Vaasan yliopisto
UNIVERSITY OF VAASA

KLAUS GROBYS

Essays on Empirical Asset Pricing

ACTA WASAENSIA 316

BUSINESS ADMINISTRATION 129
ACCOUNTING AND FINANCE

Reviewers

Professor James W. Kolari
JP Morgan Chase Professor of Finance
Texas A&M University
Department of Finance
College Station, Texas 77843-4218 USA

Professor Mika Vaihekoski
Professor of Finance
Turku School of Economics
Department of Accounting and Finance
FI-20014 University of Turku

Julkaisija	Julkaisupäivämäärä
Vaasan yliopisto	Joulukuu 2014
Tekijä(t) Klaus Grobys	**Julkaisun tyyppi** Artikkeliväitöskirja
	Julkaisusarjan nimi, osan numero Acta Wasaensia, 316
Yhteystiedot Vaasa yliopisto Kauppatieteellinen tiedekunta Laskentatoimi ja rahoitus PL 700 65101 Vaasa	**ISBN** ISBN 978–952–476–574–9 (print) ISBN 978–952–476–575–6 (online)
	ISSN ISSN 0355–2667 (Acta Wasaensia 316, print) ISSN 2323–9123 (Acta Wasaensia 316, online) ISSN 1235–7871 (Acta Wasaensia. Business administration 129, print) ISSN 2323–9735 (Acta Wasaensia. Business administration 129, online)
	Sivumäärä 172 — **Kieli** Englanti

Julkaisun nimike

Esseitä arvopapereiden hinnoittelusta

Tiivistelmä

Tämä väitöskirja koostuu kuudesta esseestä, joissa tutkitaan osakkeiden hinnoittelua ja hinnoittelun säännönmukaisuuksia poikkileikkausaineiston avulla. Ensimmäisessä esseessä tutkitaan, kuinka osakemarkkinat reagoivat muutoksiin Yhdysvaltain liittovaltion budjettialijäämässä. Tutkimustulokset osoittavat, että muutokset inflaatiokorjatussa budjettialijäämässä vaikuttavat positiivisesti inflaatiokorjattuihin osaketuottoihin. Toinen essee hyödyntää näitä tuloksia ja esittelee uuden alijäämäshokkeihin perustuvan portfoliorakenteisen riskitekijän, jolla on suora yhteys makrotalouteen. Esseen tulokset osoittavat, että ehdotettu riskitekijä korreloi negatiivisesti taloussuhdanteen kanssa, tarjoten korkeita tuottoja taloussuhdanteen ollessa heikko. Kolmannen esseen tarkoituksena on syventyä momentum-anomaliaan kansainvälisillä osakemarkkinoilla. Tulokset osoittavat, että momentum-sijoitusstrategia on tuottanut tilastollisesti merkittäviä negatiivisia tuottoja viimeisimpien taantumien aikana. Merkittävä selittävä tekijä tulosten taustalla on vuonna 2007 alkanut rahoitusmarkkinakriisi ja sitä seurannut taantuma.

Neljäs ja viides essee tarkastelevat osakkeiden hinnoitteluun liittyvää idiosynkraattisen volatiliteetin anomaliaa. Neljäs essee tutkii anomaliaa kansainvälisillä osakemarkkinoilla. Empiiriset tulokset osoittavat, että idiosynkraattinen volatiliteetti on merkittävästi positiivisesti hinnoiteltu. Viides essee tarkastelee anomaliaa tilanteessa, jossa idiosynkraattinen volatiliteetti on etukäteen kontrolloitu likviditeetin, yrityksen koon sekä informaation epäsymmetrisyyden suhteen. Viides essee osoittaa vakaan linkin realisoidun idiosynkraattisen volatiliteetin sekä ns. momentum-romahdusten välillä.

Väitöskirjan viimeinen essee tutkii momentum-sijoitusstrategian ja valtioiden luottoluokituksen välistä suhdetta kansainvälisillä osakemarkkinoilla. Vaikka momentum-strategian tuotot ovat osittain selitettävissä yksittäisten valtioiden luottoluokituksilla, tutkimustulokset myös osoittavat, että kansainvälinen luottoriskiperusteinen riskitekijä ei pysty täysin selittämään momentum-strategiasta saatavia tuottoja.

Asiasanat

Arvopapereiden hinnoittelu, luottoluokitus, idiosynkraattinen volatiliteetti, liittovaltion budjetin alijäämä, momentum-anomalia

Publisher Vaasan yliopisto	**Date of publication** December 2014
Author(s) Klaus Grobys	**Type of publication** Selection of articles
	Name and number of series Acta Wasaensia, 316
Contact information University of Vaasa Faculty of Business Studies Accounting and Finance P.O. Box 700 FI-65101 Vaasa, Finland	**ISBN** ISBN 978–952–476–574–9 (print) ISBN 978–952–476–575–6 (online)
	ISSN ISSN 0355–2667 (Acta Wasaensia 316, print) ISSN 2323–9123 (Acta Wasaensia 316, online) ISSN 1235–7871 (Acta Wasaensia. Business administration 129, print) ISSN 2323–9735 (Acta Wasaensia. Business administration 129, online)
	Number of pages 172 — **Language** English

Title of publication

Essays on Empirical Asset Pricing

Abstract

This thesis examines cross-sectional patterns in equity returns and consists of six essays. The first essay tests whether changes in the US federal budget deficit affect stock market returns. The results suggest a positive impact from shocks in the real budget deficit to real stock market returns. Building on this result, the second essay proposes a new portfolio-based risk factor based on impulse responses from equity portfolios to changes in the US federal budget deficit. The proposed risk factor is directly linked to the macroeconomy. The results show that the new proposed risk factor is negatively correlated with the business cycle generating high payoffs when the economy is in unfavorable states. The third essay aims to deepen the understanding of the momentum anomaly in global equity markets. The findings indicate that momentum-based trading strategies in a global equity market setting generated statistically significant negative returns during the most recent recessions, whereas the severe recession of December 2007–June 2009 is the major driver of the results.

The fourth and fifth essays shed new light on the idiosyncratic volatility puzzle. The fourth essay examines this anomaly in a global equity market setting. Empirical evidence suggests that idiosyncratic volatility is significantly positively priced in the cross-section of global equity markets. The fifth essay examines this relationship in a scenario where the level of idiosyncratic volatility is ex ante controlled for liquidity, size and information asymmetry. This essay establishes a robust link between realized idiosyncratic volatility and momentum crashes.

Finally, the last essay studies the link between momentum-based trading strategies implemented in global equity markets and country-specific credit ratings. Even though momentum profits tend to be associated with country-specific credit ratings, the regression analysis reveals that a world credit risk factor cannot fully explain the momentum profits.

Keywords

Asset pricing, Credit rating, Idiosyncratic volatility, Federal budget deficit, Momentum anomaly, Momentum crash

ACKNOWLEDGEMENTS

I started my PhD studies in the winter of 2012. Before entering academia, I worked as an analyst in the financial industry under a considerably high workload. As I was used to working, I had hardly any problems adapting to the notably high workload that a doctoral student typically meets when starting the coursework associated with PhD studies. I moved from Stockholm to Vaasa on November 9, 2012, and my first lecture in Helsinki was on November 12, 2012. About two weeks before this, I met Professor Sami Vähämaa the first time.

At the end of October 2012, I decided to visit my friend Toni in Vaasa. During my one-week stay in Finland, Toni persuaded me to apply for doctoral studies at the University of Vaasa. So, on October 21, 2012, three days before I left Vaasa, I sent the following e-mail to Professor Jussi Nikkinen: "I am currently visiting a friend of mine here in Vaasa. If you have time tomorrow, in the afternoon, for instance, I could come in for an informal meeting…On Wednesday, I have to fly back to Stockholm though." On October 23, I received the following e-mail from Professor Sami Vähämaa: "Dear Klaus, Jussi forwarded your e-mail to me. You may come to talk with me briefly today. I'll be at my office between 1-2 pm. Best wishes, Sami Vähämaa." The problem was that it was about 1.15 pm when I read this e-mail because Toni and I had been at the gym. So, one can imagine how we had to hurry so that I could make it in time to meet Professor Sami Vähämaa before 2 pm. It was about quarter to 2 pm when I knocked on his office door the first time. I guess I left a relatively good impression because on November 3, I received the desired reply from Professor Sami Vähämaa: "… you can start preparing for a move to Vaasa. I'll contact the Graduate School of Finance on Monday and inform them that you are attending the course which starts on Nov 14." He even prepared an employment contract for me so that I had initial funding for my studies. This was the starting point that changed my life.

It has become extremely difficult to enter academia because the competition among applicants has dramatically increased in the last decade. I am especially grateful to Sami for both giving me the opportunity to do my PhD studies in Finland at the University of Vaasa and for acting as my supervisor. I hope that I managed to live up to your expectations.

Special acknowledgement is owed to the pre-examiners of this dissertation, Professor James Kolari from Texas A&M University and Professor Mika Vaihekoski from Turku School of Economics. Their insightful and detailed comments improved this dissertation and provided good ideas for future research.

Empirical asset pricing was the first doctoral course that I was to attend at the Graduate School of Finance (GSF) in Helsinki. One part of the course was taught by Dr. Peter Nyberg, who is an Assistant Professor at the Aalto University School of Business. Azer (2005, p.69), who investigated how people acquire the qualities necessary to become good teachers concluded: "Excellent teachers serve as role models, influence career choices, and enable students to reach their potential."

That is why I wish to thank Dr. Peter Nyberg, who is not only an extraordinary talented academic lecturer but who also inspired me to do research on empirical asset pricing.

I want to emphasize that the Department of Accounting and Finance at the University of Vaasa offers an excellent working environment. I wish to thank all of my colleagues in the Department for both having a large role in making it fun to come to work and for providing me with useful comments on my papers. From the Department of Mathematics and Statistics, I am grateful to Professor Seppo Pynnönen and Dr. Bernd Pape for giving me useful comments and advice on my papers.

I also want to thank Dr. Mikko Leppämäki, who is the director of GSF, for both establishing a doctoral program of the highest standards and for accepting me as a GSF Fellow from January 2013 onwards. The doctoral courses taught at the GSF built the cornerstone of my acquired knowledge, enabling me to do research in finance. Dr. Mikko Leppämäki also organized national and Nordic workshops, where I received valuable comments on my papers. Perhaps unsurprisingly, Dr. Peter Nyberg has regularly acted as discussant for my research papers, and I am most grateful for his input to date.

I also want to thank Professor Janne Äijö. When I entered the second year of my PhD studies, Janne offered me the opportunity to establish, introduce and teach a new Master's-level course in finance: Advanced Topics in Finance – Quantitative Financial Data Analysis in Matlab. It was the first time that such a course in which Master's students learned coding in a matrix-based language applied to financial questions had been offered at the University of Vaasa. I very much appreciate Professor Äijö's faith in me and my skills, and I hope that I managed to live up to his expectations.

During my doctoral studies, I received financial support for my research projects from OP-Pohjola Group Research Foundation and the Ella and Georg Ehrnrooth Foundation. I wish to thank for the generous funding of these two foundations. I also do not want to forget to thank the GSF for proving me further funding during the first year of my PhD studies.

Last but not least, I wish to thank my friends and family. In particular, I wish to thank my friend Toni Lehtimäki. Not only did Toni encourage me to apply to the doctoral studies program at the University of Vaasa, but he also allowed me to stay at his place for a couple of months after I was admitted to the university, which enabled me to fully focus on my initial doctoral courses. He has always provided me with support and valuable advice with respect to all aspects of life, whenever needed.

Finally, and most significantly, I want to thank my parents, Klaus and Karola, for always being there for me, providing me with love, affection, and encouragement.

Even in my early childhood, you taught me the value of education and the importance of moral and virtues.

Vaasa, November 2014

Klaus Grobys

Contents

This thesis consists of an introductory chapter and the following six essays:

1. Grobys, K. (2013). An empirical analysis of changes of the impact of federal budget deficits on stock market returns: Evidence from the US economy. *Applied Economics Letters* 20, 921-924.

2. Grobys, K. (2013). Returns to public debt: The US federal budget deficit and the cross-section of equity returns. Proceedings of the 3rd Auckland Finance Meeting 2013.

3. Grobys, K. (2014). Momentum in global equity markets in times of troubles: Does the economic state matter? *Economics Letters* 123, 100-103.

4. Grobys, K. (2014). Idiosyncratic volatility and global equity markets, *Applied Economics Letters* (forthcoming).

5. Grobys, K. (2014). Idiosyncratic volatility and momentum crashes. Working paper, University of Vaasa.

6. Grobys, K. (2014). Momentum, sovereign credit ratings and global equity markets, *Applied Economics Letters* (forthcoming).

1 INTRODUCTION

The behavior of asset prices is crucial to many key decisions, not only for institutional investors but also for most people in their daily lives. The choice between saving in the form of cash, bonds or stocks, for instance depends, on the investor's expectation of the risks and returns associated with these different forms of saving. Asset prices are also of fundamental importance for the macroeconomy as they provide essential information for key economic decisions concerning physical investments and consumption. Given the important role of asset prices in many decisions, one key question in financial economics is how to assign the correct value to an asset that pays off a stream of uncertain future cash flows. The most intuitive solution appears to be simple: The price or present value of any asset today should be equal to the expected discounted value of its corresponding future cash flows. Different approaches on how to assess the correct present value of assets have been discussed in the finance literature and referred to as discounted cash flow models. The discount rate used in these models is typically a weighted average cost of capital that reflects the risk of the future pay offs. Apart from the risk-free rate, the discount rate also incorporates the individual risk premium of an asset that investors demand because they want to be compensated for the individual cash flow risk. Consequently, assets that have riskier pay offs should have a lower price than similar assets that have less risky pay offs, simply because investors command a higher risk premium for more risky assets. In the theoretical equilibrium then, asset prices should clear the market. Hence, uncovering the interdependence of risk and return is a central issue in financial research.

Fundamental asset pricing theory derives asset prices via the maximization problem of a representative investor's utility. As a result, asset pricing theory implies that only consumption matters: Consumption is low when marginal utility is high and high when marginal utility is low. Cochrane (2005, p.41) points out: "The consumption-based model is, in principle, a complete answer to all asset pricing questions […]." In a standard consumption-based asset pricing model of type studied by Lucas (1978), Shiller (1981) and Hansen and Singleton (1983), the quantity of stock market risk is measured by the covariance of the excess stock return with the consumption growth, whereas the price of risk is the coefficient of relative risk aversion of the representative investor. However, consumption-based asset pricing models face some severe problems: the high average stock return and low riskless interest rate imply that the expected excess return on stock, the equity premium, is high. The smoothness of consumption, however, makes the covariance of stock returns with consumption low. As a result, the equity premium could only be explained by an unreasonably high coefficient of risk aversion. The empirical fact that the average real stock return was so high in relation to the real interest rate has been referred to as an “equity premium puzzle” by Mehra and Prescott (1985, p.158). Since the standard model struggles to explain asset pricing phenomena such as the high ratio of equity premium to the standard deviation of stock returns simultaneously with stable aggregate consumption growth, for instance, proxies for consumption risk are plausible alternatives in empirical asset pricing tests, as pointed out in Savov (2011).[1] Consequently, a key topic in empirical asset pricing research is to explore which variables could act as proxies for consumption risk.

The step from theoretically motivated consumption-based asset pricing models to the well-known capital asset pricing model (CAPM) as elucidated by Sharpe (1964) and Lintner (1965) appears to be straight forward: The CAPM can be derived by the consumption-based capital asset pricing model if the assumption is made that the return on the market portfolio of all risky assets is perfectly negatively correlated with the marginal utility of consumption.[2] Fama and French (2003, p.1) state: “The capital asset pricing model (CAPM) of William Sharpe (1964) and John Lintner (1965) marks the birth of asset pricing theory (resulting in a Nobel Prize for Sharpe in 1990). Before their breakthrough, there were no asset pricing models built from first principles about the nature of tastes and investment opportunities and with clear testable predictions about risk and return. Four decades later, the CAPM is still widely used in applications, such as estimating the cost of equity capital for firms and evaluating the performance of managed portfolios. And it is the centerpiece, indeed often the only asset pricing model taught in MBA level investment courses.”

The CAPM, in turn, has some important implications. First, investors always combine the risk free asset with the market portfolio of risky assets. Second, investors will be compensated only for the risk that they cannot diversify, referred to as systematic risk or market risk. The risk associated with an asset is measured by its individual beta which is the ratio of covariance between the asset’s returns divided by the market variance. Third, investors can expect returns from their investment that are in line with the corresponding risk implying a linear relationship between the asset’s expected return and its beta. Although an elegant theoretical contribution, the empirical performance of the CAPM has been rather poor

---

1 Other empirical outcomes that the standard consumption-based model cannot explain are the high level and volatility of the stock market, the low and comparatively stable interest rates, the cross-sectional variation in expected portfolio returns, and the predictability of excess stock market returns over medium to long-horizons.

2 Note that the derivation of the CAPM in a consumption-based capital asset pricing model implies a one-period model set-up.

because of its failure in explaining many cross-sectional patterns in assets. For instance, Banz (1981) examined the relationship between the total market value of the common stock of a firm and its return. His results show that in the 1936-1975 period, the common stock of small firms had, on average, higher risk-adjusted returns than the common stock of large firms. This finding is also referred to as the *size effect* or *size anomaly*. As another example, Basu (1977) explored the relationship between the investment performance of equity securities and their price-to-earnings (P/E) ratios. His results indicated that in the 1957-1971 period, the low P/E portfolios earned on average higher absolute and risk-adjusted rates of returns than the high P/E securities. Finally, Fama and French (1992, p.464), who essentially consolidated the findings of Banz (1981) and Basu (1977), ended the era of the CAPM by stating: "We are forced to conclude that the SLB model does not describe the last 50 years of average stock returns."[3]

In the wake of the seminal paper by Fama and French (1992), empirical asset pricing research attempted to uncover the underlying fundamental risk sources of the *size anomaly* and *value anomaly*. Another wide strand of empirical asset pricing literature documented other types of anomalies. For instance, Jegadeesh and Titman (1993) explored trading strategies that buy past winners and sell past losers. Their results show that in the 1965-1989 period, selling stocks that had the lowest cumulative returns over the prior 3-12 month period and buying stocks that had the highest cumulative returns over the prior 3-12 month period yielded significant profits. For instance, a strategy that selects stocks based on the past six months' returns and holds them for six months realizes a compound excess return of 12.01% per year on average. Jegadeesh and Titman (1993, p.89) also stated: "Additional evidence indicates that the profitability of the relative strength strategies are not due to their systematic risk." This result led to a considerable stream of literature focused on revealing what drives the so-called *momentum anomaly*. Nyberg and Pöyry (2013), who explored the association between firm-level asset changes and return momentum emphasize that few stock market anomalies, have received as much attention among researchers as the momentum effect first documented by Jegadeesh and Titman (1993). Even almost two decades after its initial discovery, the momentum anomaly remains an intellectual curiosity. Momentum-based trading is a simple strategy that buys stocks with the highest returns over the past three to 12 months and sells stocks with lowest returns over the same horizon produces profits that remain large after standard adjustments of risk. The persistence of the momentum effect may justify the abundance of theoretical

---

[3] Fama and French (1992) use the term SLB as an abbreviation for the Sharpe (1964), Lintner (1965) and Black (1972) model which corresponds to the CAPM

and empirical research that has been directed at uncovering the underlying drivers for the large payoffs from the trading strategy.

More recent cross-sectional anomalies that have been intensively discussed in the empirical asset pricing literature are, among others, the *asset growth anomaly* as documented in Cooper et al. (2008), the *credit risk anomaly* in line with Avramov et al. (2007, 2009, 2013) and Campbell et al. (2008), and the *idiosyncratic volatility anomaly* as documented first by Ang et al. (2006).[4] While one strand of finance research is focused on determining new cross-sectional patterns in asset returns, another strand of follow-up literature attempts to explain these phenomena. All these anomalies have in common that they cannot be explained by traditional empirical asset pricing models such as the CAPM.

The empirical fact that many cross-sectional patterns in security returns cannot be explained by traditional asset pricing models, such as the CAPM, motivated a notable body of research that introduced new asset pricing models. For instance, only one year after ending the era of the CAPM, Fama and French (1993) proposed a three-factor asset pricing model by adding size and value factors in addition to the market risk factor in the CAPM.[5] Carhart (1997) argued for the addition of the momentum factor, based upon the momentum effect documented first by Jegadeesh and Titman (1993), to the Fama and French three-factor model. This model, often referred to as the Carhart four-factor model or the Fama and French four factor model, acted and still acts alongside the Fama and French three-factor model as a benchmark model in empirical asset pricing research. In a more recent study, Novy-Marx (2013) proposed a new four-factor model that incorporates the

---

[4] Cooper et al. (2008) investigated the cross-sectional relation between firm asset growth and subsequent stock returns. Their results indicated that in the 1968-2003 period, firms with low asset growth rates earned subsequent annualized risk-adjusted returns of 9.1% on average, while firms with high asset growth rates earned -10.4%. The large pay off differential of 19.5% per year is highly significant.
Furthermore, Avramov et al. (2007, 2009, 2013) and Campbell et al. (2008) asserted that firms exhibiting a high credit risk generate statistically lower returns compared to firms having a low credit risk. This cross-sectional effect is often referred to as the *credit risk anomaly* or *credit risk puzzle*.
Ang et al. (2006) examined the pricing of aggregate volatility risk in the cross-section of stock returns. Their results showed that in the 1963-2000 period, the portfolio of stocks with the highest idiosyncratic volatility earned significantly lower returns than the portfolio of stocks with the lowest idiosyncratic volatility. The cross-sectional price of idiosyncratic volatility risk is estimated at about -1% per month and robust to controlling for size, value, momentum, and liquidity effects.

[5] The size factor is the average return on the three small portfolios minus the average return on the three big portfolios, whereas the value factor is the average return on the two value portfolios minus the average return on the two growth portfolios.

market factor, industry-adjusted value and momentum factors as well as a gross profitability factor. His results indicated that in the 1973-2010 period, his new four-factor model appeared to perform better than the Fama and French four-factor model pricing a wide range of anomalies. Again, Fama and French (2014) consolidated their three-factor model with the profitability effect identified by Novy-Marx (2013) and proposed a five-factor model by adding profitability and investment factors to their former three-factor benchmark model.

Although elegant empirical contributions, all proposed asset pricing models mentioned above lack theoretical foundations. It is still an open question as to what fundamental risk sources, if any, these empirically motivated risk factors are proxying for. For example, to rationalize the momentum factor incorporating a zero-cost strategy of a portfolio that is long on stocks that generated the highest cumulative returns over the last 12-month period and short on stocks that generated the lowest cumulative returns over the same period, it would follow that this zero-cost strategy tends to perform poorly in some states of nature that the investors consider to be particularly bad. Following Lucas (1978) and Breeden (1979), in order to be a valid measure of the state of nature, a variable should be a function of the growth rate of consumption.

The ongoing challenge for empirical asset pricing research is to find some theoretically motivated proxy for the state of nature that captures the riskiness of the cash flow patterns in the cross-section of security returns and, though this, can provide an explanation for the well-documented differences in expected returns.

This doctoral thesis, *Essays on Empirical Asset Pricing*, is positioned within the general empirical asset pricing framework. The first essay in this thesis tests whether changes in the US federal budget deficit affect stock market returns. The US federal budget deficit is a key macroeconomic variable in the US and has increased continuously for several decades. In the wake of the downgrading of the US economy, the US federal budget deficit and its impact on domestic macroeconomic variables have generated a great deal of public attention. The second essay makes use of the findings of the first essay and constructs a portfolio-based risk factor based upon impulse responses from equity portfolios to changes in the US federal budget deficit. Consequently, the proposed risk factor is directly linked to the macroeconomy and, thus, is economically motivated. The third essay aims to deepen the understanding of the momentum anomaly in global equity markets and extends the studies of Daniel and Moskowitz (2013) and Novy-Marx (2012). The fourth and fifth essays shed new light on the puzzle that was documented by Ang et al. (2006, 2009): when realized idiosyncratic volatility for individual stocks is estimated relative to the Fama and French three-factor model, the measured quantity of idiosyncratic risk has an apparently negative relationship with the cross-section of stock returns in the following period. While the fourth essay examines this apparent anomaly in a global equity market setting, the fifth essay examines this relationship in a scenario where the level of idiosyncratic volatility is ex ante controlled for liquidity, size, and information asymmetry. Finally, the last essay extends Avramov et al.'s (2007, 2012) studies and investigates the link between momentum-based trading strategies implemented in global equity markets and country-specific credit ratings.

The remainder of the introduction to the thesis proceeds as follows. Section two presents a brief overview of relevant asset pricing theory, and the next section briefly discusses the six essays and their contribution to the literature. The last section concludes.

2 A BRIEF OVERVIEW OF ASSET PRICING THEORY

2.1 Good states and bad states: The link between consumption and investment decisions

Let us initially assume that each individual has to choose a consumption process $c = (c_t)_{t\in\tau}$ where $\tau = \{0,1,\dots,T\}$ and c_t denote the random or state-dependent consumption at time *t*.[6] Moreover, the individual has to choose a trading strategy $\boldsymbol{\theta} = (\boldsymbol{\theta_t})_{t=0,1,\dots,T-1}$, where $\boldsymbol{\theta_t}$ represents the portfolio held from time *t* until *t*+1. The trading strategy $\boldsymbol{\theta_t}$ is an *I*-dimensional adapted stochastic process $\theta_t = (\theta_{1t},\dots,\theta_{It})^T$ depending on the information available to the individual at time *t*. Let us also assume that the individual has an income process $e = (e_t)_{t\in\tau}$, where e_0 denotes the initial wealth and e_t is the possible state-dependent income obtained at time *t*. A trading strategy $\boldsymbol{\theta}$ generates a dividend process D^{θ}. Immediately before time *t*, the portfolio is given by θ_{t-1} and thus the investor obtains the dividends $\boldsymbol{\theta_{t-1}D_t}$ at time *t*. The investor then immediately rebalances the portfolio to $\boldsymbol{\theta_t}$ after time *t*. The net gain D_t^{θ} at time *t* is then given by,

$$D_t^{\theta} = \boldsymbol{\theta_{t-1}D_t} - (\boldsymbol{\theta_t} - \boldsymbol{\theta_{t-1}})\boldsymbol{P_t} = \boldsymbol{\theta_{t-1}}(\boldsymbol{P_t} + \boldsymbol{D_t}) - \boldsymbol{\theta_t P_t}, \tag{1}$$

where $\boldsymbol{P_t}$ and $\boldsymbol{D_t}$ denote the price and dividend vectors of the assets at time *t*. Furthermore, let us assume for simplicity that a representative individual has a time-additive expected utility function $u(.)$, where it is typically assumed that $u(.)$ is concave. At time 0, therefore, the individual faces therefore the general maximization problem:

$$\max_{\theta} u(c_0) + \textstyle\sum_{t=1}^{T} e^{-\delta t} E[u(c_t)] \tag{2a}$$

$$s.t.\;\; c_0 \le e_0 - \boldsymbol{\theta_0 P_0},\;\text{ and }\; c_t \le e_t + D_t^{\theta},\;\text{ where} \tag{2b}$$

---

[6] The following examples are based on chapters 3, 6 and 8 in Munk (2013).

$t = 1, \dots, T$, and $c_0, c_1, \dots, c_T \geq 0$.

The parameter δ in Equation (2a) denotes the time preference rate of the individual, which is typically assumed to be less than one, implying that the individual prefers to consume sooner rather than later. Using Equation (1), the constraint on time *t* consumption, given by Equation (2b), can be written as

$$c_t \leq e_t + \boldsymbol{\theta_{t-1}}(\boldsymbol{P_t} + \boldsymbol{D_t}) - \boldsymbol{\theta_t P_t} \tag{2c}$$

Furthermore, it is assumed that the non-negativity constraint on consumption is automatically satisfied and that the budget constraints hold as equalities. The problem of Equations (2a)-(2c) can then be formulated as

$$\max_\theta u(e_0 - \boldsymbol{\theta_0 P_0}) + \sum_{t=1}^{T} e^{-\delta t} E[u(e_t + \boldsymbol{\theta_{t-1}}(\boldsymbol{P_t} + \boldsymbol{D_t}) - \boldsymbol{\theta_t P_t})] \tag{3}$$

The only term involving in the initially chosen portfolio $\theta_0 = (\theta_{10}, \dots, \theta_{I0})^T$ will thus be given by

$$u(e_0 - \boldsymbol{\theta_0 P_0}) + e^{-\delta t} E[u(e_1 + \boldsymbol{\theta_0}(\boldsymbol{P_1} + \boldsymbol{D_1}) - \boldsymbol{\theta_1 P_1})].$$

The first-order conditions with respect to θ_{i0} and θ_{it} imply that

$$P_{i0} = E\left[e^{-\delta} \frac{u'(c_1)}{u'(c_0)}(P_{i1} + D_{i1})\right], \text{ and}$$

$$P_{it} = E\left[e^{-\delta} \frac{u'(c_{t+1})}{u'(c_t)}(P_{it+1} + D_{it+1})\right]. \tag{4}$$

The terms c_t and c_{t+1} in Equation (4) denote the optimal consumption rates of the individual. Moreover, the stochastic discount factor $\zeta = (\zeta_t)_{t\epsilon\tau}$ from the individual's optimal consumption process can be defined with $\zeta_0 = 1$ and

$$\frac{\zeta_{t+1}}{\zeta_t} = \frac{e^{-\delta}u'(c_{t+1})}{u'(c_t)}, \text{ where} \tag{5}$$

$$\zeta_t = \frac{\zeta_t}{\zeta_{t-1}}\frac{\zeta_{t-1}}{\zeta_{t-2}}\dots\frac{\zeta_1}{\zeta_0}$$

$$= e^{-\delta}\,\frac{u'(c_t)}{u'(c_{t-1})}\; e^{-\delta}\,\frac{u'(c_{t-1})}{u'(c_{t-2})}\dots e^{-\delta}\,\frac{u'(c_1)}{u'(c_0)}$$

$$= e^{-\delta t}\,\frac{u'(c_t)}{u'(c_0)}. \tag{6}$$

Equation (6) defines the full stochastic discount factor process, whereas Equation (5) defines the stochastic discount factor over a single period. Equations (5) and (6) show that the stochastic discount factor ζ_t, the random variable determining the expected returns on assets, has the theoretical interpretation as the intertemporal rate of substitution (IMRS). Since $u(.)$ is a concave function, the marginal utility $u'(.)$ is high when the underlying consumption is low. That means that when the economy is in a bad state (typically characterized by low aggregate consumption), marginal utilities tend to be high, whereas the reverse arguments should hold for periods when the economy is in a good state. In periods when the economy is weak, investors value an extra payoff more than they would when marginal utilities are lower. It follows that financial assets that generate high payoffs in economic times where the marginal utility of an investor is high will be more attractive to the investor than assets that tend to generate these payoffs when marginal utilities are low. Therefore, assets that generate high payoffs in good economic times must provide higher expected returns to persuade investors to include them in their portfolios.

The consumption-based asset pricing theory, as invented by Rubinstein (1976), Lucas (1978) and Breeden (1979), is the cornerstone of modern asset pricing and links stochastic discount factors to the optimal consumption and investment decisions of individuals. Apart from time-additive expected utility functions, other types of utility functions, such as Habit formation utilities, have been discussed in the literature.[7] However, the expression in Equation (6) is very general and Munk (2013) shows that this equation also holds in a continuous-time framework. What has asset pricing theory to tell us how individual assets are priced?

2.2 Fundamental asset pricing theory: What sources of risks drive expected returns?

Let us consider the most general setting in a continuous-time framework where the stochastic discount factor process is given, as in Equation (6), by

$$= e^{-\delta t} \frac{u'(c_t)}{u'(c_0)}. \tag{7}$$

Furthermore, let the general dynamics of consumption, the stochastic discount factor, and an individual asset be given by the stochastic processes

$$dc_t = c_t[\mu_{ct} dt + \boldsymbol{\sigma}_{ct}^T d\boldsymbol{z}_t], \tag{8}$$

$$d\zeta_t = -\zeta_t\left[r_t^f dt + \boldsymbol{\lambda}_t^T d\boldsymbol{z}_t\right], \tag{9}$$

$$\mu_{it} + \delta_{it} - r_t^f = \boldsymbol{\sigma}_{it}^T \boldsymbol{\lambda}_t, \tag{10}$$

where in Equation (8) μ_{ct} is the expected relative growth rate of consumption and $\boldsymbol{\sigma}_{ct}$ is the vector of sensitivities of consumption growth to the exogenous shocks to the economy, whereas the variance of relative consumption growth may be

[7] For a detailed overview, see chapter 6 and 8 in Munk (2013).

given by $\|\boldsymbol{\sigma}_{ct}\|^2$. In Equations (9) and (10), μ_{it} is the expected capital gain of asset *i* at time *t*, δ_{it} denotes the dividend of asset *i* at time *t*, r_t^f is the risk-free rate and $\boldsymbol{\sigma}_{it}^T\boldsymbol{\lambda}_t$ measures the covariance between asset i and the stochastic discount factor, whereas $\boldsymbol{\lambda}_t$ denotes the market price of risk measuring the volatility dynamics of the stochastic discount factor or pricing kernel, respectively.

Given the dynamics of the consumption and the definition in Equation (7), the dynamics of ζ_t can be obtained by an application of Itô's Lemma on the function $f(t,c) = e^{-\delta t}u'(c)/u'(c_0)$. The relevant derivatives are

$$\frac{\partial f}{\partial t}(t,c) = -\delta e^{-\delta t}\frac{u'(c)}{u'(c_0)},\ \frac{\partial f}{\partial c}(t,c) = e^{-\delta t}\frac{u''(c)}{u'(c_0)},\ \frac{\partial^2 f}{\partial c^2}(t,c) = e^{-\delta t}\frac{u'''(c)}{u'(c_0)},$$

which implies that

$$\frac{\partial f}{\partial t}(t,c_t) = -\delta e^{-\delta t}\frac{u'(c_t)}{u'(c_0)} = -\delta\zeta_t, \tag{11}$$

$$\frac{\partial f}{\partial c}(t,c_t) = e^{-\delta t}\frac{u''(c_t)}{u'(c_0)} = \frac{u''(c_t)}{u'(c_t)}\zeta_t = -v(c_t)c_t^{-1}\zeta_t, \tag{12}$$

$$\frac{\partial f}{\partial c^2}(t,c_t) = e^{-\delta t}\frac{u'''(c_t)}{u'(c_0)} = \frac{u'''(c_t)}{u'(c_t)}\zeta_t = \kappa(c_t)c_t^{-2}\zeta_t, \tag{13}$$

where the term $v(c_t) = -c_t u''(c_t)/u'(c_t)$ denotes the relative risk aversion of the individual, and where the term $\kappa(c_t) = c_t^2 u'''(c_t)/u'(c_t)$ is positive under the assumption that the absolute risk aversion of the individual is decreasing in the level of consumption. Therefore, the dynamics of the stochastic discount factor can be expressed as

$$d\zeta_t = -\zeta_t\left[\left(\delta + v(c_t)\mu_{ct} - \tfrac{1}{2}\kappa(c_t)\|\boldsymbol{\sigma}_{ct}\|^2\right)dt + v(c_t)\boldsymbol{\sigma}_{ct}^T d\boldsymbol{z}_t\right]. \tag{14}$$

Comparing Equation (14) with (9), it becomes that evident that

$$r_t^f = \delta + v(c_t)\mu_{ct} - \tfrac{1}{2}\kappa(c_t)\|\boldsymbol{\sigma}_{ct}\|^2, \tag{15}$$

$$\boldsymbol{\lambda}_t = v(c_t)\boldsymbol{\sigma}_{ct}^T, \text{ and} \tag{16}$$

$$\mu_{it} + \delta_{it} - r_t^f = v(c_t)\boldsymbol{\sigma}_{it}^T\boldsymbol{\sigma}_{ct} = v(c_t)\rho_{ict}\|\boldsymbol{\sigma}_{it}\|\|\boldsymbol{\sigma}_{ct}\|. \tag{17}$$

The fundamental economic implications of Equations (15)-(17) are the cornerstone for modern asset pricing theory. Equation (16) defines the market price of risk process, whereas Equation (15) gives the interest rate at which the market will clear. The short-term interest rate is determined by the individuals time preference rate δ, the expected growth rate of consumption μ_{ct} and the variance of aggregate consumption growth. This implies that when people in the economy are impatient and have a high demand for current consumption (δ is high), the equilibrium interest rate must be high so that the individuals have incentives to save now. Because $v(c_t)$, which measures the relative risk aversion of the representative individual, is positive, higher expected growth in aggregate consumption increases the equilibrium interest rate. As individuals expect higher future consumption, and, as a result, lower future marginal utility, savings or postponed consumption, respectively, have lower value. Hence, a higher return on savings is required to maintain market clearing.

Furthermore, $u'''(.)$ is typically assumed to be positive, which means that the representative individual has decreasing absolute risk aversion. This implies, however, that higher uncertainty about future consumption requires a lower return from the risk-free asset because individuals will appreciate secure payoffs, and, hence, a lower risk-free rate is required to clear the market. In particular, Equation (17) shows that the excess rate of return on asset *i* over the instant following time *t* is driven by $\boldsymbol{\sigma}_{it}^T\boldsymbol{\sigma}_{ct}$ or ρ_{ict}, which are the covariance and correlation respectively between the rate of return on asset *i* and the consumption growth rate, whereas $\|\boldsymbol{\sigma}_{it}\|$ and $\|\boldsymbol{\sigma}_{ct}\|$ are the volatilities of the rate of return on asset *i* and the consumption growth rate, respectively. From Equation (17), it follows that financial assets are priced so that the expected excess return on asset *i* is given by the product of the relative risk aversion of the representative individual and the covariance between the return of asset *i* and the growth rate of aggregate consumption. This is also one key result in the consumption-based capital asset pricing model in the spirit of Breedon (1979). As a result, the theoretical model suggests that idiosyncratic or asset-specific risk should not lead to higher expected returns but only the shared co-movement of the individual asset returns with the systematic risk factor should matter for asset pricing.

2.3 Empirical asset pricing: What variables proxy for consumption growth?

The failure of the simple consumption-based capital asset pricing model in explaining the cross-section of equity returns has been intensively discussed in the finance literature. If a simple consumption-based model is applied to the US data, the historical US equity premium is an order of magnitude greater than can be rationalized in the context of the standard neoclassical paradigm of financial economics. This so-called *equity premium puzzle* was first pointed out by Mehra and Prescott (1985). The high average stock return and low riskless interest rate imply that the expected excess return on stock, the equity premium, is high. However, the smoothness of consumption makes the covariance of stock returns with consumption low.[8] As a result, the equity premium can only be explained by an unreasonably high coefficient of risk aversion. According to Shiller (1982), Hansen and Jagannathan (1991) and Cochrane and Hansen (1992), building on the work of Rubinstein (1976), the equity premium puzzle is that an extremely volatile stochastic discount factor is required to match the ratio of the equity premium to the standard deviation of stock returns.

Due to the failure of the standard consumption-based model, a whole battery of alternative consumption-based asset pricing models have been proposed in the finance literature. For instance, Campbell and Cochrane (1999), building on the work of Abel (1990) and Constantinides (1990), have proposed a model type capturing time-variation in the price of risk, referred to as the habit formation model. Even though Campbell and Cochrane's (1999) calibrated model yields empirical-

---

[8] The empirical standard deviation of annual relative changes in aggregate consumption was about 2.0% for the US economy over the second half of the 20th century, whereas the standard deviation of the annual rate of return on the US stock market was about ten times larger.

ly reasonable levels of the expected return and volatility of stocks returns, the relative risk aversion is still unreasonably high. As emphasized in Cochrane (2005, p.41): "The consumption-based model is, in principle, a complete answer to all asset pricing questions, but works poorly in practice." Consumption-based asset pricing models typically make use of consumption growth as a stochastic discount factor that determines expected risk premiums. Unfortunately, consumption data are low frequency and too smooth. As a result, in the area of empirical asset pricing, much attention has been paid to finding proper variables capable of acting as plausible proxies for consumption risk.

