Lappeenranta
University of Technology

Jyri Kinnunen

RISK-RETURN TRADE-OFF AND AUTOCORRELATION

Thesis for the degree of Doctor of Science (Economic and Business Administration) to be presented with due permission for public examination and criticism in Auditorium 1382 at Lappeenranta University of Technology, Lappeenranta, Finland, at noon on the 13th of December, 2013.

Acta Universitatis
Lappeenrantaensis 551

Supervisors	Docent Minna Martikainen Department of Business Economics and Law School of Business Lappeenranta University of Technology Finland
	Professor Jussi Nikkinen Department of Accounting and Finance Faculty of Business Studies University of Vaasa Finland
Reviewers	Professor Johan Knif Department of Finance and Statistics Hanken School of Economics Finland
	Professor Gregory Koutmos Charles F. Dolan School of Business Fairfield University USA
Opponent	Professor Johan Knif Department of Finance and Statistics Hanken School of Economics Finland

ISBN 978-952-265-517-2
ISBN 978-952-265-518-9 (PDF)
ISSN-L 1456-4491
ISSN 1456-4491

Lappeenrannan teknillinen yliopisto
Yliopistopaino 2013

ABSTRACT

Jyri Kinnunen

RISK-RETURN TRADE-OFF AND AUTOCORRELATION

Lappeenranta, 2013
50 pages

Acta Universitatis Lappeenrantaensis 551
Diss. Lappeenranta University of Technology
ISBN 978-952-265-517-2, ISBN 978-952-265-518-9 (PDF), ISSN-L 1456-4491, ISSN 1456-4491

A trade-off between return and risk plays a central role in financial economics. The intertemporal capital asset pricing model (ICAPM) proposed by Merton (1973) provides a neoclassical theory for expected returns on risky assets. The model assumes that risk-averse investors (seeking to maximize their expected utility of lifetime consumption) demand compensation for bearing systematic market risk and the risk of unfavorable shifts in the investment opportunity set. Although the ICAPM postulates a positive relation between the conditional expected market return and its conditional variance, the empirical evidence on the sign of the risk-return trade-off is conflicting. In contrast, autocorrelation in stock returns is one of the most consistent and robust findings in empirical finance. While autocorrelation is often interpreted as a violation of market efficiency, it can also reflect factors such as market microstructure or time-varying risk premia.

This doctoral thesis investigates a relation between the mixed risk-return trade-off results and autocorrelation in stock returns. The results suggest that, in the case of the US stock market, the relative contribution of the risk-return trade-off and autocorrelation in explaining the aggregate return fluctuates with volatility. This effect is then shown to be even more pronounced in the case of emerging stock markets. During high-volatility periods, expected returns can be described using rational (intertemporal) investors acting to maximize their expected utility. During low-volatility periods, market-wide persistence in returns increases, leading to a failure of traditional equilibrium-model descriptions for expected returns. Consistent with this finding, traditional models yield conflicting evidence concerning the sign of the risk-return trade-off.

The changing relevance of the risk-return trade-off and autocorrelation can be explained by heterogeneous agents or, more generally, by the inadequacy of the neoclassical view on asset pricing with unboundedly rational investors and perfect market efficiency. In the latter case, the empirical results imply that the neoclassical view is valid only under certain market conditions. This offers an economic explanation as to why it has been so difficult to detect a positive trade-off between the conditional mean and variance of the aggregate stock return. The results highlight the importance, especially in the case of emerging stock markets, of noting both the risk-return trade-off and autocorrelation in applications that require estimates for expected returns.

Keywords: risk-return trade-off, autocorrelation, ICAPM, volatility, volume, asset pricing

UDC 330.131.7:336.76:51.001.57

To my wife and daughter

ACKNOWLEDGEMENTS

I would like to acknowledge the contributions of a number of people.

As an undergraduate, I was fortunate to participate in a finance course lectured by Professor Mika Vaihekoski. His expertise and research perspectives opened my eyes and made me appreciate the value of the long slog of research work. I am indebted to Mika in many ways, but particularly for the spark that led to my own research. His invaluable advice and encouragement, especially at the early stage of my doctoral studies, cannot be understated.

Once the neurons were firing, my supervisors played a key role in this project. It was a great privilege to have Professor Minna Martikainen as my first supervisor. Minna provided me the opportunity to show my capabilities as a researcher. Her belief in what I was doing and personal motivation made me aspire to making a serious scholarly contribution. I am truly grateful to her for guidance and support, both in scientific and personal matters. I hope our cooperation will continue for many years to come. I also sincerely thank Professor Jussi Nikkinen, my second supervisor, for his advice and encouragement. Both helped me find my research niche.

