6 Does China co-moves with other international markets?

U.S. economic policy uncertainty has been to the focal economic point due to the 2007-2009 global Financial and Credit Crisis which was spread globally and as a result, there is ample literature that is dealing with these ramifications on its own and other countries' economy and financial markets. There are studies that examined the stock markets co-move and attributed to economic fundamentals and market contagion. Initially, Solnik (1974) and Stulz (1981) stated that there are some macroeconomic fundamentals that are in common and affected simultaneously in the same way different economic states.

According to Ross (1989), market volatility contains public information flows and that drives co-movements level to be associated with the volatility dynamic. King and Wadhwani (1990) stated that the source of trading independent of its volume in one market had implications to other markets. Cha and Seeking (2000) examined four Asian emerging economies; Hong Kong, Taiwan, South Korea and Singapore and found higher co-movements with the US and Japan stock markets in 1987 US stock market crash. This situation worsens during the Asian Financial Crisis in 1997. Tay and Zhu (2000) examined the spillovers implications on price and volatility for the Pacific Rim markets. Also, they found that the information which impelled market volatility in one market can be speedily transmitted to another market region, performing in significant co-movements. Connolly and Wang (2003) proved that the release of macroeconomic news drove the co-movements in America, Britain and Japan stock markets. Lai and Tseng (2010) examined extreme and conventional dependences among the G7 stock markets and the Chinese and found the Chinese stock market hedged and ideal for the G7 stock markets.

Huang (2011) found the Chinese market at the highest level of dependence and variance across Japan market and the Pacific Rim. Zhang and Li (2014) examined the co-movement between the Chinese and US stock markets from 2000 to 2012 and found no long-term cointegration relationship within the two largest markets. They stated that the US stock market had strong impact mainly when the Chinese market experienced extreme movements. The correlation between the two markets were time-varying and had an upward trend in 2008 Financial Crisis. Generally, the long co-movements within stock markets are triggered from fundamentals, while the market contagion affected the short-term co-movements.

Pástor and Veronesi (2012) investigated how the government policy changes affected the stock prices and showed that the stock prices fell during the announcement of a substitute policy. They also examined the connection between political uncertainty and risk premia, by using a policy uncertainty index. Jinjarak (2014) also investigated the link between equity returns, economic integration, and economic shocks and stated that trade integration rose from international equity returns to oil prices, and to the US Federal Reserve funds rates among countries. Han, Qi, and Yin (2016) examined the effects of EPU[12] spillovers from developed economies to China and found that the downtrend of export, industrial production, equity price, and the exchange rate are implications of the US EPU. Han et al. (2016) verified it in turn as the Chinese economy were affected more from the EPU of the US and less from the EPU of the UK. Baker, Bloom, and Davis (2016) documented that political uncertainty drove the risk premium and the political uncertainty on correlation, volatility, and risk premia. That result became stronger during weakening economies. Baker et al. (2016) found the policy uncertainty to be correlated with higher stock price volatility at susceptible industries, such as health care, finance, and infrastructure construction. Chen, Jiang, and Tong (2016) found that the China's EPU affected the time series variation of Chinese stock market returns. Specifically, they found that the China's EPU negatively forecast future stock market returns. Li and Peng (2017) investigated the eminent ramifications that an innovation of U.S. economy policy uncertainty would have on the co-movement of China's A and B stock markets with the U.S. stock market and ended up that a greater rose or fall in US policy uncertainty would lower the magnitude of an alternative co-movement between these two stock markets. Their result implied that changes in US EPU possible affected the trades in the US stock market, while parallel changed the co-movements from the Chinese stock markets to the U.S. stock.

Hu, Kutan and Sun (2018) found that the shocks of EPU in U.S. influenced the returns of Chinese A-shares negatively significant, by using a lag of one week from March 2006 to April 2016. The small and emerging size stocks became even more susceptible to shocks in U.S. EPU than on big and value stocks. What is more, I found that firms coming from the sectors of manufacturing, information technology, and media industries in China were more susceptible to shocks in US EPU. Shocks of US EPU implicated less firms that belonged in agriculture and real estate industries. Hu, Kutan and Sun (2018) stated that China's A-shares declined more at higher returns, lower market capitalization, weaker operating profitability, higher asset growth, and better past year's cumulative returns on shocks of US EPU. As China is growing the investor attention and become a more solid and economic important player around the rest financial markets, the EPU of China tends to have higher influences on equity markets of business-related countries with China. Considering the international diversification, the investors should be concentrated more on how different sectors of a country's equity

[12] EPU is the abbreviation of economic policy uncertainty.

market are reacted across different shocks of EPU at the US, China, Japan, Germany, and the UK. Following this way, investors maximize their benefits from international diversification.

4.2.7 Momentum uncertainty and manipulation

Information uncertainty is related with the ambiguity of new information to the firm valuation and popularity. Jiang et al. (2005) found that for the U.S. stock markets the level of information uncertainty is positively significant and correlated with investor overconfidence and arbitrage costs. These combinations effects yield to greater momentum returns and lower future returns for firms with high Information uncertainty. Cheema and Nartea (2014) extended the previous study using different behavioral biases induced by culture. Cultural differences in individualism, overconfidence, self-attribution, self-enhancement, and optimism stated important influence to designate the eventual direction of the relationship between information uncertainty, momentum, and future returns.

Chui et al. (2010) stated that the cross-country differences are explained by cultural differences. Countries which pointed low score on individualism index of Hofstede (2001) were prone to lower momentum returns. The individualism index of Hofstede (2001) emerges the level of individuals focused on their own abilities and differentiating themselves. China reflected low individualism index across countries. Cheema and Nartea (2014) found that higher information uncertainty did not drive exclusively in lower future returns in China, fact that is out of practice for the U.S. Namely, they found that through some information uncertainty proxies, firms with high information uncertainty noted higher future returns.

China exhibits more administrative and political control from its government to its financial institutions, than does other governments in developed economies. The Chinese market proofs less constraints on government action than can be found in other economies and financial markets. Under these conditions, the Chinese administrative power is a prominent weapon able to eliminate Financial crises. China's authorities can freeze the trading or propose meetings between stakeholders to stop eminent debt from being distressed or correct the value of the assets when it is reduced. In that way Chinese authorities prevent further market panic. The Chinese government can even forbit investors protest from probable investment product defaults by compelling payouts to these parties, even though the risk was originally clear to the investors herd. These measurements compose a powerful bulwark against market contagion. A manipulation of the Chinese stock market had already begun.

The Congress established the Securities and Exchange Commission (SEC) in 1934 to eliminate stock market manipulation. Besides, manipulative activities declined on the main exchanges, continued to be brought out serious issues in emerging financial markets. Manipulation could be occurred with various ways, like actions taken by insiders that affected the stock price and false outburst of information or rumors.

Parties such as corporate insiders, brokers, underwriters, large shareholders, and market makers are possible to be manipulators. Manipulation is associated with greater stock volatility, larger liquidity, and high returns across the manipulation duration. Allen and Gale (1992) shown that trade manipulation is possible when the investors had no clear view about the quality of information on the firm's prospects or were prone to manipulate the stock price for making profits. In general, the market efficiency varies on the kind of trader each time. These are the seekers of information and the manipulators. Aggarwal and Wu (2006) found that manipulation was also created by the rose of the number of information seekers as they led to lower market efficiency. That evidence came opposed to what the theory had supported. They mentioned that enforcement of antimanipulation led to higher arbitrage activities and thus could improve the market efficiency.

China's financial market has fundamental regulations different from other mature economies with unique characteristics. China started its financial development late. China could not follow the steps of global financial market evolution and aimed its focus on the requirements of its own economic and financial development. Specifically, the Chinese financial market focused on serving the government's economic agenda and needs. China's financial market lacks sound credit system. Richard Hicks highlighted that the commercial prosperity of Western countries counted on currency, law, and credit. China targets to become an advanced economy, following the international market state. These expectations call China to give direct solution to its financial structural market problems and create an advanced financial system that meet the sustainable development of the real economy. The new financial system must be characterized as well structured, efficient, stable, inclusive, and competitive. On this basis, China aspires to establish a healthy development pattern with domestic reform and liberalization.

In the stock market, false news is another method of stock price manipulation, which generally defined as information released to the public that was incorrect and later denied. Following the empirical research of Huberman and Regev (2001), Carvalho et al. (2011), Ullah et al. (2014), the fake or false news generates abnormal returns and alters the trading volume. Also, there are studies documented that institutions regularly know about news before these outbursts. Ullah et al. (2014), stated that transmitter of false news could potentially made enormous profits by taking advantage of their eminent trading based on false information released. Benabou and Laroque, (1992), Bagnoli and Lipman (1996), Bommel (2003), Engelen and Liedekerke, (2007) found that false news was also a determinant element of price manipulation. Lia, Wanga and Bao (2018) tracked institutional order flow around the release of false news in the Chinese stock market. They found the institutions to acquire early any information about false news releases. That fact implied that there were prerelease order flows of false news sentiments and market reactions. They found that the early information might source from the media outlets releasing false news, and the institutions change their initial positions several days after the denial releases rather during the news breaks.

4.2.8 Momentum, risk, and market dynamics

Investors have the tendency to underreact to new public information, extended the time length of the information to be incorporated into prices, as stated Barberis et al. (1998). Hong and Stein (1999) found that price continuation was a result of involvement of the momentum traders and of the news watchers. Momentum traders count on historical data, while news watchers search for private information. Momentum is partially based on this time lag that news watchers lead with the underreaction of slow transition of private information, creating price continuation. That underreaction captures the overreacted momentum trader's attention creating long term reversals. In a similar study of Daniel et al. (1998), investors showed overconfident with the management of private but did not with the public information, exhibiting overconfidence and self-attribution bias. Higher momentum returns stood for stocks that are characterized as hard to value. Based on Einhorn (1980) and Daniel et al. (1998) investors acquired more confidence when the feedback is slower than at immediate and clear information. Also, positive and significant became the relation between momentum returns and idiosyncratic risk when the price was difficult at evaluation.

According to the literature on China momentum returns, the momentum followed the bear market trend. Such result is validated also across several country momentum returns. These financial markets are Japan, Malaysia, Indonesia, Korea, Hong Kong, and Singapore and exhibited higher continuous market trend than transitions. That result comes to an agreement with the overconfidence and self-attribution model of Daniel et al. (1998) and is opposed to the underreaction model of Hong and Stein (1999). In such countries, the relation between momentum and idiosyncratic volatility is eliminated even during continues market trends. Hanauer (2014) found that Japan exhibited higher momentum returns when the market conditions were preserved in the same state and attributed the low Japan momentum returns at different market dynamics. Cheema and Nartea (2017) found that China momentum returns became stronger on markets continuous trends under the same state, mainly on downside market and not at transition in different states. As they mentioned "momentum returns in China exclusively followed down market states" arguing more with Daniel et al.'s model, while the absence of a positive relation between momentum returns and idiosyncratic volatility rejects both the underreaction and the overconfidence and self-attribution stories of momentum. Cheema and Nartea (2017) found support for the overconfidence and self-attribution story from their results on market dynamics and momentum.

Arena et al., (2008) found a strong positive relationship within price momentum and idiosyncratic volatility in US which reinforced the underreaction and overconfidence theory. In that way, the momentum anomaly constitutes inevitable, because of idiosyncratic risk limiting arbitrage. However, McLean (2010) in a similar study found no significant relation between momentum returns and idiosyncratic volatility, attributed the Arena et al. (2008) results to constraints of elimination of small size and low-priced stocks. Finally, he mentioned that momentum effect is result of transaction cost and that idiosyncratic risk did not restrict the arbitrage of momentum returns. Cheema and Nartea (2017), stated that there is no link between momentum and idiosyncratic risk for significant arbitrage cost on momentum returns about China while in US the results are rather mixed.

Zhao et al. (2019), examined the systemic risk of China's stock market by using high frequency of 5-minute intraday transaction, during the crashes of 2008 and 2015. The market index and liquidity experienced deep drop after the crashes of 2008 and 2015.The systemic risk was enlarged during the crash in 2008 and such risk evolved into high abnormal level before 2015 crash. Zhao et al. (2019) stated that long term relation exists between security margin trading and systemic risk volatility using Johansen co-integration test. They show that the margin financing Granger caused the volatility of systemic risk in bear market, which constitute the government response to attribute negative on the systemic risk of China's stock market.

Another dynamic factor across markets is the liquidity. In financial economics the liquidity across financial assets varies over time (Chordia et al. (2000) and Korajczyk and Sadka (2008)). Avramov and Chordia (2006) suggested that expected returns could be explained under non-risk firm characteristics, such as the liquidity risk and momentum. Narayan, and Zheng (2010) stated that the Chinese stock market, known as an emerging market, viewed extraordinary growth and high risk and volatility. They found that the model of Avramov and Chordia (2006) was to be proposed when they examined the market liquidity risk factor, by using the size, the turnover rate, and the book-to-market ratio on the Chinese stock market. An, Ho and Zhang (2020) examined the dynamics of the liquidity premium in the Chinese stock market and estimated the degree of contribution of the firm size, the idiosyncratic volatility, and the market liquidity betas. They described a stark contrast between the Chinese and US stock market on liquidity premium originated as a benchmark time spot the 2011. The Chinese liquidity premium became more and more significant after the 2011, while US showed the opposite trend. That US liquidity premium decline may be attributed to the increased arbitrage-related transactions (Ben-Rephal et al. (2015)). An, Ho and Zhang (2020) results stated that firm size accounts for 45%-65% of the liquidity premium and the idiosyncratic volatility contributes at least 60% to the liquidity premium, by using the Amihud liquidity measure.

4.2.9 The Chinese investor sentiment

Ni, Wang and Xue (2015) stated that abnormal phenomena in the stock market could explain documents that other financial theories failed, such as the CAPM model (Sharpe, 1964), the macroeconomic factor model (Chen et al., 1986) and the three-factor model (Fama and French, 1993). That gap is covered by the investor sentiment (Kahneman and Tversky (1979), De Long et al. (1990), Mehra and Sah (2002), Baker and Wurgler (2006), Brown and Cliff (2005), etc.). Many empirical results found that investor sentiment played a systematic and significant role in stock prices (e. g., Lee, Jiang, & Indro, 2002; Brown & Cliff, 2004, 2005; Baker & Wurgler, 2006, 2007; Kumar & Lee, 2006;

Yu & Yuan, 2011; Baker, Wurgler, & Yuan, 2012; Seybert & Yang, 2012; Stambaugh, Yu, & Yuan, 2012, 2014, 2015; Li, 2015; Li & Yang, 2017; Gao & Yang, 2018).

De Long et al. (1990) distinguished stock market participants into two categories. These are the rational and the noise traders. Both investors sharped important roles in the pricing of stocks. The fundamental value of stock prices caused by rational investors while the premium risk influenced by noise traders. Brown and Cliff (2004) stated that investor sentiment influences stock valuation and caused propensity of speculation and optimism or pessimism. Mehra and Sah (2002) and Baker and Wurgler (2006) verified that sentiment on individual and institution investors constituted critical affection on stock returns. Previous literature on the predictive power of sentiment had focused on US and other developed markets (Brown and Cliff 2004, 2005; Baker and Wurgler 2006, 2007; Huang et al. 2014), and end up that sentiment was a powerful long-term contrarian predictor. High sentiment is connected to low market returns in the long-term, creating market revision over time. The contrarian predictability is more likely to happened in the cross section, while Baker and Wurgler (2007) attributed the predictability to the mean-reverting pattern of sentiment. Baker and Wurgler (2006, 2007) employed principal component analysis and contracted the composite market sentiment index. They highlighted the need to measure correct the investor sentiment to examine then the investor sentiment affection on stock prices.

The investor sentiment is important to explain stock returns due to further limits of arbitrage, unexpected crisis and losses, and unbalances. McMillan (2003), Ding et al. (2004), Zhang and Semmler (2009), and Schmeling (2009) found that investor sentiment is an explanatory variable for nonlinearity and asymmetry in stock returns. The investor sentiment, for short-term periods, touched higher significant levels at highest stock returns, while in the long-term periods small stocks returns became negative. The youngest stocks are subjected to easier arbitrage than the largest ones. Brown and Cliff (2005) examined the U.S. stock market from 1963 to 2001 and found that investor sentiment is more effective to newly formed, small size and to unprofitable companies' stocks. That reversal effect confirmed the investors' overreaction in the Chinese stock market since Chinese stocks traded at a premium when investors became more optimistic for stocks (Kumar and Lee (2006) and Chen (2013)). That assumption constitutes the investor sentiment a driving force on excess stock returns. Baker and Wurgler (2006), Lemmon and Portniaguina (2006) found that the investor sentiment on Chinese stock market affected more the growth of stocks and the riskier among the stock market, than their value. The stocks with previous characteristics consisted difficult to be priced and vulnerable under the investor sentiment. Less susceptible firms to investor sentiment were those of long earning history and with stable dividends.