The cornerstone of empirical asset pricing is the fundamental asset pricing equation that ties the return on any financial asset to the economy-wide stochastic discount factor ζ_t,

$$1 = E_t[\zeta_{t+1} R_{it+1}]. \tag{18}$$

In Equation (18), $E_t[.]$ is the conditional expectation at time t and R_{it+1} is the gross return on asset i, where $i = 1, \dots, N$. Equation (18) is referred to as the law of one price and it is the fundamental empirical asset pricing equation because it is valid irrespective of investor preferences. However, inserting Equation (7) in (18), we get

$$1 = E_t\left[e^{-\delta t}\frac{u'(c_t)}{u'(c_0)} R_{it+1}\right]. \tag{19}$$

Furthermore, because $E_t[\zeta_{t+1} R_{it+1}] = E_t[\zeta_{t+1}]E_t[R_{it+1}] + cov[\zeta_{t+1}, R_{it+1}]$, from Equation (18) it follows that

$$E_t[R_{it+1}] - R_{f,t} = -R_{f,t} cov[\zeta_{t+1}, R_{it+1}], \tag{20}$$

where the gross risk-free rate $R_{f,t}$ is defined as $R_{f,t} = 1/E_t[\zeta_{t+1}]$. Equation (20) implies that the risk premium on a financial asset is given by the negative covariance of the return on the asset with the stochastic discount factor. As a result, assets that exhibit a negative covariance with the stochastic discount factor have positive risk premiums because investors demand a higher expected return from the asset as a compensation for the riskiness. However, assets that exhibit a positive covariance with the pricing kernel ζ_{t+1} have negative risk premiums. From Equation (19) it becomes evident that ζ_{t+1} has the interpretation of an IMRS. Since the utility function of the representative individual in the consumption-based asset pricing framework is concave, the marginal utility is high when consumption is low, which may be the case in the presence of bad states in the economy. Hence, financial assets that provide high payoffs when the economy is in a bad state must be more attractive to the investors than assets that generate these high payoffs when the economy is in a good state and marginal utilities are low. As a consequence, assets that have a positive correlation with the stochastic discount factor, meaning they generate high payoffs when the economy is in a good state, must provide higher expected returns to persuade investors to include them in their portfolios. Hence, Equation (18) satisfies the theoretical implications of Equation (17). However, in contrast to Equation (17), Equations (18) and (19) are easily testable empirically with actual data if some reasonable assumptions concerning ζ_{t+1} are taken into account.

Ross (1976) in particular developed the arbitrage pricing theory (APT) linking expected returns to risk factors that may proxy for the stochastic discount factor. The APT was originally developed in a one-period framework and rests upon three fundamental assumptions: First, equity returns can be described by a factor model. Second, there is a sufficient quantity of securities to diversify away idiosyncratic risk. Third, well-functioning security markets do not allow for the existence of arbitrage opportunities. If the stochastic discount factor is linear in *K* risk factors F_{it+1} with $i = 1, \dots, K$, then the model is given by

$$\zeta_{t+1} = b_0 + b_1 F_{1t+1} + \cdots + b_K F_{Kt+1} \tag{21}$$

The classical CAPM in the spirit of Sharpe (1964) and Lintner (1965) where *K*=1 may be referred to as the Mother of all linear factor models. Other examples for factor models are the Fama and French (1993) three-factor model or Carhart's (1997) four-factor model where *K*=3 and *K*=4, respectively. However, Munk (2013) highlighted that the general theoretical results of the consumption-based asset pricing framework are not challenged by factor models because they do not invalidate the consumption-based asset pricing framework. They are however, understood as special cases that are easier to apply and test. Consequently, risk factors should generally help to explain the typical investors' marginal utilities of consumption.

If Equation (21) is plugged into Equation (18), we get an expression that can be easily empirically tested, for instance, by using the generalized methods of moments (GMM) technique, as proposed by Hansen (1982):

$$1 = E_t[(b_0 + b_1 F_{1t+1} + \cdots + b_K F_{Kt+1}) R_{it+1}]. \tag{22}$$

Factors can be either traded assets or factors that are not returns. In most empirical asset pricing models, including the Fama and French (1993) three-factor model, which serves as a benchmark model in empirical asset pricing research, the risk factors are excess returns. A common way to evaluate a factor model is to estimate the following multivariate time-series regression,

$$R_{it+1}^{excess} = \alpha_i + \beta_{i1} F_{1t+1} + \cdots + \beta_{iK} F_{Kt+1} + \varepsilon_{it+1} \tag{23}$$

where $R_{it+1}^{excess} = R_{it+1} - R_{f,t}$ and N is the number of test assets. If the factors are pricing the test assets correctly, the α_i parameters should be jointly not different from zero. The test statistic testing the joint significance of the parameters α_i was developed by Gibbsons et al. (1989) who showed, moreover, that this test is also about the mean-variance efficiency of the factors included in the analysis. Finally, Fama and MacBeth (1973) proposed a two-pass methodology, often referred to as Fama-MacBeth-regressions (FM), that can be used even if the factors are not traded assets. A prominent way to implement cross-sectional regressions is to estimate the time-series parameters β_{ij} for all N assets via OLS estimation first, as formulized in Equation (23). Let the estimated parameters of equation (23) be stacked into a matrix $\widehat{\boldsymbol{\beta}} = (\mathbf{1}, \widehat{\boldsymbol{\beta}}_{i1}, \ldots, \widehat{\boldsymbol{\beta}}_{iK})$ where $\widehat{\boldsymbol{\beta}}$ is of dimension $N \times (K+1)$.[9] Then, the corresponding risk-premiums for those *K*-factors can be estimated via the following second OLS-regression, given by

[9] Note: The first column vector in $\widehat{\boldsymbol{\beta}}$ is a vector of ones. If the factors are not traded assets, the intercept in the second regression need not be equal to zero. On the other hand, the intercept is often also included in cross-sectional regression that accounts for traded assets simply because an ordinary *t*-test of the intercept in the second regression can identify systematic mispricing of the model.

$$\hat{\boldsymbol{\lambda}} = \left(\hat{\boldsymbol{\beta}}^T \hat{\boldsymbol{\beta}}\right)^{-1} \hat{\boldsymbol{\beta}}^T \overline{\boldsymbol{R}}^{ex} \tag{24}$$

where the $(N+1)\times 1$ vector $\overline{\boldsymbol{R}}^{\boldsymbol{ex}} = (1, \bar{R}_1^{ex}, \dots, \bar{R}_N^{ex})$ stacks the estimated time series averages of the test assets into a vector. Then, the $(K+1)\times 1$ vector $\hat{\boldsymbol{\lambda}}$ contains the associated risk premiums. A factor is said to be priced when the corresponding risk premium is statistically significant different from zero. It is important to note, however, that the *t*-statistics estimated in the second step have to be estimated by using the Shanken (1992) correction, which accounts for the additional uncertainty that enters the model through the estimated regressors from the first step. The model of Equation (24) produces pricing errors $\hat{\boldsymbol{\alpha}}$ of

$$\hat{\boldsymbol{\alpha}} = \overline{\boldsymbol{R}}^{ex} - \hat{\boldsymbol{\lambda}} \hat{\boldsymbol{\beta}}. \tag{25}$$

The model is assumed to price the test assets correctly, if and only if the pricing errors are jointly equal to zero, where the pricing errors are asymptotically distributed as $\hat{\boldsymbol{\alpha}}^T cov[\hat{\boldsymbol{\alpha}}]^{-1} \hat{\boldsymbol{\alpha}} \sim \chi^2(N-K)$. Finally, the cross-sectional *R*-squared is often employed as an indicator of how well the model explains the cross-section of financial asset returns.

3 SUMMARY OF THE ESSAYS

This doctoral thesis, *Essays on Empirical Asset Pricing*, consists of six essays. All essays are single authored. Four out of these six essays have already been published in refereed journals. This section provides a brief overview of the essays and their contribution to the literature.

3.1 An empirical analysis of changes of the impact of federal budget deficits on stock market returns: Evidence from the US economy

In February 2010, the new Greek government of George Papandreou admitted that a flawed statistical procedure had previously existed before the new government had been elected and revised the 2009 deficit in Greece from a previously estimated 6%-8% to an alarming 12.7% of the GDP. On April 27, Standard & Poor's slashed Greece's sovereign debt rating to BB+. As a consequence, equity markets worldwide and the Euro currency declined. In the wake of the Greek government-debt crisis, much attention has been paid to the question of how to manage federal budget deficits. In particular, the US has been running an ever-increasing budget deficit for decades, ending in a downgrading the nation's creditworthiness on Friday August 5, 2011, for the first time in history. However, changes in the federal budget deficit are also associated with different effects on the financial sphere from a micro perspective.

While Roley and Schall (1988) reported that increases in the structural deficit have historically led to slight increases in stock prices, later studies by Darrat and Brocato (1994) and Ewing (1998) reported negative relationships between stock prices and federal deficits.

The purpose of this paper is first to clarify whether a significant relationship between changes in the federal deficit and stock market returns does exist. Second, the potential impact on the federal budget deficit on stock market returns is explored. The third issue is to clarify whether the potential relationship has changed over time. In contrast to Ewing's study (1998), this paper makes use of vector-autoregression (VAR) models and the sequential elimination of the regressors technique as proposed by Lütkepohl and Krätzig (2004, pp.165-71), accounting for the endogeneity problem. For an investor, it may be important to discover the impact of changes in the federal budget deficit and on stock market returns because Darrat and Brocato (1994) highlighted that deficit risk has an impact on the whole economy and thus cannot be diversified away. Since the deficit risk cannot be diversified away, it may be a systematic risk and, by this, associated with the stochastic discount factor as in Equation (17) in the introduction.

This paper contributes to the existing literature by highlighting a significant impact from real changes in the federal budget deficit on real stock market returns. A Granger causality test of the reduced VAR model in subsamples implies that the changes in the US federal budget deficit are Granger causal for the stock market in both subsamples. Interestingly, while stock market returns are not Granger causal for the budget deficit on the commonly applied 5% significance level for the first subsample, this does not hold any longer for the second sample. Estimated impulse response functions for the first subsample indicate that a shock to the deficit of 1% results in a simultaneous increase of 2.39% in real stock market returns. After seven quarters, the cumulative increase in stock market returns is estimated at 7.99%. However, the results indicate that this positive effect is considerably weakened in the later subsample. The results indicate that while the causality origins from the fundamental sphere in the earlier subsample, the more recent sample also shows a significant impact from the financial sphere following to the fundamental one.

3.2. Returns to public debt: The US federal budget deficit and the cross-section of equity returns

Like the previous paper, this essay is connected to the academic literature that attempts to identify reliable associations between macroeconomic variables and equity returns (Chen et al. 1986; Chang and Pinegar 1989, 1990; Fama 1990, 1991; Flannery and Protopapadakis 2002). Chan et al. (1998) reported that macroeconomic factors generally perform poorly in explaining variations in equity returns. In particular, the impact of federal government stimulus on the domestic economy has been debated for many years. Darrat and Brocato (1994) emphasize in particular the role of the federal budget deficit as a macro-finance variable. Since deficit risk cannot be eliminated through diversification, this risk should be priced according to financial theory, as shown in Equation (17) of the introduction. Recent studies confirm that changes in the federal budget deficit have a significant impact on stock market returns (Laopodis 2009, 2012; Grobys 2013). Nevertheless, no study has been undertaken that investigates the asset pricing implications of changes in the federal budget deficit in a portfolio-based approach in the spirit of Fama and French (2008).

The purpose of this essay is to explore the asset pricing implications of changes in the federal budget deficit. This essay is motivated by the growing body of literature that models the relation between macro-finance variables and expected returns and contributes to the prior literature in the following respects: First, a portfolio-based systematic risk factor based upon changes in the US federal budget deficit was constructed. A novel aspect of this essay is the proposed approach to generating a portfolio-based risk factor that involves employing cumulative impulse response functions based on iteratively updated VAR models. Furthermore, it identifies whether traditional empirical asset pricing models, such as the Fama and French (1993) three-factor model, are capable of explaining the risk factor related to changes in the budget deficit. Finally, the essay explores the extent to which the new proposed risk factor can help to explain the cross-section of equity returns.

This essay contributes to the literature by establishing a significant and robust connection between the US federal budget deficit risk and equity returns. Shifts in the budget deficit have the ability to predict future returns. A zero-cost strategy for conducting a new risk factor related to changes in the budget deficit risk is proposed. This zero-cost portfolio is long on equity portfolios that exhibit the highest negative cumulative impulse responses to orthogonalized shocks in the budget deficit process and short on equity portfolios that exhibit the least cumulative impulse responses to orthogonalized shocks in the budget deficit returns. Fama and MacBeth's (1973) cross-sectional regressions show that the new proposed risk factor is statistically significantly priced irrespective of which model specification is considered. The economic magnitude of this new risk factor varies between -1.16% and -1.20% per quarter. Thus, the economic magnitude is approximately the same as the value premium. Moreover, the results offer strong evidence that the new proposed risk factor is negatively associated with the business cycle; that is, in economic downturns, the payoff appears to be considerably higher than when the economy is in a good state. Finally, employing test portfolios sorted by cumulative impulse response function shows that the new risk factor alone is able to explain 73% of the cross-section of the test assets' returns. Taken together, the results presented in this essay provide strong indications that changes in the budget deficit appear to be relevant for describing the cross-section of equity returns.

3.3 Momentum in global equity markets in times of troubles: Does the economic state matter?

This paper relates to the literature that studies the momentum anomaly. The momentum anomaly, as first documented by Jegadeesh and Titman (1993), has received a great deal of attention in empirical research. Nyberg and Pöyry (2013) highlighted that even two decades after its discovery, the momentum anomaly remains an intellectual curiosity: a simple trading strategy that is long on stocks with highest returns over the past three to 12 months and short on stocks with lowest returns over the same horizon generates profits that remain large after standard adjustments of risk. In a more recent study, Daniel and Moskowitz (2013) added an interesting finding to this debate. While Chordia and Shivakumar (2002) found that momentum pay offs appear to be negative but statistically not different from zero during recessions, the findings of Daniel and Moskowitz (2013) indicate that the momentum portfolio exhibits a strong up- and down-beta differential in bear markets. This optionality appears to be largely related to the loser portfolio. When market conditions improve, these losers make strong gains that in turn lead to a momentum crash. However, no study has been undertaken that investigates the profitability of momentum strategies during recessions in the context of global equity markets.

The purpose of this paper is to explore the profitability of international momentum strategies during the economic downturns since Rouwenhorst's (1997) study. Different momentum strategies are considered and where most other studies focus on the US stock market, this study employs a sample of 21 foreign stock indices. All indices are divided into quartiles based on their cumulative past returns to implement zero-cost portfolios. Since this study adopts the perspective of a US investor, it relies on the S&P 500 is employed for risk adjustment.

This paper contributes to the existing first by identifying the profitability of momentum strategies implemented in a global equity market setting during the most recent economic recessions. Second, in extending Novy-Marx's (2012) analysis to a global equity market setting, it assesses whether intermediate past performance offers more beneficial information to internationally aligned investors in the USA than recent past performance can. The results of this paper diverge from others in finding that momentum-based trading strategies in a global equity market setting generate statistically significant negative returns, at least during the most recent recessions, irrespective of whether the strategies are based on intermediate or recent past performance. Although strategies based on intermediate past performance appear to be market neutral, they did not generate positive returns during the most recent recessions. The empirical findings indicate that the severe recession of December 2007–June 2009 is the major driver of this result. Integrating these results with Jegadeesh and Titman's (1993) back-testing results and Daniel and Moskowitz's (2013) recent findings confirms that momentum strategies may bring a risk of extraordinarily high negative returns following large market declines.

3.4 Idiosyncratic volatility and global equity markets

This paper is connected to the literature studying the role of idiosyncratic risk in the cross-section of equity returns. It was stated in the previous section that under a correctly specified asset pricing model, idiosyncratic risk should not predict expected returns. Fama and MacBeth (1973) documented that once the CAPM-beta is controlled for, idiosyncratic risk estimated from a simple market model is not priced in the cross-section of average stock returns. However, the association between realized idiosyncratic volatility and stock returns has received a great deal of attention in the academic literature. In particular, Ang et al. (2006, 2009) employed short-window regressions on daily data and showed that a value-weighted portfolio of stocks with the highest level of idiosyncratic risk relative to the Fama and French (1993) three-factor model in the previous month tends to generate anomalously low returns in the subsequent month. However, Huang et al. (2010, 2011) found that the negative relation between realized idiosyncratic volatility and stock returns appears to be driven by the value-weighting scheme. Interestingly, no study has confirmed Ang et al.'s (2006, 2009) findings in a global equity market setting, taking into account different countries' domestic stock indices as an investment opportunity set.

The purpose of this paper is to explore the relationship between idiosyncratic volatility and future returns on a portfolio level in global equity markets. It uses an investment opportunity set of 52 different stock indices to do so. Each of the stock indices is a well-diversified basket of at least 20 stocks. All stock indices are divided into quintiles based on their past realized idiosyncratic volatility relative to a global portfolio comprising all stock indices. The zero-cost strategy is long on the group containing the stock indices with highest idiosyncratic volatility and short on the group containing the stock indices with the lowest idiosyncratic volatility. Moreover, this essay considers the perspective of an internationally aligned investor and employs different global asset pricing model specifications for risk adjustment.

The paper contributes to the existing literature in the following ways. First, Ang et al.'s (2006, 2009) analyses are extended to a global equity market setting. In doing so, the study assesses whether realized idiosyncratic volatility is priced in the cross-section of global equity markets. Second, it identifies if this strategy is related to the business cycle. For internationally aligned investors, uncovering the risks associated with global investment vehicles and the underlying driving forces is a key issue. It is especially important to understand the association between patterns in equity returns and economic conditions. The findings of this paper indicate that idiosyncratic risk is positively priced in the cross-section of global equity markets. While this result diverges from the finding s of Ang et al. (2006, 2009), who found a negative relationship, it implies that the typical globally aligned investor holds an under-diversified portfolio, as economic theory suggests that expected returns are unrelated to idiosyncratic risk if investors hold fully-diversified portfolios. Notably, the study also found that the zero-cost strategy does not appear to be associated with the business cycle. Finally, a regression analysis reveals that traditional global asset pricing models, such as the global Fama and French model, cannot explain the spread.

3.5 Idiosyncratic volatility and momentum crashes

As with previous paper, this essay relates to the literature addressing the role of idiosyncratic risk in asset pricing. While on the firm level, a positive relation between idiosyncratic volatility and stock returns has been documented by Malkiel and Xu (2002), Spiegel and Wang (2006), Chua et al. (2010), Fu (2009) and Huang et al. (2010), there is not yet a consensus on the portfolio level. In contrast to Ang et al. (2006), Bali and Cakici (2008) did not find such evidence for a negative or significant link between idiosyncratic risk and the cross-section of expected returns after excluding the smallest, least liquid and lowest priced stocks. Their result holds for both the value-weighted and equal-weighted portfolios. Nevertheless, Ang et al. (2009) confirmed their previous findings from 2006 in equity markets other than the USA. While Bali and Cakici (2008) account for liquidity and size, no study has been undertaken controls ex-ante for potential information asymmetry.

The purpose of this essay is twofold. First, it examines the relationship between idiosyncratic volatility and future returns on a portfolio level in a scenario where the level of idiosyncratic volatility is ex ante controlled for both liquidity, size and information asymmetry. Institutional investors and large investors are typically focused on large caps with high liquidity and low information asymmetry. Second, it investigates the seasonality of the idiosyncratic volatility spread. In the process, the spread is regressed on a dummy variable indicating the month of January. More importantly, based upon the results of the previous regression analysis, the essay explores the link between momentum crashes in the spirit if Daniel et al. (2012) and idiosyncratic volatility.

This essay contributes to the existing literature in the following respects. First, it extends the contributions of Ang et al. (2006), Bali and Cakici (2008) and Huang et al. (2010, 2011) by adopting the analysis of portfolios sorted by idiosyncratic volatility in a stock universe consisting exclusively of large firms with high liquidity and the lowest possible information asymmetry. This essay differs from Bali and Cakici (2008) in that the concern about size and liquidity is addressed by focusing exclusively on firms that were listed in the S&P 500. Second, motivated by Bali and Cakici's (2008) and Huang at al.'s (2011) critique, and in contrast to Ang et al. (2006), the essay operates with equal-weighted portfolios. Thus, it ensures that any potential effect cannot be driven by a value-weighting scheme. Finally, motivated by the empirical results of the previous regression analysis, it investigates whether a link between momentum crashes and payoffs from a zero-cost strategy formed on realized idiosyncratic volatility can be established. There has been no study yet undertaken that investigates a potential link between these two strategies.

This essay differs from previous research in finding that portfolios with higher idiosyncratic volatility generate statistically significant higher returns. The zero-cost portfolio that is long in stocks with the highest idiosyncratic volatility and short in stocks with the lowest idiosyncratic volatility significantly generates an average return of 1.17% per month. The positive relationship between realized idiosyncratic volatility and expected returns is consistent with economic theory suggesting that investors demand compensation for not being able to diversify risk. Moreover, in the month of January the raw spread generates an additional return of 4.14% per month, confirming findings from Doran et al.'s (2008) study. Notably, a sample-split analysis suggests that the positive relation between realized idiosyncratic volatility and expected returns arises due to the survivor sample consisting of firms that remain in the S&P 500. Additional robustness checks also support this finding. Finally, matching the outliers of the zero-cost strategy sorted by realized idiosyncratic volatility with momentum crashes, as in Daniel et al.

(2012), shows that the idiosyncratic volatility strategy generates continuously large positive pay offs whenever momentum crashes occurred. After controlling for momentum crashes by including a dummy variable that indicates the occurrence of momentum crashes the risk-adjusted pay offs of the equally-weighted zero-cost strategy based on idiosyncratic volatility become insignificant on a common significance level. However, the dummy variable indicating momentum crashes is associated with statistically significantly large positive pay offs. Hence, the idiosyncratic volatility strategy implemented in the S&P 500 universe may act as a hedge for the momentum strategy.

3.6 Momentum, sovereign credit ratings and global equity markets

This paper is related to both the line of research that studies the momentum anomaly and the line of research focusing on proxies for the economy-wide stochastic discount factor. As mentioned in the previous section, one of the difficulties of consumption-based asset pricing is the low quality of aggregate consumption data: Consumption data is known to suffer from time aggregation issues and problems associated with the seasonal adjustment procedures applied to the national consumption series, something pointed out in Grossman et al. (1987), Wheatley (1988), and Breeden et al. (1989). Consequently, a broad stream of literature has focused on finding alternative variables that may act as proxies. For instance, Avramov et al. (2012) argued that portfolios of international stock indices sorted by country-specific credit risk predict future returns. Furthermore, Avramov et al. (2007) established a link between momentum profits and credit rating. Their study indicated that momentum profits are statistically significant only for strategies implemented by firms exhibiting a high credit risk. Although investing in global equity markets has become an important tool for risk diversification in the financial industry, little attention has been paid to momentum strategies applied in global equity markets.

The purpose of this paper is first to explore if a link between country-specific credit ratings and internationally invested momentum exists. To do so, it accounts for different momentum strategies invested in global equity markets by employing 23 foreign stock indices. All indices are divided into quartiles corresponding to their cumulative past returns to implement zero-cost portfolios. For each momentum group and strategy, the corresponding credit risk is proxied by the average country-specific credit rating and investigated further. Second, the paper assesses whether momentum profits can be explained by a world credit risk factor. In the process, all indices are divided into terciles based on their past credit rating to implement the world credit risk factor. In a time-series regression analysis, the paper explores whether the credit risk factor can explain momentum profits.

This paper contributes to the existing literature first by extending Avramov et al.'s (2007) study to an international equity market setting. That enables the assessment of whether globally implemented momentum strategies are associated with country-specific credit risk. For internationally aligned investment managers, revealing the risks associated with investment vehicles is fundamentally important. Moreover, by extending the study of Grobys (2014), the paper identifies whether internationally implemented momentum strategies can be explained by the global Fama and French (1998) risk factors. Finally, the study assesses whether a world credit risk factor as detailed by Avramov et al. (2012) is capable of explaining these momentum profits.

In contrast to previous research, the results of this paper indicate that only momentum-based trading strategies based on intermediate past performance are profitable, as was proposed by Novy-Marx (2012). Notably, the profits are driven by the winner portfolio and cannot be explained by the Fama and French (1998) global factor model. Moreover, only the winner portfolio appears to be associated with a higher average country-specific risk in comparison to the other portfolios. The spread between countries exhibiting a high credit risk and countries having a low credit risk is statistically significantly positive, supporting Avramov et al.'s (2012) findings. Even though momentum profits tend to be associated with country-specific credit ratings, the world credit risk factor proposed by Avramov et al. (2012) cannot fully explain the momentum profits either.

4 CONCLUDING REMARKS

This dissertation studies issues related to empirical asset pricing. It is of great importance and interest not only to academicians but also to the financial industry and practitioners to understand what is driving the cross-sectional differences in assets returns. The first essay of this dissertation tests whether changes in the US federal budget deficit affect stock market returns and attempts to uncover a link between stock market returns and movements in a key macroeconomic fundamental. The second essay proposes a new portfolio-based risk factor based on cumulative response functions from equity portfolios to changes in the US federal budget deficit. Previous research has attempted to identify reliable associations between macroeconomic variables and equity returns but has concluded that macroeconomic factors generally perform poorly in explaining variations in equity returns (Chan et al. 1998; Flannery and Protopapadakis 2002). This essay breaks new ground in empirical asset pricing research and shows that the federal budget deficit as a macro-finance variable can assist in predicting future equity returns.

The third essay aims to deepen the understanding of the momentum anomaly in global equity markets and shows that momentum strategies implemented in a global equity market setting are subject to momentum crashes. The fourth and fifth essay shed new light on the idiosyncratic volatility puzzle. While the fourth essay studies the idiosyncratic volatility puzzle in an international investment context, the fifth essay establishes a robust link between idiosyncratic volatility and momentum crashes. The last essay investigates whether momentum-based trading strategies implemented in global equity markets can be explained by a world credit risk factor, as proposed by Arvamov et al. (2012).

The findings of this thesis have some important implications for practitioners and policymakers. For the financial industry, the thesis offers new insights into cross-sectional patterns in asset returns. For instance, the outcome of the analysis related to globally invested momentum strategies may have direct implications for the hedge fund industry in formulating and implementing asset allocation decisions and creating investment vehicles. For policymakers, the results of the thesis might be useful in macroeconomic policy formulations that involve an increase in the federal budget deficit. While positive innovations to the changes in the federal budget deficit process resulted in higher stock market returns 40 years ago, this effect has considerably weakened over time. Finally, firms that exhibit the highest negative cumulative impulse responses to orthogonalized shocks in the budget deficit process tend to generate lower expected returns than firms that exhibit the least cumulative impulse responses. The corresponding risk-adjusted payoff of this strategy is -1.4% per quarter.

REFERENCES

Abel, A.B. (1990). Asset prices under habit formation and catching up with the Joneses. *American Economic Review Papers and Proceedings* 80, 38–42.

Ang, A., Hodrick, R.J., Xing, Y. & Zhang, X. (2006). The cross section of volatility and expected returns. *Journal of Finance* 61, 259–299.

Ang, A., Hodrick, R.J., Xing, Y. & Zhang, X. (2009). High Idiosyncratic Volatility and Low Returns: International and Further US Evidence. *Journal of Financial Economics* 91, 1–23.

Avramov, D., Chorida, T., Jostova, G. & Philipov, A. (2007). Momentum and Credit Rating. *Journal of Finance* 62, 2503–2520.

Avramov, D., Chordia, T., Jostova, G. & Philipov, A. (2009). Credit Ratings and The Cross-Section of Stock Returns. *Journal of Financial Markets* 12, 469–499.

Avramov, D., Chorida, T., Jostova, G. & Philipov, A. (2012). The World Price of Credit Risk. *Review of Asset Pricing Studies* 2, 112–152.

Avramov, D., Chordia, T., Jostova, G. & Philipov, A. (2013). Anomalies and Financial Distress. *Journal of Financial Economics* 108, 139–159.

Azer, S.A. (2005). The qualities of a good teacher: how can they be acquired and sustained? *Journal of the Royal Society of Medicine* 98, 67–69.

Bali, T.G. & Cakici, N. (2008). Idiosyncratic Volatility and the Cross Section of Expected Returns. *Journal of Financial and Quantitative Analysis* 43, 29–58.

Banz, R.W. (1981). The Relationship Between Return and the Market Value of Common Stocks. *Journal of Financial and Quantitative Anaysis* 14, 421–441.

Basu, S. (1977). The investment performance of common stocks in relation to their price–earnings ratios: a test of the efficient markets hypothesis. *Journal of Finance* 32, 663–682.

Black, F. (1972). Capital Market Equilibrium with Restricted Borrowing. *Journal of Business* 45, 444–455.

Breeden, D. (1979). An intertemporal asset pricing model with stochastic consumption and investment opportunities. *Journal of Financial Economics* 7, 265–296.

Breeden, D.T., Gibbons, M.R. & Litzenberger, R.H. (1989). Empirical Test of the Consumption-Oriented CAPM. *Journal of Finance* 44, 231–262.

Campbell, J.Y. & Cochrane, J.H. (1999). By force of habit: a consumption-based explanation of aggregate stock market behavior. *Journal of Political Economy* 107, 205–251.

Campbell, J.Y., Hilscher, J. & Szilagyi, J. (2008). In Search of Distress Risk. *Journal of Finance* 63, 2899–2939.

Carhart, M. (1997). On Persistence in Mutual Fund Performance. *Journal of Finance* 52, 57–82.

Chan, L.K.C., Karceski, J. & Lakonishok, J. (1998). The Risk and Return from Factors. *Journal of Financial and Quantitative Analysis* 33, 159–188.

Chang, E.C. & Pinegar, J.M. (1989). Seasonal Fluctuations in Industrial Production and Stock Market Seasonal. *Journal of Financial and Quantitative Analysis* 24, 59–74.

Chang, E.C. & Pinegar, J.M. (1990). Stock Market Seasonal and Prespecified Multifactor Pricing Relations. *Journal of Financial and Quantitative Analysis* 25, 517–533.

Chen, N., Roll, R. & Ross, S.A. (1986). Economic Forces and the Stock Market. *Journal of Business* 59, 383–403.

Chordia, T. & Shivakumar, L. (2002). Momentum, business cycle, and time-varying expected Returns. *Journal of Finance* 57, 985–1019.

Chua, C.T., Goh, J.C. & Zhang, Z. (2010). Expected volatility, unexpected volatility and the cross-section of stock returns. *Journal of Financial Research* 33, 103–123.

Cochrane, J.H. (2005). Asset Pricing. Princeton, New Jersey: Princeton University Press.

Cochrane, J.H. & Hansen, L.P. (1992). Asset Pricing Exploration for Macroeconomics. *NBER Macroeconomics Annual* 7, 15–165.

Constantinides, G. (1990). Habit formation: a resolution of the equity premium puzzle. *Journal of Political Economy* 98, 519−543.

Cooper, M.J., Gulen, H. & Schill, M.J. (2008). Asset growth and the cross-section of stock returns. *Journal of Finance* 63, 1609–1652.

Daniel, K., Jagannathan, R. & Kim, S. (2012). Tail risk in momentum strategy returns. *Working paper*, *Columbia University*.

Daniel, K.D. & Moskowitz, T.J. (2013). Momentum crashes. *Columbia Business School working paper*.

Darrat, A. & Brocato, J. (1994). Stock market efficiency and the federal budget deficit: another anomaly? *The Financial Review* 29, 49–75.

Ewing, B.T. (1998). The impact of federal budget deficits on movements in the stock market: evidence from Australia and France. *Applied Economics Letters* 5, 649–651.

Fama, E.F. (1990). Stock Returns, Expected Returns, and Real Activity. *Journal of Finance* 45, 1089–1108

Fama, E.F. (1991). Efficient Capital Markets: II. *Journal of Finance* 46, 1575–1617.

Fama, E.F. & French, K.R. (1992). The cross-section of expected stock returns. *Journal of Finance* 46, 427–466.

Fama, E.F. & French, K.R (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics* 33, 3–56.

Fama, E.F. & French, K.R. (1998). Value versus Growth: The International Evidence. *Journal of Finance* 53, 1975–1999.

Fama, E.F. & French, K.R. (2003). The CAPM: Theory and Evidence. *Working paper* No. 03-26 *Center for Research in Security Prices University of Chicago*.

Fama, E.F. & French, K.R. (2008). Dissecting Anomalies. *Journal of Finance* 63, 1653–1678.

Fama, E.F. & French, K.R. (2014). A Five-Factor Asset Pricing Model. *Fama-Miller Working Paper*.

Fama, E.F. & MacBeth, J.D. (1973). Risk, return, and equilibrium: Empirical tests. *Journal of Political Economy* 71, 607–636.

Flannery, M. & Protopapadakis, A. (2002). Macroeconomic factors do influence aggregate stock returns. *Review of Financial Studies* 15, 751–782.

Fu, F. (2009). Idiosyncratic risk and the cross-section of expected stock returns. *Journal of Financial Economics* 91, 24–37.

Gibbson, M.R., Ross, S.A. & Shanken, J. (1989). A Test of the Efficiency of a Given Portfolio. *Econometrica* 57, 1121–1152.

Grobys, K. (2013). An empirical analysis of changes of the impact of federal budget deficits on stock market returns: evidence from the US economy. *Applied Economics Letters* 20, 921–924.

Grobys, K. (2014). Momentum in global equity markets in times of troubles: Does the economic state matter? *Economics Letters* 123, 100–103.

Grossman, S., Melino, A. & Shiller, R. (1987). Estimating the Continous-Time Consumption-Based Asset-Pricing Model. *Journal of Business and Economic Statistics* 5, 315–328.

Hansen, L.P. (1982). Large Sample Properties of Generalized Method of Moments Estimators. *Econometrica* 50, 1029–1054.

Hansen, L.P. & Jagannathan, R. (1991). Restrictions on intertemporal marginal rates of substitution implied by asset returns. *Journal of Political Economy* 99, 225–262.

Hansen, L.P. & Singleton, K.J. (1983). Stochastic consumption, risk aversion, and the temporal behavior of asset returns. *Journal of Political Economy* 91, 249–268.

Huang, W., Liu, Q., Rhee, S.G. & Zhang, L. (2010). Return reversals, idiosyncratic risk, and expected returns. *Review of Financial Studies* 23, 147–168.

Huang, W., Liu, Q., Rhee, S.G. & Zhang, L. (2011). Another look at idiosyncratic volatility and expected returns. *Journal of Investment Management* 9, 26–51.

Jegadeesh, N. & Titman, S. (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. *Journal of Finance* 48, 35–91.

Laopodis, N.T. (2009). Fiscal policy and stock market efficiency: Evidence of the United States. *The Quarterly Review of Economics and Finance* 49, 633–650.

Laopodis, N.T. (2012). Dynamic Linkages among Budget Deficits, Interest Rates and the Stock Market. *Fiscal Studies* 33, 547–570.

Lintner, J. (1965). The valuation of risk assets and the selection of risky investments in stocks portfolios and capital budgets. *Review of Economics and Statistics* 47, 13–37.

Lucas, R.E. (1978). Asset prices in an exchange economy. *Econometrica* 46, 1429–1446.

Lütkepohl, H. & Krätzig, M. (2004). Applied Time Series Econometrics, Cambridge University Press, New York, NY.

Malkiel, B.G. & Xu., Y. (2002). Idiosyncratic risk and security returns. *Working Paper, University of Texas at Dallas*.

Mehra, R. & Prescott, E. (1985). The equity premium puzzle. *Journal of Monetary Economics* 15, 145–161.

Munk, K. (2013). Financial Asset Pricing Theory. Oxford University Press, UK.

Novy-Marx, R. (2012). Is momentum really momentum? *Journal of Financial Economics* 103, 429–453.

Novy-Marx, R. (2013). The other side of value: The gross profitability premium. *Journal of Financial Economics* 108, 1–28.

Nyberg, P. & Pöyry, S. (2013). Firm Expansion and Stock Price Momentum. *Review of Finance* 18, 1465–1505.

Roley, V.V. & Schall, L.D. (1988). Federal deficits and the stock market. *Economic Review – Federal Reserve Bank of Kansas City* 73, 17–27.

Roll, R. (1977). A critique of the asset pricing theory's tests; part I: On past and potential testability of the theory. *Journal of Financial Economics* 4, 129–176.

Ross, S.A. (1976). The arbitrage theory of capital asset pricing. *Journal of Economic Theory* 13, 341–360.

Rouwenhorst, K.G. (1997). International Momentum Strategies. *Journal of Finance* 53, 267–284.

Rubinstein, M. (1976). The valuation of uncertain income streams and the pricing of options. *Bell Journal of Economics* 7, 407–425.

Savov, A. (2011). Asset Pricing with Garbage. *Journal of Finance* 66, 177–201.

Shanken, J. (1992). On estimation of beta-pricing models. *Review of Financial Studies* 5, 1–33.

Sharpe, W.F. (1964). Capital asset prices: a theory of market equilibrium under conditions of risk. *Journal of Finance* 19, 425–442.

Shiller, R. (1981). Do stock prices move too much to be justified by subsequent changes in dividends? *American Economic Review* 71, 421–436.

Shiller, R.J. (1982). Consumption, asset markets, and macroeconomic fluctuations. *Carnegie Mellon Conference Series on Public Policy* 17, 203−238.

Spiegel, M. & Wang, X. (2006). Cross-sectional variation in stock returns: Liquidity and idiosyncratic risk. Working Paper, Yale University.

Wheatley, S. (1988). Some Tests of the Consumption-Based Asset Pricing Model. *Journal of Monetary Economics* 22, 193–215.

Applied Economics Letters, 2013
Vol. 20, No. 9, 921–924, http://dx.doi.org/10.1080/13504851.2013.765534

Routledge
Taylor & Francis Group

An empirical analysis of changes of the impact of federal budget deficits on stock market returns: evidence from the US economy

Klaus Grobys

Department of Accounting & Finance, University of Vaasa, FI-65101 Vaasa, Finland
E-mail: grobys.finance@gmail.com

We investigate the causality between the real federal budget deficit returns and real stock market returns for the US economy. We divide the overall sample into two sub-samples running from 1968:1 to 1988:3 and from 1988:4 to 2011:3. In contrast to earlier studies, we find a significant positive relationship between real stock market returns and real federal budget deficit returns for both samples. Moreover, we find that the stochastic interrelations between these variables have considerably changed over time.

Keywords: federal budget deficits; stock markets; Granger Causality; impusle response

JEL Classification: E00; G12; G10; H30; H60

I. Introduction

In the wake of the current Euro Crisis, a lot of attention is paid towards the management of federal budget deficits. Increasing federal debts are associated with different effects with respect to the financial sphere. From an investor's perspective, who wants to invest in the equity market, it may be of major importance to figure out how an increase in federal budget deficits may impact the stock market. In earlier studies, Roley and Schall (1988) describe three potential channels of how changes in the federal deficit may influence stock prices, namely through changes in the aggregate economic output, interest rates and inflation. From a theoretical perspective, they conclude that the net effect on stock prices may be unclear. However, Darrat and Brocato (1994) argue that the expected sign of the budget deficit effect on stock returns is expected to be negative due to the implicit interest rate effect.

The results from empirical studies are ambiguous: while Roley and Schall (1988) report that increases in the structural deficit have historically led to slight increase in stock prices, later studies of Darrat and Brocato (1994) and Ewing (1998) report negative relationships between stock prices and federal deficits. Darrat and Brocato (1994) and Ewing (1998) conclude that the US stock market and the Australian and French stock markets are inefficient with respect to the federal budget deficit, respectively.

Ewing (1998) makes use of the concept of Granger Causality in order to examine stock market efficiencies: in an efficient market, the information contained in past deficits would have previously been incorporated into stock prices. Hence, past information about federal budget deficits should in line with Ewing (1998) provide no explanatory power for current stock prices. Following earlier studies, we want to investigate first whether a significant relationship between federal deficit returns and stock market returns exist. Second, we examine how high the potential impact is. The third issue is to clarify whether the potential relationship has changed over time. In contrast to Ewing (1998) who operates with a single equation model, we employ a more general Vector-Autoregressive (VAR) model in order to account for the endogeneity problem. From an investor's point of view, uncovering the impact of federal deficits to the stock market may be of major importance as the impact of the deficit is common to all stocks which means that this aspect of market risk cannot be diversified away, as emphasized by Darrat and Brocato (1994). In contrast to earlier studies, we compare two samples of data and find a significant positive relationship between real stock market returns and the real federal budget deficit returns for both samples the later and earlier one. Moreover, we find that the stochastic interrelations between these variables have considerably changed over time.