I wish to express my gratitude to my reviewers, Johan Knif and Gregory Koutmos. Their valuable comments and insights improved the quality of this dissertation. Furthermore, some of the ideas presented here came out of Professor Knif's comments as an opponent at a doctoral defense four years ago. Similarly, part of the ideas originated from a doctoral course taught by Professor Koutmos.

One of the best experiences during my doctoral studies was the Graduate School of Finance (GSF). In addition to its excellent PhD program, the GSF offered great opportunities to meet fellow doctoral students and researchers with similar interests. The first GSF lecturer I met was Dr. Peter Nyberg. Besides being an inspiring finance instructor, Peter indelibly influenced my thinking about the aims and methods of asset-pricing research. He always had a moment to talk and share his knowledge with everyone – something every PhD student appreciates. Among the many great people I met through the GSF, I must mention Andrew Conlin, Fredrik Le Bell, and Denis Davydov. I quickly found we shared common views on doctoral studies. I thank all of you for many interesting discussions and fun moments we shared over the years.

I am grateful to the Graduate School of Finance and Dr. Mikko Leppämäki, Director of the GSF, for providing funding for my doctoral studies. A GSF-fellowship made my doctoral studies possible. I also thank the Niilo Helander Foundation for financial support at the early stage of my doctoral studies.

Most of the writing of this dissertation took place at the Department of Business Economics and Law, School of Business, Lappeenranta University of Technology (LUT). I sincerely thank Professor Jaana Sandström, Dean of LUT School of Business, for providing the facilities to carry out this research. I wish to thank my colleagues, especially Kashif Salem, Sheraz Ahmed, Juha Soininen, Eero Pätäri, Timo Leivo, Elena Fedorova, and Mikael Collan, for sharing the past years with me at the department. I have many warm memories from our time together.

I would not have completed this dissertation without the continuing support of those closest, my loving family. I owe a debt of gratitude to my grandparents, who, by their example, have always inspired me to do my best. To my brother Teemu: Thank you for always believing in me. Mom and Dad, I am truly thankful to you. Since my first steps, I have enjoyed your loving support. I am also grateful for everything you have taught me, especially your values and creativity – both have been irreplaceable over the past years.

Finally, and most significantly, the last years have been much more than just research work. I now share a life with a wonderful wife and beautiful daughter, Elina and Anni, who made this journey more than worth the effort. To my wife and daughter: Thank you for being there for me. You always kept me smiling. All that this project required seems insignificant by comparison.

Lahti, November 2013

Jyri Kinnunen

TABLE OF CONTENTS

PART A: OVERVIEW OF THE THESIS

PART B: ARTICLES

PART A: OVERVIEW OF THE THESIS

1. INTRODUCTION

1.1. Background

A trade-off between return and risk plays a central role in financial economics: prices of financial assets reflect delay and risk in future payoffs of assets. Specifically, the neoclassical approach to asset pricing is based on risk-averse investors seeking to maximize their expected utility. Supply and demand for an asset determines its price, which, in equilibrium, reflects investor preferences and the risk associated with the asset's future payoffs. A risky payoff pattern implies a low asset price, or equivalently, a high rate of return. The neoclassical approach has been dominant for nearly a half century, but interest in behavioral finance arose in the 1980s after discovering that human decision-making departs from neoclassical assumptions about investor preferences and unboundedly rational behavior. The neoclassical and behavioral approaches are often treated as mutually exclusive, but in fact are closely intertwined in empirical research.

The intertemporal capital asset pricing model (ICAPM) of Merton (1973) lies at the core of neoclassical analysis. While the ICAPM provides a theoretically elegant description for expected returns on risky assets that accounts for the dynamic nature of financial markets (a feature lacking in static single-period equilibrium models), the empirical evidence for an intertemporal relation between expected returns and risk is inconclusive. On the other hand, there is little dispute that stock returns exhibit autocorrelation, which was long seen as a violation of market efficiency. Many researchers still interpret autocorrelation as evidence against the neoclassical doctrine, but care must be taken as autocorrelation may arise from a number of sources.

The ICAPM was introduced a decade after the frame-braking capital asset pricing model (CAPM) of Sharpe (1964) and Lintner (1965), which, along the efficient market theory and arbitrage-based option-pricing theory, started the reign of neoclassical finance (Shiller, 2006). Building on Markowitz's (1952) mean-variance portfolio theory, the classic CAPM suggests that expected excess return on a risky asset is proportional to its covariance with the market portfolio. The CAPM has been remarkably successful, due in part to its ease of interpretation. Basically, risk-averse investors require compensation for bearing systematic market risk, while idiosyncratic asset-specific risk should not affect expected returns.