Kling and Gao (2008) stated that the impact of sentiment on returns was greater for markets with binding arbitrage constraints. Schmeling (2009) found that these effects were closer to culturally attitude and herding. Huang et al. (2009) applied the investor sentiment index using EGARCH model and found that upward investor sentiment led to positively related and downward investor sentiment drove to negatively related with stock returns across the Chinese stock market, respectively. Chen et al. (2014) examined the Chinese sentiment index and found the forecasting side of sentiment index across the market movements, but sentiment index incorporated both rational and irrational parts that stated ambiguous the forecasting power. Ni, Wang and Xue (2015) found the investor sentiment significant for 24 months in a row. Zhu and Niu (2016) used the China's A-share listed companies from 2002 to 2011 and built the sentiment index counted on principal component analysis and studied its effect under the perspective of the expected earnings growth and the required rate of return. They documented that through the investor sentiment the expected earnings growth and the required rate of return possible yield to changes. That result implies the investor sentiment responsible for affection in the stock prices. They stated also that the sentiment effect during pessimistic period were completely different from other sentiment periods, and that both the accounting information and investor sentiment could give explanations for the stock price trend. What is more, Zhu and Niu (2016) found the accounting information as more credible on stocks which exhibited with stable earnings. Besides, the investor sentiment incorporated the asymmetric effect on stock prices and that constituted the need for more focus on stocks that characterized for their high information uncertainties.

Li, (2015) and Li and Yang, (2017) stated that the probability distribution of investor sentiment had fat tails. The fat tail and distortion to the left caused due to extremely small value, and the fat tail on the right caused from large value. Most of the values of investor sentiment were lying at the lower and upper portion of the distribution. The empirical research scarcely evidences the effects of extreme values of investor sentiment on stock prices. Li and Yang (2017) empirically examined on cross-section and time-series the effects that individual stock investor sentiment had on stock prices. Their results led that individual stock sentiment had more impact on small-firm stock prices than did for big-firm stock prices. The individual stock sentiment experienced sharper stock prices fluctuations in the downturns than during expansions. Li (2020) examined the relationship among the stock returns and investor sentiment across the Chinese stock market. She found that when the change in investor sentiment is minimal (dramatic) then its correlation with the changes of stock return was positive (negative). That result showed the momentum effect. What is more, the level of reversal effect created extremely optimistic sentiment, which was greater than that of pessimistic sentiment, which shows a significant asymmetry.

4.3 Data

The dataset is composed of nine significant international indexes, and two upcoming alternative money market investment proposals that have stimulated the general investment herd attention for its upward trends, the cryptocurrencies of Bitcoin and Ethereum. The selection of these markets covers a global and wide range of the strongest economies coming from the US (S&P500 and RUSSELL 1000), France (CAC), Germany (DAX), and China covering Hong Kong and Shanghai (HIS, SSE50, CSI300, CSI500, and SSE).

The S&P500 consists of the 500 largest stock performance companies listed on stock exchanges in the US. The Russell 1000 index represents the 1000 top companies by market capitalization in the US. The CAC index stands as a capitalization-weighted measure of the 40 most significant stocks among the 100 largest market caps on the Euronext Paris. The DAX is a blue-chip stock market index consisting of the 30 major German companies trading on the Frankfurt Stock Exchange. The HSI index represents a freefloat-adjusted market-capitalization-weighted stock-market index in Hong Kong. The SSE50 is the stock index of Shanghai Stock Exchange, representing the top 50 companies. The CSI300 is a capitalization-weighted stock market index designed to replicate the performance of the top 300 stocks traded on the Shanghai Stock Exchange and the Shenzhen Stock Exchange. The CSI500 index consists of the largest remaining 500 A-Share stocks without considering both the CSI 300 index constituents and the largest 300 stocks. The SSE is a stock market index of all stocks (A shares and B shares) that are traded at the Shanghai Stock Exchange.

I retrieve the international market indexes dataset from the Datastream database and Yahoo Finance webpage[13]. From the FRED database I acquire the Bitcoin (ticker: CBBTCUSD) and the Ethereum (ticker: CBETHUSD).

Our sample analysis starts from January 1995 and ends to August 2020 across all indexes except from the SSE50, the CSI300, and the CSI500, where the available data started from their first date of trade at 01/02/2004, 01/04/2005, and 01/15/2007, respectively. The cryptocurrency of Bitcoin and Ethereum data begins also later, noted their first day of trade at 12/01/2014 and 05/18/2016, accordingly. The data format is both on monthly and quarterly base. To take full advantage of the sample, I split it into twelve critical sub-periods, from which seven sub-periods comes for the US, five sub-periods stands for China and two sub-periods characterized by joint experiences. I choose to split the sample based on the critical dates of the US and China, because of their completely different form, their peculiarity in its market characteristics and their capability to yield ramifications and to create turbulence globally. The sample split criteria are depicted on Table 4.1.

[13] The yahoo webpage is https://finance.yahoo.com/ .

The US separation was based on NBER data, on VIX and Monetary policy announcements, all taken from the FRED database, so as to capture the growth and recession periods, and important economic events. The Chinese sub-periods are separated with criteria their political changes, economic expansion, economic recovery after Credit Crisis and for its latest shocks. I add two more periods for its significance the last two years of the full sample. These sub-periods are the embargo between the US and Chinese economies and the Corona virus (Covid-19) which established a new era the last two years. These sub-periods come as follows:

Table 4.1: Sample split criteria.

Critical dates on US economy.

1. the Expansion I: 1992-2001(August),
2. the 2001 WTC Attack: 2001(September)-2002,
3. the Expansion II: 2003-2007(June),
4. the Early Credit Crisis: 2007(July)-2008(August),
5. the Lehman Collapse and Recession: 2008(September)-2009,
6. the Fiscal Policy Battle of currency crisis and sovereign debt crisis: 2010-2013(October),
7. the US Recovery period: 2013(November)-2017(December),

Critical dates on China economy.

8. the Policy intervention from government: 1994(August)-1996(Mid-January),
9. the Expansion and the Asian Financial Crisis: 1996(Mid-January)-2001(Mid-June),
10. the Reduction of state-owned shares and reform of Non-tradable Shares (before the Credit Crisis): 2001(Mid-June)-2007(October).
11. 4000 billion RMB economics stimulus and Economic recovery: 2008(November)-2014(June).
12. Shocking market: 2014(August)-2019.

Sub-periods of common features.

13. the US-China trade war: 2018(January)-2020,
14. the Covid-19: 2019(December)-2020.

We next present a short discussion with historical monthly adjusted closing price on international indexes and cryptocurrencies from 1995 to 2020. Figure 4.1 is comprised of five charts that are separated, inter alia, by their domestic currency and their geographical position.

Figure 4.31: Historical monthly adjusted closing price of S&P500 and RUSSEL 1000 indexes from 1995 to 2020.

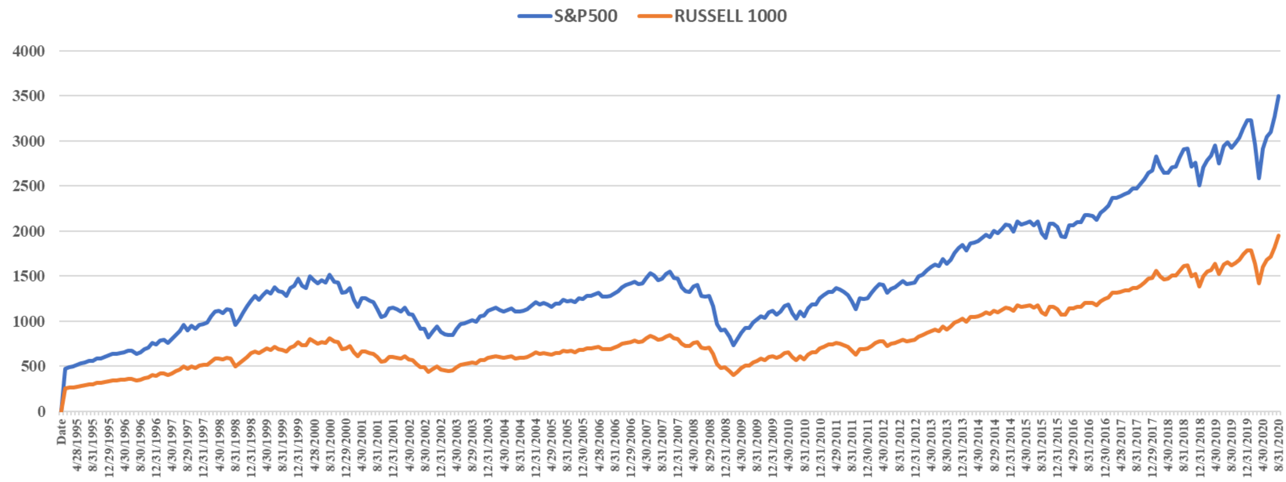


Figure 4.3: Historical monthly adjusted closing price of DAX and CAC indexes from 1995 to 2020.

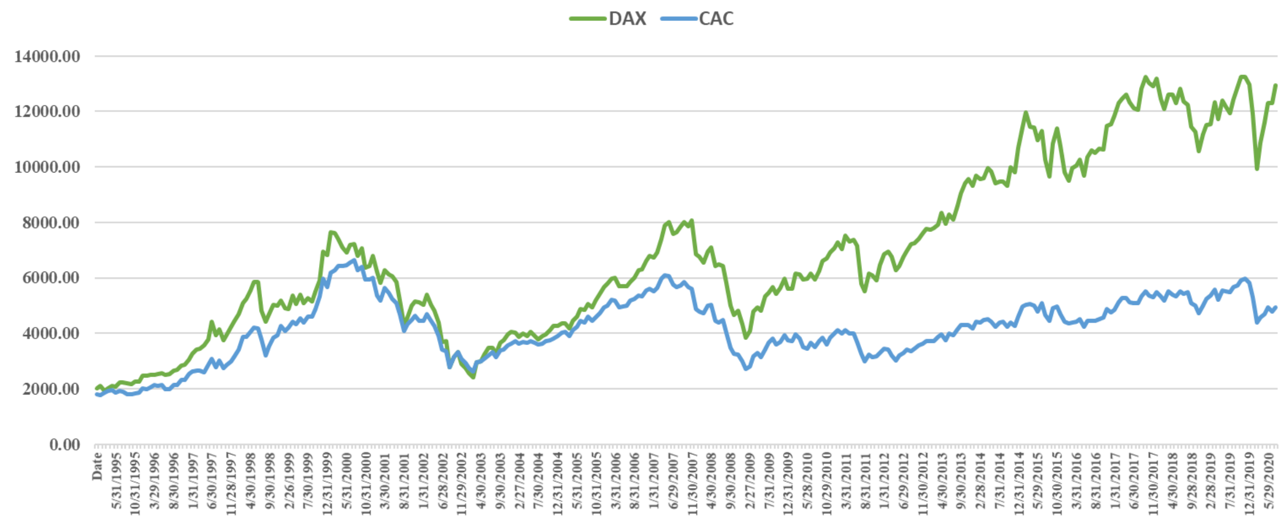


Figure 4.3: Historical monthly adjusted closing price of CSI300, CSI500, SSE50 and SSE indexes from 1995 to 2020.

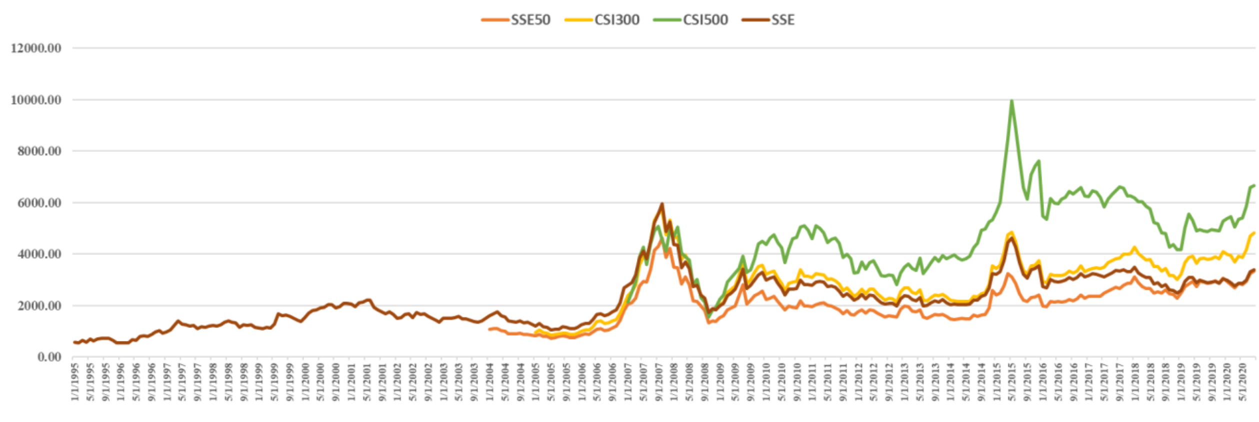
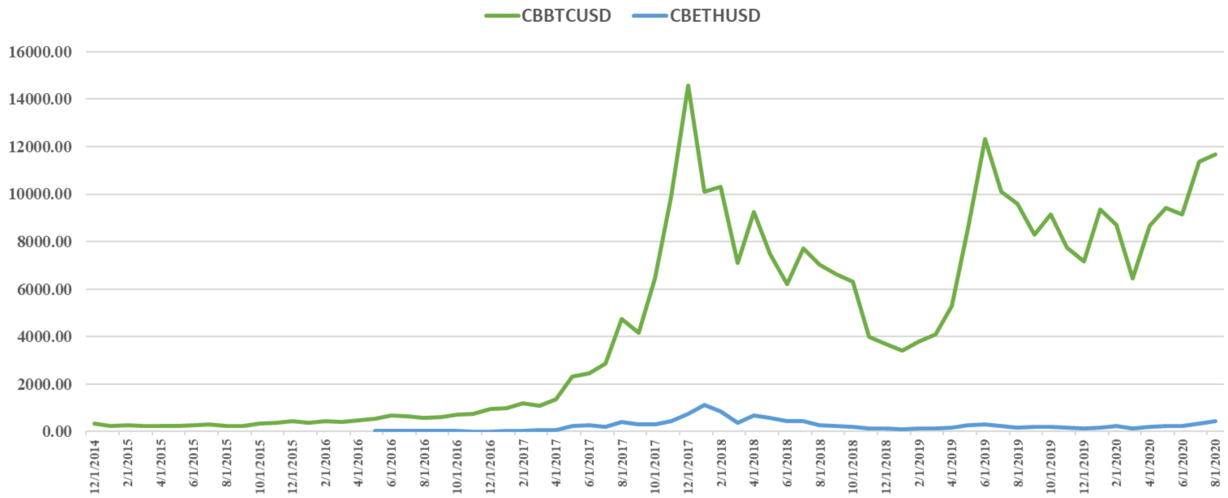


Figure 4.3 : Historical monthly adjusted closing price of HSI index from 1995 to 2020.

Figure 4.3: Historical monthly adjusted closing price of Bitcoin and Ethereum from 2014 to 2020.



Initially, in Figure 4.1, I observe that the US indexes, the S&P500 and RUSSELL 1000, share the same ups and downs across the timeline, with the S&P500 to experience sharper price volatilities. It is obvious through indexes prices that the US economy experienced two expansions periods at 1992(January)-2001(August) and at 2003(January)-2007(June), having quickly overcome the 2001 WTC Attack at 2001(September)-2002(December). In the next sub-period of 2007(July)-2008(August) the early Credit Crisis burst out with these eminent messages quickly coming true, revealing the Lehman Collapse and Recession at 2008(September)-2009(December). The results speak for themselves, by noting an all-time drop for both S&P500 and RUSSELL 1000 indexes. The adjusted closing prices started to view again an upward trend at 2010(January)-2013(October), while the US economy suffered from fiscal policy battle of currency crisis and from sovereign debt crisis. The slope of adjusting closing price continued its rocket route triggered from the recovery period, starting at November 2013 until December 2018, while from the middle of 2019 and after, the US economy viewed globally turbulences on its slope from Covid-19.