II. Empirical Framework and Results

Quarterly observations of the US federal deficit data for the period 1967:4–2011:3 are obtained from the Federal Reserve Bank of St. Lois.[1] Following Darrat and Brocato (1994), we neglect data prior to 1967:4 to avoid an apparent shift in 1967 from a regime of approximately balanced budgets. Stock market data of the Dow Jones 30 index are downloaded at yahoo.-com covering the same period. The data are adjusted for inflation and, hence, given in real terms. We compute the ordinary returns of both time series and test for integration. Both return series are found to be stationary.[2] We divide the series of real returns in two samples. The first sample contains data from 1968:1 to 1988:3, whereas the second sample contains data from 1988:4 to 2011:3. In contrast to Ewing (1998), we employ for both samples under consideration a general VAR model as the latter does not impose arbitrary exogeneity restrictions on the variables. The model is then given by

$$\boldsymbol{Y}_t = \mathbf{A}_1 \boldsymbol{Y}_{t-1} + \cdots + \mathbf{A}_p \boldsymbol{Y}_{t-p} + \mathbf{D}\boldsymbol{X} + \boldsymbol{E}_t \qquad (1)$$

where $\boldsymbol{Y}_t$ is a 2×1 vector containing the real federal deficit returns (which will in the following be referred to as *deficit*) and the real stock market returns (which will in the following be referred to as *stocks*), $\boldsymbol{X}$ is a 2×1 vector containing a constant and time-dependent deterministic term and $\boldsymbol{E}_t$ is a 2×1 vector of random variables which is assumed to be multivariate normally distributed with expectation of zero and covariance matrix $\boldsymbol{\Sigma}$. Furthermore, $\mathbf{A}_1, ..., \mathbf{A}_p$ and $\mathbf{D}$ are 2×2 parameter matrices. Since we operate with quarterly observations, we choose a lag order of $p = 4$ which may be a common practice when operating with quarterly data. In order to hold the models parsimoniously, we make use of the econometric technique referred to as *sequential elimination of regressors*, as described in detail in Brüggemann and Lütkepohl (2001). Thereby, we take into account the value of $c_T = 2$ for the AIC criterion, as suggested by Lütkepohl and Krätzig (2004, p. 124). The reduced models will be employed for testing for Granger Causality and estimating impulse response functions. Labelling the reduced models' parameter estimates with *, we rewrite the bivariate system in Equation 1 as follows:

$$\begin{aligned}\begin{pmatrix} y_{1,t} \\ y_{2,t} \end{pmatrix} &= \begin{pmatrix} a^*_{11,1} & a^*_{12,1} \\ a^*_{21,1} & a^*_{22,1} \end{pmatrix} \begin{pmatrix} y_{1,t-1} \\ y_{2,t-1} \end{pmatrix} + \cdots \\ &\quad + \begin{pmatrix} a^*_{11,p} & a^*_{12,p} \\ a^*_{21,p} & a^*_{22,p} \end{pmatrix} \begin{pmatrix} y_{1,t-p} \\ y_{2,t-p} \end{pmatrix} \\ &\quad + \begin{pmatrix} d^*_{11} & d^*_{12} \\ d^*_{21} & d^*_{22} \end{pmatrix} \begin{pmatrix} c \\ t \end{pmatrix} + \begin{pmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \end{pmatrix} \qquad (2)\end{aligned}$$

If the deficit is not Granger Causal for the stocks, the parameters $a^*_{21,1}, ..., a^*_{21,p}$ will not be significantly different from zero. Hence, we test (a) the following pair of hypotheses:

$$H_0 : a^*_{21,1} = ... = a^*_{21,p} = 0 \text{ against } H_1 : \\ \text{at least one of } \left\{a^*_{21,1}, ..., a^*_{21,p}\right\} \text{ is } \neq 0$$

Furthermore, we examine if the stocks are not Granger Causal for the deficit and test (b) the following pair of hypotheses:

$$H_0 : a^*_{12,1} = ... = a^*_{12,p} = 0 \text{ against } H_1 : \\ \text{at least one of } \left\{a^*_{12,1}, ..., a^*_{12,p}\right\} \text{ is } \neq 0$$

Moreover, we want to examine the relevance of the stochastic interrelations and, hence, for the adequacy of the selected VAR model framework. Hence, we test (c) for instantaneous causality and consider the following pair of hypotheses:

$$H_0 : \mathrm{E}\left(\varepsilon_{1,t}\varepsilon'_{2,t}\right) \neq 0 \text{ against } H_1 : \mathrm{E}\left(\varepsilon_{1,t}\varepsilon'_{2,t}\right) \neq 0$$

After performing causality tests, we investigate the response of stocks to shocks of one percent point in

[1] See http://research.stlouisfed.org/fred2/categories/106.

[2] The Augmented–Dickey–Fuller-test statistics are –7.33 and –2.21 for the real Dow Jones 30 returns and real federal deficit returns, respectively. The critical values for the 5 and 10% significance levels are –1.94 and –1.62, respectively.

the deficit process. Thereby, we make use of the Wold Moving Average (MA) representation of the process in Equation 1, given by

$$\boldsymbol{Y}_t = \boldsymbol{E}_t + \Phi_1 \boldsymbol{E}_{t-1} + \Phi_2 \boldsymbol{E}_{t-2} + \cdots \tag{3}$$

where $\Phi_S = \sum_{j=1}^{S} \Phi_{S-j} \mathbf{A}_j$ and Φ_0 is the identity matrix. Furthermore, we use orthogonal innovations by employing the Cholesky decomposition of the covariance matrix which is described in detail by Lütkepohl and Krätzig (2004, pp. 165–71). Thereby, we order the variables such that the deficit may impact the stocks. The *sequential elimination of regressors* technique suggests eliminating 12 and 11 of 20 parameters in samples 1 and 2, respectively. The multivariate LM test for serial correlation and the multivariate Autoregressive Conditional Heteroscedasticity-Lagrange Multiplier (ARCH-LM) test give no evidence of potential misspecification.[3] Furthermore, recursive coefficient estimates give no reason for any concerns regarding eventual parameter instability for the first sample. Interestingly, the second sample shows relative uncertainty concerning the parameters of the lagged stocks in the deficit equation. However, these parameters appear to be stable after the year 1999/00. Further, Table 1 shows the results for testing the hypotheses (a)–(c). We notice that the deficit is Granger Causal for the stocks in both samples. However, the test results concerning stocks appear to be more challenging: even though stocks are not Granger Causal for the deficit on the common 5% significance level for sample 1, this does not hold any longer for the second sample. Moreover, the estimated correlation of 0.30 between stocks and deficit is statistically significant for the first sample only. The estimated correlation of –0.14 of the second sample is not significant, and hence, the null hypothesis of 'no correlation' cannot be rejected. The estimated impulse responses for an increase in the deficit by 1% are shown in Table 2. In contrast to earlier studies by Darrat and Brocato (1994) and Ewing (1998) who suggest a negative relationship between the deficit and stock returns, we cannot support these findings in our VAR framework: considering the first sample, a shock of the deficit of 1% results in a simultaneous increase of 2.39% in stocks. After seven quarters, the cumulative increase in stocks is 7.99%. These results become different when taking into account the second sample: after a slight decrease in stocks, the impulse to the shock becomes positive from the seventh quarter onwards. It takes about 2 years until the initial shock of 1% is converted into a cumulative increase in stocks of about 2%.

Table 1. Testing for causality

Causality hypothesis	Test value	Distribution	*p*-value
Sample 1 (1968:1–1988:3)			
(a)	21.19*	$\chi(3)$	0.0001
(b)	3.08	$\chi(1)$	0.0793
(c)	5.89	$\chi(1)$	0.0152
Sample 2 (1988:4–2011:3)			
(a)	8.61	$\chi(2)$	0.0135
(b)	25.18*	$\chi(3)$	0.0000
(c)	0.09	$\chi(1)$	0.7675

Note: *significant on a 1% significance level.

Table 2. Orthogonal impulse responses

Time (in quarters)	Sample 1	Sample 2
0	2.39	–0.17
1	4.60	–1.13
2	5.56	–1.39
3	7.72	–1.51
4	7.63	–0.14
5	7.26	–0.22
6	7.58	–0.21
7	7.99	0.16
8	8.05	0.88
9	8.07	0.96
10	8.07	1.07
11	8.10	1.32
12	8.13	1.66

III. Conclusion

Roley and Schall (1988) conclude that stock prices would increase if the output gain from stimulative fiscal policy outweighed any increase in interest rates and risk. Taking into account the relatively low interest rates in the US economy, we conclude that the stimulus in the wake of the US fiscal policy outweighed the risk in the US economy so far. Roley and Schall (1988, p. 17) give the following explanation: 'Perhaps investors did not consider budget deficits a problem. Or perhaps the stimulative fiscal policy led to such a strong economic expansion that stocks became increasingly attractive investments despite concerns that high budget deficits would raise interest rates and inflation.' However, we recognize that the

[3]The multivariate LM test for serial correlation including 5 lags shows a *p*-value of 0.5797, whereas the multivariate Autoregressive Conditional Heteroscedasticity-Lagrange Multiplier test shows a *p*-value 0.6158 concerning sample 1. The corresponding figures regarding sample 2 are 0.8616 and 0.2912.

results from second sample indicate that the effect has considerably changed over time. Moreover, we recognize a structural change concerning the stochastic interrelations between the fundamental variable federal deficit and the financial one. While the first sample under investigation showed that the causality origins from the fundamental sphere, the more recent sample shows a significant impact from the financial sphere to the fundamental one, too.

References

Brüggemann, R. and Lütkepohl, H. (2001) Lag selection in subset VAR models with an application to a U.S. monetary system, in *Econometric Studies: A Festzeitschrift in Honour of Joachim Frohn*, (Eds.) R. Friedmann, L. Knü ppel and H. Lü tkepohl, LIT Verlag, Münster, pp. 107–28.

Darrat, A. F. and Brocato, J. (1994) Stock market efficiency and the federal budget deficit: another anomaly?, *The Financial Review*, **29**, 49–75.

Ewing, B. T. (1998) The impact of federal budget deficits on movements in the stock market: evidence from Australia and France, *Applied Economics Letters*, **5**, 649–51.

Lütkepohl, H. and Krätzig, M. (2004) *Applied Time Series Econometrics*, Cambridge University Press, New York, NY.

Roley, V. V. and Schall, L. D. (1988) Federal deficits and the stock market, *Economic Review – Federal Reserve Bank of Kansas City*, **73**, 17–27.

Returns to public debt: The US federal budget deficit and the cross-section of equity returns

Klaus Grobys[1*a]

**University of Vaasa, Wolffintie 34, 65200, Vaasa, Finland.*

Abstract

This paper investigates the implications of changes in the US federal budget deficit for asset pricing. A portfolio-based risk factor related to changes in the budget deficit is formulated and its cross-sectional properties are analyzed. The average spread between equities exhibiting the highest negative cumulative impulse responses to shocks in the budget deficit and equities exhibiting the least sensitivity is found to be significantly negative. Traditional asset pricing cannot explain this pattern. The spread appears to be highly correlated with the business cycle and generates high payoffs when the economy is in a poor state.

***JEL* classifications:** G12; G14

Keywords: Asset pricing, US federal budget deficit, equity returns, macroeconomic risk

[1] Email: klaus.grobys@uwasa.fi; grobys.finance@gmail.com. Phone: +358 (0)46 611 0151.

[a] I received valuable comments from seminar participants at a research seminar in accounting and finance at the University of Vaasa and the 2013 Auckland Finance Meeting. I wish to thank Jesper Haga, James Kolari, Adrian Lee, Lars Lochstoer, Peter Nyberg, Bernd Pape, Seppo Pynnönen, and Sami Vähämaa and for valuable comments.

1. Introduction

On Friday August 5, 2011, Standard & Poor's announced it had downgraded the credit rating of the United States for the first time in history. A major reason for downgrading the nation's creditworthiness was the enormous federal budget deficit that has increased continuously for several decades. In the wake of the downgrading, the US federal budget deficit and its impact on domestic macroeconomic variables have generated a great deal of public debate. The impact of federal government stimulus measures on the domestic economy has been debated for many years. For instance, Alesia et al. (2002) investigated the effects of taxation and expenditure on investment in OECD countries and found that increases in public spending substantially reduce profits and thus investment, even after many years. Changes in the federal budget deficit are also associated with different effects on the financial sphere from a micro perspective. A number of papers have examined the association between the federal budget deficit variable and the stock market.

Darrat and Brocato (1994) investigated the efficiency of the US stock market as it pertains to a number of major macro-finance variables. Their findings indicate that the stock market may be inefficient with regard to the federal budget deficit. Ewing (1998) examined whether the federal budget deficits in Australia and France have an impact on the stock markets of the respective countries. Consistent with the findings of Darrat and Brocato (1994), Ewing's results indicate that in both Australia and France, examining the past deficit can provide information about future movements in the stock market. Empirical findings from Darrat and Brocato (1994) and Ewing (1998), which both indicated that changes in the budget deficit are Granger-causal for stock market returns, have been confirmed by Laopodis (2009, 2012) and Grobys (2013).

The purpose of this paper is to investigate the asset pricing implications of changes in the federal budget deficit. This paper is motivated by the growing body of literature that models the relationship between macro-finance variables and expected returns.[2] Despite the previous literature, no study has been undertaken that investigates asset pricing implications of changes in the federal budget deficit with a portfolio-based approach, in the spirit of Fama and French (2008). This paper contributes to the literature in the following aspects: First, it generates a portfolio-based systematic risk factor based on changes in the US federal budget deficit. The proposed approach to generating a portfolio-based risk factor, which involves employing cumulative impulse response functions based upon iteratively estimated vector autoregressive (VAR) models, is a novel aspect of the paper. Second, the study identifies whether traditional portfolio-based risk factors are capable of explaining the risk factor related to changes in the budget deficit. Third, the study examines the extent to which the new risk factor can help to explain a cross-section of equity returns.

The presence of Granger causality indicates the employment of impulse response functions that are economically meaningful in this context. In a bivariate VAR model, the corresponding impulse response functions can be interpreted as measures of future returns that firm i is expected to generate when the budget deficit is subject to a shock. In the first step of the empirical analysis, a portfolio-based procedure in the spirit of Fama and French (2008) was extended by first dividing a set of equity portfolios into 20 groups based on their cumulative impulse response to orthogonalized shocks in the budget deficit process. Subsequently, the returns of quarterly rebalanced consecutive zero-cost strategies, which are long on the group of equity portfolios exhibiting the highest negative cumulative impulse responses to shocks in the

[2] Relevant papers within this strand of literature include Bodie (1976), Fama (1981, 1990, 1991), Geske and Roll (1983), Pearce and Roley (1983, 1985), and Flannery and Protopapadakis (2002).

budget deficit process and short on all other groups of equity portfolios, were examined. Since the cumulative impulse response functions also depend on the underlying forecast horizon, zero-cost strategies were investigated for different forecast horizons.

Next, the zero-cost strategy associated with the optimal forecast horizon corresponding to a long-term horizon of 23 periods was treated as a risk factor and investigated further. The result is an analysis of a sample spanning more than 30 years of quarterly data. The proposed sorting methodology reveals a strong interaction between cumulative impulse responses and future returns: the raw spread between the equity portfolio group (PG) comprising the equity portfolios exhibiting the highest negative and lowest cumulative impulse responses is -1.27% per quarter with a heteroskedasticity robust *t*-value of -2.48. Risk-adjusting the spread using Carhart's (1997) four-factor model slightly increased the economic magnitude of the spread to -1.42% per quarter with a heteroskedasticity robust *t*-value of -2.84, indicating statistical significance on any level. The conducted spread appears to be negatively associated with the business cycle and to generate high payoffs when the economy is in a poor state.

Furthermore, the ability of the proposed risk factor to explain the cross-section of equity returns was investigated. The traditional capital asset pricing model (CAPM) derived from the work of Sharpe (1964), Lintner (1995), and Black (1972), and Fama and French's (1993) three-factor model were employed. None of these standard asset pricing models could explain the cross-section of test assets sorted by industry and cumulative impulse responses to shocks in the budget deficit process. Moreover, the cross-sectional risk premium of the deficit-related risk factor was found to be economically important, ranging between -0.97% and -2.89% per quarter, depending on the model specification. Given the set of test portfolios, the new risk factor alone was able to explain 47% of the cross-section of equity returns. Taken together, the results presented in this paper provide strong evidence that changes in the budget deficit are relevant for describing the cross-section of equity returns.

The remainder of this paper is organized as follows: The second section provides more detail on the background to the paper. The third section presents the data and results from the proposed sorting methodology. Bivariate VAR models for a large set of equity portfolios were established and the corresponding cumulative impulse response functions for different forecast horizons were implemented. For each forecast horizon under consideration, the equity portfolios were sorted into 20 groups based on estimated cumulative impulse responses to shocks in the budget deficit. Then, various zero-cost strategies were investigated, depending on the respective forecast horizon, by buying the group of equity portfolios exhibiting the highest negative cumulative impulse response and consecutively selling all other PGs. The optimal zero-cost portfolio was employed for pricing the cross-section of equity returns. Conclusions are presented in the last section.

2. Background

Flannery and Protopapadakis (2002) argued that macroeconomic variables are excellent candidates for systematic risk factors because macroeconomic changes may have a simultaneous impact on companies' cash flows and can affect the risk-adjusted discount rate. Moreover, economic conditions may affect the number and type of available real investment opportunities. However, Chan et al. (1998) highlighted that macroeconomic factors generally perform poorly when employed to explain variations in equity returns. Many studies have tried to identify reliable associations between macroeconomic variables and equity returns (Chen et al., 1986, Chang and Pinegar, 1989, 1990; Fama, 1990, 1991; Flannery and Protopapadakis, 2002). Darrat and Brocato (1994) in particular emphasized the role of the federal budget deficit as a macro-finance variable. They highlighted that variation in the federal budget deficit can be considered an argument for non-idiosyncratic risk structure being related to the entire stock universe. More precisely, they argued that deficit risk cannot be eliminated through diversification and, consequently, this risk should be priced according to financial theory. In particular, the long-standing public policy concerns regarding chronic excessive federal spending and the observed link between the size of the deficit and the business cycle may contribute to the belief that variation in the deficit factor could have a high information quotient for rational investors.

Furthermore, Darrat and Brocato (1994) described various channels through which changes to the federal budget deficit can affect investors' expectations concerning future cash flows and the discount rate. Both arguments are integral parts of the conventional discounted cash flow model. A simple discounted cash flow model for stock price determination can be given by

$$P_{i,t} \left| \Omega_t = E\left(\sum_{t=0}^{N} \frac{EPS_{i,t}}{\left(1+d_i\right)^t} \right| \Omega_t \right) \tag{1}$$

where P_{it} denotes the stock price of firm *i* at time *t*, EPS_i denotes the earnings per share of firm *i*, d_i is the firm specific discount rate, and *T* is the number of time periods taken into account. Equation (1) also shows that the expected earnings of a company depend on the current information set of the investor at time *t*. The firm specific discount rate is the sum of the risk-free rate and a firm specific risk premium. The theoretical belief that the budget deficit effect on stock returns can be expected to be a negative sign rests upon the assumption that deficits exert upward pressure on the nominal interest rate. However, an increase in the budget deficit can be occasioned by an increase in government spending, a decrease in government revenues (i.e., reduced taxes), or a mixture of both, with all these policies intended to stimulate the economy.

It is logical that if the government reduces the tax burden of companies, the profits of firms will increase when all other factors are equal. The same argument holds if the government increases public spending and, as a consequence, increases subventions for firms. Moreover, the government also has the option to decrease the tax burden of private households, which, in turn, is likely to result in an increased budget deficit. However, Elmendorf and Mankiw (1999) pointed out that conventional analysis indicates that this policy will stimulate consumption, at least in the short-term. In turn, an increase in consumption will, ceteris paribus, lead to an increase in corporate profits.

In summary, the theoretical belief that the expected sign of the budget deficit effect on stock returns is negative implies that a higher budget deficit leads to an increase in interest rates and, moreover, that the negative effect of an increased risk-free rate is larger than the positive effect of an increased value of expected earnings per share (EPS) at the individual firm level. However, anecdotal evidence contradicts this theoretical belief. The US has been running an ever-increasing budget deficit for decades, while the risk-free rate has simultaneously declined. Even if we assume that the theory holds, the negative effect of rising interest rates would not occur instantaneously in this case but would be subject to a time lag and thus appear at an undetermined time in the future. Hence, the expected sign of the budget deficit effect on stock returns may be ambiguous.[3]

Since changes in the budget deficit are understood as risks that have a long-term effect on the entire economy, it can also be assumed that firms exhibiting high long-term sensitivity to deficit risk are a riskier proposition than firms exhibiting low long-term sensitivity to the deficit risk.

---

[3] Recent empirical findings from Laopodis (2012) and Grobys (2013) examined the impulse response of the US stock market to shocks in the US federal budget deficit process. Their findings provide empirical evidence that shocks in the budget deficit process result in positive impulse responses of the US stock market. However, Laopodis (2012) found that the impulse response function is positive only in the three months immediately after the shock.

Traditional economic theory suggests that the spread between firms that are more risk inclined and firms that are less risk inclined is positive. The long-term effect of fiscal policy is well-known in the macroeconomic literature and is commonly referred to as the multiplier effect. In turn, shocks in the deficit process have a long-term effect on organizational cash flows. Therefore, rational investors require a risk premium for holding stocks of companies whose expected generated returns are affected by public spending. This is because positive shocks to the budget deficit rate increase the long-term cash flow of firms that exhibit high positive long-term sensitivity to deficit risk, whereas negative budget deficit shocks decrease the cash flows of those firms over an extended period.[4] As a consequence, the spread between firms exhibiting high long-term sensitivity to the deficit risk and firms exhibiting low long-term sensitivity should be positively priced because it reflects a systematic risk. In the parlance of Novy-Marx (2013, p.2), this reasoning is "consistent with risk based pricing".

In contrast to traditional portfolio-based risk factors such as small minus big (*SMB*) and high minus low (*HML*) proposed by Fama and French (1993), or the momentum (*MOM*) factor proposed by Jegadeesh and Titman (1993) and Carhart (1997), the portfolio-based risk factor related to deficit risk proposed in this study is directly linked to the macro economy. Since changes in the budget deficit affect the entire economy simultaneously, this risk cannot be diversified away (Darrat and Brocato 1994). For equities, it seems natural to consider changes in fundamental macro-finance variables to be major drivers of equity returns. Previous research has attempted to identify reliable associations between macroeconomic variables and equity returns but has concluded that macroeconomic factors generally perform poorly in explaining variations

[4] Analogously, positive shocks to the budget deficit rate decrease the long-term cash flow of firms that exhibit high negative long-term sensitivity to deficit risk, whereas negative budget deficit shocks increase the cash flows of those firms over an extended period.

in equity returns (Chan et al. 1998; Flannery and Protopapadakis 2002). The current paper breaks new ground in empirical asset pricing research and shows that the federal budget deficit as a macro-finance variable can assist in predicting future equity returns. While developing a new theoretical model is beyond the scope of this paper, it is possible to state that any theory that attempts to explain the cross-section of equity returns should be consistent with the empirical facts linking changes in the budget deficit and future equity returns.

3. Data

To serve as proxies for the US federal budget deficit, I downloaded the series Federal Debt Held by Foreign & Institutional Investors (series: FDHBFIN), Federal Debt Held by Federal Reserve Banks (series: FDHBFRBN) and Federal Debt Held by Private Investors (series: FDHBPIN) data series from the Federal Reserve Bank of St. Louis.[5] The data series are available from the first quarter of 1970 onwards (the notation 1970:1 is used here to designate years and quarters). I compounded the proxy for the US federal budget deficit simply as the sum of these three series by quarter and then compounded the corresponding quarterly returns. Furthermore, I obtained the following research equity portfolios from Kenneth French's website[6]: 100 value-weighted research equity portfolios formed on size and book-to-market ratio, 25 value-weighted research equity portfolios formed on size and momentum, 49 value-weighted research equity portfolios formed on industry, 25 value-weighted equity research portfolios sorted by size and short-term reversal and 25 value-weighted equity research portfolios sorted by size and long-term reversal. In total, I employed 224 research value-weighted equity portfolios as input assets for the sorting methodology. Operating with equity portfolio returns instead of individual stock returns is

[5] See http://research.stlouisfed.org/fred2/categories/106.

[6] See http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

logical in the context of this analysis for the following reasons: First, equity portfolios are not as *noisy* as individual stocks and reduced noise in the return series may have a positive effect on the accuracy of the parameter estimates for the impulse response functions. Second, operating with equal-weighted averages in PGs consisting of value-weighted equity portfolios eliminates, via construction, the risk that the results could be driven by outliers, such as microcaps, as defined by Fama and French (2008). Third, each of the equity portfolios employed to develop the sorting methodology itself contains a basket of value-weighted equities exhibiting the same characteristics. Consequently, these assets (equity portfolios) can be interpreted as proxies for firms that share similar characteristics. The corresponding data for the risk factors such as the market risk, *SMB*, *HML*, *MOM,* and risk-free rate were also obtained from Kenneth French's website. I matched all data series against the data for the US federal budget deficit and compounded the quarterly returns. The overall data set accounts for 172 quarterly observations running from 1970:2 to 2012:4.

4. Sorts on cumulative impulse response forecasts

For each equity portfolio i=1,..,224, I used a rolling time window of ten years of quarterly data starting in 1970:2 and estimated the following bivariate VAR model:

$$\mathbf{Y}_{it} = \mathbf{c}_i + \mathbf{A}_{i2}\mathbf{Y}_{it-2} + \mathbf{A}_{i3}\mathbf{Y}_{it-3} + \mathbf{A}_{i4}\mathbf{Y}_{it-4} + \mathbf{E}_{it}, \tag{2}$$

where $\mathbf{Y}_{it}$ is a 2×1 vector containing the proxy for changes in the federal budget deficit and the returns of equity portfolio i , $\mathbf{E}_{it}$ is a 2×1 vector of random variables with covariance matrix $\mathbf{\Sigma}_i$, $\mathbf{c}_i$ is a 2×1 vector of constants and $\mathbf{A}_{ip}$ with $p = 1,...,4$ denote 2×2 parameter matrices. I selected only equity portfolios with no missing return entries in both the in-sample rolling time window spanning ten years and the out-of-sample holding period (one quarter ahead). The current value of the budget deficit is not included in the information set Ω_t of the investor because updated figures for the current budget deficit take some six to ten weeks to be released and become publically available. Therefore, the first lag of the VAR model was skipped. In line with Lütkepohl and Krätzig (2004), a lag order of p=4 is common practice when operating with quarterly data and was also used in Darrat and Brocato (1994) and Grobys (2013). Next, I investigated the response of the returns of equity portfolio i to orthogonalized shocks in the budget deficit process of one standard deviation, making use of the Wold's moving-average (MA) representation of the process, given by equation (2):

$$\mathbf{Y}_{it} = \mathbf{\Theta}_{i0}\mathbf{\Psi}_{it} + \mathbf{\Theta}_{i1}\mathbf{\Psi}_{it-1} + \mathbf{\Theta}_{i2}\mathbf{\Psi}_{it-2} + \ldots \tag{3}$$

where $\mathbf{\Theta}_{ik} = \mathbf{\Phi}_{ik}\mathbf{P}_i$ and $\mathbf{\Psi}_{it} = \mathbf{P}_i^{-1}\mathbf{E}_{it}$ with k={1, 2,…}, $\mathbf{\Phi}_{iS} = \sum_{j=1}^{S}\mathbf{\Phi}_{iS-j}\mathbf{A}_{ij}$ and $\mathbf{\Phi}_{i0}$ is a 2×2 identity matrix. The matrix $\mathbf{P}_i$ is a lower triangular and denotes the Cholesky decomposition of the covariance matrix $\mathbf{\Sigma}_i$ of the residuals of equation (2) which is described in detail in Lütkepohl and Krätzig (2004, pp.165-171). Moreover, I used the Cholesky ordering method, meaning that the first element, $y_{1,it}$ in the vector $\mathbf{Y}_{it}$, corresponds to the changes in the federal budget deficit and the second element, $y_{2,it}$, corresponds to the returns of equity portfolio i. Then, I compounded the cumulative impulse response of the respective equity portfolio to orthogonalized shocks in the budget deficit process of one standard deviation. If equity portfolios are considered as proxies for firms, cumulative impulse response functions have a useful economic meaning. They measure the expected cumulative future return that a firm generates, given an investors' current information set Ω_t at time *t*, if an innovation corresponding to one standard deviation in the budget deficit process occurs. It can be assumed that firms exhibiting similar sensitivity to changes in the budget deficit move together.[7]

Furthermore, I compounded the cumulative impulse response (CIR) functions for forecast horizons k=1,…,32. Then, for each forecast horizon *k*, I divided the overall sample of equity portfolios into 20 groups. Since the estimated cumulative impulse response functions showed non-linear patterns, I sorted all portfolios in order of highest negative to highest positive impulse responses to shocks in the budget deficit process. PG 1 contained the 5% of equity portfolios exhibiting the highest negative cumulative impulse responses, PG 20 contained the 5% of equity portfolios exhibiting the highest positive cumulative impulse responses, and PG 10 contained equities exhibiting on average, the least response to shocks. Then, I compounded the corresponding zero-cost portfolios by buying PG 1 and consecutively selling PGs 2 to 20, given the forecast horizon *k*. The strategies were updated at the beginning of each quarter.

I used a rolling time window of ten years of quarterly data to estimate the VAR models. For instance, the initial portfolio allocation began in 1980:1, whereas the estimation procedure accounts for data from 1970:2 to 1979:3. The second allocation began in 1980:2 and accounts for data from 1970:3 to 1979:4, and so on. The overall portfolio allocation procedure covers the period from 1980:1 to 2012:4, corresponding to 132 quarterly observations. Furthermore, I employed Carhart's (1997) four-factor model to risk-adjust the zero-cost portfolios, depending

[7] When the US government determines a fiscal program to stimulate the economy, irrespective of whether that program involves direct subvention for firms or a lowered tax burden, the program is highly likely to continue for the duration of the period of a government, which is generally at least four years ahead.

on both the forecast horizon k and PG i by running the following OLS regressions for all k=1,…,32 and i=2,…,20 zero-cost portfolios:

$$DEF_{ikt} = \alpha_{ik} + \beta_{1ik}MRF_t + \beta_{2ik}SMB_t + \beta_{3ik}HML_t + \beta_{4k}MOM_t + \varepsilon_{ikt} \quad (4)$$

In equation (4), DEF_{ikt} denotes the returns of the constructed zero-cost portfolio based on a cumulative impulse response forecast accounting for a forecast horizon of k and long/short strategy PG 1 – PG i, MRF_t denotes the market factor, SMB_t and HML_t are the common size and value related risk factors of Fama and French and MOM_t denotes the momentum factor in line with Carhart (1997). The residuals ε_{ikt} are assumed to follow a white noise process, β_{1ik}, β_{2ik}, β_{3ik}, and β_{4ik} denote the sensitivity of DEF_{ikt} against these risk factors and α_{ik} corresponds to the risk-adjusted return of zero-cost portfolio k and long/short strategy (PG 1 – PG i).

The results are reported in Table I and II. Generally, it is evident that, on average, the spreads are negative. The CIRs appear to be non-linear. Figure I shows the CIRs of the sorted portfolios for the last formation period running from 2002:4 to 2012:3 and a forecast horizon of k=3. The corresponding out-of-sample returns for different strategy combinations are reported in the first column of Table I Panel A and Table II Panel A. The CIRs for the sorted portfolios differ, depending on the time-window, and forecast-horizon, while the shapes are typically the same. The higher the chosen forecast horizon, the more extreme the left- and right hand-tails of the distribution.

Moreover, the Carhart (1997) model has only a limited ability able to explain the variation of the zero-cost portfolios. Considering Table II, it is evident that an entire battery of zero-cost strategies is statistically significantly different from zero. The statistical significance of the raw excess returns tends to increase as the forecast horizon increases. For instance, considering a forecast horizon of k=16, we see that ten out of 19 zero-cost strategies generating raw-spreads are statistically different from zero at a common 5% level. It is also evident that the magnitude of the spread generally increases when moving from strategy (PG 1 – PG 2) to (PG 1 – PG 10) and decreases when moving from strategy (PG 1 – PG 14) to (PG 1 – PG 20). This is reasonable as the average sensitivities decrease when moving from PG 1 to PG 10 and then increase again when moving from PG 10 to PG 20. A forecast horizon of k=4 and strategy (PG 1 – PG 19) exhibits the highest statistical significance, corresponding to a raw return of -1.44% per quarter with a heteroskedasticity robust t-statistic of -3.04. The corresponding risk-adjusted return is -1.17% per quarter with a heteroskedasticity robust t-statistic of -2.48, indicating statistical significance at a common 5% level. Table I shows that, based upon past information, implementing this sorting methodology leads to an entire battery of zero-cost strategies that are potential candidates for portfolio-based risk factors linked to macroeconomic deficit risk.

The empirical finding that longer forecast horizons generally lead to economically relevant and statistically significant zero-cost strategies may have arisen due to *matching maturities*: given that new information arrives at time t, rational investors update their information set while anticipating the long-term effect of innovations in the budget deficit process. Once the US government has agreed on a fiscal program to stimulate the economy, that program is highly likely to be pursued throughout the term of the current government. Because rational investors formulate their expectations according to this common long-standing assumption, they require a risk premium with matching maturities. However, from an asset pricing point of view, the spreads between PG 1 and PG *i* where i={2,…,10} should be positive because PG 1 is the most risky portfolio compared to PG 2 to PG 10. Next, I investigated the asset pricing implications of the optimal spread for the cross-section of equity returns.

Even though Novy-Marx (2013) studied a different issue related to the profitability premium, he faced a similar problem since many different profitability measures have been discussed in the academic literature. Novy-Marx (2013, p.3) argued that, "determining the best measure of economic productivity is, however, ultimately an empirical question". His study adopted the profitability measure that exhibits the highest statistical significance in the cross-sectional analysis of stock returns. Extending the statistical selection criterion applied by Novy-Marx (2013), the selection criteria used here for the optimal spread also simply considers statistical significance. Based upon this intuitive selection criteria, I found that a forecast horizon of k=23 and strategy (PG 1 – PG 10) with heteroskedasticity robust t-statistic corresponding to -2.84 and risk-adjusted economic magnitude of -1.42% per quarter was the most informative spread from a statistical point of view.[8] Hence, this zero-cost portfolio is investigated in more detail in the analysis below.

The *DEF* factor is a zero-cost portfolio that is long in PG 1 (i.e., the group exhibiting the highest negative cumulative impulse response to an orthogonalized shock in the budget deficit return process of one standard deviation) and long in PG 10 (e.g., the group exhibiting the least response to a orthogonalized shock in the budget deficit process of one standard deviation). Table III illustrates the average excess returns and the average risk-adjusted returns for group

[8] Since the residuals of the regression equation for risk-adjusting the spread do not exhibit any autocorrelation, the heteroskedasticity robust estimates are reported. However, it may be worth noting that the Newey–West t-statistics (Newey and West, 1987) are even higher and exhibit a corresponding t-value of -3.16.

i=1,…,20, given a forecast horizon of k=23. It can be seen that the excess returns are non-linear and increase when moving from PG 1 to PG 20. PG 1 and PG 2 generate average excess raw returns that are not statistically different from zero. Moving from PG 3 to PG 15, it can be observed that the average raw excess returns of all PGs are statistically significant at a minimum 5% significance level. PG 15 generated the largest average raw excess return out-of-sample with a magnitude of 2.50% per quarter with a corresponding heteroskedasticity robust t-statistic of 2.98. The risk-adjusted return spread between PG 1 and PG 10 is -1.42% per quarter with a heteroskedasticity robust t-statistic of -2.84. I also performed the LM test for first-order autocorrelation. The p-value of 0.47 suggests that the spread is independently distributed.

The next element of the process was to investigate the correlations between the *DEF* factor and the ten Fama and French industries. In doing so, I considered the sample period from 1980:1 to 2012:4 that corresponds to the portfolio allocation. The data for the risk factors and the industries were downloaded from Kenneth French's website. The correlation matrix is shown in Table IV. On one hand, the *DEF* factor appears to be modestly correlated with the *SMB*, *HML*, *MOM*, and market factor. On the other hand, the *DEF* factor appears to be modestly negatively correlated with the ten industries, to roughly the same extent as the *HML* factor.

5. The budget deficit and the cross section of equity returns

5.1 Can traditional asset pricing models explain the sorting of test portfolios by their sensitivities to shocks in the US federal budget deficit process?

The next step was to investigate whether traditional asset pricing models are able to explain the sorting of test portfolios by cumulative impulse responses to shocks in the budget deficit process and to assess the asset pricing implications of the *DEF* factor. I employed the 20 PGs in excess returns sorted by cumulative impulse responses to shocks in the budget deficit process as test assets.[9] I also added 49 value-weighted test portfolios sorted by industry to the set of test asset.[10] Hence, I used a total of 69 portfolios as test assets. I ran five cross-sectional regressions, employing different risk factors in succession, to price this set of test assets. These regressions involved the CAPM as derived from the work of Sharpe (1964), Lintner (1995), and Black (1972), and Fama and French's (1993) three-factor model. The rationale behind using the previously mentioned factor models is that the proposed *DEF* factor is also portfolio-based, even though the underlying process is macro fundamental. The construction of this portfolio-based risk factor associated with the macro economy is a novel aspect of this paper.

The R-squared for each model specification and the Wald test statistic for testing the pricing errors were also estimated. Operating with excess returns means the constant in the Fama–MacBeth regressions (Fama and MacBeth, 1973) can be considered a weak test of pricing errors because a statistically significant intercept indicated a systematic pricing error of the respective model. I used the 132 quarterly observations running from 1980:1–2012:4 to estimate the Fama–MacBeth (1973) regressions. Since I employed a rolling-time window of 60 observations to estimate the time-varying betas, the estimation period is from 1995:1 to 2012:4.[11]

First, I employed the *DEF* factor as described in the previous section. The results are reported in Table V Panel A. The second cross-sectional regression shows that in a one-factor model specification, the *DEF* factor alone can explain 47% of the cross-sectional variation in expected returns. The CAPM model specification is even able to explain 82% of the cross-section of expected returns. Interestingly, in two out of three models the *DEF* factor is priced on 1% level.

---

[9] See Table III.

[10] I downloaded the corresponding data from Kenneth French's website and compounded the quarterly returns series. Then, I subtracted the risk-free rate for the corresponding three month period to retrieve the excess returns.

[11] Using a rolling-time window of 60 observations is common practice in the Fama-MacBeth approach.

Surprisingly, the *HML* factor does not seem to be priced in this sample. Adding the *DEF* factor to the Fama and French's (1993) three-factor model, the *DEF* factor does not exhibit a significant risk premium. The insignificance of the *DEF* factor in the Fama and French's (1993) three-factor model is contrary to the finding of the previous section, where it is documented that the risk-adjusted spread is of economic magnitude -1.42% per quarter with heteroskedasticity robust *t*-statistic of -2.84. This seemingly discrepancy between time-series setting and cross-sectional approach is, however, left for future research.

Next, I checked the robustness of the *DEF* factor and created a modified *DEF* factor.[12] The modified *DEF* factor is constructed by selling PG 10 and buying 0.5·PG 1 and 0.5·PG 20. From Table III and Figure I it becomes evident that PG 1 and PG 20 are those portfolios that exhibit the largest cumulative impulse response to shocks to the changes in the federal budget deficit. Again, I employed a total of 69 test assets including 49 value-weighted portfolios sorted by industry and 20 equal-weighted portfolios sorted by cumulative impulse responses to shocks in the budget deficit process.[13] The results are reported in Table V Panel B and provide a very similar picture as those in Panel A.

5.2 Anomaly or compensation for business cycle risk?

From an empirical point of view, a possible explanation as to why the spread related to the budget deficit risk is negative is that this zero-cost portfolio generates high payoffs in poor states of the economy. To empirically investigate the association between the *DEF* factor and the business cycle, I followed Nyberg and Pöyry (2013) and categorized each period from 1980:1 to 2012:4 as expansionary or recessionary based on the classifications made by the NBER. More

[12] I am grateful to James Kolari for suggesting this rolling-window estimation approach.
[13] Since all input portfolios used in the sorting procedure for constructing the 20 test assets are already value-weighted, equal-weighted portfolios are employed as test assets.

precisely, based upon the NBER dating, I categorized the following periods as recessionary: January 1980–July 1980, July 1981–November 1982, July 1990–March 1991, March 2001–November 2001, and, finally, December 2007–June 2009. A total of 17 of 132 quarters were coded as recessionary periods. I regressed the *DEF* factor on a constant and a dummy variable indicating the recessionary periods. Notably, the estimated constant has a magnitude of -1.57 per quarter with a corresponding *t*-statistic of -2.97, indicating statistical significance at any level. The parameter estimate related to the recession dummy variable is 2.62% per quarter with a *t*-statistic of 1.78, indicating statistical significance at a 10% level at least. I also checked the residuals of the regression. The *p*-value of the LM test statistic concerning testing first-order autocorrelation is 0.94, whereas the p-value of the ARCH-LM test statistic for testing conditional heteroskedasticity is 0.62, suggesting that the *DEF* factor is independently distributed.[14]

Next, I coded the initial quarter of the beginning of each recessionary period as expansionary, implying that the effect from the real economy to the financial sphere lags. This approach is similar to that used by Nyberg and Pöyry (2013) and resulted in 13 recessionary quarters within the sample. Then, I estimated the regression equation again, resulting in a parameter estimate of -1.40% per quarter for the constant with a *t*-value of -2.34 and a parameter estimate of 4.01% per quarter for the recession dummy with a corresponding *t*-value of 2.11, indicating statistical significance at a common 5% level. Again, as before, I checked the residuals and found no evidence for autocorrelation or ARCH effects. These results offer strong evidence that the *DEF* factor is indeed negatively associated with the business cycle and that, in economic downturns, the payoffs appear to be considerably higher than when the economy is in a good state.

[14] The tests are robust even when testing for higher order autocorrelation in the first and second order moments. In unreported results, I executed both tests by consecutively accounting for up to five lags. The *p*-value of all test statistics are clearly larger than 0.05.

6. Discussion

Many papers have attempted to explain the value premium and establish robust links between it and other factors. Most recently, Novy-Marx (2013) proposed a profitability premium associated with the value premium. It is worth mentioning that the raw excess return of Novy-Marx's (2013) profitability premium is 0.93 in quarterly terms with a *t*-statistic of 2.49. However, the deficit risk-related premium proposed in this paper exceeds Novy-Marx's (2013) profitability premium in both economic magnitude and statistical significance. Furthermore, Novy-Marx's (2013) profitability premium and the value premium of Fama and French (1993) exhibit a correlation coefficient of -0.57, implying that a profitability strategy is also a growth strategy and hence may act to hedge value strategies. Regressing the deficit-related risk premium on the Carhart (1997) four-factor model shows that the sensitivities against the *HML* and market factor are statistically not different from zero. However, the loadings against the *SMB* and *MOM* factors are -0.23 and 0.23, with corresponding heteroskedasticity robust *t*-values of -2.02 and 3.06, indicating that the investment strategy related to the *DEF* factor tends towards investment in large caps and winners. However, -1.42% of the spread per quarter cannot be explained by Carhart's (1997) four-factor model. Moreover, the orthogonal property between the *DEF* and *HML* factors implies that this strategy could be employed to reduce the portfolio risk for value strategies.

Considering the cross-section of equity returns, it is apparent that the *DEF* factor has noteworthy asset pricing implications. The risk premium is negatively priced in the cross-section. Interestingly, the traditional *HML* and the proposed *DEF* factor do not appear to be priced in the presence of the *SMB* factor when running cross-sectional Fama–MacBeth regressions. This finding is somewhat contrary to the evidence of the time series framework and needs to be investigated more in detail in future work. Furthermore, the empirical finding of Granger causality between changes in the budget deficit and stock returns has been interpreted to some degree as 'disturbing' (see Laopodis 2009) as it indicates market inefficiency. If changes to the budget deficit affect stock markets, then standard economic theory suggests that the expected sign of the budget deficit should be negative (e.g., Darrat and Brocato, 1994; Laopodis, 2009, 2012) simply because higher deficits are assumed to lead to increased interest rates. A higher budget deficit is expected to act through this interest rate channel to exert a negative effect on the stock market. The portfolio-based approach used to construct the *DEF* factor is long on the portfolio of equities exhibiting highest the negative cumulative impulse response to shocks in the budget deficit process and short in equity portfolios exhibiting the least sensitivity to shocks.

The spread of this investment strategy is statistically significantly negative and generates large positive payoffs when the economy is in a poor state. This also makes economic sense because in bad economic times, the government has incentives to increase public spending, which, in turn, may result in positive innovations in the budget deficit process. As a result, firms with higher long-term sensitivity to such innovations generate higher returns than firms exhibiting lower responses to innovations, because they benefit more from government spending. On the other hand, when the economy is good and increased public spending by the government is not needed, firms exhibiting the least response to shocks in the budget deficit process should generate higher returns than those exhibiting more sensitivity to innovations in the budget deficit process. This is also the rationale for the empirical findings reported in Table III. Since the good economic times have lasted considerably longer than the bad times, the average spread between equities exhibiting the highest negative cumulative impulse response to shocks in the budget deficit process and equities exhibiting the least sensitivity to shocks is (unconditionally) negative.

Furthermore, many papers related to empirical asset pricing research have employed deciles or quintiles when conducting portfolio-based risk factor analysis. These studies typically use individual stocks instead of equity portfolios. It is noteworthy that, on average, 196 portfolios were taken into account when sorting the 20 PGs, meaning that each of the 20 groups sorted by cumulative impulse responses to shocks in the budget deficit process contained an average of around ten equally-weighted portfolios that were baskets of value-weighted equity portfolios. Operating with deciles or even quintiles lowers both the spread and its statistical significance. This is because, in contrast to traditional sorts with respect to *size*, *momentum*, or *book-to-market value*, the sorting procedure that makes use of cumulative impulse response forecasts of the equity portfolios is non-linear.[15]

[15] Moreover, Fama and French (1993, 1996, 2008) conducted their *SMB* and *HML* risk factor sorts by market capitalization and *book-to-market ratio*, respectively. The momentum risk factor employed in Carhart's (1997) four-factor model uses cumulative past returns as sorting criteria, which can easily be compounded by summing past returns of the return series itself. Kolari et al. (2008) investigated the relation between the cross-section of US stock returns and foreign exchange rates and formulated a zero-investment risk factor related to foreign exchange rate sensitivities. Their study sorted portfolios with respect to their sensitivities against the exchange-rate time series and ended up with 25 groups where Group 1 contained the stocks exhibiting the lowest sensitivity to changes in the exchange rate, whereas Group 25 contained those stocks exhibiting the highest sensitivity to changes in the exchange rate. The study also found a non-linear association. Apparently, non-linear patterns encourage making use of wider spreads. This study mirrors Kolari et al. (2008) in terms of non-linear association and, consequently, the risk factor is formed based upon 20 groups. Moreover, Kolari et al. (2008) sorted their 25 portfolios by their sensitivity to the exchange-rate time series, which is a suitable approach when the chosen time series lacks correlation. However, macroeconomic time series such as quarterly changes in GDP or changes in the budget deficit are typically higher-order and auto-correlated; therefore, the econometric impulse response technique is more suitable to investigate stochastic interrelations between changes in the budget deficit and equity returns.

7. Conclusion

Macroeconomic variables are reasonable candidates for systematic risk factors because macroeconomic changes simultaneously have an impact on many organizations in the economy (Flannery and Protopapadakis, 2002). However, Chan et al. (1998) underlined that macroeconomic factors generally perform poorly in explaining variations in equity returns. Many papers have attempted to identify reliable associations between macroeconomic variables and equity returns. The current research establishes a significant and robust connection between the US federal budget deficit risk and equity returns. Shifts in the budget deficit have the ability to predict future returns. A zero-cost strategy for a new risk factor related to deficit risk is proposed. This zero-cost portfolio is long on equity portfolios that exhibit the highest negative cumulative impulse responses to orthogonalized shocks in the budget deficit process and short on equity portfolios that exhibit the lowest cumulative impulse responses to orthogonalized shocks in budget deficit changes. After risk adjustment, the sample average return of the spread used as a risk factor remains statistically significant at even a 1% level. This result provides strong evidence that this new risk factor related to budget deficit risk is negatively priced, while generating large positive payoffs when the economy is performing poorly.

Cross-sectional analysis shows also that the risk premium is of economic importance and is statistically significant. In addition, the current research establishes a new avenue of asset pricing research focused on revealing the associations between the cross-section of equity returns and macro-fundamental variables in a traditional portfolio-based asset pricing approach. While developing a new theoretical model is beyond the scope of this paper, we conclude that any theory that attempts to explain the cross-section of equity returns should be consistent with the empirical facts linking changes in the budget deficit and future equity returns.

References

Alesina, A., Ardagna, S., Perotti,, R. and Schiantarelli, F., 2002. Fiscal policy, profits, and investment. American Economic Review 92, 571–589.

Black, F., 1972. Capital market equilibrium with restricted borrowing. Journal of Business 45, 444–455.

Bodie, Z., 1976. Common Stocks as a Hedge Against Inflation. Journal of Finance 3, 459–470.

Burnside, C., 2007. Empirical Asset Pricing and Statistical Power in the Presence of Weak Risk Factors. NBER Working Papers 13357, National Bureau of Economic Research, Inc.

Chang, E.C., and Pinegar, J.M., 1989. Seasonal Fluctuations in Industrial Production and Stock Market Seasonal. Journal of Financial and Quantitative Analysis 24, 59–74.

Chang, E.C., and Pinegar, J.M., 1990. Stock Market Seasonal and Prespecified Multifactor Pricing Relations. Journal of Financial and Quantitative Analysis 25, 517–533.

Chan, L.K.C., Karceski, J., and Lakonishok, J., 1998. The Risk and Return from Factors. Journal of Financial and Quantitative Analysis 33, 159–188

Chen, N., Roll, R., and Ross, S.A., 1986. Economic Forces and the Stock Market. Journal of Business 59, 383–403.

Cochrane, J., 2005. Asset Pricing, rev. ed. *Princeton NJ*.

Darrat, A., and Brocato, J., 1994. Stock market efficiency and the federal budget deficit: another anomaly? The Financial Review 29, 49–75.

Elmendorf, D.W., and N.G. Mankiw, 1999. Government Debt, ed. by J. B. Taylor, and M. Woodford, vol. 1 of Handbook of Macroeconomics. Elsevier.

Ewing, B.T., 1998. The impact of federal budget deficits on movements in the stock market: evidence from Australia and France, Applied Economics Letters 5, 649–651.

Fama, E.F., 1981. Stock Returns, Real Activity, Inflation, and Money. American Economic Review 71, 545–565.

Fama, E.F.. and MacBeth, J., 1973. Return, risk and equilibrium: Empirical tests. Journal of Political Economy 81, 607–636.

Fama, E.F., 1990. Stock Returns, Expected Returns, and Real Activity. Journal of Finance 45, 1089–1108

Fama, E.F., 1991. Efficient Capital Markets: II. Journal of Finance 46, 1575–1617.

Fama, E.F., and French, K.R., 1993. Common risk factors in the returns on stocks and bonds. Journal of Financial Economics 33, 3−56.

Fama, E.F., and French, K.R., 1996. Multifactor Explanations of Asset Pricing Anomalies. Journal of Finance 51, 55–84.

Fama, E.F., and French, K.R., 2008. Dissecting Anomalies. Journal of Finance 63, 1653−1678.

Flannery, M., Protopapadakis, A., 2002. Macroeconomic factors do influence aggregate stock return. Review of Financial Studies 15, 751−782.

Geske, R., and Roll, R., 1983. The Fiscal and Monetary Linkage Between Stock Returns and Inflation. Journal of Finance 38, 1−34.

Grobys, K., 2013. An empirical analysis of changes of the impact of federal budget deficits on stock market returns: evidence from the US economy. Applied Economics Letters 20, 921–924.

Jegadeesh, N., and Titman, S., 1993. Returns to buying winners and selling losers: Implications for stock market efficiency. Journal of Finance 48, 35–91.

Johansen, S., 1995. Likelihood based Inference in Cointegrated Vector Autoregressive Models, Oxford University Press. Oxford.

Kolari, J.W., Moorman, T.C., and Sorescu, S.M., 2008. Foreign exchange risk and the cross-section of stock returns. Journal of International Money and Finance 27, 1074–1097.

Laopodis, N.T., 2009. Fiscal policy and stock market efficiency: Evidence of the United States. The Quarterly Review of Economics and Finance 49, 633–650.

Laopodis, N.T., 2012. Dynamic Linkages among Budget Deficits, Interest Rates and the Stock Market. Fiscal Studies 33, 547–570.

Lewellen, J., Nagel, S., and Shanken, J., 2010. A skeptical appraisal of asset pricing tests. Journal of Financial Economics 96, 175–194.

Lintner, J., 1965. The valuation of risk assets and the selection of risky investments in stocks portfolios and capital budgets. Review of Economics and Statistics 47, 13–37.

Lütkepohl, H. and Saikkonen, P., 2000. Testing for cointegrating rank of a VAR process with a time trend. Journal of Econometrics 95, 177–198.

Lütkepohl, H. and Krätzig, M., 2004. Applied Time Series Econometrics, Cambridge University Press, New York, NY.

Newey, W.K., and West, K.D., 1987. A Simple, Positive Semi-definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix. Econometrica 55, 703–708.

Novy-Marx, R., 2013. The other side of value: The gross profitability premium. Journal of Financial Economics 108, 1–28.

Nyberg, P. and Pöyry, S., 2013. Firm Expansion and Stock Price Momentum. Review of Finance 18, 1465–1505.

Pearce, D.K., and V.V. Roley, 1983. The Reaction of Stock Prices to Unanticipated Changes in Money: A Note. Journal of Finance 38, 1323–1333.

Pearce, D.K., and V.V. Roley, 1985. Stock Prices and Economic News. Journal of Business 58, 49–67.

Sharpe, W.F., 1964. Capital asset prices: a theory of market equilibrium under conditions of risk. Journal of Finance 19, 425–442.

Table I: Zero-cost portfolios

For each quarter *t,* I estimated a bivariate VAR model of lag order p=4 for all equity portfolios. Each VAR model contained the changes in the US federal budget deficit and the respective equity portfolio returns. Then, for each VAR model, I estimated the Wold's moving average representation and standardized the parameter matrices by employing the Cholesky decomposition of the covariance matrix and used the Cholesky ordering for the variables described in detail in Lütkepohl and Krätzig (2004, pp.165-171). I estimated the CIR functions accounting for a forecast horizon of k=1,…,32 quarters for a standardized shock in the US federal deficit process of one standard deviation for each VAR model. I sorted all equity portfolios with respect to their cumulative impulse responses depending on the forecast horizon k into 20 portfolio groups (PGs). The first PG contains the 5% of equity portfolios exhibiting the highest negative cumulative impulse responses, whereas the last PG contains the 5% of equity portfolios exhibiting the highest positive cumulative impulse responses. Then, I created the zero-cost portfolio for forecast horizon k and portfolio group i by buying PG 1 and buying PG i and i=1,…,20. To estimate the VAR-models, I used a rolling time window accounting for ten years of quarterly data starting in 1970:2. The strategies were updated at the beginning of each quarter. The initial portfolio allocation began in 1980:1. The sample period ran from 1980:1-2012:4. The data for the US federal deficit were downloaded from the Federal Reserve Bank of St. Louis, whereas the data for the equity portfolios were downloaded from Kenneth French's website. In Table I the results for different long/short strategies are reported. Each strategy is short in PG 1 which exhibits the highest negative cumulative impulse responses. Panels A-C report average raw excess returns. Heteroskedasticity robust *t*-statistics are given in parentheses.

Panel A

Strategy	Forecast horizon									
	3	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
1-2	0.10	-0.20	0.07	0.32	-0.11	0.15	0.20	-0.13	0.20	-0.03
	(0.18)	(-0.49)	(0.16)	(0.80)	(-0.30)	(0.31)	(0.50)	(-0.36)	(0.48)	(-0.08)
1-3	-1.03*	-0.79	-0.52	-0.25	-0.47	-0.13	-0.72	-0.81*	-0.86	-0.66
	(-1.71)	(-1.44)	(-0.92)	(-0.50)	(-0.85)	(-0.23)	(-1.32)	(-1.87)	(-1.60)	(-1.36)
1-4	-0.25	-0.71	-0.36	-0.29	-0.74	-0.38	-0.69	-0.68	-0.48	-0.49
	(-0.48)	(-1.42)	(-0.67)	(-0.64)	(-1.32)	(-0.76)	(-1.27)	(-1.48)	(-1.03)	(-1.07)
1-5	-0.52	-0.49	-0.65	-0.38	-0.91	-0.09	-0.87	-0.49	-0.85	-0.57
	(-0.96)	(-1.23)	(-1.16)	(-0.72)	(-1.50)	(-0.16)	(-1.41)	(-1.00)	(-1.63)	(-1.28)
1-6	-0.56	-0.57	-0.41	-0.20	-0.70	-0.02	-0.74	-0.20	-0.58	-0.03
	(-1.00)	(-1.31)	(-0.69)	(-0.40)	(-1.02)	(-0.03)	(-1.12)	(-0.37)	(-1.01)	(-0.06)
1-7	-0.66	-0.92*	-0.65	-0.17	-1.00	0.38	-0.99	-0.41	-0.96*	-0.56
	(-1.23)	(-1.91)	(-1.00)	(-0.32)	(-1.51)	(0.61)	(-1.58)	(-0.71)	(-1.74)	(-0.98)
1-8	-0.95*	-1.10**	-0.50	-0.29	-0.79	-0.22	-0.75	-0.36	-0.76	-0.49
	(-1.65)	(-2.18)	(-0.84)	(-0.65)	(-1.33)	(-0.43)	(-1.24)	(-0.73)	(-1.38)	(-0.97)
1-9	-0.68	-0.90*	-0.88	-0.29	-0.78	0.06	-0.92	-0.62	-0.72	-0.13
	(-1.20)	(-1.66)	(-1.50)	(-0.62)	(-1.37)	(0.11)	(-1.64)	(-1.32)	(-1.44)	(-0.26)
1-10	-1.21*	-1.16**	-0.88	-0.53	-1.09*	-0.45	-1.14**	-0.69	-1.06**	-0.55
	(-1.95)	(-2.39)	(-1.49)	(-1.20)	(-1.85)	(-0.89)	(-2.11)	(-1.46)	(-2.20)	(-1.15)
1-11	-0.99	-0.65	-0.75	-1.04**	-1.15**	-0.64	-1.35**	-0.96*	-1.22**	-0.87*
	(-1.62)	(-1.23)	(-1.29)	(-2.37)	(-2.09)	(-1.30)	(-2.36)	(-1.93)	(-2.48)	(-1.73)
1-12	-0.82	-0.66	-0.96	-0.69	-1.05*	-0.72	-0.90	-0.82	-0.79	-0.69
	(-1.42)	(-1.49)	(-1.64)	(-1.43)	(-1.80)	(-1.35)	(-1.61)	(-1.54)	(-1.56)	(-1.33)
1-13	-0.49	-0.84*	-0.66	-0.39	-0.79	-0.26	-0.87	-0.67	-0.92*	-0.52
	(-0.81)	(-1.79)	(-1.13)	(-0.78)	(-1.36)	(-0.51)	(-1.60)	(-1.37)	(-1.88)	(-1.05)
1-14	-0.73	-1.23***	-1.24**	-0.70	-0.90	-0.46	-1.06*	-0.87*	-0.87*	-0.91*
	(-1.21)	(-2.87)	(-2.12)	(-1.46)	(-1.62)	(-0.95)	(-1.90)	(-1.86)	(-1.78)	(-1.93)
1-15	-0.58	-1.35***	-0.60	-0.66	-1.00*	-0.89*	-1.22*	-1.23***	-1.20**	-1.15**
	(-0.97)	(-2.94)	(-0.95)	(-1.52)	(-1.65)	(-1.74)	(-2.16)	(-2.59)	(-2.30)	(-2.45)
1-16	-0.86	-0.79	-0.64	-0.97**	-0.90	-0.63	-0.75	-0.92*	-0.79	-0.82*
	(-1.34)	(-1.47)	(-0.98)	(-2.21)	(-1.49)	(-1.28)	(-1.20)	(-1.87)	(-1.36)	(-1.74)
1-17	-0.80	-0.86	-1.00	-0.71	-1.12*	-0.37	-1.05	-0.61	-0.77	-0.56
	(-1.24)	(-1.59)	(-1.54)	(-1.38)	(-1.73)	(-0.65)	(-1.61)	(-1.10)	(-1.30)	(-1.07)
1-18	-0.68	-0.72	-0.98	-0.53	-1.12*	-0.35	-1.04*	-0.52	-0.98*	-0.38
	(-1.13)	(-1.31)	(-1.63)	(-1.12)	(-1.72)	(-0.72)	(-1.69)	(-1.02)	(-1.79)	(-0.78)
1-19	-0.70	-1.44***	-1.00	-0.76*	-0.90	-0.60	-0.87	-0.90*	-0.57	-0.74*
	(-1.00)	(-3.04)	(-1.42)	(-1.73)	(-1.30)	(-1.25)	(-1.32)	(-1.93)	(-0.97)	(-1.68)
1-20	-0.54	-1.19***	-0.81	-0.75*	-0.95	-0.51	-0.94	-0.85*	-0.83	-0.83*
	(-0.75)	(-2.60)	(-1.21)	(-1.69)	(-1.44)	(-1.09)	(-1.49)	(-1.85)	(-1.52)	(-1.83)

*Statistically significant on a 10% level

**Statistically significant on a 5% level

***Statistically significant on a 1% level

Panel B

Strategy	Forecast horizon									
	13	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**
1-2	0.71	-0.03	0.16	-0.52*	0.93**	0.05	0.40	-0.40	0.13	-0.21
	(1.54)	(-0.06)	(0.38)	(-1.75)	(2.05)	(0.13)	(1.14)	(-1.11)	(0.38)	(-0.52)
1-3	-0.25	-0.78*	-0.88*	-1.01**	-0.39	-0.57	-0.67	-0.63	-0.89*	-0.43
	(-0.47)	(-1.68)	(-1.66)	(-2.25)	(-0.70)	(-1.35)	(-1.25)	(-1.37)	(-1.72)	(-1.00)
1-4	0.03	-0.59	-0.54	-0.79*	0.07	-0.53	-0.37	-0.62	-0.46	-0.44
	(0.06)	(-1.27)	(-1.10)	(-1.65)	(0.13)	(-1.28)	(-0.69)	(-1.42)	(-0.86)	(-1.01)
1-5	-0.46	-0.47	-0.77	-0.68	-0.24	-0.54	-0.75	-0.55	-1.01*	-0.25
	(-0.84)	(-1.00)	(-1.40)	(-1.44)	(-0.41)	(-1.29)	(-1.31)	(-1.19)	(-1.74)	(-0.59)
1-6	-0.24	-0.06	-0.80	-0.19	-0.18	0.23	-0.40	-0.02	-0.76	0.09
	(-0.40)	(-0.11)	(-1.37)	(-0.35)	(-0.27)	(0.50)	(-0.62)	(-0.05)	(-1.19)	(0.20)
1-7	-0.61	-0.69	-1.11**	-0.83	-0.45	-0.60	-0.95	-0.59	-1.02*	-0.46
	(-1.10)	(-1.21)	(-2.08)	(-1.45)	(-0.73)	(-1.13)	(-1.57)	(-1.10)	(-1.67)	(-0.87)
1-8	-0.23	-0.60	-0.78	-0.94*	-0.22	-0.76	-0.63	-0.78	-0.88	-0.50
	(-0.41)	(-1.12)	(-1.39)	(-1.77)	(-0.35)	(-1.51)	(-1.01)	(-1.51)	(-1.43)	(-0.99)
1-9	-0.56	-0.22	-1.06**	-0.71	-0.57	-0.49	-0.89	-0.51	-0.98*	-0.46
	(-1.09)	(-0.42)	(-2.06)	(-1.33)	(-0.99)	(-1.05)	(-1.60)	(-1.09)	(-1.73)	(-1.04)
1-10	-0.63	-0.75	-1.12**	-0.74	-0.52	-0.44	-1.01*	-0.59	-1.23**	-0.33
	(-1.32)	(-1.52)	(-2.27)	(-1.45)	(-0.96)	(-1.01)	(-1.85)	(-1.30)	(-2.32)	(-0.77)
1-11	-0.71	-0.79	-1.16**	-1.09**	-0.53	-0.90**	-1.09*	-0.91*	-1.22**	-0.81*
	(-1.36)	(-1.56)	(-2.28)	(-2.20)	(-0.89)	(-1.98)	(-1.89)	(-1.97)	(-2.15)	(-1.81)
1-12	-0.63	-0.83	-1.07**	-1.13**	-0.55	-0.86*	-0.87	-1.07**	-1.18**	-0.84
	(-1.24)	(-1.48)	(-2.12)	(-2.10)	(-0.92)	(-1.78)	(-1.55)	(-2.11)	(-2.10)	(-1.63)
1-13	-0.54	-0.51	-0.92*	-0.90*	-0.30	-0.84*	-0.67	-0.96**	-0.81	-0.75*
	(-1.10)	(-1.01)	(-1.92)	(-1.79)	(-0.55)	(-1.80)	(-1.25)	(-2.07)	(-1.49)	(-1.68)
1-14	-0.59	-1.02**	-0.92*	-1.32***	-0.35	-1.19***	-0.93	-1.17***	-1.09*	-0.87**
	(-1.18)	(-2.05)	(-1.68)	(-2.61)	(-0.57)	(-2.66)	-1.62	(-2.54)	(-1.91)	(-1.97)
1-15	-0.61	-0.94*	-1.09*	-1.16**	-0.47	-0.87**	-0.92	-0.88**	-1.08*	-0.58
	(-1.15)	(-1.87)	(-1.99)	(-2.42)	(-0.77)	(-2.01)	(-1.59)	(-2.03)	(-1.86)	(-1.32)
1-16	-0.43	-0.73	-1.04*	-0.84	-0.40	-0.63	-0.72	-0.83*	-1.05*	-0.57
	(-0.72)	(-1.47)	(-1.84)	(-1.60)	(-0.63)	(-1.31)	(-1.19)	(-1.73)	(-1.72)	(-1.21)
1-17	-0.48	-0.67	-0.89	-0.85	-0.34	-0.64	-0.79	-0.73	-0.91	-0.42
	(-0.80)	(-1.23)	(-1.48)	(-1.53)	(-0.51)	(-1.29)	(-1.24)	(-1.46)	(-1.43)	(-0.91)
1-18	-0.54	0.49	-1.04*	-0.89*	-0.45	-0.68	-0.82	-0.73	-1.04*	-0.82**
	(-1.03)	(-0.93)	(-1.91)	(-1.73)	(-0.73)	(-1.57)	(-1.37)	(-1.64)	(-1.69)	(-2.04)
1-19	-0.20	-0.73	-0.82	-1.09**	-0.29	-0.84**	-0.67	-0.90**	-0.83	-0.69*
	(-0.34)	(-1.55)	(-1.33)	(-2.28)	(-0.45)	(-2.16)	(-1.06)	(-2.25)	(-1.31)	(-1.80)
1-20	-0.44	-0.83*	-0.87	-1.07**	-0.26	-0.87*	-0.70	-0.92*	-0.94	-0.75*
	(-0.82)	(-1.71)	(-1.53)	(-2.08)	(-0.42)	(-1.97)	(-1.12)	(-2.03)	(-1.49)	(-1.76)

*Statistically significant on a 10% level

**Statistically significant on a 5% level

***Statistically significant on a 1% level

Panel C

Strategy	Forecast horizon									
	23	**24**	**25**	**26**	**27**	**28**	**29**	**30**	**31**	**32**
1-2	-0.03	-0.37	-0.07	-0.13	0.11	-0.47	0.46	-0.52	0.38	-0.56
	(-0.09)	(-0.93)	(-0.19)	(-0.32)	(0.32)	(-1.13)	(1.10)	(-1.41)	(0.93)	(-1.46)
1-3	-0.94*	-0.32	-0.96*	-0.31	-0.85*	-0.61	-0.49	-0.83*	-0.58	-0.60
	(-1.72)	(-0.69)	(-1.81)	(-0.62)	(-1.68)	(-1.29)	(-1.00)	(-1.74)	(-1.10)	(-1.24)
1-4	-0.51	-0.54	-0.60	-0.48	-0.46	-0.50	-0.08	-0.58	-0.26	-0.70
	(-1.03)	(-1.16)	(-1.22)	(-1.04)	(-0.91)	(-1.14)	(-0.16)	(-1.28)	(-0.51)	(-1.50)
1-5	-0.99*	-0.34	-0.97*	-0.39	-0.79	-0.55	-0.52	-0.67	-0.65	-0.49
	(-1.83)	(-0.73)	(-1.86)	(-0.81)	(-1.32)	(-1.23)	(-0.89)	(-1.46)	(-1.09)	(-1.03)
1-6	-0.86	-0.06	-0.89	0.19	-0.64	0.02	-0.26	-0.08	-0.35	-0.03
	(-1.37)	(-0.12)	(-1.44)	(0.36)	(-0.98)	(0.05)	(-0.40)	(-0.14)	(-0.55)	(-0.07)
1-7	-1.17**	-0.33	-1.22**	-0.28	-1.05*	-0.44	-0.76	-0.54	-1.04*	-0.56
	(-2.04)	(-0.61)	(-2.15)	(-0.51)	(-1.81)	(-0.83)	(-1.33)	(-1.00)	(-1.81)	(-1.00)
1-8	-0.89	-0.72	-1.06*	-0.66	-0.67	-0.71	-0.34	-0.86*	-0.53	-1.08**
	(-1.54)	(-1.40)	(-1.82)	(-1.32)	(-1.12)	(-1.54)	(-0.58)	(-1.70)	(-0.90)	(-2.16)
1-9	-1.07*	-0.34	-1.13**	-0.20	-0.83	-0.29	-0.63	-0.46	-0.83	-0.46
	(-1.99)	(-0.70)	(-2.12)	(-0.40)	(-1.48)	(-0.62)	(-1.13)	(-0.92)	(-1.48)	(-0.91)
1-10	-1.23**	-0.58	-1.33***	-0.47	-1.13**	-0.68	-0.87*	-0.88*	-0.98*	-0.82*
	(-2.48)	-1.33	(-2.74)	-1.05	(-2.21)	(-1.61)	(-1.77)	(-1.87)	(-1.99)	(-1.79)
1-11	-1.27**	-0.81*	-1.27*	-0.81*	-1.05*	-0.90*	-0.71	-1.07**	-0.71	-1.12**
	(-2.40)	(-1.70)	(-2.38)	(-1.65)	(-1.85)	(-1.95)	(-1.26)	(-2.14)	(-1.24)	(-2.25)
1-12	-1.12**	-0.91*	-1.21**	-0.82	-1.00*	-0.94*	-0.56	-1.04**	-0.69	-1.01*
	(-2.17)	(-1.77)	(-2.36)	(-1.54)	(-1.84)	(-1.87)	(-0.96)	(-1.96)	(-1.20)	(-1.90)
1-13	-0.88*	-0.66	-1.02*	-0.40	-0.82	-0.40	-0.47	-0.57	-0.67	-0.45
	(-1.67)	(-1.42)	(-1.94)	(-0.89)	(-1.51)	(-0.94)	(-0.89)	(-1.23)	(-1.26)	(-0.99)
1-14	-1.02*	-0.72	-1.04*	-0.52	-0.76	-0.65	-0.66	-0.74	-0.86*	-0.74
	(-1.89)	(-1.58)	(-1.93)	(-1.10)	(-1.39)	(-1.45)	(-1.29)	(-1.53)	(-1.70)	(-1.55)
1-15	-1.39***	-0.78*	-1.32**	-0.80*	-1.11*	-0.78*	-0.82	-0.90*	-0.99*	-0.85*
	(-2.78)	(-1.77)	(-2.49)	(-1.78)	(-1.95)	(-1.80)	(-1.43)	(-1.90)	(-1.73)	(-1.76)
1-16	-1.18**	-0.73	-1.20**	-0.62	-1.06*	-0.72	-0.68	-1.00**	-0.84	-1.02**
	(-2.06)	(-1.50)	(-2.07)	(-1.31)	(-1.75)	(-1.56)	(-1.16)	(-2.14)	(-1.41)	(-2.19)
1-17	-0.95	-0.67	-0.94	-0.64	-0.79	-0.74*	-0.38	-0.98**	-0.59	-1.05**
	(-1.58)	(-1.47)	(-1.56)	(-1.37)	(-1.31)	(-1.68)	(-0.63)	(-2.02)	(-0.99)	(-2.33)
1-18	-1.00*	-0.89**	-1.19**	-0.80**	-1.02*	-0.96**	-0.79	-1.11***	-0.98*	-1.08***
	(-1.72)	(-2.15)	(-2.04)	(-1.97)	(-1.72)	(-2.44)	(-1.37)	(-2.62)	(-1.71)	(-2.58)
1-19	-0.89	-0.82**	-0.88	-0.63	-0.64	-0.79**	-0.15	-0.96**	-0.31	-0.94**
	(-1.47)	(-1.98)	(-1.45)	(-1.54)	(-1.03)	(-2.03)	(-0.26)	(-2.23)	(-0.53)	(-2.24)
1-20	-1.01*	-0.83*	-1.08*	-0.79*	-0.89	-0.89**	-0.60	-1.02**	-0.78	-0.98**
	(-1.76)	(-1.88)	(-1.85)	(-1.87)	(-1.47)	(-2.14)	(-1.05)	(-2.27)	(-1.31)	(-2.25)

*Statistically significant on a 10% level

**Statistically significant on a 5% level

***Statistically significant on a 1% level

Table II: Risk-adjusted zero-cost portfolios

For each quarter *t,* I estimated a bivariate VAR model of lag order *p*=4 for all equity portfolios. Each VAR model contained the changes in the US federal budget deficit and the respective equity portfolio returns. Then, for each VAR model, I estimated the Wold's moving average representation and standardized the parameter matrices by employing the Cholesky decomposition of the covariance matrix and used the Cholesky ordering for the variables described in detail in Lütkepohl and Krätzig (2004, pp.165-171). I estimated the CIR functions accounting for a forecast horizon of *k*=1,…,32 quarters for a standardized shock in the US federal deficit process of one standard deviation for each VAR model. I sorted all equity portfolios with respect to their cumulative impulse responses depending on the forecast horizon *k* into 20 portfolio groups (PGs). The first PG contains the 5% of equity portfolios exhibiting the highest negative cumulative impulse responses, whereas the last PG contains the 5% of equity portfolios exhibiting the highest positive cumulative impulse responses. Then, I created the zero-cost portfolio for forecast horizon *k* and portfolio group *i* by buying PG 1 and buying PG *i* and *i*=1,…,20. To estimate the VAR-models, I used a rolling time window accounting for ten years of quarterly data starting in 1970:2. The strategies were updated at the beginning of each quarter. The initial portfolio allocation began in 1980:1. The sample period ran from 1980:1-2012:4. The data for the US federal deficit were downloaded from the Federal Reserve Bank of St. Louis, whereas the data for the equity portfolios were downloaded from Kenneth French's website. In Table II the results for different long/short strategies are reported. Each strategy is short in PG 1 exhibiting the highest negative cumulative impulse responses. Panels A-C report the risk-adjusted returns. For risk adjustment, Carhart's (1997) four-factor model was employed. Heteroskedasticity robust *t*-statistics are given in parentheses.

Panel A

Strategy	Forecast horizon								
	3	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
1-2	-0.10	-0.31	0.07	0.42	-0.32	0.43	0.13	-0.16	-0.07	-0.10
	(-0.19)	(-0.69)	(0.15)	(0.82)	(-0.82)	(0.65)	(0.30)	(-0.32)	(-0.13)	(-0.25)
1-3	-1.00	-1.15	-0.12	-0.37	-0.48	0.04	-0.74	-0.98	-1.13	-0.94
	(-1.35)	(-1.57)	(-0.18)	(-0.50)	(-0.88)	(0.05)	(-1.31)	(-1.64)	(-1.64)	(-1.48)
1-4	-0.06	-0.82	-0.08	-0.48	-0.61	-0.32	-0.65	-0.73	-0.46	-0.63
	(-0.10)	(-1.20)	(-0.14)	(-0.73)	(-1.04)	(-0.44)	(-1.08)	(-1.10)	(-0.95)	(-1.00)
1-5	-0.14	-0.20	-0.21	-0.67	-0.79	-0.02	-0.46	-0.37	-0.63	-0.65
	(-0.23)	(-0.49)	(-0.34)	(-0.94)	(-1.20)	(-0.02)	(-0.65)	(-0.72)	(-1.15)	(-1.43)
1-6	-0.37	-0.42	-0.07	-0.44	-0.78	-0.22	-0.93	-0.57	-0.90	-0.41
	(-0.56)	(-0.97)	(-0.10)	(-0.78)	(-0.86)	(-0.32)	(-1.03)	(-0.82)	(-1.28)	(-0.60)
1-7	-0.25	-0.70	-0.45	-0.32	-0.77	0.14	-0.92	-0.59	-1.10	-0.82
	(-0.43)	(-1.40)	(-0.50)	(-0.53)	(-0.89)	(0.21)	(-1.10)	(-0.91)	(-1.61)	(-1.20)
1-8	-0.73	-1.37**	-0.12	-0.07	-0.65	0.10	-0.51	-0.42	-0.72	-0.76
	(-1.11)	(-2.20)	(-0.16)	(-0.14)	(-1.02)	(0.20)	(-0.69)	(-0.92)	(-1.26)	(-1.57)
1-9	-0.43	-1.30*	-0.48	-0.40	-0.68	0.36	-0.76	-0.59	-0.65	-0.22
	(-0.63)	(-1.89)	(-0.74)	(-0.83)	(-1.04)	(0.68)	(-1.23)	(-1.27)	(-1.35)	(-0.49)
1-10	-1.51*	-1.17**	-0.43	-0.78	-0.91	-0.37	-0.98*	-0.77	-1.05**	-0.86*
	(-1.89)	(-2.24)	(-0.64)	(-1.57)	(-1.53)	(-0.64)	(-1.67)	(-1.48)	(-2.32)	(-1.78)
1-11	-1.14	-0.61	-0.33	-0.86	-0.71	-0.47	-0.98	-0.97*	-1.01*	-0.93
	(-1.30)	(-1.00)	(-0.54)	(-1.61)	(-1.26)	(-0.85)	(-1.44)	(-1.66)	(-1.98)	(-1.58)
1-12	-0.77	-0.63	-0.48	-0.84	-0.80	-0.49	-0.64	-0.89	-0.72	-0.72
	(-1.12)	(-1.36)	(-0.63)	(-1.47)	(-1.07)	(-0.72)	(-0.91)	(-1.36)	(-1.27)	(-1.23)
1-13	-0.15	-0.91	-0.24	-0.15	-0.69	-0.39	-0.72	-0.78	-0.79	-0.75
	(-0.18)	(-1.44)	(-0.32)	(-0.18)	(-1.03)	(-0.58)	(-1.02)	(-1.28)	(-1.32)	(-1.22)
1-14	-0.29	-1.06**	-0.80	-0.68	-0.69	-0.11	-0.77	-0.89*	-0.75	-1.07**
	(-0.35)	(-2.09)	(-1.20)	(-1.12)	(-1.20)	(-0.19)	(-1.20)	(-1.73)	(-1.45)	(-2.01)
1-15	-0.44	-1.21***	0.05	-0.72	-0.53	-0.65	-0.74	-1.22***	-0.96	-1.24***
	(-0.71)	(-2.73)	(0.06)	(-1.41)	(-0.63)	(-1.08)	(-0.90)	(-2.56)	(-1.36)	(-2.54)
1-16	-1.03	-0.50	-0.01	-0.79	-0.54	-0.41	-0.32	-0.85	-0.47	-0.84*
	(-1.40)	(-0.74)	(-0.01)	(-1.58)	(-0.68)	(-0.72)	(-0.37)	(-1.61)	(-0.65)	(-1.72)
1-17	-0.80	-0.71	-0.82	-0.54	-1.12	0.05	-1.11	-0.32	-0.95	-0.38
	(-1.07)	(-1.04)	(-1.07)	(-0.90)	(-1.62)	(0.08)	(-1.48)	(-0.51)	(-1.54)	(-0.61)
1-18	-0.50	-0.41	-0.60	-0.26	-1.07*	0.11	-1.06*	-0.28	-1.12**	-0.21
	(-0.65)	(-0.65)	(-0.99)	(-0.49)	(-1.74)	(0.22)	(-1.72)	(-0.47)	(-2.20)	(-0.36)
1-19	-0.80	-1.17**	-1.04	-0.60	-0.94	-0.09	-0.89	-0.67	-0.82	-0.70
	(-0.88)	(-2.48)	(-1.20)	(-1.21)	(-1.19)	(-0.18)	(-1.10)	(-1.36)	(-1.23)	(-1.52)
1-20	-0.53	-0.94**	-0.17	-0.33	-0.53	0.15	-0.43	-0.36	-0.48	-0.42
	(-0.65)	(-2.01)	(-0.23)	(-0.74)	(-0.71)	(0.29)	(-0.57)	(-0.92)	(-0.87)	(-1.07)