Figure 4.2 shows the historical trend of adjusted closing prices of two European indexes, the DAX (Germany) and the CAC (France) indexes, which share the same ups and downs but in different scaling and intensity. The European indexes are directly connected and affected by the US announcements and policies decisions. Hussain (2011) examined simultaneously the policy announcements and the international stock market response on an intraday basis and indicated that the results of the monetary policy decisions generally affect instant and significant influence on stock index returns and volatilities in both the European and the US markets. The two indexes noted their first peak in the early of 2000 and later in the middle of 2007, just before the outburst of the bubble of the Credit Crisis. Historic highs for DAX and CAC mentioned during the first months of 2015, the second semester of 2017 and at last quarter of 2019 before the start of Covid-19, while historic low levels stated between the last quarter of 2002 and the first quarter of 2003 and also during January of 2009. After the drop of prices in January 2009, the difference between these two indexes increase dramatically, with the DAX double and triple its price from CAC, exhibiting the strength of DAX index among other European indexes.

Figure 4.3 stand for the Chinese SSE50, CSI300, CSI500 and SSE indexes. These indexes across sample exhibit the same ups and downs and very similar characteristics among them, with the CSI500 being the most intense Chinese index. In Chinese stock market history, there are two high peaks that distinguish at first sight. Initially, during the middle of 2007 and just before the spread of global crisis, the government stated reduction of state-owned shares and reform of non-tradable shares. The second and double high peak mentioned in May of 2015, almost nine months after the beginning of the Chinese shocking in its market and the gradual reduction of the index until December 2018. Although the HSI index is the Hong Kong market index and belongs to China, it trades on different currency (HKD). Figure 4.4 show that the HSI is an even more volatile index from that of CSI500, since there are many more ups and downs. Critical high levels for HSI index were during the middle of 2007 and the first quarter of 2018, three times higher than that of SSE.

Finally, in Figure 4.5, I present the monthly closing price of the two cryptocurrencies. Bitcoin was launched in January of 2009. Bitcoin is considered by many to be the future form of currency and transaction worldwide. Bitcoin bases on peer-to-peer technology and is independent from any central authority or banks. Bitcoin signaled the need of radically new form of digital money that operates outside the shadow of governments and corporations. Bitcoin cannot be manipulated, devalued, and revalued by any institution or state. Therefore, there is complete transparency. It is based on the simple method of supply and demand through an algorithm and the blockchains which maintain the whole system. Bitcoin is managing the transactions and the issuing of bitcoins is carried out collectively by the network. Also, its holders are not at risk of unlimited inflation and the transactions are immediately and publicly available. One of the successes of bitcoin is because its issue number is specific, and, in the future, it is predetermined to reach 21 million, while currently, around 18.5 million bitcoins have been mined. That leaves less than three million that have yet to be introduced into circulation. This means that this e-currency cannot be used to issue additional bitcoin units for a deliberate government game or other malicious owner. This makes it a meritocratic and reliable trading medium. Also, its divisibility is an additional advantage as its price can start from 0.00001.

Ethereum is the cryptocurrency of the Ethereum network and is arguably the second most popular digital token after Bitcoin. Indeed, it consists the second-largest cryptocurrency by market cap, among the Ethereum and the Bitcoin. Ethereum is a technology that permits you send cryptocurrency to anyone losing only a small fee. It also gives life to various applications that everyone can use, and no one can take down just like the Bitcoin. Ethereum is based on Bitcoin's innovation, but with some differences. Both let the users use digital money without payment providers or banks, but it is Ethereum that is programmable. Ethereum permits running commands on the Ethereum platform and is further used by developers to build and run applications on the platform. That permit the use for lots of different digital assets, even Bitcoin. That fact consists the Ethereum more than payments. It is a marketplace of financial services, games and apps that can't steal data or censor the users.

The historical value background of the first cryptocurrency ever created, the Bitcoin, skyrocketed to unprecedented levels in its hitherto short life. Indicatively a unit of bitcoin in December 2014 costed 340$, while for the following 4 years the cost of one bitcoin was 430.35$, 960.81$, 14565.05$, 3691.86$ and 7158.01$ for December of 2015, 2016, 2017, 2018, and 2019 respectively. The growth rate is rather more impressive, as it is 24%, 80%, 272%, -137%, 66% times more in contrast with the previous year beginning from 2014. Finally, another impressive statistic is that from the beginning of 2017 until the end of that year the Bitcoin price rose 271%. On the other hand, the Ethereum cryptocurrency kept much lower profile, considering that its price was 14.16$ at 5/31/2016 and the maximum peak was at 1105.01$ at 1/31/2018.

4.4 Methodology

For each one of the sub-samples' periods, I calculate the log returns, the realized volatility and the realized correlation coefficient for S&P500, RUSSELL 1000, CAC, DAX, HIS, SSE50, CSI300, CSI500, and SSE indexes and for the two cryptocurrencies on monthly and quarterly frequency. The log returns are constructed as:

$$r_i = ln\left(\frac{P_t}{P_{t-1}}\right) \text{ where } P_t \text{ is the value of an index at time t} \quad (1)$$

Log returns are favored over arithmetic returns since multi-period log returns calculated as the sum of one period log returns. Moreover, log returns on small values are about to attribute the same as raw results. The realized volatility is the assessment of variation in returns for an investment product by analyzing its historical returns within a defined time-period. It is derived from the realized variance and measure the price variability of the intraday returns. For the estimation part, first I calculate the log returns of the index prices as in equation (1) and then I sum over the past N square returns. The square root of the realized variance is the realized volatility and depicts as follow:

$$RVol_t = \sqrt{\sum_{t=1}^{N} r_t^2} \quad (2)$$

The realized correlation coefficient comes from the $RCov_t^{(m)}$ divided by the square roots of the realized volatility estimators of the two assets, $RV_{t,a}^{(m)}$ and $RV_{t,b}^{(m)}$, where m → ∞.

$$RC_t^{(m)} = \frac{RCov_t^{(m)}}{\sqrt{RC_{t,a}^{(m)}} - \sqrt{RC_{t,b}^{(m)}}} = \frac{\sum_{t=1}^{m} r_{a,i,m} r_{b,i,m}}{\sqrt{\sum_{t=1}^{m} r_{a,i,m}^2}\sqrt{\sum_{t=1}^{m} r_{b,i,m}^2}} \quad (3)$$

Through the realized correlation estimations, I can explore the relationships between markets with the cryptocurrencies across the twelve sub-periods. Based on these performance statistics I move on to further computations with some grand descriptive statistics, which are the min, max, mean, median on each log returns and realized volatility across all sub-periods on monthly and quarterly base, to capture a better picture and understanding for the international markets and cryptocurrencies.

Our innovative subject matter is to explore the characteristics of the Chinese stock market and its relationship with other financial markets. The innovation does not stand with the subject matter itself but rather with the approach used to do the cross-comparisons. In first level there is an extended and very detailed literature review on the historical evolution and characteristics of the Chinese stock market in general. The review covers every aspect of the Chinese market that has appear hitherto in the literature and provides a foundational framework for the rest of the analysis. Finally, I do a detailed comparison of my results with a focus on comparing the structure of these averages across time in my sub-samples and also on comparing the major and developed markets with the Chinese market. I provide a thorough commentary on these results and their implication for investment decision making.

4.5 Descriptive analysis of announcements effects

In this chapter I discuss three performance statistics. These are the average returns, the average realized volatility and average realized correlation, using a sample split counting on critical dates of the US and China economy, and Corona virus 2019. I perform the analysis both on monthly and quarterly frequency. Figures 4.6 and 4.7 present the results of the average monthly returns on international indexes and cryptocurrencies from 1995 to 2020. Also, it shows two bar charts one for all international indexes and another concerning the comparison with cryptocurrencies.

Following Figure 4.6, for the sample of 1995-2020 the average monthly returns are very similar with the Chinese indexes surpassed those of the US and Europe. The Expansion I phase indicated very similar results with that of the full sample, while during the 2001 WTC Attack all indexes suffered significant losses and stated negative average monthly returns. The Expansion II period left the average returns significant higher with the Chinese CSI500 noted an all-time high peak surpass the 0.1. Across the Early Credit Crisis period the results were by far worse than the 2001 WTC Attack for all indexes, while during the Lehman collapse and recession the results are mixed. The US and European indexes continued their losses, but the Chinese indexes stated positive significant returns. These trends between the US, European and Chinese indexes meant to inverted in the next sub-period of Fiscal Policy battle of currency crisis and sovereign debt crisis. Finally, for the US Recovery sub-period the average returns were positive among all indexes but lower from Expansion II sub-period. Considering now the critical dates of Chinese announcements and reforms, the initial policy intervention from government shaped a positive era on returns for all indexes, which continued at lower bound during the Expansion and the Asian Financial Crisis of January 1996 to June 2001. The reduction of state-owned shares and reform of non-tradable shares, just before the great Credit Crisis, reminded a lot the US Expansion II sub-period. The last two critical Chinese sub-periods maintained similar levels of positive average returns. Under these sub-periods, China stated 4000 billion RMB economic stimulus and Economic Recovery, which after August 2014 tended to a market Shock and last in 2019. The January of 2018 started as a new era for the international trade, since US and China announced between them trade embargoes. The average returns for the US indexes were higher than the almost zero returns of Europe and Chinese indexes. Finally, the average returns were significant higher from December 2019 to September 2020 for Chinese and the US indexes, with the latter being at lower levels during the Covid-19. The same levels of average returns did not exist for European indexes, which were destroyable and negative.

Following the results in Figure 4.7, the cryptocurrencies by far surpassed the average returns of all countries indexes across all sub-periods. The Bitcoin and Ethereum exhibited huge monthly returns, where its difference with the rest of the indexes were beyond the initial expectations and exceeded multiple times the rest indexes' returns. In particular, the US Recovery sub-period was primarily the highest noted average returns for cryptocurrencies, while the worst was during the embargo sub-period between 2018 and 2020. Even during the Covid-19 the Bitcoin was more than double of the Ethereum returns and more than seven times higher from the Chinese SSE index.

Figure 4.6: Average monthly returns on international indexes.

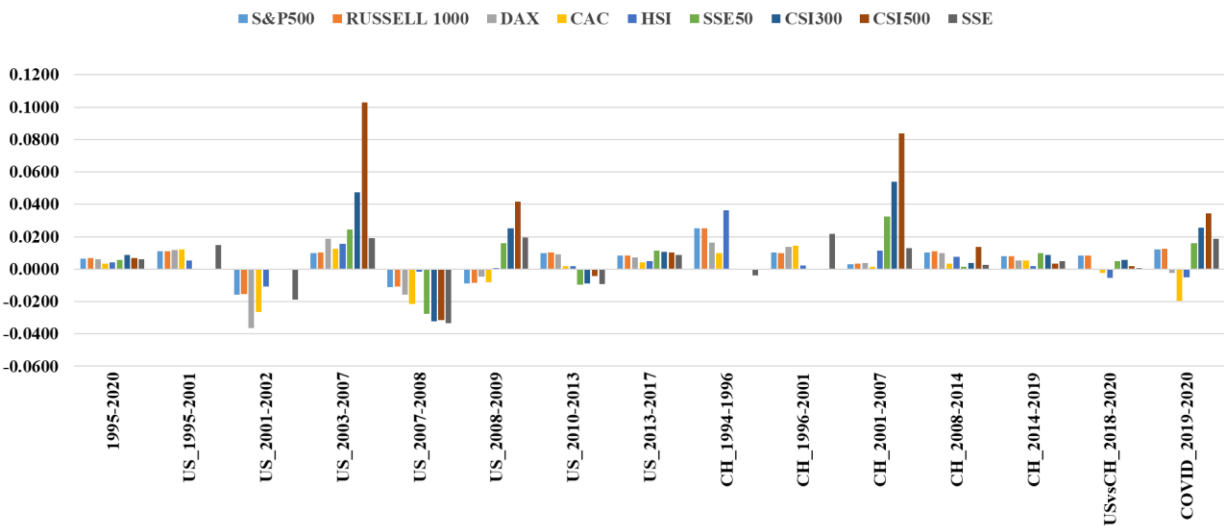


Figure 4.7: Average monthly returns on international indexes and cryptocurrencies.

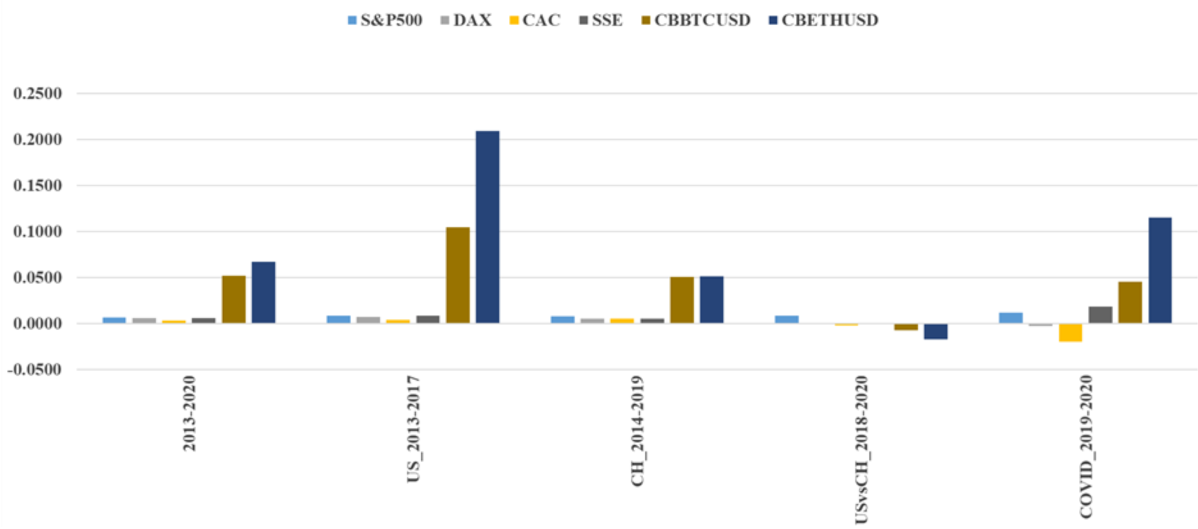


Figure 4.8 and 4.9 display the average monthly realized volatility on international indexes and cryptocurrencies from 1995 to 2020. The average monthly realized volatility in Figure 4.8 has a more stable pattern than that of the average monthly returns, across all sub-periods. Initially, for the full sample of 1995-2020, the realized volatility is very clear and representative on average in relation to

other sub-periods. The Chinese indexes noted the highest volatility, with the CSI500 exceeded the 0.08, while significantly at lower levels are the US indexes, with the S&P500 merely point out 0.045.

Figure 4.8: Average monthly realized volatility on international indexes.