*Statistically significant on a 10% level

**Statistically significant on a 5% level

***Statistically significant on a 1% level

Panel B

Strategy	Forecast horizon									
	13	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**
1-2	0.34	-0.07	-0.13	-0.72**	1.13**	-0.23	0.40	-0.57	0.17	-0.33
	(0.62)	(-0.12)	(-0.23)	(-2.17)	(2.10)	(-0.50)	(1.03)	(-1.27)	(0.4)5	(-0.64)
1-3	-0.55	-0.95	-1.24*	-1.34**	-0.26	-0.86	-0.63	-1.01	0.88	-0.76
	(-0.82)	(-1.57)	(-1.71)	(-2.21)	(-0.39)	(-1.59)	(-1.02)	(-1.61)	(1.46)	(-1.26)
1-4	0.11	-0.66	-0.44	-0.98	0.71	-0.60	0.15	-0.79	0.14	-0.62
	(0.22)	(-1.04)	(-0.85)	(-1.55)	(1.04)	(-1.09)	(0.24)	(-1.34)	(0.23)	(-1.00)
1-5	-0.39	-0.36	-0.73	-0.77*	0.33	-0.43	-0.25	-0.60	0.63	-0.20
	(-0.67)	(-0.68)	(-1.22)	(-1.66)	(0.44)	(-0.99)	(-0.34)	(-1.12)	(0.90)	(-0.47)
1-6	-0.64	-0.35	-1.09	-0.70	-0.00	0.02	-0.35	-0.34	0.69	-0.24
	(-0.87)	(-0.52)	(-1.63)	(-1.06)	(-0.00)	(0.05)	(-0.41)	(-0.64)	(0.79)	(-0.51)
1-7	-0.79	-0.91	-1.31**	-1.10	-0.07	-0.74	-0.69	-0.83	0.72	-0.66
	(-1.13)	(-1.35)	(-2.04)	(-1.63)	(-0.08)	(-1.16)	(-0.83)	(-1.28)	(0.84)	(-1.02)
1-8	-0.22	-0.60	-0.73	-1.11**	0.30	-0.94*	-0.24	-1.04*	0.59	-0.80
	(-0.38)	(-1.06)	(-1.22)	(-2.12)	(0.38)	(-1.75)	(-0.33)	(-1.70)	(0.88)	(-1.52)
1-9	-0.55	-0.16	-1.06**	-1.04**	-0.12	-0.67*	-0.53	-0.79*	0.58	-0.61*
	(-1.09)	(-0.33)	(-2.07)	(-2.10)	(-0.18)	(-1.75)	(-0.82)	(-1.88)	(0.83)	(-1.75)
1-10	-0.68	-0.93*	-1.17**	-0.86	-0.02	-0.46	-0.72	-0.75	0.98	-0.47
	(-1.42)	(-1.76)	(-2.36)	(-1.64)	(-0.02)	(-1.12)	(-0.99)	(-1.58)	(1.44)	(-1.18)
1-11	-0.72	-0.72	-1.15**	-1.35**	-0.13	-1.09**	-0.91	-1.15**	0.92	-1.00**
	(-1.24)	(-1.25)	(-2.06)	(-2.51)	(-0.17)	(-2.28)	(-1.41)	(-2.27)	(1.42)	(-2.15)
1-12	-0.65	-0.79	-1.00*	-1.39**	0.04	-1.10*	-0.33	-1.47**	0.74	-1.28*
	(-1.12)	(-1.23)	(-1.75)	(-2.17)	(0.05)	(-1.82)	(-0.42)	(-2.21)	(0.97)	(-1.95)
1-13	-0.47	-0.64	-0.71	-1.28**	0.46	-1.25**	-0.02	-1.41**	0.13	-1.14**
	(-0.80)	(-1.02)	(-1.25)	(-2.19)	(0.65)	(-2.16)	(-0.03)	(-2.41)	(0.20)	(-2.01)
1-14	-0.52	-1.02*	-0.61	-1.40**	0.51	-1.13**	-0.23	-1.21**	0.40	-0.59
	(-0.98)	(-1.75)	(-0.82)	(-2.47)	(0.60)	(-2.34)	(-0.28)	(-2.35)	(0.50)	(-1.44)
1-15	-0.39	-0.76	-0.90	-1.19**	0.19	-0.77*	-0.36	-0.88*	0.53	-0.43
	(-0.53)	(-1.42)	(-1.17)	(-2.31)	(0.21)	(-1.77)	(-0.41)	(-1.84)	(0.60)	(-0.98)
1-16	-0.20	-0.65	-1.06*	-0.64	0.16	-0.29	-0.34	-0.57	0.65	-0.34
	(-0.28)	(-1.24)	(-1.75)	(-1.03)	(0.21)	(-0.58)	(-0.47)	(-1.06)	(0.91)	(-0.74)
1-17	-0.70	-0.43	-1.13*	-0.75	0.13	-0.43	-0.69	-0.68	0.90	-0.37
	(-1.06)	(-0.67)	(-1.70)	(-1.09)	(-0.16)	(-0.78)	(-0.89)	(-1.12)	(1.22)	(-0.74)
1-18	-0.68	-0.17	-1.21**	-1.00*	-0.14	-0.71*	-0.60	-0.84*	0.87	-0.75*
	(-1.44)	(-0.30)	(-2.34)	(-1.98)	(-0.19)	(-1.79)	(-0.87)	(-1.90)	(1.12)	(-1.95)
1-19	-0.55	-0.56	-1.12	-1.09**	-0.12	-0.75**	-0.61	-0.83**	0.76	-0.54
	(-0.82)	(-1.12)	(-1.61)	(-2.26)	(-0.15)	(-2.07)	(-0.77)	(-2.04)	(0.99)	(-1.49)
1-20	-0.10	-0.29	-0.53	-0.67	0.62	-0.40	0.03	-0.54	0.21	-0.35
	(-0.16)	(-0.67)	(-0.85)	(-1.43)	(0.78)	(-1.12)	(0.04)	(-1.33)	(0.27)	(-1.04)

*Statistically significant on a 10% level

**Statistically significant on a 5% level

***Statistically significant on a 1% level

Panel C

Strategy	**Forecast horizon**									
	23	**24**	**25**	**26**	**27**	**28**	**29**	**30**	**31**	**32**
1-2	-0.29	-0.54	-0.21	-0.51	0.06	-0.52	0.48	-0.79*	0.46	-0.76
	(-0.54)	(-1.11)	(-0.46)	(-0.98)	(0.16)	(-0.98)	(0.98)	(-1.66)	(1.02)	(-1.48)
1-3	-1.25*	-0.62	-1.15*	-0.70	-0.95	-0.74	0.51	-1.11*	0.52	-0.66
	(-1.78)	(-0.98)	(-1.79)	(-1.07)	(-1.62)	(-1.14)	(0.91)	(-1.76)	(0.87)	(-1.03)
1-4	-0.28	-0.73	-0.20	-0.74	-0.02	-0.60	0.43	-0.72	0.22	-0.80
	(-0.56)	(-1.15)	(-0.38)	(-1.17)	(-0.03)	(-0.98)	(0.70)	(-1.27)	(0.35)	(-1.32)
1-5	-0.95*	-0.37	-0.66	-0.55	-0.40	-0.52	0.02	-0.75	0.19	-0.49
	(-1.73)	(-0.80)	(-1.21)	(-1.06)	(-0.55)	(-1.19)	(0.03)	(-1.56)	(0.26)	(-1.03)
1-6	-1.07	-0.43	-1.03	-0.19	-0.71	-0.17	0.27	-0.34	0.33	-0.27
	(-1.50)	(-0.87)	(-1.34)	(-0.35)	(-0.79)	(-0.36)	(0.30)	(-0.60)	(0.38)	(-0.52)
1-7	-1.17*	-0.55	-1.03	-0.60	-0.84	-0.63	0.39	-0.74	0.73	-0.71
	(-1.74)	(-0.86)	(-1.44)	(-0.92)	(-1.03)	(-0.97)	(0.47)	(-1.13)	(0.92)	(-1.10)
1-8	-0.97*	-1.05*	-0.96	-1.12**	-0.54	-0.89*	0.22	-1.11*	0.40	-1.13**
	(-1.70)	(-1.85)	(-1.60)	(-1.97)	(-0.77)	(-1.81)	(0.32)	(-1.92)	(0.57)	(-2.09)
1-9	-0.98*	-0.61	-0.88*	-0.51	-0.46	-0.43	0.49	-0.63	0.74	-0.60
	(-1.77)	(-1.48)	(-1.68)	(-1.16)	(-0.72)	(-1.12)	(0.69)	(-1.42)	(1.06)	(-1.50)
1-10	-1.42***	-0.83*	-1.37***	-0.81*	-0.97	-0.85**	0.64	-1.24***	0.73	-1.09**
	(-2.84)	(-1.94)	(-2.59)	(-1.78)	(-1.45)	(-2.16)	(0.95)	(-2.56)	(1.07)	(-2.37)
1-11	-1.19**	-1.19**	-1.02*	-1.37**	-0.67	-1.21**	0.26	-1.47***	0.06	-1.53***
	(-2.14)	(-2.26)	(-1.72)	(-2.45)	(-0.90)	(-2.40)	(0.34)	(-2.63)	(0.08)	(-2.63)
1-12	-0.74	-1.42**	-0.71	-1.40**	-0.45	-1.28**	0.29	-1.39**	0.16	-1.31*
	(-1.26)	(-2.16)	(-1.21)	(-2.04)	(-0.66)	(-2.02)	(0.36)	(-2.01)	(0.20)	(-1.93)
1-13	-0.45	-1.01*	-0.46	-0.51	-0.16	-0.14	0.21	-0.34	0.06	-0.08
	(-0.65)	(-1.71)	(-0.66)	(-1.01)	(-0.21)	(-0.33)	(0.28)	(-0.69)	(0.08)	(-0.18)
1-14	-0.64	-0.66	-0.54	-0.42	-0.18	-0.35	0.23	-0.44	0.44	-0.33
	(-0.92)	(-1.47)	(-0.78)	(-0.82)	(-0.24)	(-0.80)	(0.41)	(-0.82)	(0.79)	(-0.65)
1-15	-1.39***	-0.82*	-1.18**	-0.94*	-0.92	-0.74*	0.53	-0.91*	0.73	-0.75
	(-2.57)	(-1.70)	(-2.02)	(-1.85)	(-1.27)	(-1.81)	(0.72)	(-1.76)	(1.02)	(-1.48)
1-16	-1.17**	-0.55	-1.01	-0.52	-0.86	-0.41	0.43	-0.99**	0.55	-0.98**
	(-2.02)	(-1.08)	(-1.65)	(-1.03)	(-1.24)	(-0.94)	(0.63)	(-2.06)	(0.79)	(-2.06)
1-17	-1.22*	-0.88*	-1.05	-0.97*	-0.76	-0.87*	0.21	-1.23**	0.45	-1.12**
	(-1.98)	(-1.75)	(-1.63)	(-1.87)	(-1.02)	(-1.92)	(0.26)	(-2.26)	(0.56)	(-2.22)
1-18	-1.16*	-0.91**	1.19*	-0.88**	-0.87	-0.89**	0.60	-1.13**	0.78	-1.03**
	(-1.69)	(-2.26)	(-1.69)	(-2.06)	(-1.08)	(-2.20)	(0.76)	(-2.65)	(1.02)	(-2.44)
1-19	-1.16*	-0.78*	-1.02	-0.63	-0.70	-0.58	0.15	-0.82*	0.01	-0.74*
	(-1.76)	(-1.90)	(-1.48)	(-1.49)	(-0.90)	(-1.56)	(0.24)	(-1.86)	(0.02)	(-1.76)
1-20	-0.60	-0.51	-0.53	-0.58	-0.27	-0.46	0.02	-0.67*	0.15	-0.54
	(-1.01)	(-1.34)	(-0.84)	(-1.49)	(-0.36)	(-1.39)	(0.03)	(-1.66)	(0.20)	(-1.42)

*Statistically significant on a 10% level

**Statistically significant on a 5% level

***Statistically significant on a 1% level

Table III: Quarterly sorts conditioned on cumulative impulse responses to shocks in the US federal budget deficit process of one standard deviation

For each quarter *t,* I estimated a bivariate VAR model of lag order p=4 for all equity portfolios. Each VAR model contained the changes in the US federal budget deficit and the respective equity portfolio returns. Then, for each VAR model, I estimated the Wold's moving average representation and standardized the parameter matrices by employing the Cholesky decomposition of the covariance matrix and used the Cholesky ordering for the variables described in detail in Lütkepohl and Krätzig (2004, pp.165-171). I estimated the CIR functions accounting for a forecast horizon of k=1,…,32 quarters for a standardized shock in the US federal deficit process of one standard deviation for each VAR model. I sorted all equity portfolios with respect to their cumulative impulse responses depending on the forecast horizon k into 20 portfolio groups (PGs). The first PG contains the 5% of equity portfolios exhibiting the highest negative cumulative impulse responses, whereas the last PG contains the 5% of equity portfolios exhibiting the highest positive cumulative impulse responses. Then, I created the zero-cost portfolio for forecast horizon k=23 and buying PG 1 and selling PG 10. To estimate the VAR-models, I used a rolling time window accounting for ten years of quarterly data starting in 1970:2. The strategy was updated at the beginning of each quarter. The initial portfolio allocation began in 1980:1. The sample period ran from 1980:1-2012:4. The data for the US federal deficit were downloaded from the Federal Reserve Bank of St. Louis, whereas the data for the equity portfolios were downloaded from Kenneth French's website. Panel A shows the average raw excess returns, the average risk-adjusted return and the p-value of LM tests for autocorrelation concerning the residuals of the corresponding risk-adjusted models for PG i with i=1,…,10. Panel B shows the corresponding estimates for PG i with i =11,…,20. Heteroskedasticity robust t-values are given in parentheses.

Panel A: Group 1-10				Panel B: Group 11-20 and (1-10)			
Group	**Average excess returns**	**Average risk-adjusted returns**	**LM test (p-value)**	**Group**	**Average excess returns**	**Average risk-adjusted returns**	**LM test (p-value)**
1	1.10	-0.80*	0.24	**11**	2.37***	0.39	0.02
	(1.49)	(-1.69)			(2.74)	(1.12)	
2	1.14	-0.51	0.00	**12**	2.22***	-0.06	0.07
	(1.57)	(-0.82)			(2.60)	(-0.20)	
3	2.04***	0.45	0.74	**13**	1.98**	-0.35	0.43
	(2.80)	(0.82)			(2.40)	(-0.91)	
4	1.61**	-0.52*	0.24	**14**	2.12**	-0.16	0.59
	(1.96)	(-1.84)			(2.53)	(-0.46)	
5	2.09**	0.14	0.05	**15**	2.50***	0.59**	0.95
	(2.50)	(0.41)			(2.98)	(2.04)	
6	1.96**	0.27	0.70	**16**	2.28***	0.37	0.84
	(2.43)	(0.50)			(2.70)	(1.09)	
7	2.27***	0.37	0.66	**17**	2.05**	0.42	0.57
	(2.90)	(0.70)			(2.42)	(1.19)	
8	1.99**	0.17	0.13	**18**	2.10**	0.35	0.99
	(2.36)	(0.58)			(2.45)	(0.73)	
9	2.17***	0.18	0.11	**19**	1.99**	0.36	0.82
	(2.58)	(0.60)			(2.24)	(0.72)	
10	2.33***	0.62*	0.14	**20**	2.11**	-0.20	0.95
	(2.73)	(1.73)			(2.25)	(-0.64)	
				(1-10)	-1.23**	-1.42***	0.47
					(-2.48)	(-2.84)	

*Statistically significant on a 10% level

**Statistically significant on a 5% level

***Statistically significant on a 1% level

Table IV: Correlations between risk factors and industries

For each quarter *t,* I estimated a bivariate VAR model of lag order p=4 for all equity portfolios. Each VAR model contained the changes in the US federal budget deficit and the respective equity portfolio returns. Then, for each VAR model, I estimated the Wold's moving average representation and standardized the parameter matrices by employing the Cholesky decomposition of the covariance matrix and used the Cholesky ordering for the variables described in detail in Lütkepohl and Krätzig (2004, pp.165-171). I estimated the CIR functions accounting for a forecast horizon of k=1,…,32 quarters for a standardized shock in the US federal deficit process of one standard deviation for each VAR model. I sorted all equity portfolios with respect to their cumulative impulse responses depending on the forecast horizon k into 20 portfolio groups (PGs). The first PG contains the 5% of equity portfolios exhibiting the highest negative cumulative impulse responses, whereas the last PG contains the 5% of equity portfolios exhibiting the highest positive cumulative impulse responses. Then, I created the zero-cost portfolio for forecast horizon k=23 and buying PG 1 and selling PG 10. To estimate the VAR models, I used a rolling time window accounting for ten years of quarterly data starting in 1970:2. The strategy was updated at the beginning of each quarter. The initial portfolio allocation began in 1980:1. The sample period ran from 1980:1-2012:4. The data for the US federal deficit were downloaded from the Federal Reserve Bank of St. Louis, whereas the data for the equity portfolios were downloaded from Kenneth French's website.

Correlation matrix of risk factors and the 10 Fama and French industries

DEF	1	-0.36	-0.36	0.10	0.39	-0.30	-0.31	-0.32	-0.18	-0.36	-0.26	-0.35	-0.24	-0.35	-0.34
Market		1	0.43	-0.36	-0.19	0.75	0.80	0.91	0.60	0.87	0.75	0.84	0.74	0.53	0.90
SMB			1	-0.16	-0.24	0.25	0.46	0.40	0.16	0.45	0.17	0.46	0.14	0.01	0.39
HML				1	-0.21	-0.12	-0.02	-0.19	-0.09	-0.55	-0.23	-0.28	-0.40	0.06	-0.10
MOM					1	-0.14	-0.35	-0.21	-0.02	-0.20	-0.16	-0.15	0.00	-0.07	-0.22
NoDur						1	0.64	0.80	0.40	0.52	0.61	0.84	0.81	0.59	0.80
Durbl							1	0.84	0.45	0.69	0.58	0.74	0.48	0.39	0.82
Manuf								1	0.63	0.75	0.64	0.81	0.69	0.52	0.89
Enrgy									1	0.47	0.43	0.38	0.38	0.56	0.54
HiTech										1	0.65	0.72	0.58	0.37	0.71
Telcm											1	0.66	0.57	0.56	0.70
Shops												1	0.73	0.46	0.85
Hlth													1	0.49	0.71
Utils														1	0.59

Note: *MFF* denotes the excess market return, *SMB* (Small Minus Big) is the average return on a small portfolio minus the average return on a big portfolio, *HML* (High Minus Low) is the average return on a value portfolio minus the average return on a growth portfolio, whereas *MOM* is the average return on a high prior return portfolio minus the average return on a low prior return portfolio. A detailed description of these risk factors and the ten industry sectors is provided on Kenneth's French website.

Table V Panel A: Fama-MacBeth regressions

For each quarter *t,* I estimated a bivariate VAR model of lag order p=4 for all equity portfolios. Each VAR model contained the changes in the US federal budget deficit and the respective equity portfolio returns. Then, for each VAR model, I estimated the Wold's moving average representation and standardized the parameter matrices by employing the Cholesky decomposition of the covariance matrix and used the Cholesky ordering for the variables described in detail in Lütkepohl and Krätzig (2004, pp.165-171). I estimated the CIR functions accounting for a forecast horizon of k=1,…,32 quarters for a standardized shock in the US federal deficit process of one standard deviation for each VAR model. I sorted all equity portfolios with respect to their cumulative impulse responses depending on the forecast horizon k into 20 portfolio groups (PGs). The first PG contains the 5% of equity portfolios exhibiting the highest negative cumulative impulse responses, whereas the last PG contains the 5% of equity portfolios exhibiting the highest positive cumulative impulse responses. Then, I created the zero-cost portfolio for forecast horizon k=23 and buying PG 1 and selling PG 10. To estimate the VAR-models, I used a rolling time window accounting for ten years of quarterly data starting in 1970:2. The strategy was updated at the beginning of each quarter. The initial portfolio allocation began in 1980:1. The sample period ran from 1980:1-2012:4. The data for the US federal deficit were downloaded from the Federal Reserve Bank of St. Louis, whereas the data for the equity portfolios were downloaded from Kenneth French's website. I compounded the excess returns for all 20 PGs sorted by cumulative impulse responses and used these portfolios as test assets (see Table III). I also added 49 value-weighted industry portfolios in excess form to the set of test asset. All cross-sectional OLS regressions included a constant term. Since I used a rolling time-window of 60 quarters to estimate the time-varying betas used in the Fama MacBeth regression, the sample for the cross-sectional analysis ran from 1995:1 to 2012:4. The corresponding t-values are given in parentheses. Apart from the parameter estimates for the different asset pricing models, I also report the corresponding R-squared value, the test statistic of the Wald-test of the pricing errors, and the corresponding p-value. The corresponding data for the *MRF*, *SMB*, *HML*, and *MOM* factors were a downloaded from Kenneth's French website.

Constant	MRF	SMB	HML	DEF	R-squared	Wald test	p-value
-0.23 (-0.43)	2.28** (2.30)				0.82	231.09	0.00
0.02 (0.05)				-2.89*** (-2.63)	0.47	498.99	0.00
-0.22 (-0.42)	1.77* (1.77)			-1.98*** (-2.74)	0.82	248.75	0.00
0.17 (0.43)	1.58* (1.65)	1.82** (2.26)	-1.84 (-1.33)		0.82	483.13	0.00
-0.00 (-0.00)	1.59* (1.65)	2.02** (2.25)	-1.88 (-1.44)	-0.97 (-1.47)	0.83	484.39	0.00

*Statistically significant on a 10% level

**Statistically significant on a 5% level

***Statistically significant on a 1% level.

Table V Panel B: Fama-MacBeth regressions with modified *DEF* factor

For each quarter *t,* I estimated a bivariate VAR model of lag order p=4 for all equity portfolios. Each VAR model contained the changes in the US federal budget deficit and the respective equity portfolio returns. Then, for each VAR model, I estimated the Wold's moving average representation and standardized the parameter matrices by employing the Cholesky decomposition of the covariance matrix and used the Cholesky ordering for the variables described in detail in Lütkepohl and Krätzig (2004, pp.165-171). I estimated the CIR functions accounting for a forecast horizon of k=1,…,32 quarters for a standardized shock in the US federal deficit process of one standard deviation for each VAR model. I sorted all equity portfolios with respect to their cumulative impulse responses depending on the forecast horizon k into 20 portfolio groups (PGs). The first PG contains the 5% of equity portfolios exhibiting the highest negative cumulative impulse responses, whereas the last PG contains the 5% of equity portfolios exhibiting the highest positive cumulative impulse responses. Then, I created the zero-cost portfolio for forecast horizon k=23 and buying PG 10 and selling (PG 1 and PG 20)/2. To estimate the VAR-models, I used a rolling time window accounting for ten years of quarterly data starting in 1970:2. The strategy was updated at the beginning of each quarter. The initial portfolio allocation began in 1980:1. The sample period ran from 1980:1-2012:4. The data for the US federal deficit were downloaded from the Federal Reserve Bank of St. Louis, whereas the data for the equity portfolios were downloaded from Kenneth French's website. I compounded the excess returns for all 20 PGs sorted by cumulative impulse responses and used these portfolios as test assets (see Table III). I also added 49 value-weighted industry portfolios in excess form to the set of test asset. All cross-sectional OLS regressions included a constant term. Since I used a rolling time-window of 60 quarters to estimate the time-varying betas used in the Fama MacBeth regression, the sample for the cross-sectional analysis ran from 1995:1 to 2012:4. The corresponding t-values are given in parentheses. Apart from the parameter estimates for the different asset pricing models, I also report the corresponding R-squared value, the test statistic of the Wald-test of the pricing errors, and the corresponding p-value. The corresponding data for the *MRF*, *SMB*, *HML*, and *MOM* factors were downloaded from Kenneth's French website.

Constant	MRF	SMB	HML	DEF	R-squared	Wald test	p-value
-0.23 (-0.43)	2.28** (2.30)				0.82	231.09	0.00
0.21 (0.45)				-2.21** (-2.26)	0.28	1032.90	0.00
-0.15 (-0.29)	1.83* (1.87)			-0.86* (-1.71)	0.82	259.89	0.00
0.17 (0.43)	1.58* (1.65)	1.82** (2.26)	-1.84 (-1.33)		0.82	483.13	0.00
0.04 (0.09)	1.56 (1.62)	2.51** (2.51)	-2.14 (-1.58)	-0.28 (-0.58)	0.83	534.97	0.00

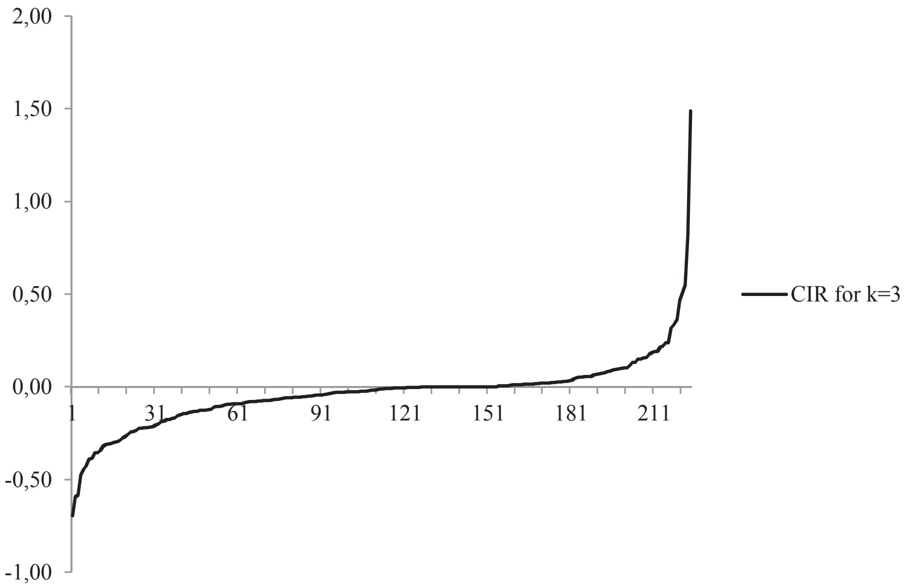
*Statistically significant on a 10% level

**Statistically significant on a 5% level

***Statistically significant on a 1% level.

Figure I: Non-linear cumulative impulse response (CIR) functions

For each quarter *t,* I estimated a bivariate VAR model of lag order p=4 for all equity portfolios. Each VAR model contained the changes in the US federal budget deficit and the respective equity portfolio returns. Then, for each VAR model, I estimated the Wold's moving average representation and standardized the parameter matrices by employing the Cholesky decomposition of the covariance matrix and used the Cholesky ordering for the variables described in detail in Lütkepohl and Krätzig (2004, pp.165-171). I estimated the CIR functions accounting for a forecast horizon of k=1,…,32 quarters for a standardized shock in the US federal deficit process of one standard deviation for each VAR model. I sorted all equity portfolios with respect to their cumulative impulse responses depending on the forecast horizon k into 20 portfolio groups (PGs). The first PG contains the 5% of equity portfolios exhibiting the highest negative cumulative impulse responses, whereas the last PG contains the 5% of equity portfolios exhibiting the highest positive cumulative impulse responses. Then, I created the zero-cost portfolio for forecast horizon k=23 and buying PG 1 and selling PG 10. To estimate the VAR models, I used a rolling time window accounting for ten years of quarterly data starting in 1970:2. The strategies were updated at the beginning of each quarter. The initial portfolio allocation began in 1980:1. The sample period ran from 1980:1-2012:4. The data for the US federal deficit were downloaded from the Federal Reserve Bank of St. Louis, whereas the data for the equity portfolios were downloaded from Kenneth French's website. I compounded the excess returns for all 20 PGs sorted by cumulative impulse responses and used these portfolios as test assets. Figure I illustrate the sorting procedure for k=3 based on the in-sample time window running from 2002:4 to 2012:3.The x-axis hosts the 224 input equity research portfolios sorted by the CIR function. Thereby, 100 Fama and French value-weighted equity research portfolios sorted by size and book-to-market ratio, 25 value-weighted equity research portfolios sorted by size and momentum, 49 value-weighted equity research portfolios sorted by industry, 25 value-weighted equity research portfolios sorted with respect to size and short-term reversal, and 25 value-weighted equity research portfolios sorted by size and long-term reversal are employed. The y-axis hosts the corresponding CIR forecast.


2,00
1,50
1,00
0,50
0,00
-0,50
-1,00
1
31
61
91
121
151
181
211
CIR for k=3

Economics Letters 123 (2014) 100–103

Contents lists available at ScienceDirect

Economics Letters

journal homepage: www.elsevier.com/locate/ecolet

Momentum in global equity markets in times of troubles: Does the economic state matter?☆

Klaus Grobys *

University of Vaasa, Wolffintie 34, 65200, Vaasa, Finland

HIGHLIGHTS

- Momentum-based trading strategies in global equity markets were profitable during the 1998–2013 period.
- Momentum strategies generated statistically significant negative returns during the most recent recessions.
- Negative momentum payoffs are generated in the wake of market reversals following severe market declines.

ARTICLE INFO

Article history:
Received 4 December 2013
Received in revised form
20 January 2014
Accepted 26 January 2014
Available online 3 February 2014

JEL classification:
G12
G14

Keywords:
Momentum
Global equity markets
International stock indices
Business cycle

ABSTRACT

This paper investigates the profitability of momentum-based trading strategies pursued during the most recent economic downturns in global equity markets. In contrast to previous studies, it reveals that such strategies generated statistically significant negative returns during the most recent recessions. These "momentum crashes" happen during market reversals following exceptionally large market declines, as occurred in March and April 2009.

1. Introduction

Few stock market anomalies have received the volume of attention in empirical research matching that of the momentum effect first documented by Jegadeesh and Titman (1993). More than two decades after its initial discovery, reports persist of the ongoing profitability of momentum trading strategies. Novy-Marx (2012) asserted that such strategies based on intermediate past performance generate significantly higher profits than strategies based on recent past performance. However, only a few studies focus on momentum strategies from an international investor's perspective. Rouwenhorst's (1997) empirical study provides evidence that momentum strategies were profitable for equities in 12 European markets and Rouwenhorst (1999) documents that return momentum is present among stocks listed on emerging markets' stock indices. Chan et al. (2000) examined a sample of 23 countries and employed a weighted relative strength strategy (WRSS) that bought stocks in proportion to their returns over the ranking period. Their study confirmed the findings of Rouwenhorst (1999) in the sense that momentum strategies appear to be profitable in a global equity market setting.

Jegadeesh and Titman's (1993) back-testing of momentum indicated that they occasioned enormous losses during market index rebounds in the 1930–1932 period, yet there have been subsequently surprisingly few investigations of the profitability of momentum strategies during economic downturns. While Chordia and Shivakumar (2002) found that momentum payoffs appear to be negative but statistically not different from zero during recessions, Daniel and Moskowitz (2013) showed that the momentum portfolio exhibits a strong up- and down-beta differential in bear markets. This optionality is mostly related to the loser portfolio. More precisely, when market conditions improve, these losers make strong gains which, in turn, results in a "momentum crash".

☆ I wish to thank the anonymous reviewer for useful comments. I am responsible for all errors and omissions.

* Tel.: +358 (0)40 466 3248.
E-mail addresses: klaus.grobys@uwasa.fi, grobys.finance@gmail.com.

http://dx.doi.org/10.1016/j.econlet.2014.01.028
0165-1765/

Table 1
International stock markets.

No.	Country	Stock index	Exchange rate
1	Brazil	BOVESPA Brazil	US $/Brazilian real
2	Mexico	IPC Mexico	US $/Mexican peso
3	Argentina	Merval Argentina	US/$Argentiniane Peso
4	Canada	S&P/TSX Canada	US $/Canadian dollar
5	USA	DJ 30 USA	US dollar
6	Hang Kong	Hang Seng Hong Kong	US $/Hong Kong dollar
7	China	SSE Composite Shanghai China	US $/Chinese Yuan renminbi
8	India	S&P BSE SENSEX India	US $/Indian rupee
9	Indonesia	Composite Index Jakarta Indonesia	US $/Indonesian rupiah
10	Malaysia	FTSE Bursa Malaysia KLCI Malaysia	US $/Malaysian ringgit
11	Japan	NIKKEI 225 Japan	US $/Japanese yen
12	New Zealand	NZX 50 INDEX New Zealand	US $/New Zealand dollar
13	Singapore	STI Index Singapore	US $/Singapore dollar
14	Austria	ATX Austria	US $/Euro*
15	Belgium	EURONEXT BEL-20 Belgium	US $/Euro*
16	France	CAC 40 France	US $/Euro*
17	Germany	DAX 30 Germany	US $/Euro*
18	Netherlands	AEX Netherlands	US $/Euro*
19	Switzerland	SMI Switzerland	US $/Swiss franc
20	UK	FTSE 100 UK	US $/Great British pound
21	Greece	ATHEN INDEX Greece	US $/Euro**

* The EUR exchange rate is accounted for from January 1999. Before January 1999 the following exchange rates for Austria, Belgium, France, Germany and the Netherlands were employed: US dollar/Austrian schilling, US dollar/Belgian franc, US dollar/French franc, US dollar/Deutsch mark and US dollar/Dutch guilder.
** The EUR exchange rate is accounted for from January 2001. Before January 2001, I used the US dollar/Greek drachma exchange rate.

The purpose of this paper is to investigate the profitability of international momentum strategies during the economic downturns since Rouwenhorst's (1997) study. It compares various momentum strategies and where most other studies focus on the US stock market, this study employs a sample of 21 foreign stock indices. Each of these stock indices is a well-diversified basket of foreign stocks that is used in the sorting procedure, where all indices are divided into quartiles based on their cumulative past returns to implement zero-cost portfolios. Since this paper considers the perspective of a US investor, the S&P 500 is employed for risk-adjustment.

The study contributes to the existing literature in two ways. First, it identifies the profitability of momentum strategies implemented in a global equity market setting during the most recent economic recessions. Second, by extending Novy-Marx's (2012) analysis to a global equity market setting, it assesses whether intermediate past performance offers more beneficial information for internationally aligned investors in the US than recent past performance. This is also important because investment managers operating globally must make top-down decisions on international asset allocation.

The current research diverges from past examples in finding that momentum-based trading strategies in a global equity market setting generate statistically significant negative returns, at least during the most recent recessions, irrespective of whether the strategies are based on intermediate or recent past performance. Even if strategies based on intermediate past performance are market neutral, they appear to have been unprofitable during the recent recessions. This paper is organized as follows: in Section 2 the data is described. Section 3 presents the empirical framework and findings and the last section draws conclusions.

2. Data

I downloaded monthly stock market data from 21 different countries covering the period July 1997–2013 from finance.yahoo.com. Adopting the perspective of a US investor, I adjusted the foreign monthly stock index returns by their exchange rates, downloaded from the European Central Bank and Worldbank's data-base. I also downloaded data from National Bureau of Economic Research indicating expansionary and recessionary periods for the USA from July 1998–2013.[1] Data for the monthly US risk-free rate were extracted from Kenneth's French website.[2] Table 1 presents the countries, the corresponding stock indices, and the corresponding exchange rates.

3. Empirical framework

I compounded the monthly gross returns for all foreign stock indices for the period July 1997–2013 and converted foreign stock market returns into US dollars by subtracting the corresponding monthly average exchange rate returns. I used Fama and French's (2008) portfolio approach to run the portfolio sorts for July 1998. I sorted all stock indices by their cumulative past returns in an increasing order into quartiles. The first group ("loser") contains the 25% of equal-weighted foreign stock indices exhibiting the lowest cumulative returns for the period t-6–t-2, whereas the fourth group ("winner") contains the 25% of equal-weighted foreign stock indices exhibiting the highest cumulative returns for the same period. Apart from foreign indices, the sorting procedure also incorporates the Dow Jones 30 as the domestic index. Each group forms a well-diversified equity basket containing at least 125 stocks. This strategy was updated and rebalanced at the beginning of each month and dubbed the 6-2 strategy as in Novy-Marx (2012). I also modeled the following strategies: 7-2, 8-3, 9-4, 10-5, 11-6 and 12-7. The zero-cost portfolios were compounded by selling the loser and buying the winner portfolio. The zero-cost portfolios were risk-adjusted by regressing the zero-cost portfolios on the excess returns of the S&P 500 index. The corresponding results are reported in Table 2 Panel A.

Next, I included a dummy variable in the regression with a value of 1 indicating a recessionary period and a value of 0

1 See http://www.nber.org/cycles.html.
2 See http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

Table 2
Raw excess returns and risk-adjusted excess returns.

Panel A				Panel B				
Strategy	Raw return	Risk-adjusted return		Raw return		Risk-adjusted return		
		Alpha	Beta	Constant (Expansion)	Dummy (Recession)	Alpha	Dummy (Recession)	Beta
6-2	0.79**	0.82**	−0.27***	1.00***	−1.25	1.16***	−1.98**	−0.30***
	(2.41)	(2.40)	(−2.74)	(2.86)	(−1.61)	(3.08)	(−2.42)	(−3.10)
7-2	0.79**	0.83**	−0.27***	0.99***	−1.25	1.15***	−1.97**	−0.30***
	(2.41)	(2.42)	(−2.71)	(2.86)	(−1.61)	(3.10)	(−2.42)	(−3.06)
8-3	0.31	0.32	−0.08	0.58*	−1.62*	0.64*	−1.88**	−0.11
	(0.93)	(0.95)	(−0.91)	(1.69)	(−1.84)	(1.77)	(−2.00)	(−1.27)
9-4	0.49	0.50	−0.10	0.85***	−2.16***	0.92***	−2.49***	−0.14**
	(1.53)	(1.54)	(−1.43)	(2.64)	(−2.68)	(2.76)	(−3.07)	(−2.02)
10-5	0.78**	0.81**	−0.17*	1.17***	−2.40**	1.30***	−2.91***	−0.21**
	(2.16)	(2.18)	(−1.95)	(3.32)	(−2.26)	(2.63)	(−3.05)	(−2.57)
11-6	0.98***	0.99***	−0.10	1.06***	−1.41**	1.36***	−2.19**	−0.14*
	(2.62)	(2.63)	(−1.25)	(2.88)	(1.97)	(3.53)	(−2.26)	(−1.69)
12-7	0.82**	0.83**	−0.02	1.05***	−1.41**	1.08***	−1.51**	−0.04
	(2.41)	(2.39)	(−0.22)	(2.89)	(−1.97)	(2.87)	(−1.97)	(−0.54)

* Statistically significant on a 10% significance level.
** Statistically significant on a 5% significance level.
*** Statistically significant on a 1% significance level.

Table 3
Raw excess returns and risk-adjusted excess returns for the period July 1998 to January 2006.

Panel A				Panel B				
Strategy	Raw return	Risk-adjusted return		Raw return		Risk-adjusted return		
		Alpha	Beta	Constant (Expansion)	Dummy (Recession)	Alpha	Dummy (Recession)	Beta
6-2	0.85*	0.85*	−0.36**	0.83	0.18	0.92	−0.55	−0.37**
	(1.72)	(1.69)	(−2.16)	(1.55)	(0.15)	(1.60)	(−0.47)	(−2.12)
7-2	0.85*	0.85*	−0.37**	0.83	0.18	0.91	−0.56	−0.37**
	(1.71)	(1.67)	(−2.19)	(1.58)	(0.14)	(1.59)	(−0.48)	(−2.15)
8-3	0.63	0.63	−0.10	0.64	−0.07	0.66	−0.26	−0.09
	(1.30)	(1.26)	(−0.64)	(1.20)	(−0.06)	(1.19)	(−0.19)	(−0.63)
9-4	0.71*	0.70	−0.10	0.85*	−1.19	0.88*	−1.43	−0.12
	(1.67)	(1.61)	(−0.89)	(1.83)	(−1.11)	(1.81)	(−1.36)	(−0.98)
10-5	1.28**	1.28**	−0.24*	1.48***	−1.68	1.55***	−2.21	−0.26*
	(2.54)	(2.42)	(−1.67)	(2.82)	(−0.96)	(2.80)	(−1.32)	(−1.76)
11-6	1.57***	1.57***	−0.14	1.59***	−0.13	1.62***	−0.41	−0.14
	(2.93)	(2.87)	(−1.00)	(2.64)	(−0.13)	(2.64)	(−0.37)	(−1.00)
12-7	1.24**	1.24**	−0.02	1.26**	−0.16	1.26**	−0.20	−0.02
	(2.39)	(2.38)	(−0.18)	(2.23)	(−0.15)	(2.22)	(−0.18)	(−0.19)

* Statistically significant on a 10% significance level.
** Statistically significant on a 5% significance level.
*** Statistically significant on a 1% significance level.

otherwise. The results are reported in Table 2 Panel B. Apart from the 8-3 and 9–4 strategy, all other strategies generate statistically significant positive raw and risk-adjusted returns. In Panel A, the 11-6 strategy generates the highest risk-adjusted return corresponding to 0.99% with a Newey–West (1987) t-statistic of 2.63. Without accounting for the recession dummy, the raw returns are close to the risk-adjusted returns, suggesting that the market proxy alone cannot explain the spreads. Panel B shows that the risk-adjusted recession dummy is statistically significantly negative for all strategies. Furthermore, the beta-loading of the 12-7 strategy is statistically not significant, suggesting that strategy is market neutral. Notably, the recession dummy of the momentum strategies based on recent past performance (e.g., the 6-2 and 7-2 strategies) is statistically significant only when the market factor is accounted for. Consequently, in the presence of negative stock market returns associated with recessions, the negative beta-loading slightly absorbs the negative average risk-adjusted returns.

To check the robustness of the results, I divided the overall sample into two subsamples of equal length covering the periods July 1998–January 2006 and February 2006–July 2013. Again, I regressed the zero-cost strategies on a constant and recession dummy. The results are shown in Tables 3 and 4. Interestingly, the regression results in Table 3, Panel A concerning the first subsample show that the parameters for the recession dummies are statistically not different from zero for all strategies, so supporting the findings of Chordia and Shivakumar (2002). However, the regression results in Table 4, Panel A, concerning the second sample show that the parameters for the recession dummy were significantly negative, ranging from −2.03% to −2.71% with a Newey–West (1987) t-statistic of between −2.36 and −2.85. Without accounting for the recession dummies, only momentum strategies based on recent past performance (i.e., 6-2 and 7-2 momentum strategies) produced overall sample means that were statistically different from zero on a least a 10% level. The results are robust when accounting for risk adjustments, too.

4. Conclusion

I considered the perspective of a US investor and investigated momentum strategies in global equity markets and based on both intermediate and recent past performance. The general finding of this study is that momentum-based trading strategies in global equity markets are profitable across the overall sample from July 1998 to 2013. Accounting for risk adjustments and a recession dummy reveals that all strategies generate statistically significant negative returns during recessions, a result also supported by a subsample analysis. The severe recession of December 2007–June 2009 is the major driver of this result. Integrating these results with Jegadeesh and Titman's (1993) back-testing results and Daniel and

Table 4
Raw excess returns and risk-adjusted excess returns for the period February 2006 to July 2013.

Panel A				Panel B				
Strategy	Raw return	Risk-adjusted return		Raw return		Risk-adjusted return		
		Alpha	Beta	Constant (Expansion)	Dummy (Recession)	Alpha	Dummy (Recession)	Beta
6-2	0.72*	0.79*	−0.18**	1.18***	−2.16***	1.40***	−2.84***	−0.24***
	(1.75)	(1.90)	(−2.20)	(2.75)	(−2.62)	(3.40)	(−3.31)	(−3.82)
7-2	0.72*	0.79*	−0.18**	1.18***	−2.16***	1.40***	−2.84**	−0.24***
	(1.75)	(1.90)	(−2.20)	(2.75)	(−2.62)	(3.40)	(−3.31)	(−3.82)
8-3	−0.01	0.06	−0.06	0.51	−2.48***	0.68	−2.88***	−0.12
	(0.02)	(0.14)	(−0.62)	(1.17)	(−2.85)	(1.56)	(−3.11)	(−1.65)
9-4	0.26	0.33	−0.10	0.84*	−2.71***	1.01**	−3.19***	−0.16**
	(0.56)	(0.70)	(−1.13)	(1.79)	(−2.72)	(2.18)	(−3.21)	(−2.40)
10-5	0.28	0.24	−0.10	0.84*	−2.65**	0.88*	−2.90***	−0.16**
	(0.58)	(0.49)	(−1.09)	(1.76)	(−2.36)	(1.77)	(−2.88)	(−2.02)
11-6	0.38	0.46	−0.06	0.94**	−2.69**	1.12**	−3.11***	−0.13
	(0.77)	(0.95)	(−0.64)	(2.09)	(−2.54)	(2.45)	(−3.27)	(−1.50)
12-7	0.41	0.45	−0.00	0.83*	−2.03***	0.92**	−2.21***	−0.05
	(0.96)	(1.08)	(−0.02)	(1.88)	(−2.66)	(2.02)	(−2.86)	(−0.66)

* Statistically significant on a 10% significance level.
** Statistically significant on a 5% significance level.
*** Statistically significant on a 1% significance level.

Moskowitz's (2013) recent study confirms momentum strategies bring a risk of notably high negative returns following large market declines. According to Daniel and Moskowitz (2013) these "momentum crashes" are driven by the loser portfolio due to the up- and down-beta differential in bear markets. Although Novy-Marx's (2012) 12-7 strategy has the benefit of making the generated returns appear market neutral, in severe economic recessions this strategy does not appear to be profitable either.

References

Chan, K., Hameed, A., Tong, W., 2000. Profitability of momentum strategies in the international equity markets. Financ. Quant. Anal. 35, 153–172.

Chordia, T., Shivakumar, L., 2002. Momentum, business cycle, and time-varying expected returns. J. Financ. 57, 985–1019.

Daniel, K.-D., Moskowitz, T.-J., 2013. Momentum crashes. In: Columbia Business School Working Paper.

Fama, E., French, K., 2008. Dissecting anomalies. J. Financ. 63, 1653–1678.

Jegadeesh, N., Titman, S., 1993. Returns to buying winners and selling losers: Implications for stock market efficiency. J. Financ. 48, 35–91.

Newey, W.-K., West, K.-D., 1987. A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. Econometrica 55, 703–708.

Novy-Marx, R., 2012. Is momentum really momentum? J. Financ. Econ. 103, 429–453.

Rouwenhorst, K.-G, 1999. Local return factors and turnover in emerging stock markets. J. Financ. 54, 1439–1464.

Rouwenhorst, K.-G, 1997. International momentum strategies. J. Financ. 53, 267–284.

Applied Economics Letters, 2014
http://dx.doi.org/10.1080/13504851.2014.946177

Routledge
Taylor & Francis Group

Idiosyncratic volatility and global equity markets

Klaus Grobys

Department of Accounting and Finance, University of Vaasa, Wolffintie 34, 65200, Vaasa, Finland
E-mail: klaus.grobys@uwasa.fi

This article investigates the relation of idiosyncratic volatility (IVOL) and future returns on a portfolio level in global equity markets. In contrast to previous studies (Ang *et al.* 2006, 2009), it reveals that the spread between stock indices exhibiting a high IVOL and stock indices with low IVOL is positive and unrelated to movements in the business cycle. Traditional asset pricing models cannot explain the spread.

Keywords: idiosyncratic volatility; global equity markets; international stock indices; business cycle

JEL Classification: G12; G14

I. Introduction

The relation between realized idiosyncratic volatility (IVOL) and stock returns has received a great deal of attention in the academic literature. Ang *et al.* (2006) explore the pricing of aggregate volatility risk in the cross section of stock returns in the US stock market and find that stocks with high IVOL generate lower average returns than stocks with low IVOL. While Doran *et al.* (2012) argue that the negative relation between IVOL and stock returns is limited only to months other than January; Huang *et al*. (2010, 2011) find that the negative relation between realized IVOL and stock returns appears to be a result of value-weighting the portfolio returns. However, Ang *et al.* (2009) investigate the pricing of aggregate volatility risk in the cross section of international markets and confirm Ang *et al.*'s (2006) previous findings. While on the portfolio level a consensus has not yet been achieved, it may be surprising that no study has been undertaken yet that would investigate the pricing of aggregate volatility risk in the cross section of global equity markets. This study attempts to fill this gap.

The purpose of this article is to investigate the relation between IVOL and future returns on a portfolio level in global equity markets. This study accounts for 52 different stock indices as investment opportunity set. Each of the stock indices is a well-diversified basket of at least 20 stocks. All stock indices are divided into quintiles based on their past realized IVOL relative to a global portfolio comprising all stock indices. The zero-cost strategy is long on the group containing the stock indices with highest IVOL and short on the group containing the stock indices with lowest IVOL. Furthermore, this study considers the perspective of an internationally aligned investor and employs different global asset pricing model specifications for risk adjustment.

The study contributes to the existing literature in two ways. First, by extending Ang et *al.*'s (2006, 2009) analyses to a global equity market setting, it assesses whether realized IVOL is priced in the cross section of global equity markets. Thereby, the relation between past returns and realized IVOL is also identified. Second, it is identified whether this strategy is related to the business cycle. For internationally aligned investors, it is of major importance to uncover the risks associated with global investment vehicles and the underlying driving forces. In particular, it is important to understand the association between patterns in equity returns and economic conditions. If IVOL is priced in the cross section of global equity markets, the corresponding pricing implications may be of notable relevance for investment decisions of investment managers operating globally.

Surprisingly, this current research finds that IVOL is positively priced in the cross section of global equity markets. While this result diverges from Ang et *al.* (2006, 2009) who find a negative relation, it implies that the typical globally aligned investor holds an under-diversified portfolio because economic theory suggests that expected returns are unrelated to idiosyncratic risk if investors hold fully diversified portfolios. Further, it is found that the zero-cost strategy is unrelated to the business cycle that appears to be in line with Ang *et al.* (2006). Moreover, a regression analysis reveals that traditional global asset pricing models cannot explain the spread related to IVOL. This article is organized as follows: in Section II, the data are described. Section III presents the empirical framework and the results and Section IVconcludes.

II. Data

I downloaded daily stock index data from 52 different countries covering the period February 1990 to March 2014 from Datastream (see Table 1). I also downloaded data from the National Bureau of Economic Research (NBER) indicating expansionary and recessionary periods covering the same period (see http://www.nber.org/cycles.html). Data for the global Fama and French risk factors were extracted from Kenneth's French website (see http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html). Table 1 presents the countries and the corresponding stock indices.

III. Empirical Framework

In order to be able to compare the results, I measured the IVOL in a similar manner as that by Ang *et al.*

Table 1. International stock markets

No.	Country	Stock index
Panel A		
1	Argentina	ARGENTINA MERVAL
2	Australia	ASX ALL
3	Austria	ATX
4	Bahrain	BAHRAIN ALL SHARE
5	Belgium	BEL 20
6	Brazil	BRAZIL BOVESPA
7	Canada	S&P/TSX
8	Chile	CHILE SANTIAGO SEGENERAL
9	China	SHANGHAI SE A SHARE
10	Columbia	COLOMBIA IGBC
11	Czech Republic	PRAGUE SE PX
12	Denmark	OMX Copenhagen
13	Egypt	EGYPT HERMES FINANCIAL
14	Finland	OMX HELSINKI
15	France	CAC 40
16	Germany	DAX 30
17	Greece	ATHEX
18	Hong Kong	HANG SENG
19	Hungary	BUDAPEST (BUX)
20	Iceland	OMX ICELANDALL SHARE
21	India	CNX 500
22	Israel	ISRAEL TA 100
23	Italy	FTSE MIB
24	Indonesia	IDX COMPOSITE
25	Japan	NIKKEI 225
26	Jordan	AMMAN SEFINANCIAL MARKET
27	Malaysia	FTSE BURSAMALAYSIA KLCI
Panel B		
28	Malta	MALTA SE MSE
29	Mexico	MEXICO IPC (BOLSA)
30	Morocco	MOROCCO SE CFG 25
31	The Netherlands	AEX
32	New Zealand	NZX 50
33	Norway	OSLO EXCHANGE ALL SHARE
34	Oman	OMAN MUSCAT SECURITIES MKT.
35	Pakistan	KARACHI SE 100
36	Peru	LIMA SE GENERAL
37	Philippines	PHILIPPINE SE I
38	Poland	WARSAW GENERAL INDEX
39	Portugal	PSI 20
40	Russia	RTS
41	Saudi Arabia	SAUDI TADAWUL ALL SHARE
42	South Africa	FTSE/JSE ALL SHARE
43	Singapore	STRAITS TIMES INDEX L
44	South Korea	KOREA SE COMPOSITE
45	Spain	MADRID SE GENERAL
46	Sweden	OMX STOCKHOLM

(*Continued*)

Table 1. Continued

No.	Country	Stock index
47	Switzerland	SWISS MARKET
48	Thailand	BANGKOK S.E.T.
49	Tunisia	TUNISIA TUNINDEX
50	Turkey	BIST NATIONAL 100
51	The United Kingdom	FTSE ALL SHARE
52	Venezuela	VENEZUELA SE GENERAL

(2006, 2009), Doran *et al.* (2012) and Huang *et al.* (2011). For each month, I compounded the daily residual relative to an equal-weighted global portfolio containing all stock indices.[1] The realized IVOL was compounded by multiplying the SD of daily residuals by the square root of the number of trading days in that corresponding month. To conduct portfolio-level analysis, I constructed quintile portfolios based on the ranking of the IVOL of each individual stock index in the formation month and held these portfolios for the next month. Portfolio IVOL 5 denotes the equal-weighted portfolio consisting of stock indices with the highest IVOL and IVOL 1 the equal-weighted portfolio with the lowest. I rebalanced the portfolios at the beginning of each month. The sample period for the predicted returns runs from March 1990 to March 2014.

In the first row of Table 2, the average returns for the five portfolios in the one-month holding period (month $t + 1$) immediately following the formation month are reported. Average returns increase from 0.86% per month for portfolio IVOL 1 (low IVOL stock indices) to 2.24% for portfolio IVOL 5. The difference IVOL 5 − IVOL 1 is statistically significant on any level with economic magnitude of 1.37% per month and Newey and West's (1987) t-statistic of 4.35. The IVOL is linear increasing as we move from IVOL 1 to IVOL 4 and then makes a huge jump from 1.17% to 4.04% as we move from IVOL 4 to IVOL 5. Furthermore, IVOL and past month returns appear to be positively correlated. While these findings suggest that portfolios comprising stock indices that bear a higher idiosyncratic risk generate higher returns, they appear to be contrary to Jegadeesh's (1990) short-term reversal effect because it implies positive autocorrelation between both realized IVOL and future returns and past returns and future returns.

Next, I employed the spread (IVOL 5 − IVOL 1) and regressed it on different global asset pricing model specifications. Thereby, I used a global capital asset pricing model specification, the global Fama and French three-factor model, and the global Fama and French model including the momentum factor. Since data for the global momentum risk factor were available only from November 1990 onwards, the sample period for the regression analysis runs from November 1990 to March 2014. Furthermore, I included a dummy variable in each regression with a value of 1 indicating a recessionary period in line with the NBER dates indicating recessionary periods and a value of 0 otherwise. Thereby, it is assumed that the NBER recession dates coincide with global recession dates.

The results are reported in Table 3. The economic magnitude of the spread varies between 0.95% per month and 1.14% per month, depending on the model specification, with Newey and West's (1987) t-statistics between 2.95 and 3.84. Interestingly, the recession dummy is statistically not different from zero, indicating that the strategy's payoffs are not related to business cycle movements. However, the

Table 2. Raw returns and portfolio characteristics

	IVOL 1	IVOL 2	IVOL 3	IVOL 4	IVOL 5	5–1
Return	0.86*** (3.35)	0.78** (2.56)	1.05*** (3.22)	1.22*** (3.31)	2.24*** (4.72)	1.37*** (4.35)
Idiosyncratic volatility	0.21	0.44	0.71	1.17	4.04	
Past return in % pm	0.78	0.82	0.97	1.21	2.36	

Note:
** Statistically significant on a 5% significance level.
*** Statistically significant on a 1% significance level.

[1] Since data for the global Fama and French model were not available on a daily frequency, I used an equal-weighted global portfolio as global market risk factor. For instance, Huang *et al.* (2011) report that employing only a market risk factor instead of the Fama and French factor model specification does not change the results.

Table 3. Risk-adjusted excess returns

Constant	MF	SMB	HML	MOM	Recession	R-squared
1.04*** (3.58)	0.56*** (7.48)					0.24
0.95*** (2.95)	0.57*** (7.12)				0.72 (0.98)	0.24
1.05*** (3.62)	0.56*** (7.31)	0.22** (2.39)	−0.08 (−0.86)			0.25
0.97*** (2.99)	0.56*** (6.96)	0.22** (2.34)	−0.07 (−0.80)		0.64 (0.90)	0.25
1.14*** (3.84)	0.53*** (7.08)	0.25** (2.54)	−0.12 (−1.42)	−0.09 (−1.52)		0.26
1.07*** (3.20)	0.54*** (6.70)	0.24** (2.46)	−0.11 (−1.33)	−0.09(−1.36)	0.46 (0.66)	0.26

Notes:
** Statistically significant on a 5% significance level.
*** Statistically significant on a 1% significance level.

global market factor and the global size factor appear to drive the IVOL spread. The loadings against the global market factor vary between 0.53 and 0.57 with Newey and West's (1987) t-statistics between 6.70 and 7.48. The loadings against the global size factor are also positive and exhibit about half of the economic magnitude compared to the global market factor while indicating statistical significance on a common 5% level. This suggests that stock indices bearing a higher idiosyncratic risk tend to be small and co-move with the global equity market portfolio. However, the R-squared of regression analysis varies between 0.24 and 0.26, indicating that the core fraction of the IVOL spread remains unexplained.

IV. Conclusion

I considered the perspective of an internationally aligned investor and investigated the pricing of IVOL in the cross section of global equity markets. The general finding of this study is that IVOL is positively priced. Traditional global asset pricing models cannot explain the spread related to IVOL. Since traditional economic theory suggests that expected returns are unrelated to idiosyncratic risk whether investors hold fully diversified portfolios, the findings of this current research imply that the typical globally aligned investor holds an under-diversified portfolio. Moreover, the spread related to the IVOL strategy appears to be unrelated to business cycle movements. The findings of this study give several avenues for future research. First, Campbell *et al.* (2001) who explore idiosyncratic risk on a firm level find that uncertainty on the level of individual firms has dramatically increased over time while exhibiting time variation. Future studies may aim at uncovering time variation in the IVOL spread related to global equity markets. Moreover, this current research that adopts the perspective of an internationally aligned investor may be extended to investigating the perspective of an US or European investor, respectively, in order to uncover potential exchange-rate effects. Finally, future studies may analyse whether IVOL is marginally useful in describing the cross section of global equity returns.

References

Ang, A., Hodrick, R. J., Xing, Y. *et al*. (2006) The cross-section of volatility and expected returns, *The Journal of Finance*, **61**, 259–99. doi:10.1111/j.1540-6261.2006.00836.x

Ang, A., Hodrick, R. J., Xing, Y. *et al.* (2009) High idiosyncratic volatility and low returns: international and further US evidence, *Journal of Financial Economics*, **91**, 1–23. doi:10.1016/j.jfineco.2007.12.005

Campbell, J., Lettau, M., Malkiel, B. *et al.* (2001) Have individual stocks become more volatile? An empirical exploration of idiosyncratic risk, *The Journal of Finance*, **56**, 1–43. doi:10.1111/0022-1082.00318

Doran, J. S., Jiang, D. and Peterson, D. R. (2012) Gambling preference and the new year effect of assets with lottery features, *Review of Finance*, **16**, 685–731.

Huang, W., Liu, Q., Rhee, S. G. *et al.* (2010) Return reversals, idiosyncratic risk, and expected returns, *Review of Financial Studies*, **23**, 147–68. doi:10.1093/rfs/hhp015

Huang, W., Liu, Q., Rhee, S. G. *et al.* (2011) Another look at idiosyncratic volatility and expected returns, *Journal of Investment Management*, **9**, 26–51.

Jegadeesh, N. (1990) Evidence of predictable behavior of security returns, *The Journal of Finance*, **45**, 881–98. doi:10.1111/j.1540-6261.1990.tb05110.x

Newey, W. K. and West, K. D. (1987) A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix, *Econometrica*, **55**, 703–08. doi:10.2307/1913610

Appendix: Idiosyncratic volatility and global equity markets

This appendix aims to address comments and questions raised by the pre-examiners during the review process. In order to improve the replicability of this essay, several issues related to the data and the methodology are clarified in the following:

First, this essay utilizes stock indices in domestic currencies. The use of stock indices in local currencies is implicitly acknowledged on page 1 in the following sentence: “Furthermore, this study considers the perspective of an internationally aligned investor and employs different global asset pricing model specifications for risk adjustment.” Furthermore, on page 4, it is explicitly stated that this research “may be extended to investigating the perspective of an US or European investor, respectively, in order to uncover potential exchange-rate effects”. This means that future studies may focus on investigating the idiosyncratic risk/return relationship in a setting where the returns of the stock indices are compounded in U.S. dollars or in euros in order to adapt the perspective of an U.S. investor or European investor, respectively.

Following the common practice in the asset pricing literature, stock price indices ex-dividends are used in this study.

Regarding the calculation of stock returns, the current research employs the same approach as Ang et al. (2006, 2009), Doran et al. (2012) and Huang et al. (2011). This approach is briefly described in section III of the paper: The study operates with daily returns $R_{i,t,d}$ that are typically defined as $R_{i,t,d} = (P_{i,t,d} - P_{i,t,d-1}) \cdot 100/P_{i,t,d-1}$ where $P_{i,d}$ denotes the price of stock *i* at day *d* in month *t*. A monthly return $R_{i,t}$ is typically defined as $R_{i,t} = (P_{i,t} - P_{i,t-1}) \cdot 100/P_{i,t-1}$, where $P_{i,t}$ denotes the price of stock *i* in month *t*. As mentioned on page 3, for each month *t*, the idiosyncratic volatility $IVOL_{i,t-1}$ of stock index *i* is calculated as the square root of the residual variance *i* of the following market model:

$$R_{i,t-1,d} = \alpha_{i,t-1} + R^{M}_{t-1,d} + \varepsilon_{i,t-1,d} \tag{1}$$

$$IVOL_{i,t-1} = \sqrt{VAR(\varepsilon_{i,t-1,d})} \tag{2}$$

For instance, on the last trading day of March, the daily returns from *d*=March 1 to *d*= March 31 are used to estimate the realized idiosyncratic volatility for March. Based on these estimates, stock indices are sorted in an increasing order from low to high idiosyncratic volatility. Then, the predicted return corresponds to the holding period return for the period April.

Since data for the Fama and French global three-factor model is unavailable, the current research estimates the residuals relative to above mentioned market model, where $R^M_{t-1,d}$ is the daily average return of an equal-weighted portfolio that consists of all stock indices employed and serves a simple proxy for the market factor in this setting. Huang et al. (2011) state that the "realized monthly idiosyncratic volatility is calculated by multiplying the standard deviation of daily residuals by the square root of the number of trading days in a month. For robustness check, we also use the standard deviation of the residuals from the capital asset pricing model and the raw returns to measure idiosyncratic volatility." Furthermore, in footnote 3, Huang et al. (2011) explain that they "obtain qualitatively similar results when we use the standard deviation of the residuals from the capital asset pricing model and the raw returns to measure idiosyncratic volatility." Therefore, the approach used in this essay is similar to the approach used in the robustness checks of Huang et al. (2011). The approach is explained and justified in footnote 1 with the following statement: "Since data for the global Fama and French model were not available on a daily frequency, I used an equal-weighted global portfolio as global market risk factor. For instance, Huang et al. (2011) report that employing only a market risk factor instead of the Fama and French factor model specification does not change the results."

Following the common practice in the asset pricing literature, Newey-West (1987) heteroskedasticity and autocorrelation consistent standard errors are used to calculate the *t*-statistics. The use of robust *t*-statistics is common practice in finance research due to some stylized facts. For instance, in Lütkepohl and Krätzig (2004, p.197) it is highlighted that price variations observed on speculative financial markets, measured at some higher frequency, exhibit positive autocorrelation. Moreover, periods of higher and smaller price variations alternate, which means that volatility tends to cluster. These are well-known stylized facts of financial markets. To account for these stylized facts, this study utilizes Newey-West (1987) heteroskedasticity and autocorrelation consistent standard errors.

The current study employs equally-weighted portfolio groups similar to Grobys (2014, p.101) because "each of these stock indices is a well-diversified basket" of stocks. The employed stock indices are typically market capitalization-based. Therefore, this current research employs the simple average of already weighted indices.

Figure A plots the number of stock indices against time. The lowest number of stock indices employed is 28 which, in turn, means that the minimum number of stock indices in each portfolio at any point in time is at least five.

Figure A: Evolution of the number of stock indices

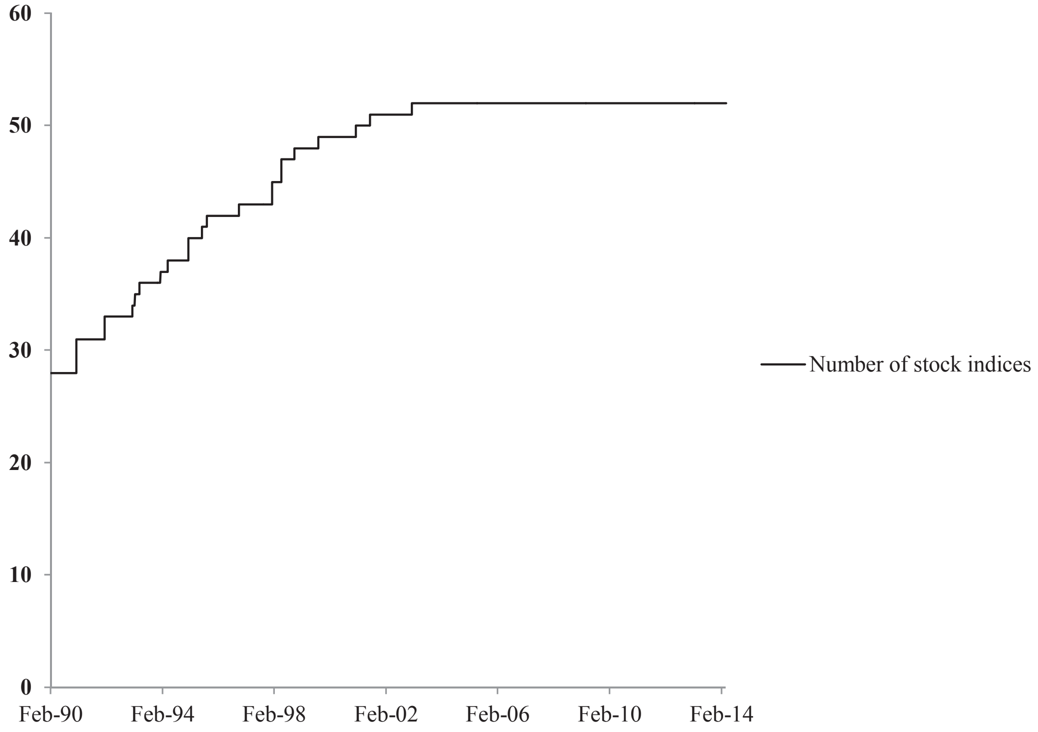


Table A reports the descriptive statistics for the equity indices used in the empirical analysis. To make the statistics comparable, the sample starts on January 3 2003 (when data for all indices were available) and ends on March 31 2014.[1]

Table A: Descriptive statistics

Panel A:

Index	S&P/TSX COMPOSITE INDEX	OMX COPENHAGEN (OMXC20)	OMX HELSINKI (OMXH)	FRANCE CAC 40	ASX ALL ORDINARIES
Mean	0.03	0.05	0.02	0.02	0.03
Median	0.06	0.07	0.02	0.03	0.05
Maximum	9.82	9.96	9.25	11.18	5.55
Minimum	-9.32	-11.06	-8.82	-9.04	-9.96
Std. Dev.	1.14	1.30	1.48	1.45	1.05
Skewness	-0.48	-0.10	-0.04	0.25	-0.59
Kurtosis	14.41	9.83	7.19	9.76	10.62
Jarque-Bera	15452.37	5499.78	2067.10	5411.58	7008.79
Probability	0.00	0.00	0.00	0.00	0.00
Observations	2829	2829	2829	2829	2829

Panel B:

Index	ATX	BEL 20	DAX 30 PERFORMANCE	ATHEX COMPOSITE	HANG SENG
Mean	0.04	0.02	0.05	0.01	0.04
Median	0.05	0.04	0.08	0.01	0.00
Maximum	12.77	9.78	11.40	14.37	14.35
Minimum	-12.14	-7.98	-7.45	-9.71	-13.67
Std. Dev.	1.60	1.30	1.45	1.82	1.56
Skewness	-0.20	0.20	0.17	0.11	0.13
Kurtosis	10.49	10.23	9.34	7.42	14.75
Jarque-Bera	6630.45	6176.81	4754.12	2309.03	16294.90
Probability	0.00	0.00	0.00	0.00	0.00
Observations	2829	2829	2829	2829	2829

[1] Note that the statistics are reported in daily terms.

Panel C:

Index	NIKKEI 225	FTSE MIB INDEX	FTSE ALL SHARE	AEX INDEX (AEX)	NZX 50
Mean	0.03	0.01	0.03	0.02	0.01
Median	0.00	0.07	0.04	0.05	0.04
Maximum	14.15	11.49	9.21	10.55	5.99
Minimum	-11.41	-8.24	-8.34	-9.14	-4.82
Std. Dev.	1.54	1.52	1.16	1.43	0.70
Skewness	-0.41	0.06	0.02	0.15	-0.32
Kurtosis	11.27	9.02	10.79	11.23	8.06
Jarque-Bera	8130.79	4275.69	7152.66	8003.50	3061.84
Probability	0.00	0.00	0.00	0.00	0.00
Observations	2829	2829	2829	2829	2829

Panel D:

Index	OSLO EXCHANGE ALL SHARE	PORTUGAL PSI	STRAITS TIMES INDEX L	MADRID SE GENERAL (IGBM)	OMX STOCKHOLM (OMXS)
Mean	0.07	0.02	0.04	0.03	0.05
Median	0.12	0.04	0.05	0.07	0.06
Maximum	9.62	10.73	7.82	14.73	9.01
Minimum	-9.25	-9.86	-8.33	-9.23	-7.12
Std. Dev.	1.49	1.18	1.19	1.47	1.35
Skewness	-0.50	0.04	-0.13	0.31	0.07
Kurtosis	9.21	12.19	8.83	11.10	7.89
Jarque-Bera	4661.62	9962.52	4016.99	7770.42	2826.30
Probability	0.00	0.00	0.00	0.00	0.00
Observations	2829	2829	2829	2829	2829

Panel E:

Index	SWISS MARKET (SMI)	RUSSIA RTS INDEX	ARGENTINA MERVAL	BAHRAIN ALL SHARE	BRAZIL BOVESPA
Mean	0.03	0.07	0.11	0.01	0.07
Median	0.05	0.08	0.05	0.00	0.04
Maximum	11.39	22.39	11.00	3.68	14.66
Minimum	-7.79	-19.10	-12.15	-4.80	-11.39
Std. Dev.	1.15	2.17	1.87	0.59	1.77
Skewness	0.21	-0.13	-0.35	-0.38	0.13
Kurtosis	11.18	15.08	7.08	9.21	8.83
Jarque-Bera	7900.81	17214.19	2018.32	4612.47	4014.54
Probability	0.00	0.00	0.00	0.00	0.00
Observations	2829	2829	2829	2829	2829

Panel F:

Index	CHILE SANTIAGO SE GENERAL (IGPA)	SHANGHAI SE A SHARE	COLOMBIA IGBC INDEX	PRAGUE SE PX	SAUDI TADAWUL ALL SHARE (TASI)
Mean	0.05	0.03	0.09	0.04	0.06
Median	0.06	0.00	0.06	0.05	0.10
Maximum	9.48	9.45	15.82	13.16	17.82
Minimum	-5.80	-11.98	-10.46	-14.94	-12.05
Std. Dev.	0.82	1.62	1.35	1.50	1.69
Skewness	-0.02	-0.20	0.04	-0.28	-0.38
Kurtosis	14.12	7.81	16.52	17.07	15.24
Jarque-Bera	14574.51	2746.37	21537.32	23373.07	17719.36
Probability	0.00	0.00	0.00	0.00	0.00
Observations	2829	2829	2829	2829	2829

Panel G:

Index	FTSE/JSE ALL SHARE	KOREA SE COMPOSITE (KOSPI)	BANGKOK S.E.T.	VENEZUELA SE GENERAL	BIST NATIONAL 100
Mean	0.07	0.05	0.06	0.21	0.08
Median	0.06	0.05	0.00	0.00	0.06
Maximum	7.07	11.95	11.16	13.25	12.89
Minimum	-7.30	-10.57	-14.84	-18.66	-12.49
Std. Dev.	1.25	1.43	1.37	1.48	1.87
Skewness	-0.08	-0.38	-0.63	-0.20	-0.13
Kurtosis	6.63	9.26	13.68	28.37	7.56
Jarque-Bera	1552.59	4684.21	13636.07	75875.85	2455.24
Probability	0.00	0.00	0.00	0.00	0.00
Observations	2829	2829	2829	2829	2829

Panel H:

Index	TUNISIA TUNINDEX	BUDAPEST (BUX)	OMX ICELAND ALL SHARE	EGYPT HERMES FINANCIAL	CNX 500
Mean	0.05	0.04	0.00	0.11	0.08
Median	0.01	0.01	0.04	0.07	0.10
Maximum	4.19	14.09	6.22	14.69	16.22
Minimum	-4.88	-11.88	-66.58	-15.80	-16.07
Std. Dev.	0.56	1.63	1.72	1.69	1.55
Skewness	-0.42	0.13	-22.71	-0.39	-0.50
Kurtosis	15.37	9.82	824.68	13.17	15.49
Jarque-Bera	18108.82	5489.76	79827308	12264.12	18498.31
Probability	0.00	0.00	0.00	0.00	0.00
Observations	2829	2829	2829	2829	2829

Panel I:

Index	IDX COMPOSITE	ISRAEL TA 100	AMMAN SE FINANCIAL MARKET	MALTA SE MSE	MEXICO IPC (BOLSA)
Mean	0.10	0.06	0.04	0.02	0.07
Median	0.09	0.01	0.00	0.00	0.08
Maximum	7.92	10.28	21.99	5.65	11.01
Minimum	-12.13	-7.20	-18.57	-4.63	-7.01
Std. Dev.	1.43	1.23	1.28	0.73	1.29
Skewness	-0.60	-0.09	0.54	0.37	0.25
Kurtosis	10.54	8.25	52.84	11.15	9.51
Jarque-Bera	6878.68	3251.51	292996.90	7891.72	5031.08
Probability	0.00	0.00	0.00	0.00	0.00
Observations	2829	2829	2829	2829	2829

Panel J:

Index	KARACHI SE 100	LIMA SE GENERAL(IGBL)	MOROCCO SE CFG 25	OMAN MUSCAT SECURITIES MKT.	FTSE BURSA MALAYSIA KLCI
Mean	0.09	0.09	0.04	0.05	0.04
Median	0.07	0.04	0.02	0.00	0.03
Maximum	8.60	13.67	6.24	10.41	4.35
Minimum	-8.30	-12.45	-5.32	-10.43	-9.50
Std. Dev.	1.39	1.57	0.84	1.08	0.76
Skewness	-0.29	-0.18	-0.15	-0.72	-0.97
Kurtosis	6.67	12.43	9.13	24.42	16.09
Jarque-Bera	1629.25	10505.81	4445.75	54328.08	20626.61
Probability	0.00	0.00	0.00	0.00	0.00
Observations	2829	2829	2829	2829	2829

Panel K:

Index	PHILIPPINE SE I(PSEi)	WARSAW GENERAL INDEX
Mean	0.07	0.05
Median	0.01	0.04
Maximum	9.82	6.27
Minimum	-12.27	-9.68
Std. Dev.	1.32	1.30
Skewness	-0.47	-0.39
Kurtosis	9.72	6.91
Jarque-Bera	5432.88	1874.79
Probability	0.00	0.00
Observations	2829	2829

References

Chan, K., Hameed, A., and Tong, W., 2000. Profitability of momentum strategies in the international equity markets. Journal of Financial and Quantitative Analysis 35, 153–172.

Grobys, K., 2014. Momentum in global equity markets in times of troubles: does the economic state matter? Economics Letters 123, 100–103.

Huang, W., Liu, Q., Rhee, S.G., and Zhang, L., 2011. Another Look at Idiosyncratic Volatility and Expected Returns. Journal of Investment Management 9, 26–51.

Lütkepohl, H., and Krätzig, M., 2004. Applied Time Series Econometrics, Cambridge University Press. New York.

Newey, W.K., and West, K.D., 1987. A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. Econometrica 55, 703–708.

Idiosyncratic volatility and momentum crashes

Klaus Grobys[1*a]

** University of Vaasa, Wolffintie 34, 65200, Vaasa, Finland.*

Abstract

This paper examines the relationship between realized idiosyncratic volatility and future stock returns in a scenario where it is ex ante controlled for size, liquidity, and information asymmetry. In contrast to earlier studies, the results demonstrate that idiosyncratic volatility and future stock returns are significantly positively correlated in the S&P 500 universe. A regression analysis reveals that the positive pay offs are driven by the same factor that causes momentum crashes.

***JEL* classification:** G12; G14.

Keywords: Idiosyncratic risk, January effect, momentum crash, S&P 500

[1] Email: klaus.grobys@uwasa.fi; grobys.finance@gmail.com. Phone: +358 (0)46 611 0151.

[a] I received valuable comments from seminar participants at the Finnish Graduate School of Finance summer workshop and the Accounting & Finance seminar at the University of Vaasa. I am grateful to Peter Nyberg, Mika Vaihekoski, Sami Vähämaa, and Janne Äijö for insightful comments.

1. Introduction

The relationship between idiosyncratic volatility and the cross section of stock returns has been extensively discussed in the finance literature. While on the firm level a positive relation between idiosyncratic volatility and stock returns has been documented by Malkiel and Xu (2002), Spiegel and Wang (2006), Chua et al. (2010), Fu (2009) and Huang et al. (2010), on the portfolio level no consensus has yet been achieved. On the one hand, Ang et al.'s (2006, 2009) empirical findings indicate that portfolios with high idiosyncratic volatility in the portfolio formation month yield a lower return in the following month than portfolios with low idiosyncratic volatility. Their empirical finding runs contrary to the theoretical models by Levy (1978) and Merton (1987) suggesting that firms with larger idiosyncratic volatility require higher returns to compensate for imperfect diversification. On the other hand, Doran et al. (2008) argue that the negative relationship between idiosyncratic volatility and stock returns is limited only to months other than January.

In a more recent study, Bali and Cakici (2008) presented an interesting extension to this debate. They found no evidence for a significant link between idiosyncratic risk and the cross section of expected returns after excluding the smallest, least liquid, and lowest priced stocks. Their result holds for both value-weighted and equal-weighted portfolios. Bali and Cakici (2008) highlight that the weighting scheme used to compute average portfolio returns affects the cross-sectional relation between idiosyncratic risk and expected returns. With regard to large caps their results indicate that the equal-weighted average return differential between lowest and highest idiosyncratic risk portfolios is a small positive number, 0.02% per month, and statistically insignificant.

Huang et al. (2010, 2011) also emphasize that the weighting scheme affects the relation between idiosyncratic risk and expected returns. As winner stocks have a relatively greater market value than loser stocks in the portfolio formation month, their return reversals drive down the value-weighted returns on the highest idiosyncratic risk portfolio in the following one-month holding period. Hence, the one-month holding period value-weighted return on the highest idiosyncratic volatility portfolio is significantly lower than that on the lowest idiosyncratic volatility portfolio. Like Bali and Cakici (2008), Huang et al. (2011) find a positive but insignificant relation between idiosyncratic risk and expected returns when using equal-weighted portfolios.

Both studies Bali and Cakici (2008) and Huang et al. (2010, 2011) use all NYSE/AMEX/NSADAQ stocks, as did Ang et al. (2006). However, there is no study available investigating this apparent puzzle in the context of a virtually efficient market, nor is there any study exploring the idiosyncratic volatility strategy pay-offs in the presence of so-called momentum crashes. This study attempts to fill these gaps.

The purpose of this paper is twofold. First, I examine the relation between idiosyncratic volatility and future returns on a portfolio level in a scenario where the level of idiosyncratic volatility is ex ante controlled for both liquidity, size and information asymmetry. Institutional investors and large investors are typically focused on large caps with high liquidity and low information asymmetry. More precisely, Chan et al. (2013) highlight that the number of index-related financial assets has increased significantly from 16% in 2001 to 33% in 2011 in the past decade. This study focuses exclusively on stocks listed on the S&P 500 index and, in the process, controls ex ante for size, liquidity and information asymmetry.[2] Following the previous

[2] According to the "S&P U.S. Indices Methodology" published by Standard & Poors in June 2012, the unadjusted market capitalization of a company listed on the S&P 500 must be at least US $ 4.0 billion, which ensures that only large caps are included. Moreover, the dollar traded to float-adjusted market capitalization must be greater than 1.0

literature, I investigate five equal-weighted portfolios sorted by idiosyncratic volatility, and thereby, different holding periods. The spread of the quintiles sorted by idiosyncratic volatility is regressed on Carhart's (1997) four-factor model for risk adjustment. In addition, subsamples of firms are investigated in more detail, where the overall sample of firms is divided into two subsamples consisting of either firms that were deleted from the S&P 500 in later periods or firms that remained in the index.

Second, I investigate the seasonality of the idiosyncratic volatility spread. In the process, the spread is regressed on a dummy variable indicating the month of January. I also account for risk adjustment and regress the spread on the Carhart (1997) model where the dummy variable for January is accounted for. Finally, the tails of the idiosyncratic volatility spread distribution are explored in more detail. Therefore, the months when the idiosyncratic volatility spread generated the 10% of lowest and 10% of highest returns are examined. Based upon the results of the previous regression analysis, I match the dates with the months where momentum crashes occurred, as reported in Table 1 in Daniel et al. (2012, p.7), as to reveal any potential link between these two investment vehicles.