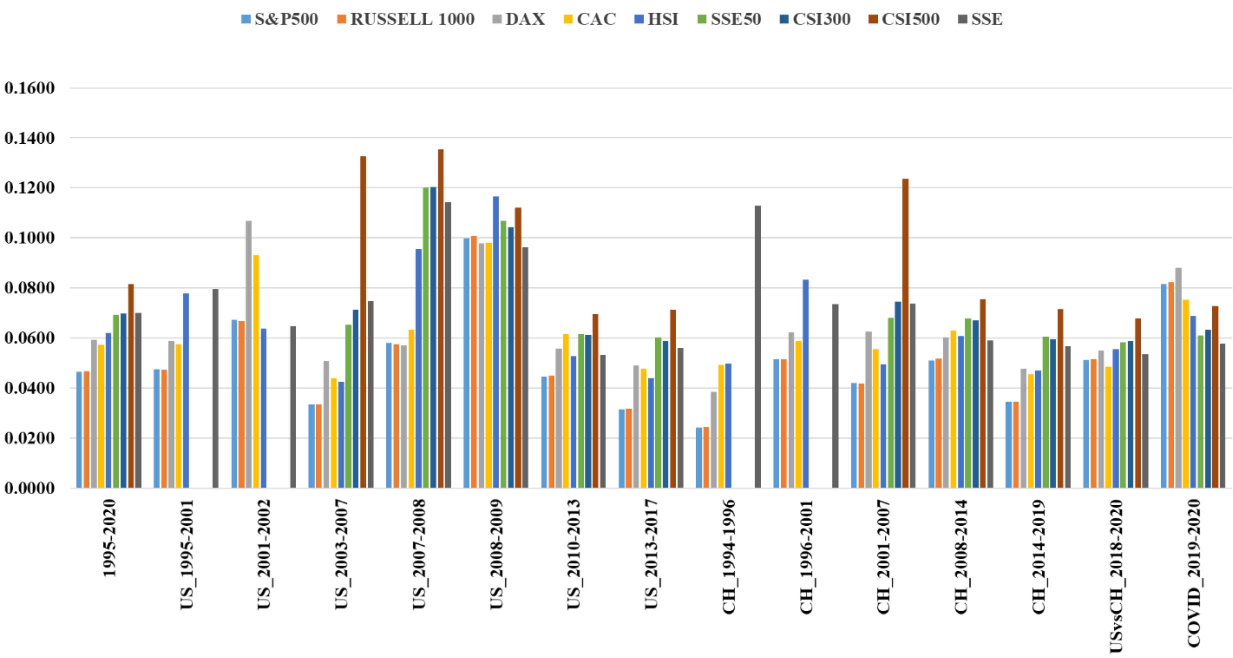
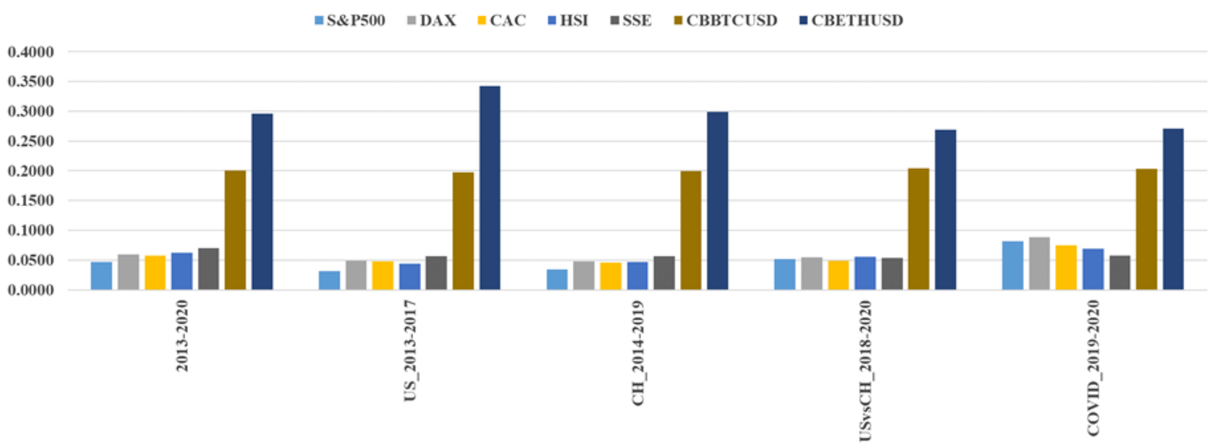


Figure 4.9: Average monthly realized volatility on international indexes and cryptocurrencies.



In particular, the S&P500 index maintains the lowest volatility level both in the whole sample 1995-2020 and across all sub-periods. The S&P500 releases its highest volatility during the critical Chinese sub-period of 1994-1996 and the US sub-period of 2010-2013, while the Covid-19 sub-period quadrupled its realized volatility. Common behavior and fluctuation levels stands for RUSSELL 1000 as these indexes have similar characteristics. Considering the realized volatility among the European indexes, the DAX has relative higher volatility both for the full sample and all sub-periods, except for the US sub-periods of 2007-2008 and 2010-2013, and Chinese sub-periods of 1994-1996 and 2008-

2014. The HSI is exhibited as one of the highest realized volatilities within the international indexes, with all time high peak stated at the US sub-periods of 2007-2008 Credit Crisis and then at 2008-2009 Lehman collapse, while the lowest level noted at the Chinese sub-period of 2014-2019 and during the embargo 2018-2020 period. Taking every Chinese index into account, the CSI500 was the most volatile index, indicating for three sub-periods in the row 62,60% (2003-2007), 65.94% (2007-2008) and 37.57% (2008-2009) times higher from the realized volatility level of full period 1995-2020.

The cryptocurrencies in Figure 4.9 are by far more volatile than the very volatile Chinese index, which justifies also the highest average returns across all sub-samples in Figure 4.7. The Bitcoin involves more risk than the Ethereum as it is the first and most valuable cryptocurrency ever created. Moreover, indicatively in the period 2013-2017 the bitcoin reached levels of 73.51% and 509.15% higher than the second Ethereum and the SSE index.

Figure 4.10 is for the average quarterly returns on international indexes. At the first level of analysis, it is easy to observe that all of them had kept their characteristics, trends, and patterns from the monthly base along all the sub-periods. Indicatively, the general order of indices between the three continents remained the same as the Chinese indexes surpassed those of the US and Europe. One significant difference is the sharp increase in the average returns from monthly to quarterly base across all sub-periods. These differences could even reach 200% compared to those of average returns among all indexes. In the full sample, the ranking between indexes remained the same, except from slight increase of SSE in contrast to CSI500 and twice higher than Figure 4.6. Furthermore, there were some additional minimal differences in their fluctuations between Figure 4.6 and 4.10 during the Chinese sub-period of 2008-2014 and the embargo sub-period of 2018-2020. Under the 2008-2014 sub-period the SSE50, CSI300 and the SSE experienced average negative quarterly return, while the same stood during the embargo sub-period for the CSI500 and SSE.

Figure 4.10: Average quarterly returns on international indexes.

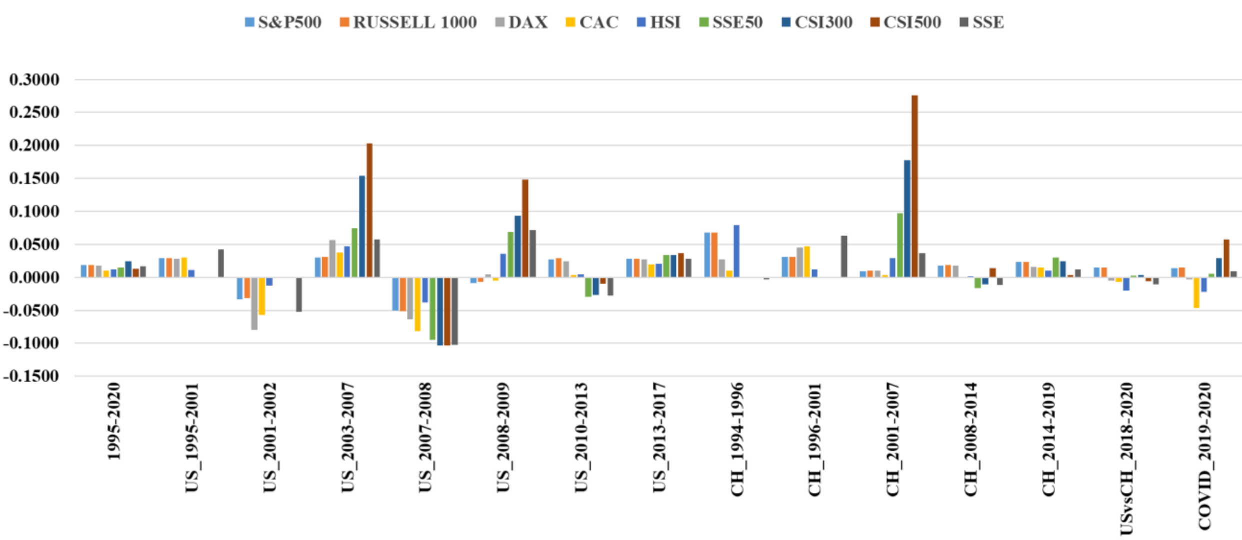
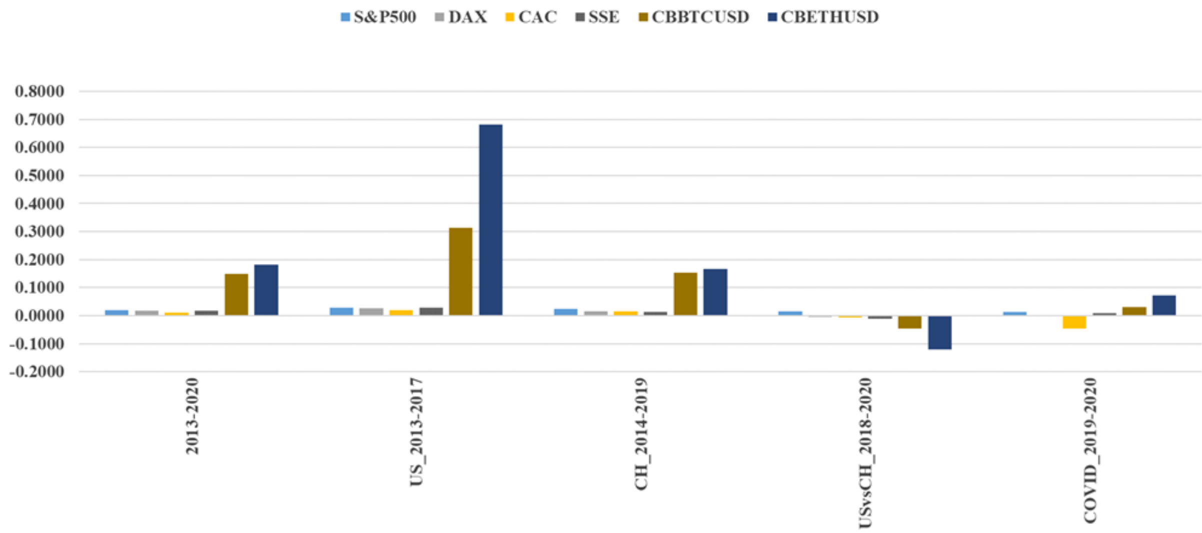


Figure 4.11: Average quarterly returns on international indexes and cryptocurrencies.



We noted the same characteristics within the relationships of the international indexes and the cryptocurrencies in Figures 4.7 and 4.11. The patterns were also the same across the full sample, the US Recovery and the Chinese market shock, while for the embargo sub-period the SSE, the Bitcoin and the Ethereum suffered significant average negative quarterly returns. Lower levels of average quarterly returns experienced also these indexes for the Covid-19 sub-period.

Figure 4.12 presents the average quarterly realized volatility on international indexes. Firstly, I observe again that all indexes had kept their characteristics, trends, and patterns from the monthly base along the sub-periods. The ranking of indices between the US, China and Europe remained the same as the Chinese indexes surpassed those of the US and Europe once again. One difference is the improvement of DAX, as the S&P500 and RUSSELL 1000 exceeded its risk during the Covid-19 sub-period. These differences could even reach 150% times at higher indexes levels of realized volatility compared to monthly base.

Figure 4.12: Average quarterly realized volatility on international indexes.

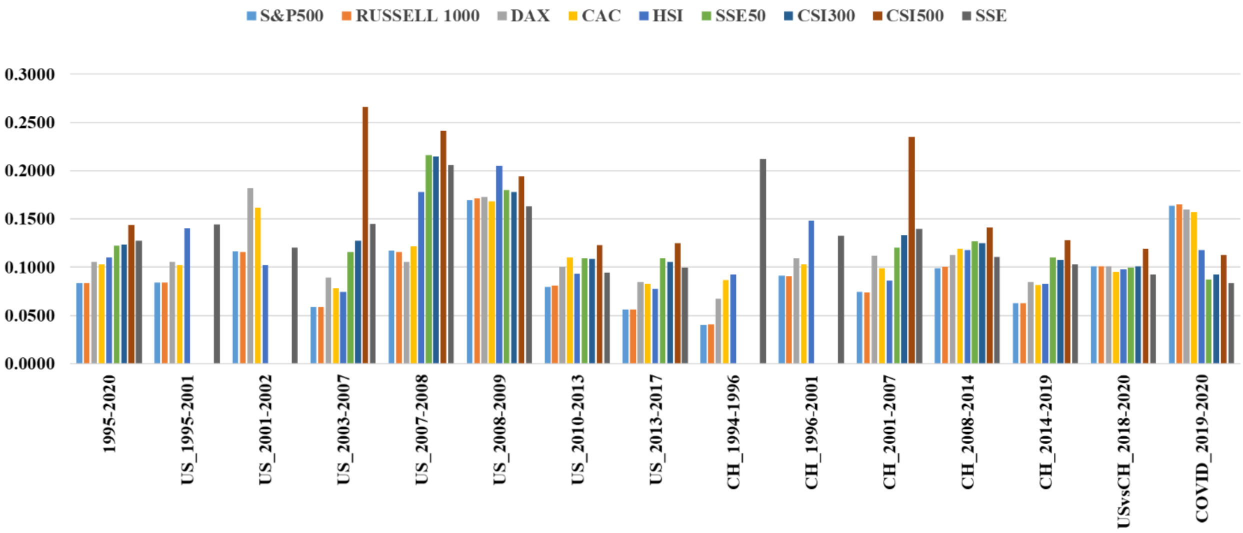
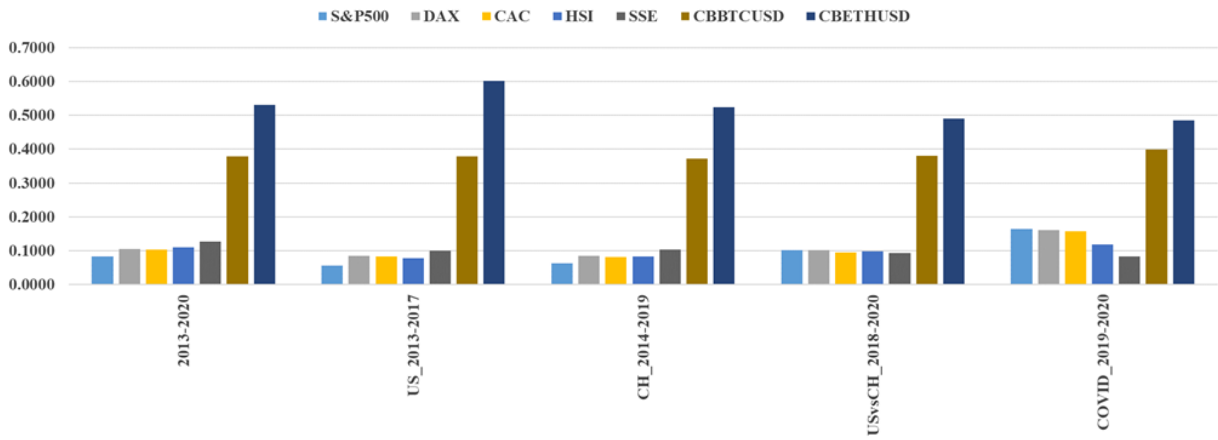


Figure 4.13: Average quarterly realized volatility on international indexes and cryptocurrencies.



The same exactly co-moves came for the international indexes and the cryptocurrencies in Figures 4.9 and 4.13. The patterns were also the same across the full sample, and the sub-periods of the US Recovery and the Chinese market shock, the embargo and for the Covid-19.

Tables 4.2 and 4.3 summarizes the prior discussion about the trend and peaks of international indexes both for the US and Chinese critical sub-periods. What is more, these Tables highlights the minimum and maximum prices within its sub-periods for the average return and realized volatility. Additionally, I perform the grand mean and median across the indexes, considering into calculations all critical sub-periods. Finally, I rank the grand means to show off the general trend between international indexes and cryptocurrencies.

Table 4.2: The grand descriptive statistics based on monthly and quarterly average returns across all sub-periods per international indexes and cryptocurrencies.

Monthly grand statistics

INDEXES	MIN	MEAN	MEDIAN	MAX	MEAN RAKING	MIN SUB-PERIOD	MAX SUB-PERIOD
SP500	-0.0158	0.0057	0.0091	0.0251	7	US_2001-2002	CH_1994-1996
RUSSELL 1000	-0.0155	0.0060	0.0092	0.0252	6	US_2001-2002	CH_1994-1996
DAX	-0.0365	0.0026	0.0062	0.0189	10	US_2001-2002	US_2003-2007
CAC	-0.0266	-0.0009	0.0027	0.0146	11	US_2001-2002	CH_1996-2001
HSI	-0.0109	0.0046	0.0021	0.0364	8	US_2001-2002	CH_1994-1996
SSE50	-0.0278	0.0079	0.0105	0.0326	5	US_2007-2008	CH_2001-2007
CSI300	-0.0324	0.0139	0.0096	0.0541	4	US_2007-2008	CH_2001-2007
CSI500	-0.0315	0.0256	0.0120	0.1029	3	US_2007-2008	US_2003-2007
SSE	-0.0333	0.0042	0.0069	0.0218	9	US_2007-2008	CH_1996-2001
CBBTCUSD	-0.0069	0.0484	0.0481	0.1044	2	USvsCH_2018-2020	US_2013-2017
CBETHUSD	-0.0170	0.0895	0.0831	0.2089	1	USvsCH_2018-2020	US_2013-2017

Quarterly grand statistics

INDEXES	MIN	MEAN	MEDIAN	MAX	MEAN RAKING	MIN SUB-PERIOD	MAX SUB-PERIOD
SP500	-0.051	0.014	0.021	0.067	7	US_2007-2008	CH_1994-1996
RUSSELL 1000	-0.051	0.015	0.021	0.068	6	US_2007-2008	CH_1994-1996
DAX	-0.080	0.008	0.017	0.057	10	US_2001-2002	US_2003-2007
CAC	-0.081	-0.002	0.004	0.047	11	US_2007-2008	CH_1996-2001
HSI	-0.038	0.011	0.011	0.079	8	US_2007-2008	CH_1994-1996
SSE50	-0.095	0.017	0.018	0.097	5	US_2007-2008	CH_2001-2007
CSI300	-0.103	0.038	0.027	0.178	4	US_2007-2008	CH_2001-2007
CSI500	-0.104	0.062	0.025	0.276	3	US_2007-2008	CH_2001-2007
SSE	-0.102	0.008	0.011	0.071	9	US_2007-2008	US_2008-2009
CBBTCUSD	-0.047	0.113	0.092	0.313	2	USvsCH_2018-2020	US_2013-2017
CBETHUSD	-0.120	0.200	0.119	0.682	1	USvsCH_2018-2020	US_2013-2017

Initially, in Table 4.2 the minimum average monthly and quarterly returns are distributed into three sub-periods. The US, European and the Hong Kong (HSI) indexes stated all time monthly minimum at the US WTC Attack period, while the rest of the Chinese indexes showed their monthly minimum at the Credit Crisis period. The results are even simpler for quarterly minimum average returns, since the lowest points for international indexes are identified during the Credit Crisis period, except from the DAX, which maintained at WTC Attack level. These results are expected due to the sharper deterioration of the world economy. The cryptocurrencies noted its lowest level during the embargo sub-period. On the other hand, the maximum average and quarterly returns showed higher scatter variation. Both for monthly and quarterly base, the US indexes reached their maximum peak during 1994-1996, the DAX peaked at Expansion sub-period, while the French index reached its high during the Chinese 1996-2001 sub-period. HSI also noted its highest peak at 1994-1996, while the SSE50 CSI300 skyrocketed during 2001-2007 sub-period. The CSI500 and the SSE, as I already mentioned previously were very volatile indexes, changed their peaks from Expansion II to Chinese 2001-2007 sub-period and from 1996-2001 sub-period to the Lehman collapse, respectively. Remarkable reference are the mean ranking results. Both for monthly and quarterly basis, the highest means came for cryptocurrencies, as expected, but then the Chinese indexes CSI300, CSI500 and SSE50 stole the top positions from US and European indexes, with the latter ended up to the lowest two positions of the mean ranking.

Table 4.3: The grand descriptive statistics based on monthly and quarterly average realized volatility across all sub-periods per international indexes and cryptocurrencies.

Monthly grand statistics

INDEXES	MIN	MEAN	MEDIAN	MAX	MEAN RAKING	MIN SUB-PERIOD	MAX SUB-PERIOD
SP500	0.0242	0.0513	0.0493	0.0998	11	CH_1994-1996	US_2008-2009
RUSSELL 1000	0.0245	0.0515	0.0494	0.1008	10	CH_1994-1996	US_2008-2009
DAX	0.0385	0.0636	0.0579	0.1068	8	CH_1994-1996	US_2001-2002
CAC	0.0441	0.0615	0.0581	0.0980	9	US_2003-2007	US_2008-2009
HSI	0.0424	0.0648	0.0581	0.1165	7	US_2003-2007	US_2008-2009
SSE50	0.0582	0.0729	0.0634	0.1201	6	USvsCH_2018-2020	US_2007-2008
CSI300	0.0587	0.0739	0.0652	0.1204	4	USvsCH_2018-2020	US_2007-2008
CSI500	0.0679	0.0932	0.0741	0.1353	3	USvsCH_2018-2020	US_2007-2008
SSE	0.0533	0.0733	0.0692	0.1144	5	US_2010-2013	US_2007-2008
CBBTCUSD	0.1971	0.2010	0.2011	0.2045	2	US_2013-2017	USvsCH_2018-2020
CBETHUSD	0.2691	0.2952	0.2848	0.3420	1	USvsCH_2018-2020	US_2013-2017

Quarterly grand statistics

INDEXES	MIN	MEAN	MEDIAN	MAX	MEAN RAKING	MIN SUB-PERIOD	MAX SUB-PERIOD
SP500	0.0398	0.0938	0.0875	0.1693	11	CH_1994-1996	US_2008-2009
RUSSELL 1000	0.0405	0.0941	0.0874	0.1713	10	CH_1994-1996	US_2008-2009
DAX	0.0676	0.1134	0.1056	0.1821	8	CH_1994-1996	US_2001-2002
CAC	0.0780	0.1119	0.1026	0.1683	9	US_2003-2007	US_2008-2009
HSI	0.0742	0.1153	0.1001	0.2051	7	US_2003-2007	US_2008-2009
SSE50	0.0873	0.1274	0.1127	0.2164	6	COVID_2019-2020	US_2007-2008
CSI300	0.0925	0.1294	0.1167	0.2150	5	COVID_2019-2020	US_2007-2008
CSI500	0.1123	0.1684	0.1343	0.2660	3	COVID_2019-2020	US_2003-2007
SSE	0.0836	0.1319	0.1267	0.2121	4	COVID_2019-2020	CH_1994-1996
CBBTCUSD	0.3712	0.3822	0.3793	0.3989	2	CH_2014-2019	COVID_2019-2020
CBETHUSD	0.4852	0.5251	0.5071	0.6010	1	COVID_2019-2020	US_2013-2017

Table 4.3 displays that the minimum average monthly and quarterly realized volatility have changes mainly for the most volatile indexes. The S&P500, RUSSELL 1000 and DAX indexes stated monthly and quarterly all-time minimum during the Chinese 1994-1996 critical sub-period and both CAC and HSI index hit its lowest level at US Expansion II. The rest of the Chinese indexes showed their monthly minimum volatility at the embargo sub-period, while changed quarterly minimum during Covid-19 sub-period. The Bitcoin and Ethereum noted its lowest monthly realized volatility level during the US Recovery and embargo sub-period, which changed quarterly to the Chinese 2014-2019 and Covid-19 sub-period, respectively. On the other hand, the maximum average and quarterly returns exhibit a more stable pattern. Both for monthly and quarterly base, the US, CAC and HSI indexes reached their maximum realized volatility during the Lehman collapse, the DAX retained its highest peak at WTC Attack sub-period, while the Chinese CSI500 and SSE altered from Credit Crisis sub-

period correspondingly to US Expansion II and 1994-1996 sub-periods. Another important change is for Ethereum, which monthly volatility launched at the embargo sub-period and quarterly at Covid-19 sub-period. Both for the monthly and quarterly realized volatility there is consistency among its mean rankings.

Figures 4.14 and 4.15 illustrate the average monthly and quarterly realized correlations for every possible pair between international indexes and cryptocurrencies. Each of the displayed columns represents the correlation between two indicators across all sub-periods, creating their own new dynamic correlation rate, representative for that pair. Therefore, each column consists of sub-periods, where each of them depends on the value they hold in the total amount of the others, and automatically creates a new percentage of its participation in this column, which is illustrated above.

Starting the analysis with the S&P500 pairs, the patterns among monthly and quarterly realized correlations are under the same notion. Generally, the S&P500 has higher realized correlation with the European indexes than with China, not only during expansion periods but also along with recession sub-periods. Indicatively, for the Expansion II sub-period the monthly correlation of S&P500 with the DAX was 0.4960, while the corresponding correlation with the HSI and CSI500 were 0.1072 and 0.1905. What is more, it is important to mention that the correlation between the US and Chinese indexes were negative for the Early Credit Crisis sub-period, while for the next sub-period of Lehman collapse the relationship turned into positive. That fact indicates a time lag of Chinese market to incorporate the global recession waves. Moving on to the next realized correlation of DAX and CAC indexes with the rest of the indexes, I observe common patterns and characteristics for monthly and quarterly. Both the European indexes experiences higher correlations with the HSI rather with the Chinese ones. The main difference between Figures 4.14 and 4.15 is the negative correlations of the DAX and CAC with CSI500 during the Expansion II and the Chinese 2001-2007 sub-periods. This fact comes to reinforce the previous contribution and add that during the new waves of prosperity there is a time lag for China market to incorporate.

For example, during the US Expansion I and the Chinese Expansion sub-period 1996-2001, the SSE correlations with the DAX and CAC were also negative. Furthermore, negative correlations exist from 1991 to 2002 and from 2007 to 2008, covering a wide range of policy announcement and economic cycles for the correlation of SSE with S&P500 and RUSSELL 1000.

Considering the cryptocurrencies correlations, I observe that for the Bitcoin the correlations became steeper and lower from monthly to quarterly. Besides, the Ethereum retained its pattern at Figures 4.14 and 4.15 except from the US Recovery sub-period, where the correlations suffered significant decreases. The Covid-19 sub-period retained higher from monthly to quarterly correlations of Bitcoin with the US and European indexes, while higher embargo correlations mentioned on monthly base for the same pairs.

Figure 4.14: Average monthly realized correlation on international indexes and cryptocurrencies.

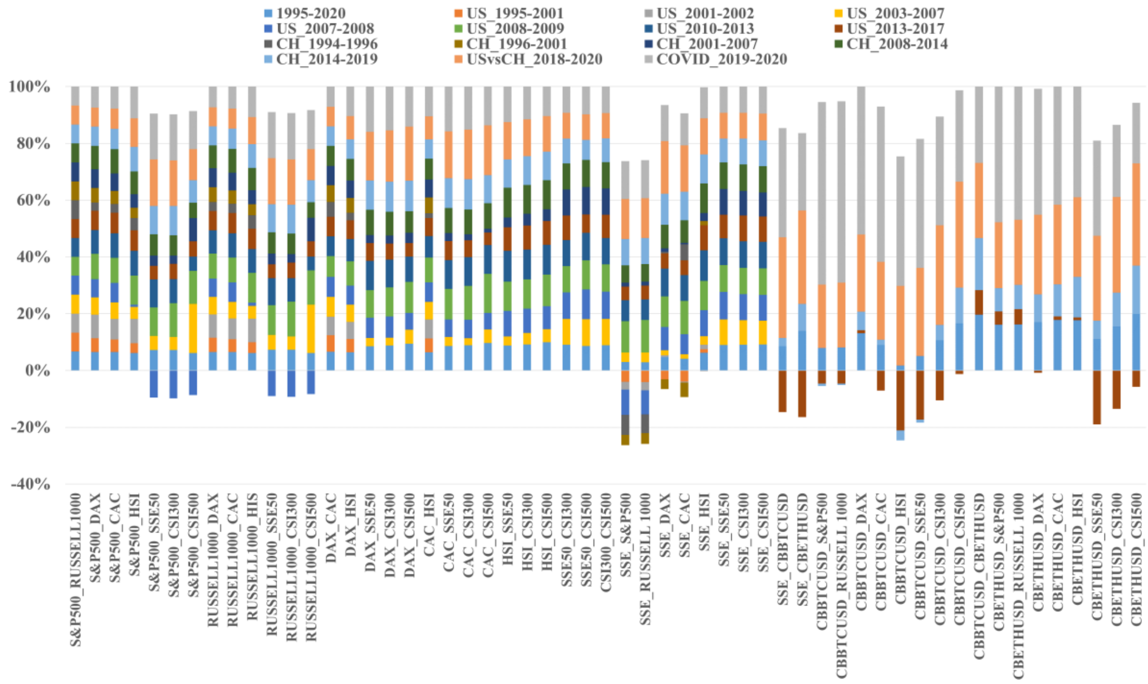
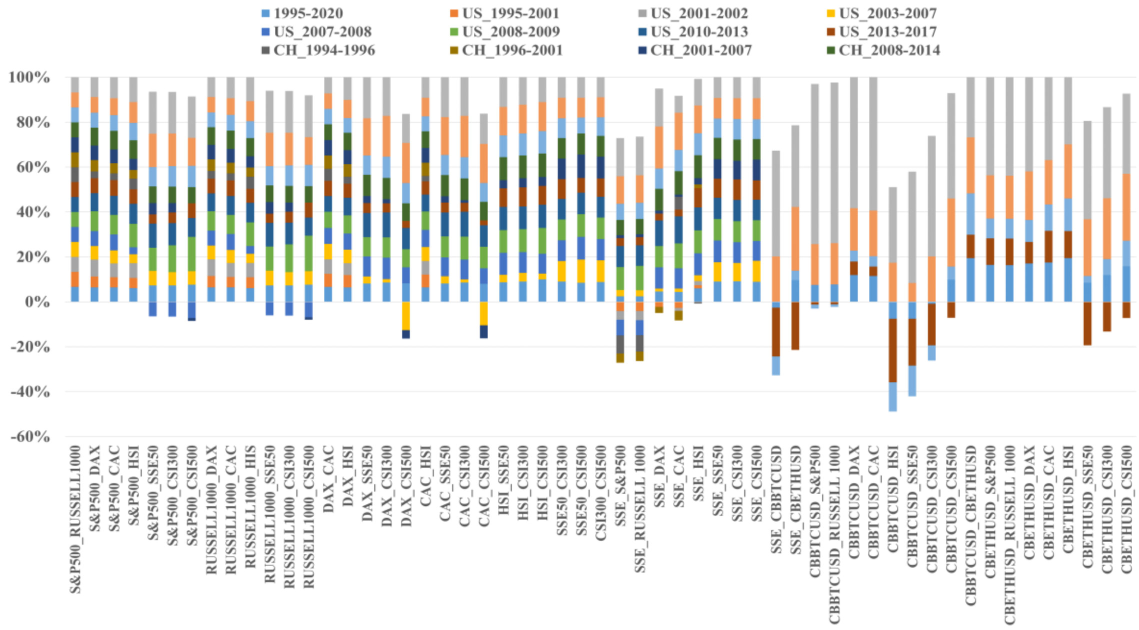


Figure 4.15: Average quarterly realized correlation on international indexes and cryptocurrencies.



Based on previous results, the Bitcoin experienced higher returns and volatilities levels among the indexes and Ethereum, and more abrupt fluctuations in their realized correlations. For instance, during the embargo sub-period, the monthly correlations were higher for the DAX, CSI300 and CSI500 indexes, while these correlations on quarterly base were reduced significantly. What is more, higher bitcoin correlation stated for the Covid-19 sub-period both in Figures 4.16 and 4.17 among all indexes, while for the US Recovery sub-period the realized correlations with HIS, SSE50 and CSI300 indexes were significant negative. However, the Ethereum correlations stated positive at higher levels in contrast to the Bitcoin, both for monthly and quarterly level. Finally, the Ethereum correlations with the DAX, CAC and HSI indexes were higher and improved from monthly to quarterly base and higher from the Chinese indexes of CSI300, CSI500 and SSE50.

The risk reward ratio is one of the common investment decision methods that investors considers for their strategy and marks the eminent prospective reward, for every currency unit in relation to the risks on an investment. Investors use risk reward ratios to challenge the expected returns of an investment with the amount of risk they must undertake to earn these returns. Figures 4.16 and 4.17 show the monthly risk reward return for international indexes and cryptocurrencies across the full sample, the US Recovery 2013-2017, the embargo 2018-2020 and the Covid-19 2019-2020 sub-periods. All Figures are adjusted into the main cross of S&P500, as such index is the oldest, exerts the greatest influence in the market, and belongs to strongest world economy.