This study contributes to the existing literature in the following respects. First, I extend the contributions of Ang et al. (2006), Bali and Cakici (2008) and Huang et al. (2010, 2011) by adopting the analysis of portfolios sorted by idiosyncratic volatility in a stock universe consisting exclusively of large firms with high liquidity and the lowest possible information asymmetry. Fama and French (2008) stress it is important to examine whether anomalies are pervasive across size groups because the seemingly anomalous pattern in a cross section of stock returns may be

---

and the minimum monthly trading volume must be at least 250,000 stocks in each of the six months leading up to the evaluation date which ensures that companies listed on the S&P 500 exhibit a reasonable price and a high liquidity (see "S&P U.S. Indices Methodology, p.5).

attributed to small and illiquid stocks. This study diverges from that of Bali and Cakici (2008) because the concern about size and liquidity is removed by focusing exclusively on firms that were listed in the S&P 500. Chan et al. (2013) note that in contrast to those of large firms in general, the underlying assets of the S&P index component stocks are subject to greater scrutiny from investors and analysts. Hence, by focusing on stocks listed in the S&P 500, I ensure ex ante that any effects are not driven by either small or illiquid stocks that represent only a small fraction of aggregate wealth, or by potential large information asymmetry.

Second, motivated by Bali and Cakici's (2008) and Huang at al.'s (2011) critiques, the current research considers equal-weighted portfolios, in contrast to Ang et al. (2006). Since Bali and Cakici (2008) and Huang at al. (2010, 2011) argue that the negative relation between future returns and realized idiosyncratic volatility, as documented in Ang et al. (2006, 2009), is particularly driven by employing a value-weighting scheme, I ensure that any potential effect cannot be driven by the latter. In doing so, this study investigates whether any potential effect may be driven by the January effect. The study thus acknowledges Doran et al. (2008) who documented that the relation between idiosyncratic risk and expected returns is significantly positive in the month of January, irrespective of the weighting scheme.

Finally, motivated by the empirical results of the previous analysis, I explore whether a link exists between momentum crashes and pay-offs of the zero-cost strategy formed on realized idiosyncratic volatility. There has to date no study investigating a potential link between these two strategies. While Fama and French (2008) and Novy-Marx (2012) confirm the ongoing profitability of momentum strategies, Daniel et al.'s (2012) findings indicate that momentum strategies involve a high tail risk. The highest losses within the 2000/01-2010/01 decade have been between -20.42% and -45.89% and, in the parlance of Daniel et al. (2012), are referred to as momentum crashes. Whenever momentum crashes occur, potential returns may be diminished. Hence, it may be important to understand how to hedge this tail risk of momentum strategies.

The current research diverges from that of Ang et al. (2006, 2009) and Guo and Savickas (2010) in finding that portfolios with higher idiosyncratic volatility generate statistically significant higher returns. The zero-cost portfolio that is long in stocks with the highest idiosyncratic volatility and short in stocks with the lowest idiosyncratic volatility generates an average return of 1.17% per month with a Newey-West (1987) *t*-statistic of 4.25. After risk adjustment, the spread is of an economic magnitude of 0.86% per month with a Newey-West (1987) *t*-statistic of 3.91. The positive relationship between realized idiosyncratic volatility is consistent with economic theory suggesting that investors demand compensation for not being able to diversify risk, as something pointed out in Malkiel and Xu (2002) and Jones and Rhodes-Kropf (2003).

Furthermore, in the month of January the raw spread generates an additional return of 4.14% per month with a Newey-West (1987) *t*-statistic of 3.48, thus confirming the findings of Doran et al. (2008) and Huang et. al. (2011) who documented a significantly positive relationship between idiosyncratic volatility and portfolio returns in January. In contrast to Doran et al. (2008), however, the spread remains significantly positive, even after accounting for risk-adjustment. A subsample analysis reveals that the relationship between realized idiosyncratic volatility and expected returns remains stable over time.

Moreover, I split the sample into two subsamples consisting of either firms that were deleted from the S&P 500 at a later point in time or firms that remain in the index. The split allows me to analyze whether the observed relation is subject to a potential merger momentum bias, for instance. Surprisingly, the results point strongly to the positive relation between realized idiosyncratic volatility and expected returns arises due to the survivor sample consisting of firms that remain in the S&P 500. Furthermore, additional robustness checks provide evidence that the effect in the survivor sample is driven by the weighting scheme.

Finally, I investigate outliers of the empirical distribution of the zero-cost portfolio in greater detail. Because the previous regression analysis for risk-adjustment reveals a significantly negative relationship between the momentum factor and the realized idiosyncratic volatility spread, I also explore the association between the outliers and the occurrence of momentum crashes in line with Daniel et al. (2012). While the strategy based on idiosyncratic volatility generated outliers of a similar magnitude to the momentum strategy, matching the dates reveals that the idiosyncratic volatility strategy continuously generated large positive pay-offs whenever momentum crashes occurred. Hence, the idiosyncratic volatility strategy implemented in the S&P 500 universe may act as a hedge for the momentum strategy. A final regression analysis reveals that the positive relation between realized idiosyncratic volatility and expected returns is driven by the same factor that causes momentum crashes. The zero-cost portfolio that is long in stocks with the highest idiosyncratic volatility and short in stocks with the lowest idiosyncratic volatility becomes insignificant or after controlling for a momentum crash dummy variable.

The paper is organized as follows. The next section presents the data and the third section describes the methodology and results. The last section concludes the study.

2. Data

The sample includes all stocks listed in the S&P 500 index accounting for the historical index composition as of October 1, 1989 the earliest index composition available in Datastream. I obtained daily prices on individual stocks from Datastream covering the period February 1973 to April 2014, and then compounded both daily and monthly returns for all stocks and the S&P 500. Daily data for the Fama and French model adopted to estimate the realized idiosyncratic volatility were obtained from Kenneth French's website. I matched the daily data from Kenneth French's website with the daily data obtained from Datastream. As shown in Figure 1, the number of firms included in the analysis due to data availability varies over time. Daily and monthly stock returns are compounded for all firms for which data were available in Datastream. Since the historical index composition as of October 1, 1989 was held constant, no firms were accounted for that entered the S&P 500 after that date.

In order to be able to compare the results, I measured the idiosyncratic volatility in the same manner as in Ang et al. (2006, 2009), Doran et al. (2008) and Huang et al. (2011). For each month, I compounded the daily residual relative to the Fama and French (1993) three-factor model for all stocks. The realized idiosyncratic volatility was compounded by multiplying the standard deviation of daily residuals by the square root of the number of trading days in that corresponding month. To check robustness, I also used the standard deviation of residuals from the Capital Asset Pricing Model (CAPM).

3. Portfolio analysis

3.1. Characteristics of the idiosyncratic volatility-sorted portfolios

To conduct portfolio level analysis, I constructed quintile portfolios based on the ranking of the idiosyncratic volatility of each individual stock in the formation month and held these portfolios for the next month. Portfolio IVOL 5 denotes the portfolio consisting of stocks with the highest idiosyncratic volatility, and IVOL 1 the portfolio with the lowest. I rebalanced the portfolios at the beginning of each month. The approach is the same as that of Ang et al. (2006), Bali and Cakici (2008) and Huang et al. (2011) except that my sample starts in February 1973 and ends in October 2013. Hence, this sample includes the financial crisis period and the strong market reversal in early 2009 when momentum crashes occurred.

In the first row of Table 1, the equal-weighted average returns for the five portfolios in the one-month holding period (month t+1) immediately following the formation month are reported.[3] Average returns increase from 0.85% per month for portfolio IVOL 1 (low idiosyncratic volatility stocks) to 1.34% for portfolio IVOL 4, and further to 2.02% per month for portfolio IVOL 5. In Table 1, the differences in average returns of IVOL 5 – IVOL 1 and IVOL 4 – IVOL 1 are also reported. The differences are statistically significant with an economic magnitude of 1.17% and 0.49% per month and Newey-West (1987) t-statistics of 4.25 and 3.32. This finding diverges from those of Huang et al. (2011) who argue that a negative relation between realized idiosyncratic volatility and future stock returns is driven mostly by the highest idiosyncratic volatility portfolio in two ways. First and most importantly, the spread between portfolios with high idiosyncratic volatility and low idiosyncratic volatility is statistically significantly positive.

[3] For instance, for estimating the idiosyncratic volatilities that were used to form portfolios for the holding period March, I used daily data incorporating all trading days in February until the last trading day in February. The predicted return is the holding period return for the month March.

Second, even if the returns are non-linear increasing as we move from portfolio IVOL 1 to portfolio IVOL 5, the spread between portfolios exhibiting a relatively higher realized idiosyncratic volatility and the portfolio with the lowest realized idiosyncratic volatility remains statistically significant when excluding the portfolio with the highest and second highest realized idiosyncratic volatility. The results of the current research indicate in contrast to Bali and Cakici (2008) and Huang at al. (2010, 2011) that the positive relationship between idiosyncratic volatility and expected returns is not exclusively driven by IVOL 5, which exhibits the highest idiosyncratic volatility.

Furthermore, this result is also consistent with the short-sale constraint explanation in Boehme et al. (2009) because the stocks listed in the S&P 500 typically have both high market capitalization and a high liquidity, which should rule out short-sale constraints. Short-sale constraints are more likely when investors trade medium or small caps or in illiquid market segments.

In the second row of Table 1, the realized idiosyncratic volatility related to each portfolio is reported. While the portfolio volatility increases linearly as we move from portfolio IVOL 1 to portfolio IVOL 4, the volatility makes a huge jump from 2.93% to 13.62% as we move from portfolio IVOL 4 to portfolio IVOL 5. A similar pattern becomes evident when considering the past portfolio returns reported in the third row of Table 1. The past returns increase linearly as we move from portfolio IVOL 1 to portfolio IVOL 4, and as we move from portfolio IVOL 4 to portfolio IVOL 5, the past portfolio return jumps from 1.39% to 2.39%. This pattern, however, might not be surprising because larger price moves in the formation period are likely to increase firm-specific volatility.

3.2. Risk adjustment and seasonality

In this section, I investigate both whether the spread between portfolio IVOL 5 and portfolio IVOL 1 can be explained by standard risk factors proposed by Fama and French (1992, 1993) and Carhart (1997) and if the return of the spread is higher in the month of January, as suggested in Doran et al. (2008) and Huang et al. (2011). First, I regressed the raw spread simply on a dummy variable with a value of 1 in the month of January and a value of 0 in any other month. Then, I investigated whether the spread could be explained by standard risk factors. In doing so, I followed Fama and French (2008) and regressed the spread between portfolio IVOL 5 and portfolio IVOL 1 on Carhart's (1997) four-factor model. Finally, I controlled for the January effect and regressed the spread the on Carhart's (1997) four-factor model including the dummy for January. The results are reported in Table 2. The regression analysis reveals that the dummy variable indicating the month of January appears to be statistically significant on the 1% level. The economic magnitude of the dummy variable is 4.14% indicating a notably higher pay-off in the month of January.

Furthermore, regressing the spread on Carhart's (1997) four-factor model specification actually increases the statistical significance of the spread. The economic magnitude of the spread is 0.97% per month after risk adjustment with a Newey-West (1987) *t*-statistic of 3.91. The loadings against the market, size and momentum factors are statistically significant on any level. On the one hand, the positive loadings against the market factor and the size factor indicate that stocks with high realized idiosyncratic volatility tend to be driven by relatively smaller stocks having a relatively higher sensitivity to market movements. On the other hand, the negative loadings against the momentum factor indicate that stocks with high realized idiosyncratic volatility tend to be driven by loser stocks. Interestingly, the four-factor asset pricing model is capable of explaining 62% of the variation of the realized idiosyncratic volatility spread. The loadings against those risk factors remain statistically significant after accounting for the dummy for January, while the economic magnitude and statistical significance of the January effect decreases notably.

3.3. Are the results subject to an index-addition-bias?

The analysis employed the S&P 500 composition as of October 1, 1989, which was the earliest available index composition. The sample period starting from February 1973 gives rise to the question of whether the results are biased. Investors in the pre-October 1989 period could not have known which firms would later be included in the S&P 500. In other words, there is a concern over whether firms that were added to the S&P 500 might have performed very well in the pre-October 1989 period. To address this concern, I included a dummy variable in the previous regression analysis. The dummy variable has a value of 0 until September 1989 and a value of 1 from October 1989 onwards. The first part of the sample included 199 monthly observations, whereas the second part of the sample accounted for 295 monthly observations. Whether or not the spread is driven by an index-addition-bias, I would expect the corresponding dummy variable to be statistically significantly negative. The results are reported in rows five to seven in Table 2. The dummy variable *Oct 1989* has virtually no impact on the parameter estimates, and furthermore, is insignificant for all regression model specifications. This finding indicates that the positive relationship between idiosyncratic volatility and expected returns is not driven by a potential index-addition-bias.

3.4 Are the results driven by firms that are deleted from the index in later periods?

Chan et al. (2013), who investigated the effect of S&P 500 additions and deletions and documented a significant long-term price increase for both added and deleted stocks while deleted stocks outperformed added stocks. In Figure 2, the evolution of the cumulative absolute number of deleted stocks is shown for the period October 1989 to April 2014. At the end of the sample period, 288 firms of 498 had been deleted. Index deletions arise because of mergers and acquisitions (50%), delistings (41%), bankruptcies (2%) and others (7%). The high percentage of mergers and acquisitions that occurred in the S&P 500 universe suggests a merger momentum effect occasioning a bias. Hence, we must query whether the IVOL 5 – IVOL 1 spread could be driven by firms that were deleted from the index in the ex-post October 1989 period. To test this hypothesis, I split the sample into two subsamples of firms. The first subsample is referred to as DELETED and comprises firms deleted from the S&P 500 in April 2014 at the latest. The second subsample comprises firms not deleted from the S&P 500. The second sample is referred to as SURVIVOR, and incorporates 210 stocks. Since a reasonable number of stocks must be accounted for when doing portfolio analysis, I considered the period October 1989 to May 2003, thus ensuring that the sample DELETED contained at least 100 large stocks. The number of stocks in the DELETED category examined varies between 288 (October 1989) and 104 (May 2003).

Then, for each subsample of stocks, I again constructed quintile portfolios based on the ranking of the idiosyncratic volatility of each individual stock in the formation month and held these portfolios for the next month. Portfolio IVOL 5 denotes the portfolio consisting of stocks with the highest idiosyncratic volatility, and IVOL 1 the portfolio with the lowest. I rebalanced the portfolios at the beginning of each month. The results are reported in Table 3, Panels A and B.

Panel A shows the portfolio groups for the sample DELETED. The differences in average returns of IVOL 5 – IVOL 1 and IVOL 4 – IVOL 1 are either only marginally significant or insignificant. Panel B shows the portfolio groups for the SURVIVOR sample. Notably, the differences in average returns of IVOL 5 – IVOL 1 and IVOL 4 – IVOL 1 are significant on a common 5% significance level and exhibit an economic magnitude of 0.77% and 0.39% per month, respectively.

Next, I accounted for risk-adjustment and regressed the spread between portfolio IVOL 5 and portfolio IVOL 1 on Carhart's (1997) four-factor model. I also controlled for the January effect and regressed the spread on Carhart's (1997) four-factor model including the dummy variable for January. The results are reported in Table 5, Panels A and B. Panel A shows the risk-adjusted spread for the sample DELETED and different model specifications. After accounting for the January effect, the spread remains positive but becomes insignificant, indicating that the marginally significant raw spread can be fully explained by the four-factor model in association with the January effect. Panel B shows the risk-adjusted spread for the SURVIVOR sample. Strikingly, the risk-adjusted spread is statistically significantly positive on any level even after accounting for the January effect and has an economic magnitude of 0.69% per month. These results indicate that the positive relationship between idiosyncratic volatility and expected returns is not driven by stocks that were deleted, but by the survivors.

As an additional robustness check, I employed the CAPM to estimate the realized idiosyncratic volatility. The results are reported in Tables 1 – 6 in the appendix. The results are virtually the same and support the previous findings. However, it may be noteworthy that the raw spread in the sample DELETED is no longer marginally significant on a 10% level which is shown in Panel A of Table 3 in the appendix. It is also evident that the returns are no longer increasing in a linear fashion as we move from IVOL 1 to IVOL 5. There is no relation between realized idiosyncratic volatility and expected returns for the sample DELETED, a finding in line with those of Bali and Cakici (2008) who find that the relationship is insignificant for large firms.

3.5. Does the weighting scheme matter?

Since Bali and Cakici (2008) and Huang at al. (2010, 2011) argue that the negative relation between future returns and realized idiosyncratic volatility, as documented in Ang et al. (2006, 2009), is particularly driven by employing a value-weighting scheme, the question arises whether the positive relationship between realized idiosyncratic volatility and future stock returns in the SURVIVOR sample is driven by the equal-weighting scheme. Consequently, I employed a value-weighting scheme and, again, constructed quintile portfolios based on the ranking of the idiosyncratic volatility of each individual stock in the formation month and held these portfolios for the next month. Portfolio IVOL 5 denotes the portfolio consisting of stocks with the highest idiosyncratic volatility, and IVOL 1 the portfolio with the lowest. I rebalanced the portfolios at the beginning of each month. Then, I regressed the spread between portfolio IVOL 5 and portfolio IVOL 1 on Carhart's (1997) four-factor model. I also controlled for the January effect and regressed the spread on Carhart's (1997) four-factor model including the dummy variable for January. The results are reported in Table 5. Consistent with the argument of Bali and Cakici (2008), it can be noted from the table that the spread is insignificant. This implies that the positive relationship between realized idiosyncratic volatility and future returns in the sample SURVIVOR in the S&P universe is largely driven by the weighting-scheme.

3.6. Outliers and momentum crashes

The results reported in Tables 2 and 4 provide evidence for a zero-cost portfolio sorted by idiosyncratic volatility being negatively correlated with the momentum factor. A negative correlation implies that the strategy's pay-offs tend to be high when pay-offs of the momentum strategy are low and vice versa. Hence, in this section I address the 10% outliers on the right- and left-hand side of the realized idiosyncratic volatility spread. In Table 6, the outliers of the distribution are reported. Panel A of Table 6 shows that the lowest 10% of the returns generated by this strategy, whereas Panel B shows the highest 10% of the return. It becomes evident that the highest positive returns are, in absolute terms, higher than the lowest generated returns. Moreover, the generated returns are positively correlated with the S&P 500 returns. This is not surprising because the positive loadings of the spread against the market factor (as shown in Tables 2 and 5) imply a positive co-movement.

Next, I collected the data for momentum crashes from Table 1 in Daniel et al. (2012, p.7). The given dates for momentum crashes are January 2001, November 2002, March 2009, April 2009 and August 2009 with corresponding returns of -42.10%, -20.42%, -39.32%, -45.89% and -24.80%. Interestingly, Panel B of Table 6 shows the returns generated by the strategy based on realized idiosyncratic volatility were always positive and of large economic magnitude whenever a momentum crash occurred. The average return of the idiosyncratic volatility spread generated in the presence of momentum crashes is 28.58%, whereas the momentum crashes generated an average return of -34.51% suggesting that the former strategy can at least to some extent work as a hedge for the latter. Finally, I coded a binary dummy variable that indicates the occurrence of momentum crash with a value of one whenever a momentum crash in line with Daniel et al. (2012) occurred and a zero otherwise. The results are reported in Table 7. The results show that high positive payoffs in the presence of momentum crashes explain the positive relationship between idiosyncratic volatility and future returns. In each model specification, the dummy variable indicating momentum crashes is statistically significant on any level. After risk adjustment, the spread of the (equally-weighted) portfolios sorted by idiosyncratic volatility becomes small in term of economic magnitude and insignificant on a common 5% level. This result indicates that the pay-offs of the spread between portfolio IVOL 5 and portfolio IVOL 1 is state-dependent and driven by the same factor that causes momentum to crash.

As a final robustness check, I again paid attention to the SURVIVOR sample and made use of the value-weighting scheme. I employed the value-weighted realized idiosyncratic volatility spread as in section 3.5 and regressed it on the same control variables as the equal-weighted spread. The results are reported in Table 8. Surprisingly, after risk-adjusting the spread by employing the Fama and French (1993) three-factor model, the spread becomes negative with an economic magnitude of -0.73% per month and statistically significant on at least a 10% level. In contrast to the previous findings that supported Bali and Cakici (2008) and Huang at al. (2010, 2011), this result is consistent with Ang et al. (2006, 2009). While the value-weighted spread turns out the generate negative returns of an economic magnitude comparable with Ang et al.'s (2006) findings, the dummy variable indicating momentum crashes is statistically significant on any level and provides evidence for that even the value-weighted spread appears to generate extraordinary high pay-offs in the presence of momentum crashes which supports the previous findings.

4. Conclusion

The idiosyncratic volatility puzzle has been intensively discussed in the academic finance literature. On the one hand, a positive relation between idiosyncratic volatility and stock returns on a firm level has been documented by Malkiel and Xu (2002), Spiegel and Wang (2006), Chua et al. (2010) and Fu (2009). However, Ang et al. (2006) report how stocks with high idiosyncratic volatility generate abysmally low average returns, and how the quintile portfolio of stocks with the highest idiosyncratic volatility earns total returns of -0.02 per month. Ang et al. (2009) confirm the negative relationship between realized idiosyncratic volatility and future returns in an international setting. Even though Ang et al. (2006, 2009) reported their results to be robust, Huang et al. (2010, 2011) and Bali and Cakici (2008) point out that that the negative relation documented in Ang et al. (2006, 2009) may largely result from the value-weighting scheme employed. A value-weighting scheme of portfolios is typically considered when the market capitalization varies considerably or small stocks are included.

Ang et al. (2006) make use of all common stocks listed on the NYSE, AMEX and NASDAQ and employ what is essentially a value-weighting scheme for their portfolios. Because the current research accounts only for large stocks listed in the S&P 500, it employs equal-weighted portfolios. Companies listed in the S&P 500 exhibit similar properties with respect to market capitalization and liquidity are also likely to be of major importance to institutional investors, too. Equal-weighted portfolios are also used in Bali and Cakici (2008) and Huang et al. (2011). In contrast to the findings of Bali and Cakici (2008) reporting that the difference between the portfolio with the highest realized idiosyncratic volatility and the portfolio with the lowest is positive yet insignificant for a subsample of large stocks, the current research finds the difference to be statistically significantly positive. The economic magnitude varies between 0.83% and

1.35% per month depending on both the risk adjustment and controlling for the month of January. The positive relationship between realized idiosyncratic volatility and future returns is consistent with economic theory (see Malkiel and Xu, 2002, Jones and Rhodes-Kropf, 2003 and Boehme et al., 2009).

Moreover, the current research establishes a robust link between the spread of portfolios sorted by realized idiosyncratic volatility and momentum crashes. Whenever a momentum crash occurred during the sample period, the idiosyncratic volatility spread generated high pay-offs. The economic magnitude of these extraordinary high pay-offs offers the opportunity to hedge these momentum crashes. After controlling for momentum crashes, the positive relationship between realized idiosyncratic volatility and future returns becomes insignificant. On the other hand, employing a value-weighting scheme makes the risk-adjusted spread negative supporting Ang et al. (2006, 2009). Notably, the dummy variable indicating momentum crashes indicates that both strategies generate high pay-offs in the presence of momentum crashes. Still, more research is needed to investigate the link between momentum pay-offs and idiosyncratic volatility in more detail.

References

Ang, A., Hodrick, R.J., Xing, Y., Zhang, X., 2006. The cross section of volatility and expected returns. Journal of Finance 61, 259–299.

Ang, A., Hodrick, R.J., Xing, Y., Zhang, X., 2009. High Idiosyncratic Volatility and Low Returns: International and Further US Evidence. Journal of Financial Economics 91, 1–23.

Bali, T.G., Cakici, N., 2008, Idiosyncratic Volatility and the Cross Section of Expected Returns, Journal of Financial and Quantitative Analysis 43, 29–58.

Boehme, R., Danielsen, B., Kumar, P., Sorescu, S., 2009. Idiosyncratic risk and the cross-section of stock returns: Merton (1987) Meets Miller (1977). Journal of Financial Markets 12, 438–468.

Brown, G., Kapadia, N., 2007. Firm-specific risk and equity market development, Journal of Financial Economics. 84, 358–388.

Carhart, M., 1997. On Persistence in Mutual Fund Performance. Journal of Finance 52, 57–82.

Chan, K., Wan Kot, H., Tang, G.Y.N., 2013, A comprehensive long-term analysis of the S&P 500 index additions and deletions, Journal of Banking and Finance 37, 4920–4930.

Chua, C.T., Goh, J.C., Zhang, Z., 2010. Expected volatility, unexpected volatility and the cross-section of stock returns. Journal of Financial Research 33, 103–123.

Daniel, K., Jagannathan, R., Kim, S., 2012. Tail risk in momentum strategy returns, working paper, Columbia University.

Doran, J.S., Jiang, D., Peterson, D.R., 2008. Gambling in the New Year? The January Idiosyncratic Volatility Puzzle. Working Paper, Florida State University

Fama, E.F., French, K.R., 1992. The cross-section of expected stock returns. Journal of Finance 47, 427–465.

Fama, E.F., French, K.R., 1993. Common risk factors in the returns on stocks and bonds. Journal of Financial Economics 33, 3–56.

Fama, E.F., French, K.R., 2008. Dissecting anomalies. Journal of Finance 63, 2971–2995.

Fink, J., Fink, K., Grullon, G., Weston, J., 2010. What drove the increase in idiosyncratic risk during the internet boom. Journal of Financial and Quantitative Analysis 45, 1253–1278.

Fu, F., 2009. Idiosyncratic risk and the cross-section of expected stock returns. Journal of Financial Economics 91, 24–37.

Guo, H., Savickas, R., 2010. Relation between time-series and cross-sectional effects of idiosyncratic variance on stock returns. Journal of Banking and Finance 34, 1637–1649.

Huang, W., Liu, Q., Rhee, S.G., Zhang, L., 2010. Return reversals, idiosyncratic risk, and expected returns. Review of Financial Studies 23, 147–168.

Huang, W., Liu, Q., Rhee, S.G., Zhang, L., 2011. Another look at idiosyncratic volatility and expected returns. Journal of Investment Management 9, 26–51.

Jegadeesh, N., 1990. Evidence of predictable behavior of security returns. Journal of Finance 28, 881–898.

Jegadeesh, N., Titman, S., 2001. Profitability of momentum strategies: an evaluation of alternative explanations. Journal of Finance 56, 699–720.

Jones, C.M., Rhodes-Kropf, M., 2003. The price of diversifiable risk in venture capital and private equity. Working Paper, Columbia University.

Malkiel, B.G., Xu., Y., 2002. IdiosyncFratic risk and security returns. Working Paper, University of Texas at Dallas.

Newey, W.K., West, K.D., 1987. A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. Econometrica 55, 703–708.

Novy-Marx, R., 2012. Is momentum really momentum? Journal of Financial Economics 103, 429–453.

Spiegel, M., Wang, X., 2006. Cross-sectional variation in stock returns: Liquidity and idiosyncratic risk. Working Paper, Yale University.

FIGURE 1. Evolution of the number of stocks

This figure shows the evolution of the number of firms that are employed in the analysis. The index composition is the one as of October 1, 1989. The index composition and the corresponding stocks are downloaded from Datastream. The *y*-axis shows the number of firms and the *x*-axis show the time period in months running from January 1973 to April 2014.

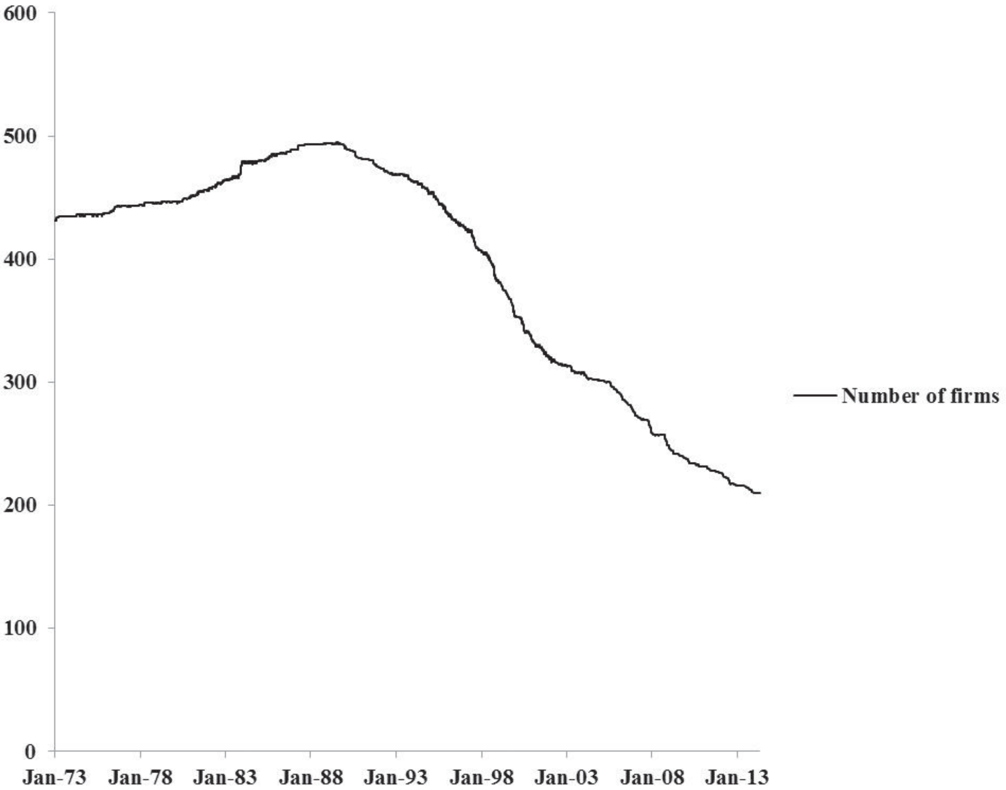


FIGURE 2. Evolution of deleted stocks

This figure shows the cumulative number of firms that are deleted from the S&P 500 index. The index composition is the one as of October 1, 1989. The index composition and the corresponding stocks are downloaded from Datastream. The *y*-axis shows the cumulative number of deleted firms and the *x*-axis show the time period in months running from October 1989 to April 2014.

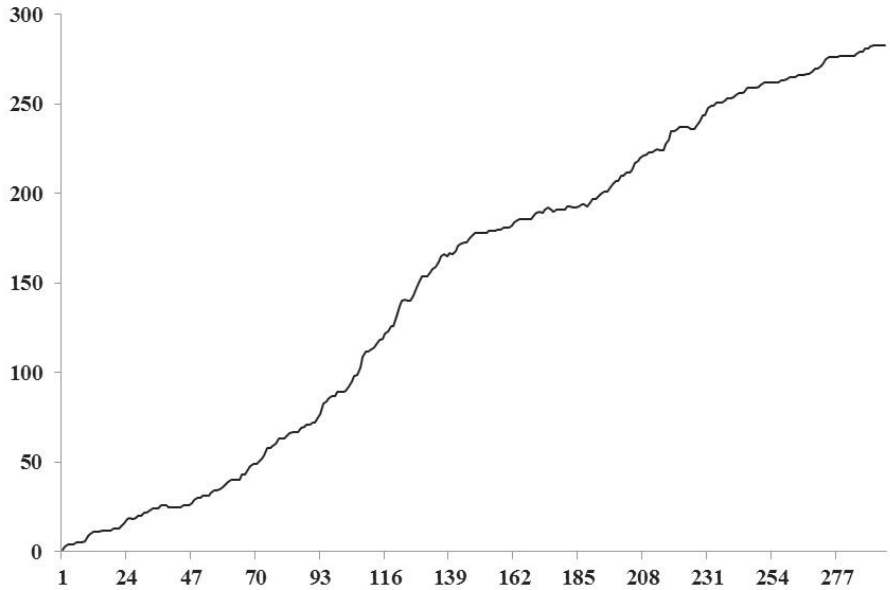


TABLE 1. Portfolios sorted by idiosyncratic volatility

This Table reports the returns, volatility and past returns of five portfolios sorted by idiosyncratic volatility. Portfolios are formed at the beginning of every month based on idiosyncratic volatility computed using standard deviation of daily residuals over the previous month. The residuals are estimated from the Fama and French (1993) model. Portfolio IVOL 1 (IVOL 5) is the portfolio of stocks with the lowest (highest) idiosyncratic volatilities. The return is the equal-weighted average monthly return measured in percentage terms in the month following the portfolio formation period. Past return is the equal-weighted average monthly portfolio return during the previous one-month formation period. Newey-West (1987) robust *t*-statistics are reported in parentheses. IVOL 5-1 (IVOL 4-1) is a zero-cost portfolio long in portfolio group 5 (group 4) and short in portfolio group 1. The sample period is from March 1973 to April 2014.

	IVOL 1	IVOL 2	IVOL 3	IVOL 4	IVOL 5	IVOL 5-1	IVOL 4-1
RET	0.85	1.07	1.23	1.34	2.02	1.17*** (4.25)	0.49*** (3.32)
IVOL	0.65	1.20	1.83	2.93	13.62		
PRIOR	0.68	0.85	1.14	1.39	2.39		

*** Statistically significant on a 1% level

TABLE 2. Risk adjustment and seasonality

This Table reports the risk-adjusted returns of a zero-cost portfolio sorted by idiosyncratic volatility. Portfolios are formed at the beginning of every month based on idiosyncratic volatility computed using standard deviation of daily residuals over the previous month. The residuals are estimated from the Fama and French (1993) model. Portfolio IVOL 1 (IVOL 5) is the portfolio of stocks with the lowest (highest) idiosyncratic volatilities. The return is the equal-weighted average monthly return measured in percentage terms in the month following the portfolio formation period. The zero-cost portfolio is long in portfolio group 5 and short in portfolio group 1. Then, the zero-cost portfolio is regressed on Carhart's (1997) four-factor model specification where *CON* denotes the risk-adjusted return, *MRF* denotes the excess returns of the CRSP index used as market factor, *SIZE* and *HML* denote the common Fama and French (1993) risk factors, whereas *MOM* denotes Carhart's (1997) momentum factor. *JAN* is a dummy variable that has a value of one in every January and a value of zero in all other months, whereas *Oct 1989* is a dummy variable that has a value of one from October 1989 – April 2014 and a value of zero in all other months. Newey-West (1987) robust *t*-statistics are reported in parentheses. The sample period is from March 1973 to April 2014.

CON	JAN	Oct 1989	MRF	SMB	HML	MOM	R-squared
1.17***							0.00
(4.25)							
0.83***	4.14***						0.04
(2.95)	(3.48)						
0.97***			0.49***	0.80***	0.14	-0.43***	0.62
(4.62)			(8.83)	(11.67)	(1.29)	(-4.12)	
0.86***	1.37*		0.49***	0.78***	0.13	-0.42***	0.62
(3.91)	(1.92)		(8.59)	(11.35)	(1.16)	(-3.92)	
1.35***		-0.29					0.00
(4.17)		(-0.57)					
1.02***	4.14***	-0.31					0.04
(3.32)	(3.47)	(-0.61)					
1.05***	1.38*	-0.32	0.49***	0.78***	0.12	-0.42***	0.62
(4.21)	(1.91)	(-0.98)	(8.57)	(11.22)	(1.12)	(-3.93)	

* Statistically significant on 10% level

** Statistically significant on 5% level

*** Statistically significant on a 1% level

TABLE 3. Portfolios sorted by idiosyncratic volatility and subsamples

This Table reports the returns, volatility and past returns of five portfolios sorted by idiosyncratic volatility. Portfolios are formed at the beginning of every month based on idiosyncratic volatility computed using standard deviation of daily residuals over the previous month. The residuals are estimated from the Fama and French (1993) model. Portfolio IVOL 1 (IVOL 5) is the portfolio of stocks with the lowest (highest) idiosyncratic volatilities. The return is the equal-weighted average monthly return measured in percentage terms in the month following the portfolio formation period. Past return is the equal-weighted average monthly portfolio return during the previous one-month formation period. Newey-West (1987) robust *t*-statistics are reported in parentheses. IVOL5-1 is a zero-cost portfolio long in portfolio group 5 and short in portfolio group 1. *DELETED* denotes the sample of firms that are deleted from the S&P 500 in April 2014 at the latest. This sample consists of between 104 to 288 stocks. *SURVIVOR* denotes the sample of firms that are not deleted from the S&P 500 as of April 2014. This sample consists of 210 stocks. The sample period is from October 1989 to May 2003.

Panel A: DELETED

	IVOL 1	IVOL 2	IVOL 3	IVOL 4	IVOL 5	IVOL 5-1	IVOL 4-1
RET	0.85	0.72	0.94	1.34	1.86	1.01* (1.76)	-0.12 (-0.40)
IVOL	0.83	1.56	2.44	4.04	23.91		
PRIOR	0.47	0.67	0.84	1.11	1.58		

* Statistically significant on a 10% level

Panel B: SURVIVOR

	IVOL 1	IVOL 2	IVOL 3	IVOL 4	IVOL 5	IVOL 5-1	IVOL 4-1
RET	0.92	0.93	1.13	1.31	1.70	0.77** (2.25)	0.39** (2.07)
IVOL	0.76	1.35	1.98	2.98	8.03		
PRIOR	0.85	0.95	1.19	1.37	1.39		

** Statistically significant on a 5% level

TABLE 4. Risk adjustment and seasonality in subsamples

This Table reports the risk-adjusted returns of a zero-cost portfolio sorted by idiosyncratic volatility. Portfolios are formed at the beginning of every month based on idiosyncratic volatility computed using standard deviation of daily residuals over the previous month. The residuals are estimated from the Fama and French (1993) model. Portfolio IVOL 1 (IVOL 5) is the portfolio of stocks with the lowest (highest) idiosyncratic volatilities. The return is the equal-weighted average monthly return measured in percentage terms in the month following the portfolio formation period. The zero-cost portfolio is long in portfolio group 5 and short in portfolio group 1. Then, the zero-cost portfolio is regressed on Carhart's (1997) four-factor model specification where *CON* denotes the risk-adjusted return, *MRF* denotes the excess returns of the CRSP index used as market factor, *SIZE* and *HML* denote the common Fama and French (1993) risk factors, whereas *MOM* denotes Carhart's (1997) momentum factor. *JAN* is a dummy variable that has a value of one in every January and a value of zero in all other months. Newey-West (1987) robust *t*-statistics are reported in parentheses. *DELETED* denotes the sample of firms that are deleted from the S&P 500 in April 2014 at the latest. This sample consists of between 104 to 288 stocks. *SURVIVOR* denotes the sample of firms that are not deleted from the S&P 500 on April 2014. This sample consists of 210 stocks. The sample period is from October 1989 to May 2003.

Panel A: DELETED

CON	JAN	MRF	SMB	HML	MOM	R-squared
1.01*						0.00
(1.76)						
1.29**		0.49***	0.76***	-0.12	-0.55***	0.52
(2.23)		(4.68)	(4.45)	(-0.61)	(-3.08)	
0.75	5.66***	0.51***	0.71***	-0.12	-0.50***	0.57
(1.45)	(2.86)	(5.13)	(4.77)	(-0.71)	(-3.19)	

* Statistically significant on 10% level

** Statistically significant on 5% level

*** Statistically significant on a 1% level

Panel B: SURVIVOR

CON	JAN	MRF	SMB	HML	MOM	R-squared
0.77**						0.00
(2.25)						
0.88***		0.44***	0.51***	-0.03	-0.36***	0.61
(3.92)		(6.45)	(5.31)	(-0.29)	(-6.75)	
0.69***	2.03**	0.44***	0.49***	-0.03	-0.34***	0.62
(3.00)	(2.10)	(6.64)	(5.32)	(-0.32)	(-6.66)	

* Statistically significant on 10% level

** Statistically significant on 5% level

*** Statistically significant on a 1% level

TABLE 5. Value-weighting scheme and the SURVIVOR sample

This Table reports the returns of five portfolios sorted by idiosyncratic volatility. Portfolios are formed at the beginning of every month based on idiosyncratic volatility computed using standard deviation of daily residuals over the previous month. The residuals are estimated from the Fama and French (1993) model. Portfolio IVOL 1 (IVOL 5) is the portfolio of stocks with the lowest (highest) idiosyncratic volatilities. The return is the value-weighted monthly return measured in percentage terms in the month following the portfolio formation period. IVOL5-1 is a zero-cost portfolio long in portfolio group 5 and short in portfolio group 1. *SURVIVOR* denotes the sample of firms that are not deleted from the S&P 500 as of April 2014. This sample consists of 210 stocks. The sample period is from March 1973 to May 2003. Newey-West (1987) robust *t*-statistics are reported in parentheses.