Figure 4.16 and 4.17 display simultaneously the average returns and realized volatilities which namely comes as the Sharpe ratio. First, I recognize common patterns both for the monthly and quarterly base across the volatilities and returns. Second, the highest risk reward was for the cryptocurrencies with Ethereum at (0.2963, 0.0671) and merely lower for the Bitcoin at (0.2006,0.0520). Third, I observe that below the S&P500 benchmark cross are the European, the HSI, and the SSE indexes. These indexes exhibited higher realized volatility, but lower average returns. That fact drives investors to a further defense positions with these risk reward ratios being really lower in contrast to the rest market opportunities. Moreover, from investment side the quarterly risk reward levels are higher from those of monthly both for average returns and realized volatilities. Furthermore, considering Figures 4.16 and 4.17 I end up that the cryptocurrencies revealed a market which being much challenged in its recent history so far and it totally showed that the returns and investment opportunities evolved quickly compared to international indices. That brings cryptocurrencies to equal levels of investor awareness with other alternative forms of investment such as those of gold and oil.

Figure 4.16: The monthly risk reward return for international indexes and cryptocurrencies across the full sample, the US Recovery 2013-2017, the embargo 2018-2020 and the Covid-19 2019-2020 sub-periods.

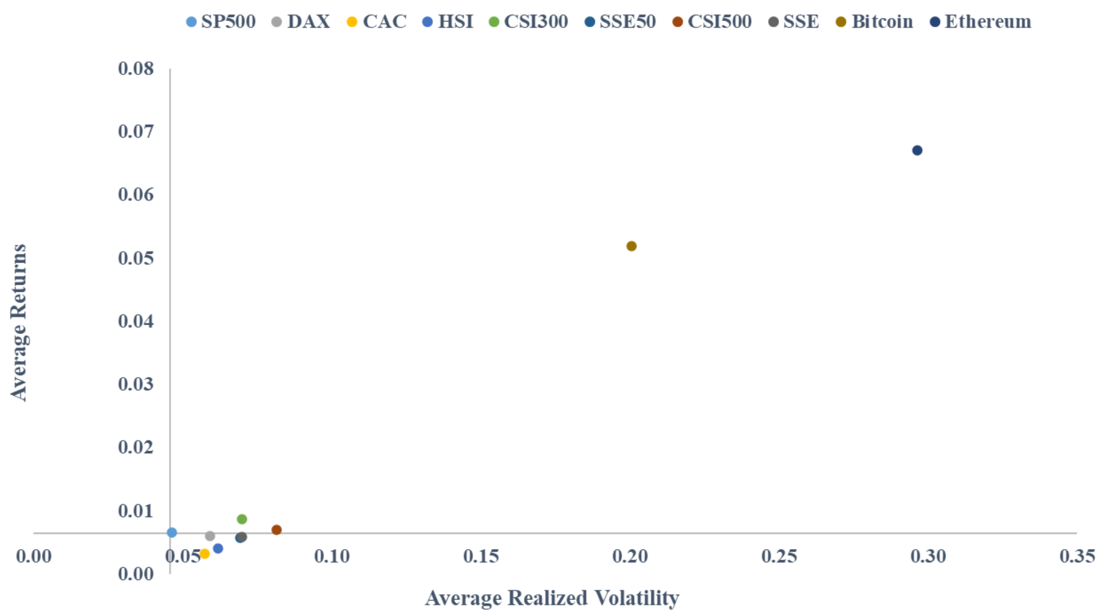
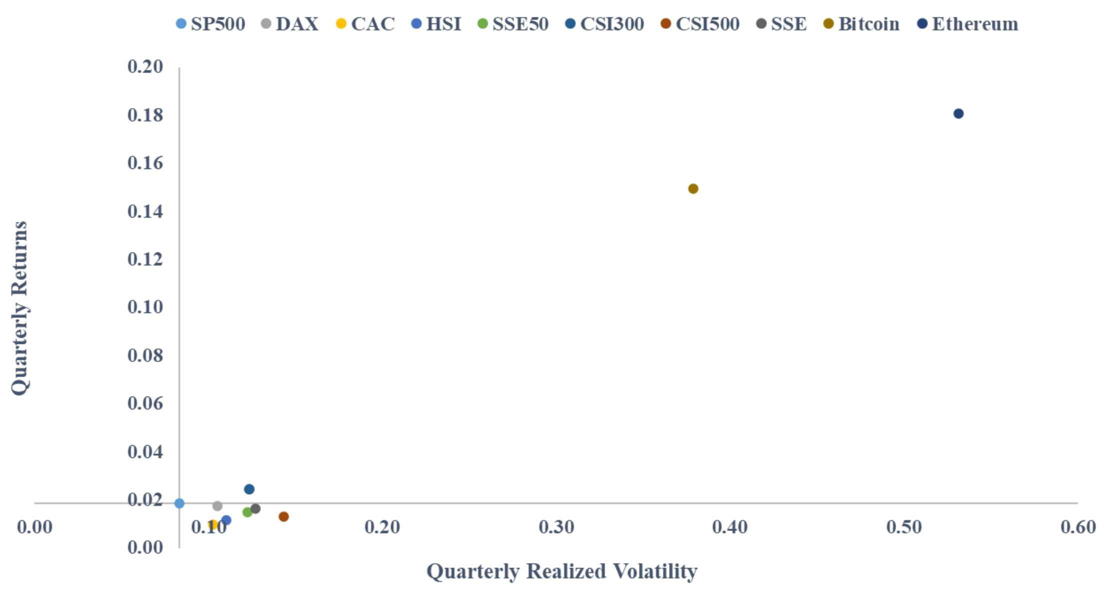


Figure 4.17: The quarterly risk reward return for International indexes and cryptocurrencies across the full sample, the US Recovery 2013-2017, the embargo 2018-2020 and the Covid-19 2019-2020 sub-periods.



4.6 Concluding Remarks

China constitutes the second largest global economy and the world's largest emerging market. According to the literature review, during the past twenty years the stock markets experienced several fluctuations. Such realized unexpected slumps in the stock market could not be justified by public market information and macroeconomic conditions. After the crisis of 2008, the market conditions got better but a second huge bubble thrived until the 2015 Chinese market crash. These turbulences are displayed very clearly across figures of historic Chinese index prices, returns, and realized volatilities trends, mainly for the CSI500, SSE50.

China’s stock market is also consisted of distinctive and unique characteristics. These characteristics are the T+1 trading mechanism, the high proportion of small and medium-sized investors, the high turnover, and the barriers on prices. The Chinese market comprises of only few delisting firms. These are characteristics of an emerging and still evolving financial market. Cushing and Madhavan (2000) and Foucault et al. (2005) suggested the need of institutional traders to study the closing stock prices, as these being exposure to overnight risk. Chen et al. (2007) stated that Chinese individual investors acquired inappropriate and irrational trading behaviors and decisions more than the institutional investors. These factors emerged full irrational investment behaviors within the Chinese stock market. Gao et al. (2018) stated that during an intraday momentum, the first half-hour returns yields positive prediction of the last half-hour return in the U.S. stock market. That fact mentioned that there is a time lag window between the two financial markets. Narayan, and Zheng (2010) stated that the Chinese stock market, known as an emerging market, viewed extraordinary growth and high risk and volatility.

Zhang and Li (2014) stated that the US stock market had strong impact mainly when the Chinese market experienced extreme movements. The correlation between the two markets were time-varying and had an upward trend in 2008 Financial Crisis. Across my empirical results, there is significant relationship between the Hong Kong index, HSI, with the US indexes. Furthermore, the HSI is adapting much quicker than the CSI500, CSI300 and SSE to US political and economic announcements.

Han, Qi, and Yin (2016) highlighted the effects of EPU spillovers from developed economies to China and found that the downtrend of export, industrial production, equity price, and the exchange rate are implications of the US EPU. They verified it in turn as the Chinese economy were affected more from the US EPU and less from the UK EPU. Baker, Bloom, and Davis (2016) documented that political uncertainty drove the risk premium and the political uncertainty on correlation, volatility, and risk premia. That result became stronger during weakening economies. Their result implied that changes in US EPU possible affected the trades in the US stock market, while parallel changed the co-movements from the Chinese stock markets to the U.S. stock. Hu, Kutan and Sun (2018) found that the EPU in U.S. influenced the returns of Chinese A-shares negatively significant, by using a lag of one week from March 2006 to April 2016. The small and emerging size stocks became even more susceptible to shocks in U.S. EPU than on big and value stocks.

Chapter 5

Conclusion

The aim of this dissertation is to shed light on the investment strategies, proposing technics, analyzing, and learning from the past financial market era and exploring new methods of how to optimize the investment decisions. This dissertation offers a well structure approach in the field of investment decision about the perception and investment activity providing economic solutions and justifications on the evolution of the markets. This is achieved through three investment strategies, which are the economic sentiment indicator (ESI), the momentum and risk reward trade off. This dissertation is not limited to one financial market but analyzes the three largest stock exchanges in the world, those of US, China and Germany, covering the international investment market characteristics and justifying in each chapter the reason and the investment strategy for which they were selected. What differentiates this dissertation from the corresponding literature is the emergence of investment strategies in a way that has not been studied so far and strengthening the investment perception by using sample split and comparative analysis. The sample split analysis is one of the novelties and contribution of this thesis, which is based on NBER data, on VIX and Monetary policy announcements, all taken from the FRED database, to capture the growth and recession periods, and important economic events, since it is known that the results are not stable in macroeconomic periods.

Chapter 2 is the first research of this dissertation and explores whether economic sentiment of a "safe heaven" country such as Germany, can influence stock returns and decrease risk as a leading indicator. During the Financial crisis of 2007, the Economic Sentiment Indicator for Germany had already started the deepest drop in its history, reaching a new historical low at the second quarter of 2009. The drop was only temporary, as Germany became the de facto "safe heaven" country and thus within two years the low became a sharp increase reaching a historical all-time high. The effect of "safe heaven" country that Germany exhibited during the crisis, the high correlation between the levels and returns of ESI-DAX from pre to post-crisis and the resulting numbers for economic sentiment pose the question as to whether economic sentiment can be used to improve the positioning on the German financial market. Also, the German market exhibited unique economic recovery in relation to other European economies and that was another motivation. I examine the link between sentiment and the performance of the German market, and how investors' herd behavior should has used such a sentiment signal to take advantage of, during the depression and beyond. I perform a careful sample-split analysis of both the characteristics of sentiment and financial market performance in various sub-periods from the 1990's until today, and also use economic sentiment as a guide for timing the German stock market. In my analysis, economic sentiment acquires a leading guide role for investors to the German market.

To explore these research questions, I used causality testing and a simple trading strategy with different thresholds to win buy and hold strategy using the ESI as a guide. The results illustrated not only the impact that ESI had on DAX returns, but also the non-linear and time-varying nature of this impact. Moreover, the DAX responded in different magnitudes of ESI changes across different periods. This is further evidence on the importance of sentiment as a predictor of future returns, as it suggests that investors could have differential responses in changing economic conditions. In the full sample for all scenarios there is statistically significant causality between ESI and DAX especially in Crisis period, in Pre-unification period until '99, Sentiment wasn't the driving force, while in Euro period, sentiment became stronger as it caused DAX. During Crisis period, sentiment was the key factor for investors' decision and in Post-crisis period ESI did not seem to cause DAX, since the dynamic of sentiment had been overcome. The results reveal that investors can outperform the buy-and hold strategy, by considering the ESI as an indicator of timing their positioning on the DAX and that in periods of higher economic uncertainty, sentiment becomes a crucial representative of economic conditions and thus a market driver for investors.

Chapter 3 documents a careful and detailed analysis of the components of the NASDAQ index, that innovative seek to assess the role and what drives momentum portfolio performance in a rather appropriately and timely selection. Momentum is one of the most commonly accepted investment class among investors and academics across all investment strategies and asset management industry. My twist consists of a three well-structured approach. I examine the role of momentum portfolio performance, beta and Sharpe ratio across different economic sub-periods from January of 1985 to December of 2017 that are identified by clear exogenous events. Second, I study the time-varying sectoral characteristics of the components of the index and discuss the post-2007/2008 increase of healthcare companies' participation in the index. Third, I perform a careful post-portfolio construction performance attribution to examine the impact of various characteristics of the portfolios themselves and the underlying fundamentals of the portfolios to explain the excess returns of momentum. These research questions are based on the weaknesses of the literature to show which are the emerging sectors in the winner momentum portfolio construction and how the highest momentum sectors shift across different critical sub-periods and change the portfolio betas. The findings align with the recent literature of asset management and momentum strategies and emerge for first time the highest sectoral percentage of momentum portfolio participation and how these findings are linked in the beta variation and portfolio expected returns across periods. The results show higher performances in recession rather than in booms in momentum portfolios expected returns, and the conditional betas explain a large part of variations in momentum specific risk. The beta highs do not share the same trend at 12-month momentum as the rest performance measures of portfolio momentum. So, there are differences across sectoral momentum betas and differences of betas across sub-periods. Furthermore, I show that the momentum portfolios expected returns are linked with positively significant betas, while when I study the Sharpe ratio the betas are negatively significant due to the incorporated risk. Finally, it is also remarkable that Technology sector exhibits the highest participation during the full sample and bull US stock market, while Health Care sector dominates at recession sub-periods, considering the top momentum 10% NASDAQ components.

Chapter 4 examines in considerable detail the characteristics of the Chinese stock market and its relationship to other international Financial markets. The Chinese market is the second largest economy and the world's largest emerging market full of the most distinctive market characteristic. These are the T+1 trading mechanism, the 90-min break, the high proportion of small and medium-sized investors, the high turnover and the barriers on prices. These are characteristics of an emerging and still evolving financial market. The innovation of the research does not stand with the subject matter alone but rather with the approach used to do the cross-comparisons with the European markets, the US markets and other Asian markets and cryptocurrencies. The literature review covers every aspect of the Chinese market that has appear hitherto in the literature and provides a foundational framework for the rest of the analysis. To understand the similarities and the differences between the Chinese, the EU and the US indexes and the cryptocurrencies, I used daily data to construct monthly returns, monthly realized volatilities, correlations and the risk reward trade off. The analysis is based on a very detailed historical sample split using critical dates of the US, China, and the Covid-19 period. I perform a detailed comparison of the results with a focus on comparing the structure of many statistics across time in different sub-samples. The results stated that China outperform systematic, Europe underperform systematic, cryptocurrencies offer the highest risk reward trade off. Also, the Cryptocurrencies exhibited the highest variability, while the financial markets share approximately the same volatility and risk but not performance. A thorough commentary is provided along with these results and their implication for investment decision making.

Finally, it is important to examine international markets, meet unique market characteristics and recognize investment opportunities across different critical sub-periods, by taking advantage different investment strategies. In this way, an investor will reinforce its knowledge on where and how to invest across different financial markets and which will be its potential results, to increase the performance and the risk reward ratio.

References

Ahn, D.H., Conrad J., and Dittmar, R.F. (2003). Risk Adjustment and Trading Strategies. Review of Financial Studies, 16: 459-485. https://doi.org/10.109/rfs/hhg001.

Andersen, T., Bollerslev, F.X., Diebold, P., and Vega, C. (2007). Real-time price discovery in global stock, bond and foreign exchange markets. Journal of International Economics, 73: 251–277. https://doi.org/10.1016/j.jinteco.2007.02.004.

Asness, C., (1994). The Power of Past Stock Returns to Explain Future Stock Returns. SSRN, working paper. https://dx.doi.org/10.2139/ssrn.2865769.

Asness, C.S., Liew, J.M., and Stevens, R.L, (1997). Parallels between the Cross- Sectional Predictability of Stock and Country Returns. Journal of Portfolio Management, 23: 79-87. https://doi.org/10.3905/jpm 1997.409606.

Asness, C.S., Moskowitz, T.J., and Pedersen, L.H., (2013). Value and Momentum Everywhere. Journal of Finance, 68 (3): 929-985. https://doi.org/10.17010/ijf/2014/v8i9/71849.

Asness, C.S., Frazzini A., Pedersen, L.H., (2012). Leverage Aversion and Risk Parity. Financial Analysts Journal, 68 (1): 47-59. https://doi.org/10.2469/faj.v68.n1.1.

Avramov, D., Chordia, T., Jostova, G., Philipov, A., (2007). Momentum and Credit Rating. Journal of Finance, 62 (5): 2503-2520. https://doi.org/10.1111/j.1540-6261.2007.01282.x.

Badrinath, S.G., Kale, J.R., Noe, T.H., (1995). Of shepherds, sheep, and the cross correlations in equity returns. Review of Financial Studies, 8 (2): 401-430. https://doi.org/10.1093/rfs/8.2.401.

Bajgrowicz, P., and O. Sxaillet. 2012. “Size, value, and momentum in international stock returns”. Journal of Financial Economics 106: 473–491.

Bai, Y. (2014). Cross-border sentiment: an empirical analysis on EU stock markets. Applied Financial Economics, 24 (4): 259–290. http://doi.org/10.1080/09603107.2013.864035

Baker, M., & Stein, J. C. (2004). Market liquidity as a sentiment indicator. Journal of Financial Markets, 7 (3): 271–299. http://doi.org/10.1016/j.finmar.2003.11.005

Baker, M., & Wurgler, J. (2006). Investor Sentiment and the Cross-Section of Stock Returns. The Journal of Finance, 61 (4): 1645–1680. http://doi.org/10.1111/j.1540-6261.2006.00885.x

Baker, M., and Wurgler J., (2007). Investor Sentiment in the Stock Market. Journal of Economic Perspectives, 21 (2): 129-152. https://doi.org/10.1257/jep.21.2.129.

Baker, M., Wurgler, J., & Yuan, Y. (2012). Global, local, and contagious investor sentiment. Journal of Financial Economics, 104 (2): 272–287. http://doi.org/10.1016/j.jfineco.2011.11.002

Bali, T.G., Brown, S.J., Caglayan, M.O., (2014). Macroeconomic risk and hedge fund returns. Journal of Financial Economics 114: 1-19. https://doi.org/10.1016/j.jfineco.2014.06.008.

Bali, T.G., and Zhou, H., (2016). Risk, Uncertainty, and Expected Returns. Journal of Financial and Quantitative Analysis, 51 (3): 707-735. https://doi.org/10.1017/S0022109016000417.

Baltas, A.N. and Kosowski, R., (2012). Improving Time-Series Momentum Strategies: The Role of Volatility Estimators and Trading Signals. SSRN Electronic Journal.

Baltas, A.N. and Kosowski, R., (2013). Momentum Strategies in Futures Markets and Trend-following Funds. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.1968996.

Baltas, A.N. and Kosowski, R., (2015). Demystifying Time-Series Momentum Strategies: Volatility Estimators, Trading Rules and Pairwise Correlations. SSRN Electronic Journal. https://doi.org/10.2139/SSRN.2140091.

Banz, R.W. (1981). The relationship between return and market value of common stocks. Journal of Financial Economics, 9: 3-18. https://doi.org/10.1016/0304-405X(81)90018-0.

Barberis, N., Shleifer, A., & Vishny, R. (1998). A Model of Investor Sentiment. Journal of Financial Economics , 49 (3): 307–343. http://doi.org/10.3386/w5926

Barone-Adesi, G., Mancini, L., & Shefrin, H. M. (2012). Sentiment, Asset Prices, and Systemic Risk. SSRN Electronic Journal. http://doi.org/10.2139/ssrn.1953621.

Barroso, P., (2014). The Bottom-up Beta of Momentum. SSRN Electronic Journal. https://dx.doi.org/10.2139/ssrn.2144204.

Barroso, P., and Santa-Clara, P., (2014). Momentum Has Its Moments. Journal of Financial Economics 116: 11-120. https://doi.org/10.1016/j.jfineco.2014.11.010.

Beber, A., and Brandt, M.W, (2009). Resolving Macroeconomic Uncertainty in Stock and Bond Markets. Review of Finance, 13 (1): 1–45. https://doi.org/10.1093/rof/rfn025

Bernard, V.L, and Thomas, J.K, (1989). Post-Earnings-Announcement Drift: Delayed Price Response or Risk Premium?. Journal of Accounting Research, 27: 1-36. https://doi.org/10.2307/2491062.

Bernard, V.L., Thomas, J.K., and Wahlen J.M., (1995). Accounting-Based Stock Price Anomalies: Separating Market Inefficiencies from Research Design Flaws. SSRN, https://ssrn.com/abstract=112328.

Bird, R., Gao, X., and YFeung, D., (2007). Time-series and cross-sectional momentum strategies under alternative implementation strategies. Australian Journal of Management, 42 (2): 230-251. https://doi.org/10.1177/0312896215619965.

BIS. 2010. BIS Quarterly Review: International Banking and Financial Market Developments, Basel: Bank for International Settlements.Brown, G. W. (1999). Volatility, Sentiment, and Noise Traders. Financial Analysts Journal, 55 (2): 82–90. http://doi.org/10.2469/faj. v55.n2. 2263

Blitz, D., Huij, J., Martens, M., (2011). Residual momentum. Journal of Empirical Finance, 18 (3): 506-521. https://doi.org/10.1016/j.jempfin.2011.01.003.

Brock, W., Lakonishok, J., LeBaron, B., (1992). Simple Technical Trading Rules and the Stochastic Properties of Stock Returns. The Journal of Finance, 4 (5): 1731–1764. https://doi.org/10.1111/j.1540-6261.1992.tb04681.x.

Brown, G. W., & Cliff, M. T. (2004). Investor sentiment and the near-term stock market. Journal of Empirical Finance, 11 (1): 1–27. http://doi.org/10.1016/j.jempfin.2002.12.001

Brown, G. W., & Cliff, M. T. (2005). Investor Sentiment and Asset Valuation. The Journal of Business, 78 (2): 405–440. http://doi.org/10.1086/427633

Chan, L.K.C., Hamao, Y., and Lakonishok J., (1991). Fundamentals and stock returns in Japan. The Journal of Finance, 46 (5). https://doi.org/10.1111/j.1540-6261.1991.tb04642.x.

Chan, L.K.C., Jegadeesh, N., Lakonishok, J., (1996). Momentum Strategies. The Journal of Finance, 51 (5): 1681-1713. https://doi.org/10.1111/j.1540-6261.1996.tb05222.x.

Chan, L.K.C., Karceski, J., Lakonishok, J., (2003). The Level and Persistence of Growth Rates. The Journal of Finance 58 (2). https://doi.org/10.1111/1540-6261.00540.

Chabot, B., Ghysels, E., and Jagannathan, R., (2014). Momentum Trading, Return Chasing, and Predictable Crashes. NBER Working Papers 20660, National Bureau of Economic Research, Inc.

Cheema, M., and Naerta, G., (2017). Momentum, idiosyncratic volatility and market dynamics: Evidence from China. Pacific-Basin Finance Journal, 46: 109-123. http://dx.doi.org/10.1016/j.pacfin.2017.09.001.

Cheema, M., and Naerta, G., (2014). Momentum returns and information uncertainty: Evidence from China. Pacific-Basin Finance Journal, 30: 173-188. http://dx.doi.org/10.1016/j.pacfin.2014.10.002.

Chen, J., and Hong, H., (2002). Discussion of Momentum and Autocorrelation in Stock Returns. Review of Financial Studies 15: 565-573. https://doi.org/10.1093/rfs/15.2.565.

Chi, L., Zhuang, X., & Song, D. (2012). Investor sentiment in the Chinese stock market: an empirical analysis. Applied Economics Letters, 19 (4): 345–348. http://doi.org/10.1080/13504851.2011.577003

Chopra, N., Lakonishok, J., and Ritter J.R., (1992). Measuring abnormal performance: Do stocks overreact? Journal of Financial Economics, 31 (2): 235-268. https://doi.org/10.1016/0304-405X(92) 90005-I.

Chordia, T., and Shivakumar, L., (2002). Momentum, Business Cycle, and Time-varying Expected Returns. The Journal of Finance, 57 (2). https://doi.org/10.1111/1540-6261.00449.

Chu, X., Gu, Z., and Zhou, H., (2019). Intraday momentum and reversal in Chinese stock market. Finance Research Letters, 30: 83-88. https://doi.org/10.1016/j.frl.2019.04.002.

Chui, A. C. W., S. Titman, and K. C. J. Wei. (2010). “Individualism and Momentum around The World.” The Journal of Finance, 65 (1): 361–392. doi:10.1111/j.1540-6261.2009.01532.x.

Claessen, H., & Mittnik, S. (2002). Forecasting stock market volatility and the informational efficiency of the DAX-index options market. The European Journal of Finance, 8 (3): 302–321. http://doi.org/10.1080/13518470110074828

Conrad J., and Kaul G., (1998). An Anatomy of Trading Strategies. The Review of Financial Studies, 11 (3): 489–519. https://doi.org/10.1093/rfs/11.3.489.

Cooper, M.J., Gutierrez C., and Hameed A., (2004). Market States and Momentum. The Journal of Finance, 59 (3). https://doi.org/10.2139/ssrn.299927.

Cutler, D.M., Poterba, J., and Summers, L.H., (1991). Speculative dynamics. Review of Economic Studies, 58: 529–546. https://doi.org/10.2307/2298010.

Daniel, K., Hirshleifer, D., and Subrahmanyam, A., (1998). Investor Psychology and Security Market Under and Overreactions. The Journal of Finance, 53 (6). https://doi.org/10.1111/0022-1082.00077.

Daniel, K., and Moscowitz, T.J., (2016). Momentum Crashes. Journal of Financial Economics, 122 (2): 221-247. https://doi.org/10.1016/j.jfineco.2015.12.002.

De Bondt W.F.M. and Thaler R.H.,(1985). Does the stock market overreact. The Journal of Finance, 40 (3). https://doi.org/10.1111/j.1540-6261.1985.tb05004.x.

De Long, J.B., Shleifer, A., and Summers, H., and Waldmann, R.J., (1990). Positive feedback investment strategies and destabilizing rational speculation. The Journal of Finance, 45: 379–395. https://doi.org/10.1111/j.1540-6261.1990.tb03695.x.

De Miguel, V., Nogales, F.J., and Uppal, R., (2013). Stock Return Serial Dependence and Out-of-sample Portfolio Performance. Review of Financial Studies, 27 (4). https://doi.org/10.2139/ssrn.1572526.

Dudler, M., Gmur B., and Malamud, S., (2014). Risk-Adjusted Time Series Momentum. Swiss Finance Institute Research Paper, 14-71. http://dx.doi.org/10.2139/ssrn.2457647.

Erb, C.B., Harvey, C.R., (2006). The strategic and tactical value of commodity futures. Financial Analysts Journal. 62: 69-97. https://doi.org/10.2469/faj.v62.n2.4084.

Fama, E.F., and French, K.R., (1988). Permanent and temporary components of stock prices. Journal of Political Economy, 96: 246-273. http://dx.doi.org/10.1086/261535.

Fama, E.F., and French, K.R., (1993). Common risk factors in the returns of stocks and bonds. Journal of Financial Economic, 33: 3-56. https://doi.org/10.1016/0304-405X(93)90023-5.

Fama, E.F., and French, K.R., (2012). Size, value, and momentum in international stock returns. Journal of Financial Economics, 105 (3): 457-472. https://doi.org/10.1016/j.jfineco.2012.05.011.

Fama, E., MacBeth, J., (1973). Risk, return and equilibrium: empirical tests. Journal of Political Economics 8: 607–636.

Fernandes, C., Gama, P. M., & Vieira, E. (2016). Does local and Euro area sentiment matter for sovereign debt markets? Evidence from a bailout country. Applied Economics, 48 (9): 816–834. http://doi.org/10.1080/00036846.2015.1088142

Fisher, K. L., & Statman, M. (2000). Investor Sentiment and Stock Returns. Financial Analysts Journal, 56 (2): 16–23. http://doi.org/10.2469/faj.v56.n2.2340

Fong, W. M., Yong, H. M., (2005). Chasing trends: recursive moving average trading rules and internet stocks. Journal of Empirical Finance. 12 (1): 43-76. https://doi.org/10.1016/j.jempfin.2003.07.002.

Foster, G., Olsen, C., and Shevlin T., (1984). Earnings Releases, Anomalies, and the Behavior of Security Returns. The Accounting Review, 59 (4): 574-603. https://www.jstor.org/stable/247321.

Franz, F.-C., & Regele, T. (2016). Beating the DAX, MDAX, and SDAX: investment strategies in Germany. Financial Markets and Portfolio Management, 30 (2): 161–204. http://doi.org/10.1007/s11408-016-0268-6

Fuertes, A.-M., Miffre, J., Rallis, G., 2010. Tactical allocation in commodity futures markets: Combining momentum and term structure signals. Journal of Banking and Finance, 34: 2530-2548. https://doi.org/10.1016/j.jbankfin.2010.04.009.

Gao, L., et al. (2018). Market intraday momentum. Journal of Financial Economics, 129: 394-414. https://doi.org/10.1016/j.jfineco.2018.05.009.

Goyal, A., and Wahal, S., (2015), Is Momentum an Echo?. Journal of Financial and Quantitative Analysis, 50 (6): 1237-1267. https://doi.org/10.1017/S0022109015000575.

Grinblatt, M., Titman, S. and Wermers, R., (1995). Momentum Investment Strategies, Portfolio Performance, and Herding: A Study of Mutual Fund Behavior. The American Economic Review, 85 (5) 1088-1105.

Grundy, B.D., and Martin, S., (2001). Understanding the Nature of the Risks and the Source of the Rewards to Momentum Investing. Review of Financial Studies, 14: 29-78.

Han, X., and Li Y. (2017). Can investor sentiment be a momentum time-series predictor? Evidence from China. Journal of Empirical Finance, 42: 212-239. http://dx.doi.org/10.1016/j.jempfin.2017.04.001.

He, X., Li, K., and Li, Y., (2015). Optimal Time Series Momentum. Quantitative Finance Research Centre, Research Paper 353, ISSN 1441-8010.

Ho, C., & Hung, C.-H. (2009). Investor sentiment as conditioning information in asset pricing. Journal of Banking & Finance, 33 (5): 892–903. http://doi.org/10.1016/j.jbankfin.2008.10.004

Hong, H., Lim, T., Stein, J.S., (2000). Bad News Travels Slowly: Size, Analyst Coverage, and the Profitability of Momentum Strategies. The Journal of Finance, 55 (1): 265-295. https://doi.org/10.1111/0022-1082.00206

Hong, H., and Stein, J.C., (1999). A Unified Theory of Underreaction, Momentum Trading and Overreaction in Asset Markets. Journal of Finance, 54 (6): 2143- 2184. https://doi.org/10.1111/0022-1082.00184.

Hong, K. J., and Satchell, S., (2015). Time Series Momentum Trading Strategy and Autocorrelation Amplification. Quantitative Finance, 15 (9): 1-17. https://doi.org/10.1080/1469768 8.2014.10 009 51.

Hou, K., Karolyi G.A., Kho B.C., (2011). What Factors Drive Global Stock Returns?. The Review of Financial Studies, 24 (8): 2527–2574. https://doi.org/10.1093/rfs/hhr013

Hou, K., Peng, L., and Xiong, W., (2009). A Tale of Two Anomalies: The Implications of Investor Attention for Price and Earnings Momentum. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.976394.

Hu, Z., Kutan, A., and Sun, P., (2018). Is U.S. economic policy uncertainty priced in China's A-shares market? Evidence from market, industry, and individual stocks. International Review of Financial Analysis, 57: 207-220. https://doi.org/10.1016/j.irfa.2018.03.015.

Huang, D., Jiang, F., Tu, J., and Zhou, G., (2014). Investor Sentiment Aligned: A Powerful Predictor of Stock Returns. Review of Financial Studies, 28 (3): 791-837. http://dx.doi.org/10.1093/rfs/hhu080.

Huang, J. -Z., M. Rossi, and Y. Wang. (2015). "Sentiment and Corporate Bond Valuations before and after the Onset of the Credit Crisis." The Journal of Fixed Income 25 (1): 34– 57. doi:10.3905/jfi.2015.25.1.034.

Hutchinson, M.C., and O'Brien, J., (2015). Time Series Momentum and Macroeconomic Risk. SSRN Electronic Journal.

Israel, R., Moskowitz, T.J., (2013). The role of shorting, firm size, and time on market anomalies. Journal of Financial Economics, 108: 275–301. https://doi.org/10.1016/j.jfineco.2012.11.005.

Jegadeesh, N., & Titman, S. (1993). Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency. The Journal of Finance, 48 (1). http://doi.org/10.2307/2328882

Jegadeesh, N., and Titman, S., (2001). Profitability of Momentum Strategies: An Evaluation of Alternative Explanations. The Journal of Finance, 56 (2): 699-720.