CON	JAN	MRF	SMB	HML	MOM	R-squared
0.12						0.00
(0.30)						
-0.03		0.52***	0.72***	0.21	-0.48***	0.18
(-0.22)		(3.38)	(3.98)	(0.82)	(-2.91)	
0.07	-1.90	0.52***	0.75***	0.23	-0.50***	0.18
(0.20)	(-1.45)	(3.46)	(4.06)	(0.89)	(-2.97)	

* Statistically significant on 10% level

** Statistically significant on 5% level

*** Statistically significant on a 1% level

TABLE 6. Upper and lower 10% of the empirical distribution

This Table reports the outliers of the zero-cost portfolio sorted by idiosyncratic volatility. Portfolios are formed at the beginning of every month based on idiosyncratic volatility computed using standard deviation of daily residuals over the previous month. The residuals are estimated from the Fama and French (1993) model. The sample period is from March 1973 to April 2014. The last column in Panel B reports the dates when momentum crashes occurred taken from Table 1 in Daniel et al. (2012, p.7).

Panel A: Lower 10%

Month	Returns in %	S&P 500 Returns
Oct 1978	-15.86	-20.42
Aug 1998	-13.89	-29.10
June 2009	-13.84	-1.10
Sept 2001	-12.36	-11.56
Sept 2011	-12.17	-7.86
Nov 2000	-12.11	-20.41
Oct 1987	-11.70	-21.89
Feb 2009	-11.07	-6.62
Sept 2008	-10.36	-6.85
Nov 2007	-10.05	-4.18

Panel B: Upper 10%

Month	Returns in %	S&P 500 Return	Momentum Crash
Apr 2009	41.27	37.16	-45.89
Jan 2001	33.24	25.82	-42.10
Aug 2009	28.51	12.75	-24.80
Jan 1975	25.45	43.90	N.A.
Mar 2009	21.84	11.01	-39.32
July 2009	19.09	7.83	N.A.
Nov 2002	18.06	24.18	-20.42
Jan 1992	16.59	16.55	N.A.
May 2009	13.91	19.55	N.A.
Dec 2009	13.67	4.10	N.A.

TABLE 7. Idiosyncratic volatility payoffs in the presence of momentum crashes

This Table reports the risk-adjusted returns of a zero-cost portfolio sorted by idiosyncratic volatility. Portfolios are formed at the beginning of every month based on idiosyncratic volatility computed using standard deviation of daily residuals over the previous month. The residuals are estimated from the Fama and French (1993) model. Portfolio IVOL 1 (IVOL 5) is the portfolio of stocks with the lowest (highest) idiosyncratic volatilities. The return is the equal-weighted average monthly return measured in percentage terms in the month following the portfolio formation period. The zero-cost portfolio is long in portfolio group 5 and short in portfolio group 1. Then, the zero-cost portfolio is regressed on Fama and French (1993) three-factor model specification where *CON* denotes the risk-adjusted return, *MRF* denotes the excess returns of the CRSP index used as market factor, *SIZE* and *HML* denote the common Fama and French (1993) risk factors. *CARSH* is a dummy variable that has a value of one in every month whenever a momentum crash occurred and a value of zero in all other months. Newey-West (1987) robust *t*-statistics are reported in parentheses. The sample period is from March 1973 to April 2014.

CON	JAN	CRASH	MRF	SMB	HML	R-squared
0.60***	3.70***	27.25***				0.29
(2.70)	(4.05)	(10.00)				
0.35*	3.27***	23.86***	0.59***			0.53
(1.95)	(3.97)	(9.29)	(10.20)			
0.27*	2.13***	22.18***	0.50***	0.71***	0.17*	0.67
(1.66)	(3.38)	(9.13)	(9.15)	(8.62)	(1.90)	

* Statistically significant on 10% level

** Statistically significant on 5% level

*** Statistically significant on a 1% level

TABLE 8. Value-weighted idiosyncratic volatility payoffs and the SURVIVOR sample in the presence of momentum crashes

This Table reports the risk-adjusted returns of a zero-cost portfolio sorted by idiosyncratic volatility. Portfolios are formed at the beginning of every month based on idiosyncratic volatility computed using standard deviation of daily residuals over the previous month. The residuals are estimated from the Fama and French (1993) model. Portfolio IVOL 1 (IVOL 5) is the portfolio of stocks with the lowest (highest) idiosyncratic volatilities. The return is the value-weighted monthly return measured in percentage terms in the month following the portfolio formation period. IVOL5-1 is a zero-cost portfolio long in portfolio group 5 and short in portfolio group 1. *SURVIVOR* denotes the sample of firms that are not deleted from the S&P 500 as of April 2014. This sample consists of 210 stocks. The zero-cost portfolio is regressed on Fama and French (1993) three-factor model specification where *CON* denotes the risk-adjusted return, *MRF* denotes the excess returns of the CRSP index used as market factor, *SIZE* and *HML* denote the common Fama and French (1993) risk factors. *CARSH* is a dummy variable that has a value of one in every month whenever a momentum crash occurred and a value of zero in all other months. Newey-West (1987) robust *t*-statistics are reported in parentheses. The sample period is from March 1973 to April 2014.

CON	JAN	CRASH	MRF	SMB	HML	R-squared
-0.41	0.34	49.78***				0.23
(-0.95)	(0.24)	(3.42)				
-0.63	-0.06	46.62**	0.55***			0.29
(-1.51)	(-0.04)	(9.29)	(4.99)			
-0.73*	-1.13	44.99***	0.49***	0.63***	0.22	0.32
(1.75)	(-0.85)	(3.09)	(3.87)	(3.38)	(1.09)	

* Statistically significant on 10% level

** Statistically significant on 5% level

*** Statistically significant on a 1% level

APPENDIX. TABLE 1. Portfolios sorted by idiosyncratic volatility

This Table reports the returns, volatility and past returns of five portfolios sorted by idiosyncratic volatility. Portfolios are formed at the beginning of every month based on idiosyncratic volatility computed using standard deviation of daily residuals over the previous month. The residuals are estimated from the CAPM. Portfolio IVOL 1 (IVOL 5) is the portfolio of stocks with the lowest (highest) idiosyncratic volatilities. The return is the equal-weighted average monthly return measured in percentage terms in the month following the portfolio formation period. Past return is the equal-weighted average monthly portfolio return during the previous one-month formation period. Newey-West (1987) robust *t*-statistics are reported in parentheses. IVOL 5-1 (IVOL 4-1) is a zero-cost portfolio long in portfolio group 5 (group 4) and short in portfolio group 1. The sample period is from March 1973 to April 2014.

	IVOL 1	**IVOL 2**	**IVOL 3**	**IVOL 4**	**IVOL 5**	**IVOL 5-1**	**IVOL 4-1**
RET	0.85	1.07	1.23	1.33	2.05	1.21*** (4.39)	0.48*** (3.32)
IVOL	0.79	1.42	2.15	3.42	15.55		
PRIOR	0.67	0.87	1.09	1.36	2.46		

*** Statistically significant on a 1% level

TABLE 2. Risk adjustment and seasonality

This Table reports the risk-adjusted returns of a zero-cost portfolio sorted by idiosyncratic volatility. Portfolios are formed at the beginning of every month based on idiosyncratic volatility computed using standard deviation of daily residuals over the previous month. The residuals are estimated from CAPM. Portfolio IVOL 1 (IVOL 5) is the portfolio of stocks with the lowest (highest) idiosyncratic volatilities. The return is the equal-weighted average monthly return measured in percentage terms in the month following the portfolio formation period. The zero-cost portfolio is long in portfolio group 5 and short in portfolio group 1. Then, the zero-cost portfolio is regressed on Carhart's (1997) four-factor model specification where *CON* denotes the risk-adjusted return, *MRF* denotes the excess returns of the CRSP index used as market factor, *SIZE* and *HML* denote the common Fama and French (1993) risk factors, whereas *MOM* denotes Carhart's (1997) momentum factor. *JAN* is a dummy variable that has a value of one in every January and a value of zero in all other months, whereas *Oct 1989* is a dummy variable that has a value of one from October 1989 – April 2014 and a value of zero in all other months. Newey-West (1987) robust *t*-statistics are reported in parentheses. The sample period is from March 1973 to April 2014.

CON	JAN	Oct 1989	MRF	SMB	HML	MOM	R-squared
1.21***							0.00
(4.39)							
0.86***	4.19***						0.04
(3.06)	(3.54)						
0.99***			0.49***	0.80***	0.14	-0.42***	0.62
(5.02)			(9.03)	(11.83)	(1.30)	(-4.21)	
0.87***	1.37**		0.49***	0.78***	0.12	-0.41***	0.62
(4.15)	(2.10)		(8.76)	(11.52)	(1.17)	(-3.98)	
1.40***		-0.33					0.00
(4.19)		(-0.63)					
1.07***	4.19***	-0.35					0.05
(3.39)	(3.53)	(-0.68)					
1.08***	1.46**	-0.35	0.49***	0.78***	0.12	-0.41***	0.62
(4.27)	(2.09)	(-1.07)	(8.75)	(11.39)	(1.11)	(-3.99)	

* Statistically significant on 10% level

** Statistically significant on 5% level

*** Statistically significant on a 1% level

TABLE 3. Portfolios sorted by idiosyncratic volatility and subsamples

This Table reports the returns, volatility and past returns of ten portfolios sorted by idiosyncratic volatility. Portfolios are formed at the beginning of every month based on idiosyncratic volatility computed using standard deviation of daily residuals over the previous month. The residuals are estimated from the CAPM. Portfolio IVOL 1 (IVOL 5) is the portfolio of stocks with the lowest (highest) idiosyncratic volatilities. The return is the equal-weighted average monthly return measured in percentage terms in the month following the portfolio formation period. Past return is the equal-weighted average monthly portfolio return during the previous one-month formation period. Newey-West (1987) robust *t*-statistics are reported in parentheses. IVOL5-1 is a zero-cost portfolio long in portfolio group 5 and short in portfolio group 1. *DELETED* denotes the sample of firms that are deleted from the S&P 500 in April 2014 at the latest. This sample consists of between 100 to 283 stocks. *SURVIVOR* denotes the sample of firms that are not deleted from the S&P 500 as of April 2014. This sample consists of 210 stocks. The sample period is from October 1989 to May 2003.

Panel A: DELETED

	IVOL 1	IVOL 2	IVOL 3	IVOL 4	IVOL 5	IVOL 5-1	IVOL 4-1
RET	0.92	0.67	0.95	0.69	1.87	0.96 (1.62)	-0.23 (-0.75)
IVOL	1.01	1.86	2.86	4.69	27.19		
PRIOR	0.43	0.73	0.88	1.03	1.59		

Panel B: SURVIVOR

	IVOL 1	IVOL 2	IVOL 3	IVOL 4	IVOL 5	IVOL 5-1	IVOL 4-1
RET	0.93	0.88	1.18	1.30	1.70	0.77** (2.22)	0.36** (2.06)
IVOL	0.94	1.62	2.34	3.47	9.26		
PRIOR	0.88	0.94	1.15	1.33	1.45		

** Statistically significant on a 5% level

TABLE 4. Risk adjustment and seasonality in subsamples

This Table reports the risk-adjusted returns of a zero-cost portfolio sorted by idiosyncratic volatility. Portfolios are formed at the beginning of every month based on idiosyncratic volatility computed using standard deviation of daily residuals over the previous month. The residuals are estimated from the CAPM. Portfolio IVOL 1 (IVOL 5) is the portfolio of stocks with the lowest (highest) idiosyncratic volatilities. The return is the equal-weighted average monthly return measured in percentage terms in the month following the portfolio formation period. The zero-cost portfolio is long in portfolio group 5 and short in portfolio group 1. Then, the zero-cost portfolio is regressed on Carhart's (1997) four-factor model specification where *CON* denotes the risk-adjusted return, *MRF* denotes the excess returns of the CRSP index used as market factor, *SIZE* and *HML* denote the common Fama and French (1993) risk factors, whereas *MOM* denotes Carhart's (1997) momentum factor. *JAN* is a dummy variable that has a value of one in every January and a value of zero in all other months. Newey-West (1987) robust *t*-statistics are reported in parentheses. *DELETED* denotes the sample of firms that are deleted from the S&P 500 at least on April 2014. This sample consists of between 100 to 283 stocks. *SURVIVOR* denotes the sample of firms that are not deleted from the S&P 500 on April 2014. This sample consists of 210 stocks. The sample period is from October 1989 to May 2003.

Panel A: DELETED

CON	JAN	MRF	SMB	HML	MOM	R-squared
0.96						0.00
(1.70)						
1.22**		0.49***	0.75***	-0.14	-0.54***	0.53
(2.03)		(4.83)	(4.44)	(-0.72)	(-2.91)	
0.69	5.55***	0.52***	0.70***	-0.14	-0.48***	0.57
(1.28)	(2.83)	(5.30)	(4.72)	(-0.83)	(-2.98)	

* Statistically significant on 10% level

** Statistically significant on 5% level

*** Statistically significant on a 1% level

Panel B: SURVIVOR

CON	JAN	MRF	SMB	HML	MOM	R-squared
0.77**						0.00
(2.22)						
0.89***		0.43***	0.53***	-0.07	-0.36***	0.65
(4.03)		(6.01)	(6.05)	(-0.71)	(-7.37)	
0.69***	2.07**	0.44***	0.51***	-0.07	-0.34***	0.66
(2.99)	(2.46)	(6.23)	(6.16)	(-0.79)	(-7.27)	

* Statistically significant on 10% level

** Statistically significant on 5% level

*** Statistically significant on a 1% level

TABLE 5. Value-weighting scheme and the SURVIVOR sample

This Table reports the returns of five portfolios sorted by idiosyncratic volatility. Portfolios are formed at the beginning of every month based on idiosyncratic volatility computed using standard deviation of daily residuals over the previous month. The residuals are estimated from the CAPM. Portfolio IVOL 1 (IVOL 5) is the portfolio of stocks with the lowest (highest) idiosyncratic volatilities. The return is the value-weighted monthly return measured in percentage terms in the month following the portfolio formation period. IVOL5-1 is a zero-cost portfolio long in portfolio group 5 and short in portfolio group 1. *SURVIVOR* denotes the sample of firms that are not deleted from the S&P 500 as of April 2014. This sample consists of 210 stocks. The sample period is from March 1973 to May 2003. Newey-West (1987) robust *t*-statistics are reported in parentheses.

CON	JAN	MRF	SMB	HML	MOM	R-squared
0.05 (0.14)						0.00
-0.14 (-0.38)		0.52*** (3.56)	0.75*** (4.07)	0.21 (0.83)	-0.51*** (-3.27)	0.19
-0.02 (-0.06)	-1.39 (-1.14)	0.53*** (3.62)	0.77*** (4.11)	0.22 (0.87)	-0.52*** (-3.26)	0.19

* Statistically significant on 10% level

** Statistically significant on 5% level

*** Statistically significant on a 1% level

Applied Economics Letters, 2014
http://dx.doi.org/10.1080/13504851.2014.922662

Momentum, sovereign credit ratings and global equity markets

Klaus Grobys

Department of Accounting and Finance, University of Vaasa, Vaasa FI-65101, Finland
E-mail: grobys.finance@gmail.com

This article investigates the link between momentum-based trading strategies implemented in global equity markets and country-specific credit ratings. The findings indicate that only the momentum strategy based on intermediate past returns generate statistically significant profits. Notably, the winner portfolios exhibit a higher average credit rating than the other portfolio groups. Surprisingly, neither global asset pricing models nor a conducted world credit risk factor can explain these profits.

Keywords: asset pricing; global equity markets; international stock indices; credit rating; momentum

JEL Classification: G12; G14

I. Introduction

An extensive body of finance literature attempts to explain the profits of momentum-based trading strategies documented first by Jegadeesh and Titman (1993). However, a consensus regarding the source and the interpretation of these profits does not exist yet. Unlike Jegadeesh and Titman (2001) who found evidence for a delayed overreaction of the winners and delayed underreaction for losers supporting behavioural explanations, Avramov *et al.* (2007) established a link between momentum profits and credit rating. Their study provides evidence for that momentum profits are statistically significant only for strategies implemented among firms exhibiting a high credit risk. Even though investing in global equity markets has become an important tool for risk diversification in the financial industry, surprisingly, little attention has been paid towards exploring momentum strategies invested in global equity markets. Studies by Rouwenhorst (1997, 1999), Chan *et al.* (2000) and Grobys (2014) indicate that momentum-based trading strategies implemented in international stock markets are profitable. However, there has been no study undertaken, yet that investigates the source of profits generated by momentum strategies implemented in international equity markets.

The purpose of this article is twofold. First, it explores whether a link between country-specific credit rating and internationally invested momentum does exist. Thereby, it accounts for different momentum strategies invested in global equity markets employing 23 foreign stock indices. All indices are divided into quartiles corresponding to their cumulative past returns to implement zero-cost portfolios. For each momentum group and strategy, the corresponding credit risk is proxied by the average country-specific credit rating and investigated further. Second, it assesses whether a world credit risk factor is capable to explain momentum profits. In doing so, all indices are divided into terciles based on their past credit rating to implement the world credit risk factor. In a time series regression analysis, it is investigated whether the conducted credit risk factor can explain momentum profits. Thereby, a whole battery of risk adjustments is accounted for, too.

The study contributes to the existing literature in three ways. First, by extending Avramov *et al.*'s (2007) study to an international equity market setting, it assesses whether globally implemented momentum strategies are associated with country-specific credit risk. For internationally aligned investment managers, uncovering risks associated with investment vehicles is of fundamental importance. Second, by extending Grobys's (2014) study, it identifies whether internationally implemented momentum strategies can be explained by the global Fama and French (1998) risk factors. Third, it assesses whether a world credit risk factor, such as proposed by Avramov *et al.* (2012), is capable to explain momentum profits.

In contrast to previous research, the current research finds that only momentum-based trading strategies based on intermediate past performance, as proposed by Novy-Marx (2012), are profitable. Interestingly, the profits are driven by the winner portfolio and cannot be explained by the Fama and French (1998) global factor model. Notably, only the winner portfolio appears to be associated with a higher average country-specific risk in comparison to the other portfolios. The spread between countries exhibiting a high credit risk and countries having a low credit risk is statistically significantly positive supporting Avramov *et al.*'s (2012) results. However, the conducted world credit risk factor in the spirit of Avramov *et al.* (2012) cannot fully explain the momentum profits either. This article is organized as follows: in Section II, the data are specified. Section III describes the methods and results. Section IV concludes.

II. Data

I downloaded country-specific credit rating data from the US credit rating agency Fitch Ratings. Fitch Ratings was one of the three ratings agencies first recognized by the Securities and Exchange Commission as a nationally recognized statistical rating organization in 1975. The first countries receiving a credit rating were, among others, the United States, the United Kingdom and Germany in August 1994. Following Avramov *et al.* (2012), I used the long-term issuer sovereign credit rating and transformed the credit rating into numerical figure as follows: AAA = 1, AA+ = 2, AA = 3, AA− = 4, A+ = 5, A = 6, A− = 7, BBB+ = 8, BBB = 9, BBB− = 10, BB+ = 11, BB = 12, BB− = 13, B+ = 14, B = 15, B− = 16, CCC = 17, CCC− = 18, CC = 19, C = 20, DDD = 21, D = 22 and RD = 23. I also downloaded monthly stock market data of 23 different countries covering the period from September 1994 to July 2013 from finance.yahoo.com. Both data sources are available to all market participants for free. Data for the global Fama and French (1998) risk factors were downloaded from Kenneth's French website. Table 1 presents the countries, the corresponding stock indices and initial ratings.

III. Methods

I take into account the perspective of an internationally aligned investor and compounded the monthly gross

Table 1. International stock markets

No.	Country	Stock index	Initial credit rating	Grade
1	Brazil	BOVESPA Brazil	1 December 1994	B+
2	Mexico	IPC Mexico	30 August 1995	BB
3	Argentina	Merval Argentina	28 May 1997	BB
4	Canada	S&P/TSX Canada	10 August 1994	AA
5	USA	DJ 30 USA	10 August 1994	AAA
6	Hong Kong	Hang Seng Hong Kong	10 August 1994	AA−
7	China	SSE Composite Shanghai China	11 December 1997	A−
8	India	S&P BSE SENSEX India	8 March 2000	BB+
9	Indonesia	Composite Index Jakarta Indonesia	4 June 1997	BBB−
10	Malaysia	FTSE Bursa Malaysia KLCI Malaysia	13 August 1998	BBB−
11	Japan	NIKKEI 225 Japan	10 August 1994	AAA
12	New Zealand	NZX 50 INDEX New Zealand	27 March 2002	AA
13	Singapore	STI Index Singapore	18 November 1998	AA+
14	Korea	KOSPI Korea	27 June 1996	AA−
15	Taiwan	TSEC weighted index Taiwan	19 November 2001	A+
16	Austria	ATX Austria	10 August 1994	AAA
17	Belgium	EURONEXT BEL-20 Belgium	10 August 1994	AA+
18	France	CAC 40 France	10 August 1994	AAA
19	Germany	DAX 30 Germany	10 August 1994	AAA
20	Netherlands	AEX Netherlands	10 August 1994	AAA
21	Switzerland	SMI Switzerland	10 August 1994	AAA
22	UK	FTSE 100 UK	10 August 1994	AAA
23	Greece	ATHEN INDEX Greece	13 November 1995	BBB−

returns for all foreign stock indices for the period from September 1994 to July 2013. To account for at least 20 different countries exhibiting a credit rating in month $t-1$, I initiated the portfolio sorts first on July 1999 using the Fama and French (2008) portfolio approach. The first group ('loser') contains 25% of equal-weighted foreign stock indices exhibiting the lowest cumulative returns for the period $t-12$ until $t-2$, whereas the fourth group ('winner') contains of 25% of equal-weighted foreign stock indices exhibiting the highest cumulative returns for the same period. This strategy, referred to as 12-2 strategy, was updated and rebalanced at the beginning of each month (Table 2). Alike, I constructed the12-7 and 6-2 strategies in line with Novy-Marx (2012) and Jegadeesh and Titman (1993), respectively. The zero-cost strategies were compounded by selling the loser and buying the winner portfolio. For each of these groups, the corresponding average credit rating at time t is compounded. The results reported in Table 2 indicate that the winner portfolio exhibits the highest average credit rating, irrespective of which strategy is taken into account. Moreover, only the 12-7 strategy generated momentum profits being statistically different from zero at the 1% level. The economic magnitude of the 12-7 spread is 0.87% per month and therewith in line with previous studies.

Next, I initiated the portfolio sorts based on the credit rating at time $t-1$ using the same set of assets. Following Avramov *et al.* (2012), I divided the whole set of stock indices into terciles. The first group ('low risk') contains 30% of equal-weighted foreign stock indices exhibiting the lowest credit risk at time $t-1$, whereas the third group ('high risk') contains 30% of equal-weighted foreign stock indices exhibiting the highest credit risk at time $t-1$. Again, this strategy was updated and rebalanced at the beginning of each month. The credit risk spread was compounded by buying the high risk and selling the low risk portfolio. Then, I employed different global model specifications of both the CAPM and Fama and French (1998) three- and four- factor models for risk adjustment. The results are reported in Table 3, Panel A, and indicate that the credit risk spread cannot be explained by any of these models. The economic magnitude of the credit risk spread varies between 0.65 and 0.75 with corresponding Newey and West's (1987) t-statistics between 2.47 and 2.66. The economic magnitude and statistical significance is in line with Avramov *et al.*'s (2012) study. This result indicates also that the country-specific credit rating data from the US credit rating agency Fitch Ratings contain the same information as the S&P Sovereign Credit Rating used in Avramov *et al.*'s (2012) study.

Finally, I investigated the profitable 12-7 strategy further by regressing the zero-cost momentum portfolio on different model specifications for risk adjustment. Thereby, I regressed the zero-cost momentum portfolio also on the constructed credit risk spread (e.g., world credit risk factor) only and the global Fama and French (1998) model specification incorroborating the world credit risk factor. The

Table 2. Momentum strategies and credit ratings

Momentum strategy	Momentum group				
Panel A: 12-7 momentum strategy and average credit rating					
12-7	Loser (L)	2	3	Winner (W)	W-L
Raw returns	0.24	0.29	0.40	1.11**	0.87***
	(0.49)	(0.46)	(0.90)	(2.13)	(2.78)
Average credit rating	5.53 (A)	3.67 (AA−)	4.30 (AA−)	7.45 (A−)	
Panel B: 12-2 momentum strategy and average credit rating					
12-2	Loser (L)	2	3	Winner (W)	W-L
Raw returns	0.19	0.38	0.62	0.80	0.61*
	(0.39)	(0.82)	(1.41)	(1.52)	(1.86)
Average credit rating	4.53	3.13	4.78	8.12	
	(A+)	(AA)	(A+)	(BBB+)	
Panel C: 6-2 momentum strategy and average credit rating					
6-2	Loser (L)	2	3	Winner (W)	W-L
Raw returns	0.42	0.43	0.49	0.77	0.35
	(0.85)	(0.96)	(1.10)	(1.55)	(1.36)
Average credit rating	5.50	3.60	4.26	7.54	
	(A)	(AA−)	(AA−)	(BBB+)	

Notes: *Statistically significant at the 10% level.
**Statistically significant at the 5% level.
***Statistically significant at the 1% level.

Table 3. Time series regressions for risk adjustments

Credit rating portfolio	Constant	Market	SMB	HML	MOM	*R*-squared
Panel A: Risk-adjustments for the credit rating portfolios						
Low risk (LR)	0.27					
	(0.62)					
Medium risk	0.33					
	(0.79)					
High risk (HR)	0.94*					
	(1.80)					
HR-LR	0.67**					
	(2.56)					
HR-LR	0.65**	0.06				0.01
	(2.47)	(1.19)				
HR-LR	0.70**	0.05	0.00	−0.09		0.02
	(2.56)	(1.04)	(0.04)	(−0.97)		
HR-LR	0.75***	0.03	0.04	−0.12	−0.07	0.02
	(2.66)	(0.51)	(0.36)	(−1.06)	(−1.12)	
Panel B: Risk-adjustments for the 12-7 momentum spread						
Constant	Market	SMB	HML	MOM	HR-LR	*R*-squared
0.87***						
(2.78)						
0.86***	0.03					0.00
(2.81)	(0.43)					
0.75**					0.18	0.03
(2.47)					(1.57)	
0.93***	0.01	0.06	−0.14			0.02
(3.04)	(0.23)	(0.52)	(−1.15)			
0.81**	0.06	−0.02	−0.08	0.14**		0.05
(2.56)	(1.16)	(−0.13)	(−0.78)	(2.01)		
0.67**	0.06	−0.02	−0.06	0.15**	0.19*	0.07
(2.12)	(1.09)	(−0.19)	(−0.59)	(2.14)	(1.73)	

Notes: *Statistically significant at the 10% level.
**Statistically significant at the 5% level.
***Statistically significant at the 1% level.

corresponding results reported in Table 3, Panel B, indicate that none of these model specifications can explain the zero-cost momentum portfolio. Unsurprisingly, the loading against the global momentum factor is statistically significantly positive with economic magnitude varying between 0.14 and 0.15. Interestingly, the loading against the world credit risk factor is marginally significant at at least a 10% level, but only in the presence of the global momentum factor. The economic magnitude of the zero-cost momentum portfolio decreases slightly after accounting for the world credit risk factor. This result indicates that the world credit risk factor can at least to some extent explain the momentum profits in global equity markets. Figure 1 illustrates both the evolution of the average credit rating for the loser (CR group 1) and winner portfolio (CR group 4) and the smoothed series employing a HP-filter with a lambda of 100. Interestingly, the spread of the evolutions appears to be mean reverting while the evolutions appear to be contrarily drifting over time implying that the average credit rating of the countries being in the winner portfolio tends to decrease while the average credit rating of the countries being in the loser portfolio tends to increase and vice versa. Unreported results show that this pattern is the same for the other momentum strategies, too.

IV. Conclusion

I take into account the perspective of an internationally aligned investor and explore the link between momentum strategies implemented in global equity markets and country-specific credit ratings. The results indicate that only the momentum strategy that is based on intermediate past returns generates profits that are statistically significant in the sample period running from July 1999 to July 2013. The winner portfolio exhibits on average a higher credit risk compared to the other portfolio groups. I construct a world credit risk factor in the same manner as proposed in the study by Avramov *et al.* (2012). This constructed world credit risk factor is statistically significantly different from zero while exhibiting the same properties as the world credit risk factor based upon the Long-Term S&P Sovereign Credit Rating, as proposed in the study by Avramov *et al.* (2012). Accounting for the world credit

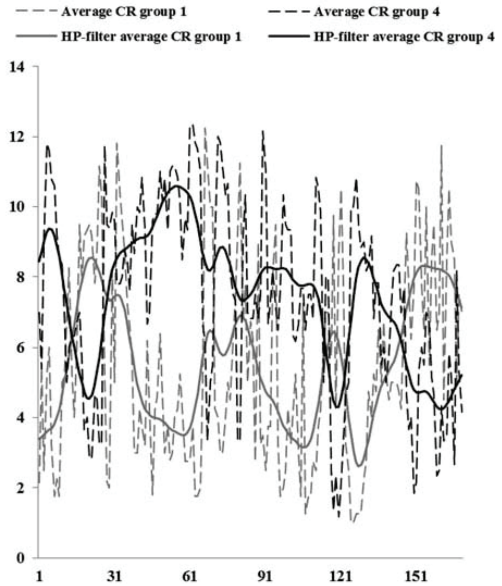


Fig. 1. Evolutions of average credit ratings related to the winner and loser portfolios of the 12-7 momentum strategy over time

risk factor indeed lowers the momentum spread, but the core fraction of the momentum profits remains unexplained and statistically significantly positive with regard to the 12-7 strategy. The evolutions of the corresponding average credit ratings of the winner and loser portfolios provide some interesting insights concerning momentum-based trading, which may be investigated further in further studies.

References

Avramov, D., Chordia, T., Jostova, G. *et al.* (2007) Momentum and credit rating, *Journal of Finance*, **62**, 2503–20. doi:10.1111/j.1540-6261.2007.01282.x.

Avramov, D., Chordia, T., Jostova, G. *et al.* (2012) The world price of credit risk, *Review of Asset Pricing Studies*, **2**, 112–52. doi:10.1093/rapstu/ras012.

Chan, K., Hameed, A. and Tong, W. (2000) Profitability of momentum strategies in the international equity markets, *Journal of Financial and Quantitative Analysis*, **35**, 153–72. doi:10.2307/2676188.

Fama, E. and French, K. (1998) Value versus growth: the international evidence, *The Journal of Finance*, **53**, 1975–99. doi:10.1111/0022-1082.00080.

Fama, E. and French, K. (2008) Dissecting anomalies, *The Journal of Finance*, **63**, 1653–78. doi:10.1111/j.1540-6261.2008.01371.x.

Grobys, K. (2014) Momentum in global equity markets in times of troubles: does the economic state matter?, *Economics Letters*, **123**, 100–3.

Jegadeesh, N. and Titman, S. (1993) Returns to buying winners and selling losers: implications for stock market efficiency, *The Journal of Finance*, **48**, 65–91. doi:10.1111/j.1540-6261.1993.tb04702.x.

Jegadeesh, N. and Titman, S. (2001) Profitability of momentum strategies: an evaluation of alternative explanations, *The Journal of Finance*, **56**, 699–720. doi:10.1111/0022-1082.00342.

Newey, W. K. and West, K. D. (1987) A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix, *Econometrica*, **55**, 703–8. doi:10.2307/1913610.

Novy-Marx, R. (2012) Is momentum really momentum?, *Journal of Financial Economics*, **103**, 429–53. doi:10.1016/j.jfineco.2011.05.003.

Rouwenhorst, K. G. (1997) International momentum strategies, *The Journal of Finance*, **53**, 267–84. doi:10.1111/0022-1082.95722.

Rouwenhorst, K. G. (1999) Local return factors and turnover in emerging stock markets, *The Journal of Finance*, **54**, 1439–64. doi:10.1111/0022-1082.00151.

Appendix: Momentum, sovereign credit ratings and global equity markets

This appendix aims to address comments and questions raised by the pre-examiners during the review process. In order to improve the replicability of this essay, several issues related to the data and the methodology are clarified in the following:

First, this essay utilizes stock indices in domestic currencies. The use of stock indices in local currencies is implicitly acknowledged on page 2 and 3 in the following sentence: "I take into account the perspective of an internationally aligned investor and compounded the monthly gross returns for all foreign stock indices for the period from September 1994 to July 2013."

Second, following the common practice in the asset pricing literature, stock price indices ex-dividends are used in this study.

Third, following the common practice in the asset pricing literature, Newey-West (1987) heteroskedasticity and autocorrelation consistent standard errors are used to calculate the *t*-statistics. The use of robust *t*-statistics is a common practice in finance research due to some stylized facts. For instance, in Lütkepohl and Krätzig (2004, p.197) it is highlighted that price variations observed on speculative financial markets, measured at some higher frequency, exhibit positive autocorrelation. Moreover, periods of higher and smaller price variations alternate, which means that volatility tends to cluster. These are well-known stylized facts of financial markets. To account for these stylized facts, this study utilizes Newey-West (1987) heteroskedasticity and autocorrelation consistent standard errors.

Fourth, the current study employs equally-weighted portfolio groups similar to Grobys (2014, p.101) because "each of these stock indices is a well-diversified basket" of stocks. The employed stock indices are typically market capitalization-based. Therefore, this current research employs the simple average of already weighted indices.

Fifth, the zero-cost strategy that is long in the country indices with the highest credit rating (HR) and short in the portfolio with lowest credit rating (LR) is referred to as "world credit risk factor" in the parlance of Avramov et al. (2012). This zero-cost portfolio (HR-LR) is tested and the results are reported in Panel A of Table. The raw spread has an economic magnitude of 0.67% per month with a Newey-West (1987) *t*-statistic of 2.56. After risk adjusting the spread by employing the global Fama-French four-factor model, the spread exhibits an economic magnitude of 0.75% per month with Newey-West (1987) *t*-statistic of 2.66, indicating statistical significance on any level. Then, the 12-7 momentum spread is risk adjusted. In doing so, I regress the momentum spread not only on the global Fama-French four-factor model, but also include also the world credit risk factor in an additional regression. The results are reported in Panel B of Table 3. When we move from Fama and French global four-factor model to the model that accounts for the world credit risk factor, the magnitude of the momentum spread slightly decreases from 0.81% to 0.67% per month with Newey-West (1987) *t*-statistics of 2.56 and 2.12, respectively. The positive loading against the world credit risk factor (e.g., 0.19) implies that winner stock indices tend to exhibit a high credit rating.

Finally, the number of stock indices used in the portfolio sorts varies over time due to credit rating and stock index data availability. Figure A plots the number of stock indices against time. The lowest number of stock indices employed is 11.

Figure A: Evolution of the number of stock indices

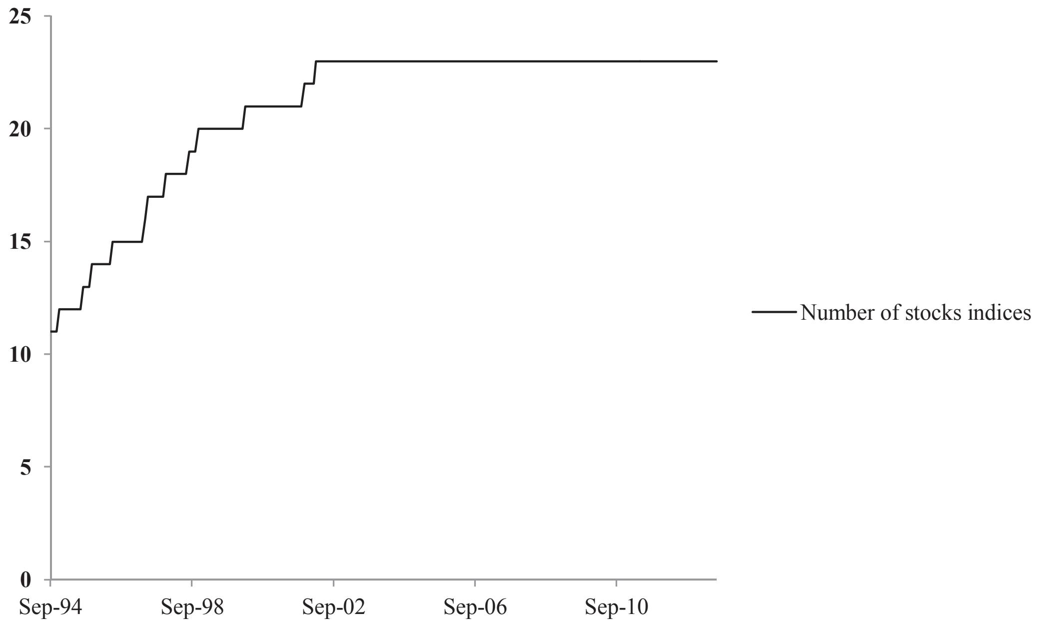


Table A reports the descriptive statistics for the equity indices used in the empirical analysis. To make the statistics comparable, the sample starts on September 2001 (when data for all indices were available) and ends on July 2013.[1]

Table A: Descriptive statistics

Panel A:

Index	BOVESPA Brazil	IPC Mexico	Merval Argentinia	S&P/TSX Canada	S&P 500 USA
Mean	1.05	0.78	0.37	0.57	0.69
Median	1.21	1.09	0.25	0.80	1.44
Maximum	15.56	13.55	12.85	8.74	21.29
Minimum	-24.80	-15.22	-23.83	-11.85	-23.94
Std. Dev.	6.55	3.82	5.85	3.60	5.53
Skewness	-0.34	-0.44	-0.69	-0.77	-0.66
Kurtosis	4.17	6.03	4.79	4.23	7.60
Jarque-Bera	8.51	46.16	23.63	18.02	106.01
Probability	0.01	0.00	0.00	0.00	0.00
Observations	111	111	111	111	111

Panel B:

Index	Hang Seng Hongkong	SSE Composite Shanghai China	S&P BSE SENSEX India	Composite Index Jakarta Indonesia	FTSE Bursa Malaysia KLCI
Mean	0.97	0.45	0.48	0.24	0.21
Median	1.23	0.80	0.84	1.44	1.20
Maximum	13.52	15.00	14.51	11.70	12.56
Minimum	-23.13	-18.83	-27.82	-21.41	-13.52
Std. Dev.	6.01	6.05	7.02	5.00	4.90
Skewness	-0.54	-0.27	-1.05	-1.36	-0.59
Kurtosis	4.50	3.60	5.37	6.25	3.34
Jarque-Bera	15.73	3.01	46.53	83.26	7.02
Probability	0.00	0.22	0.00	0.00	0.03
Observations	111	111	111	111	111

[1] Note that the statistics are reported in monthly terms.

Panel C:

Index	NIKKEI 225 Japan	NZX 50 INDEX New Zealand	STI Index Singapore	KOSPI Korea	TSEC weighted index Taiwan
Mean	0.84	1.43	0.24	0.36	0.45
Median	2.00	1.39	1.18	0.96	0.93
Maximum	16.76	13.18	11.17	10.12	8.45
Minimum	-19.19	-17.85	-19.71	-11.33	-13.02
Std. Dev.	5.37	5.22	5.39	3.73	4.02
Skewness	-0.79	-0.54	-1.06	-0.53	-0.66
Kurtosis	5.19	3.94	5.41	3.49	3.75
Jarque-Bera	33.85	9.53	47.66	6.27	10.64
Probability	0.00	0.01	0.00	0.04	0.00
Observations	111	111	111	111	111

Panel D:

Index	ATX Austria	EURONEXT BEL-20 Belgium	CAC 40 France	DAX 30 Germany	AEX Netherlands
Mean	-0.47	1.59	0.45	0.48	0.74
Median	0.43	0.53	1.05	1.11	1.21
Maximum	21.93	24.46	11.21	10.77	17.07
Minimum	-27.87	-36.75	-16.93	-16.94	-22.47
Std. Dev.	8.92	9.13	4.11	4.34	6.41
Skewness	-0.48	-0.39	-1.14	-0.84	-0.49
Kurtosis	3.67	4.87	6.17	4.95	4.54
Jarque-Bera	6.41	18.99	70.44	30.56	15.29
Probability	0.04	0.00	0.00	0.00	0.00
Observations	111	111	111	111	111

Panel E:

Index	SMI Switzerland	FTSE 100 UK	ATHEN INDEX Greece
Mean	0.64	1.53	1.90
Median	0.74	1.27	2.85
Maximum	27.45	28.26	20.13
Minimum	-24.63	-23.89	-31.42
Std. Dev.	8.88	7.29	6.63
Skewness	-0.18	-0.16	-1.15
Kurtosis	3.74	4.88	8.01
Jarque-Bera	3.16	16.92	140.49
Probability	0.21	0.00	0.00
Observations	111	111	111

References

Avramov, D., Chorida, T., Jostova, G., and Philipov, A., 2012. The World Price of Credit Risk. Review of Asset Pricing Studies 2, 112–152.

Grobys, K., 2014. Momentum in global equity markets in times of troubles: does the economic state matter? Economics Letters 123, 100–103.

Lütkepohl, H., and Krätzig, M., 2004. Applied Time Series Econometrics. Cambridge University Press. New York.

Newey, W.K., and West, K.D., 1987. A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. Econometrica 55, 703–708.