Jegadeesh N., and Titman S., (2011). Momentum. Annual Review of Financial Economics, 3: 493-509.

Johnson, T.C., (2002). Rational Momentum Effects. Journal of Finance, 57: 585-648. https://doi.org/10.1111/1540-6261.00435.

Kanas, A., (2004). Lead-lag effects in the mean and variance. Empirical Economics, 29: 575–592. https://doi.org/10.1007/s00181-004-0199-3.

Kanas, A., and Kouretas, G.P., (2005). A cointegration approach to the lead–lag effect among size-sorted equity portfolios. International Review of Economics & Finance, 14 (2): 181-201. https://doi.org/10.1016/ j.iref.2003.12.004.

Kaul G., and Nimalendran M., (1990). Price reversals: Bid-ask errors or market overreaction? Journal of Financial Economics, 28: 67-93. http://dx.doi.org/10.1016/0304-405X(90)90048-5.

Karpoff, J. M., (1987). The relation between price changes and trading volume: A survey. Journal of Financial and Quantitative Analysis, 22 (1): 109–126. https://doi.org/10.2307/2330874.

Keiber, K. L., & Samyschew, H. (2015). The role of sentiment in global risk premia. Applied Economics, 47 (20): 2073–2091. http://doi.org/10.1080/00036846.2014.1002887

Keiber, K. L., & Samyschew, H. (2018). The pricing of sentiment risk in European stock markets. The European Journal of Finance, 25 (3): 279–302. http://doi.org/10.1080/1351847x.2018.1521340

Kelsey, D., Kozhan, R., and Pang, W., (2011). Asymmetric Momentum Effects Under Uncertainty. Review of Finance, 15 (3): 603–631. https://doi.org/10.1093/rof/rfq021.

Kim, M., C.Nelson, and R. Startz, (1991). Mean Reversion in Stock Prices? A Reappraisal of the Empirical Evidence. Review of Economic Studies. 58: 515–528. https://doi.org/10.2307/2298009.

Klein, (1990), A direct test of the cognitive bias theory of share price reversals, Journal of Accounting and Economics 13: 155-166.

Konrad, E. (2009). The impact of monetary policy surprises on asset return volatility: the case of Germany. Financial Markets and Portfolio Management, 23 (2): 111–135. http://doi.org/10.1007/s11408-009-0102-5

Korajczyk, R., Sadka, R., (2004). Are momentum profits robust to trading costs? Journal of Finance, 59 (3): 1039-1082. https://doi.org/10.1111/j.1540-6261.2004.00656.x.

Lakonishok, J., Shleifer, A., and Vishny RW., (1994). Contrarian Investment, Extrapolation, and Risk. The Journal of Finance, 49 (5): 1541-1578. https://doi.org/10.1111/j.1540-6261.1994.tb04772.x.

Lakonishok, J., and Smidt S., (1986). Volume for Winners and Losers: Taxation and Other Motives for Stock Trading. The Journal of Finance, 41 (4). https://doi.org/10.1111/j.1540-6261.1986.tb04559.x.

Lane, P. R. (2012). The European Sovereign Debt Crisis. Journal of Economic Perspectives, 26 (3): 49–68. http://doi.org/10.1257/jep.26.3.49

Latane, H.A., and Jones, C.P., (1979). Standardized Unexpected Earnings 1971-77. The Journal of Finance, 34 (3): 717-724. https://doi.org/10.2307/2327437.

Lee, B., Li, W., and Wang, S., (2010). The dynamics of individual and institutional trading on the Shanghai Stock Exchange. Pacific-Basin Finance Journal, 18: 116-137. doi:10.1016/j.pacfin.2009.09.002.

Lee, M.C.C., and Swaminathan, B., (2000). Price Momentum and Trading Volume. The Journal of Finance, 55 (5): 2017-2069. https://doi.org/10.1111/0022-1082.00280.

Lee, W. Y., Jiang, C. X., & Indro, D. C. (2002). Stock market volatility, excess returns, and the role of investor sentiment. Journal of Banking & Finance, 26 (12): 2277–2299. http://doi.org/10.1016/s0378-4266(01)00202-3

Lemmon, M., and E. Portniaguina. (2006). "Consumer Confidence and Asset Prices: Some Empirical Evidence." The Review of Financial Studies 19 (4): 1499–1529. doi:10.1093/rfs/hhj038.

Lehmann, B., (1990). Fads, Martingales and Market Efficiency. Quarterly Journal of Economics, 105: 1-28. https://doi.org/10.2307/2937816.

Lesmonda, D., Schill, M., Zhou, C., (2004). The illusory nature of momentum profits. Journal of Financial Economics, 71 (3): 349-380. https://doi.org/10.1111/j.1540-6261.2004.00656.x.

Levich, R., and L. Thomas, (1993). The Significance of Technical Trading-Rule Profits in the Foreign Exchange Market: A Bootstrap Approach. Journal of International Money and Finance, 12: 451-474. https://doi.org/10.1016/0261-5606(93)90034-9.

Lewellen, J., (2002). Momentum and Autocorrelation in Stock Returns. Review of Financial Studies, 15 (2): 533-564. https://doi.org/10.1093/rfs/15.2.533.

Li, J., (2020). The momentum and reversal effects of investor sentiment on stock prices. North American Journal of Economics and Finance, 54. https://doi.org/10.1016/j.najef.2020.101263.

Li, Z., Hou, K., and Zhang, C., (2020). The impacts of circuit breakers on China's stock market. Pacific-Basin Finance Journal. https://doi.org/10.1016/j.pacfin.2020.101343.

Li, Q., Wang, J. and Bao, L., (2018). Do institutions trade ahead of false news? Evidence from an emerging market. Journal of Financial Stability, 36: 98-113. https://doi.org/10.1016/j.jfs.2018.02.001.

Li, Y., Wang, P., and Zhang, W., (2020). Does intraday time-series momentum exist in Chinese stock index futures market? Finance Research Letters, 35. https://doi.org/10.1016/j.frl.2019.09.007.

Lin, L., Schatz, L., and Sornette D., (2019). A simple mechanism for financial bubbles: time-varying momentum horizon. Quantitative Finance, 19 (6): 937-959. http://doi.org/10.1080/14697 688.2018.15 40881.

Liu, L.X., and Zhang, L., (2008). Momentum Profits, Factor Pricing, and Macroeconomic Risk, Review of Financial Studies, 21 (6): 2417-2448. https://doi.org/10.1093/rfs/hhn090.

Ljungqvist, A., Nanda, V., & Singh, R. (2006). Hot Markets, Investor Sentiment, and IPO Pricing*. The Journal of Business, 79 (4): 1667–1702. http://doi.org/10.1086/503644

Lui, L.X., Strong, N., and Xu, X., (2003). The Profitability of Momentum Investing. Journal of Business Finance & Accounting, 26 (9): 9-10. https://doi.org/10.1111/1468-5957.00286.

Lo, A., and Mackinlay, A.C., (1990). When are contrarian profits due to stock market overreaction?. Review of Financial Studies, 3: 175–206.

Lo, A., and Wang, J., (2009). Stock Market Trading Volume. The Handbook of Financial Econometrics, New York: North-Holland.

Long, J. B. D., Shleifer, A., Summers, L. H., & Waldmann, R. J. (1990). Noise Trader Risk in Financial Markets. Journal of Political Economy, 98 (4): 703–738. http://doi.org/10.1086/261703

Menkhoff, l., Sarno, l., Schmeling M., and Schrimpf A., (2012). Currency momentum strategies. Journal of Financial Economics, 106 (3): 660-684. https://doi.org/10.1016/j.jfineco.2012.06.009.

Merton, R.C., (1987). A simple model of capital market equilibrium with incomplete information. Journal of Finance, 42 (3): 483–510. https://doi.org/10.1111/j.1540-6261.1987.tb04565.x.

Miffre, J., Rallis, G., (2007). Momentum strategies in commodity futures markets. Journal of Banking and Finance 31: 1863-1886. https://doi.org/10.1016/j.jbankfin.2006.12.005.

Moskowit, T.J., and Grinblatt, M., (1999). Do Industries Explain Momentum?. Journal of Finance, 54: 1249-1290. https://doi.org/10.1111/0022-1082.00146.

Moskowitz, T.J., Ooi and Pedersen, L.H., (2012). Time-Series Momentum, Journal of Financial Economics, 104: 228-120. https://doi.org/10.1016/j.jfineco.2011.11.003

Mulvey, L., and Kim, W.C., (2008). Role of Alternative Assets in Portfolio Construction. Encyclopedia of Quantitative Risk Analysis and Assessment. https://doi.org/10.1002/9781118445112.stat03737.

Nayak, S. (2010). "Investor Sentiment and Corporate Bond Yield Spreads." Review of Behavioural Finance 2 (2): 59–80. doi:10.1108/19405979201000004

Ni, Z., Wang, D. and Xue, W., (2015). Investor sentiment and its nonlinear effect on stock returns-New evidence from the Chinese stock market based on panel quantile regression model. Economic Modelling, 50: 266-274. http://dx.doi.org/10.1016/j.econmod.2015.07.007.

Novy-Marx, R., (2012). Is momentum really momentum?. Journal of Financial Economics, 103: 429-453. https://doi.org/10.1016/j.jfineco.2011.05.003.

Okunev, J., White, D., (2003). Do momentum-based strategies still work in foreign currency markets?. Journal of Financial and Quantitative Analysis. 38: 425-448. https://doi.org/10.2307/4126758.

O'Neal, E., (2000). Industry Momentum and Sector Mutual Funds. Financial Analysts Journal, 56 (4): 37-49, https://doi.org/10.2469/faj.v56.n4.2372.

Pan, M.S., Liano K., and Huang G.C., (2004). Industry momentum strategies and autocorrelations in stock returns. Journal of Empirical Finance, 11: 185–202. http://doi.org/10.1016/j.jempfin.2003.02.001.

Poterba, J., and Summers, L., (1988). Mean Reversion in Stock Prices: Evidence and Implications. Journal of Financial Economics, 22: 25-79. https://doi.org/10.1016/0304-405X(88)90021-9.

Qiu, L. X., and I. Welch. (2006). “Investor Sentiment Measures.” SSRN Electronic Journal. doi:10.2139/ssrn.589641.

Reutter, M., Weizsäcker, J. V., & Westermann, F. (2002). SeptemBear - A seasonality puzzle in the German stock index DAX. Applied Financial Economics, 12 (11), 765–769. http://doi.org/10.1080/09603100110037504

Ross, A.S., (1989). Information and Volatility: The No-Arbitrage Martingale Approach to Timing and Resolution Irrelevancy. The Journal of Finance, 44 (1): 1-17. https://doi.org/10.1111/j.1540-6261.1989.tb02401.x.

Rouwenhorst, K.G., (1998). International Momentum Strategies. Journal of Finance, 53 (1): 267-284. http://doi.org/10.1111/0022-1082.95722.

Sadka R., (2006). Momentum and post-earnings-announcement drift anomalies: The role of liquidity risk. Journal of Financial Economics, 80 (2): 309-349. https://doi.org/10.1016/j.jfineco.2005.04.005.

Sagi, J.G., and Seasholes, M.S., (2007), Firm-specific Attributes and the Cross section of Momentum. Journal of Financial Economics 84 (2): 389-434. https://doi.org/10.1016/j.jfineco.2006.02.002.

Schmeling, M. (20090. “Investor Sentiment and Stock Returns: Some International Evidence.” Journal of Empirical Finance 16 (3): 394–408. doi:10.1016/j.jempfin.2009.01.002.

Shefrin, H., and Statman, M., (1985). The disposition to sell winners too early and ride losers too long: theory and evidence. Journal of Finance, 40: 777-791. https://doi.org/10.1111/j.1540-6261.1985.tb050002.x.

Shi, H., and Zhou W., (2017). Time series momentum and contrarian effects in the Chinese stock market. Physica A, 483: 309-318. http://dx.doi.org/10.1016/j.physa.2017.04.139.

Shleifer, H., and Summers, L.H., (1990). The noise trader approach to finance. Journal of Economic Perspectives, 4 (2): 19-33. https://doi.org/10.1257/jep.4.2.19.

Smales, L. (2017). The importance of fear: investor sentiment and stock market returns. Applied Economics, 49 (34): 3395–3421. http://doi.org/10.1080/00036846.2016.1259754

Solt, M. E., & Statman, M. (1988). How Useful is the Sentiment Index? Financial Analysts Journal, 44 (5): 45–55. http://doi.org/10.2469/faj.v44.n5.45

Spyrou, S. (2013). "Investor Sentiment and Yield Spread Determinants: Evidence from European Markets." Journal of Economic Studies 40 (6): 739–762. doi:10.1108/jes-01-2012-0008.

Tian, S., Wu, E., and Wu Q., (2018). Who exacerbates the extreme swings in the Chinese stock market? International Review of Financial Analysis, 55: 50-59. http://dx.doi.org/10.1016/j.irfa.2017.10.009

Tse, Y., (2015). Momentum strategies with stock index exchange-traded funds. The North American Journal of Economics and Finance, 33: 134-148. https://doi.org/10.1016/j.najef.2015.04.003.

Tversky A., and Kahneman D., (1974), Judgment under Uncertainty: Heuristics and Biases. Science. Vol. 185, Issue 4157: 1124-1131. https://doi.org/10.1126/science.185.4157.1124.

Vayanos, D., and Woolley, P., (2013). An Institutional Theory of Momentum and Reversal, Review of Financial Studies, 26: 1087-1145. https://doi.org/10.1093/rfs/hht014.

Vieito, J. P., Wong, W.-K., & Zhu, Z.-Z. (2015). Could the global financial crisis improve the performance of the G7 stocks markets? Applied Economics, 48 (12), 1066–1080. http://doi.org/10.1080/00036846.2015.1093083

Wang, Y.-H., Keswani, A., & Taylor, S. J. (2006). The relationships between sentiment, returns and volatility. International Journal of Forecasting, 22 (1), 109–123. http://doi.org/10.1016/j.ijforecast.2005.04.019

Wang, P., and Xu, L., (2012). Stock Market Bubbles and Unemployment. SSRN Electronic Journal. https://doi.org/10.1007/s00199-015-0906-7

Wang, S., Xu, K., and Zhang, H., (2019). A microstructure study of circuit breakers in the Chinese stock markets. Pacific-Basin Finance Journal, 57: 101-174. https://doi.org/10.1016/j.pacfin.2019.101174.

Watkins, B., (2003). Riding the wave of sentiment: an analysis of return consistency as a predictor of future returns. Journal of Behavioral Financial, 4: 191-200. https://doi.org/10.1207/s15427579jpfm0404 _2

Wu, H., Ma, C., and Yue S., (2017). Momentum in strategic asset allocation. International Review of Economics and Finance, 47: 115-127. http://dx.doi.org/10.1016/j.iref.2016.10.009.

Yang, D. and Zhang, Q., (2000). Drift-independent volatility estimation based on high, low, open, and close prices. Journal of Business. 73 (3): 477-491.

Yin, L., and Wei, Y., (2020). Aggregate profit instability and time variations in momentum returns: Evidence from China. Pacific-Basin Finance Journal, 60. https://doi.org/10.1016/j.pacfin.2020.101276.

Zhang, B., (2020). T+1 trading mechanism causes negative overnight return. Economic Modelling, 89: 55-71. https://doi.org/10.1016/j.econmod.2019.10.013.

Zhang, B., and Li, X., (2014). Has there been any change in the comovement between the Chinese and US stock markets? International Review of Economics and Finance, 29: 525-536. http://dx.doi.org/10.1016/j.iref.2013.08.001.

Zhang, Y., Ma, F., and Zhu, B., (2019). Intraday momentum and stock return predictability: Evidence from China. Economic Modelling, 76: 319-329. https://doi.org/10.1016/j.econmod.2Zhao,018.08.009.

Zhao, S., Chen, X. and Zhang, J., (2019). The systemic risk of China's stock market during the crashes in 2008 and 2015. Physica A, 520: 161-177. https://doi.org/10.1016/j.physa.2019.01.006.

Zhu, B., and Niu, F., (2016). Investor sentiment, accounting information and stock price: Evidence from China. Pacific-Basin Finance Journal, 38: 125-134. http://dx.doi.org/10.1016/j.pacfin.2016.03.010.