One reason for the CAPM's lasting legacy is the fact that identification of an alternative model that consistently outperforms the CAPM in empirical work has been elusive. The classic CAPM, even though it is derived from a strict set of assumptions, continues to influence academic research and the non-academic financial community. It is still used as the benchmark model against which new theories and performance of portfolio managers are evaluated. The CAPM has been modified in several ways over the years, including taxes (Brennan, 1970), nonmarketable assets (Mayers, 1972), international aspects (e.g., Solnik, 1974; Stulz, 1981), and liquidity (Acharya and Pedersen, 2005). The zero-beta CAPM of Black (1973) relaxes the assumption of risk-free lending and borrowing. The case of incomplete portfolio diversification is another interesting example. Merton (1987) and Levy (1978) show that if investors fail to diversify their portfolios in an optimal way, idiosyncratic asset-specific risk can contain pricing information, as documented by Fu (2009).

Nevertheless, the CAPM fails to explain several pricing anomalies (e.g., momentum and size effect). This has led to the development of multifactor models such as the Arbitrage Pricing Theory of Ross (1976) and the Fama-French (1993) three-factor model.[1] Discovery of pricing anomalies also pushed research into the realm of behavioral finance.[2]

The models discussed above are all static single-period models. Real-life investors, however, consider their investment-consumption decisions in a dynamic multi-period environment. Merton (1973) assumes that, instead of a static one-period portfolio choice, investors act to maximize their expected utility of lifetime consumption. As a result, the ICAPM suggests that investors are compensated for bearing systematic market risk and the risk of unfavorable shifts in the investment opportunity set. The ICAPM implies a dynamic multifactor description for expected returns. While an intertemporal risk-return relation holds in equilibrium for all risky assets, implications of the ICAPM can be tested at the aggregate market level.

The ICAPM postulates a positive relation between the conditional expected return on the market portfolio and its own conditional variance (risk-return trade-off). The coefficient linking the two variables measures relative risk aversion of the representative investor, capturing the investor’s reluctance to take wealth bets. If the representative investor is risk averse, the risk-return trade-off should be positive, i.e., investors are compensated for bearing systematic market risk. Despite of an impressive body of research (e.g., Ghysels, 2005; Guo and Whitelaw, 2006; Brandt and Wang, 2010; Nyberg, 2012), however, empirical evidence concerning the sign of the risk-return trade-off is conflicting. Studies often report a negative or weak relation between the conditional mean and variance of the aggregate stock return.

In contrast to the challenges of documenting a positive risk-return relation, autocorrelation in stock returns is a robust empirical finding, especially for short-horizon returns.[3] Unsurprisingly, risk-return trade-off studies usually report serial dependence in stock returns. A first-order autoregressive term, when added as an additional regressor along the conditional variance of

[1] For an overview on cross-sectional pricing anomalies, see Fama and French (2008).
[2] For an overview of behavioral finance, see Barberis and Thaler (2003).
[3] For an overview on autocorrelation research, see Campbell et al. (1997) and Anderson et al. (2012).

the aggregate return, is consistently found to be significant (e.g., Ghysels, 2005; De Santis and Imrohoroglu, 1997; Nelson, 1991; Bollerslev et al., 1988). More surprising perhaps is the fact that the relation between significant autocorrelation and inconclusive risk-return results has largely evaded scrutiny, even if an autoregressive term is included to account for nonsynchronous trading or test whether lagged returns help forecast future returns (the latter practice is closely related to market efficiency research).

Autocorrelation in stock returns, a departure from the random walk hypothesis, was long seen as evidence against market efficiency. Indeed, before the work of e.g., LeRoy (1973), Rubinstein (1976), and Lucas (1978), prices were assumed to follow martingales in efficient markets, implying that when prices fully reflect all information, returns should be like coin flips. However, equilibrium models such as the ICAPM suggest that if conditional second moments of returns or risk preferences vary over time, excess returns can be time-varying and predictable. The modern view on return predictability states that prices should follow martingales after controlling for dividends and weighting by marginal utility. This implies the well-known joint hypothesis encountered in empirical work: only if an asset pricing model is correct and the financial market is efficient should past returns (or other additional variables) not be helpful in forecasting future returns.

The joint hypothesis illustrates how closely neoclassical and behavioral finance are intertwined in empirical research. Pricing anomalies are anomalies only with respect to the tested asset-pricing model. In other words, autocorrelation is evidence against market efficiency only if we control for time-varying expected returns using the correct equilibrium model. This exposes many empirical results that otherwise bolster the behavioral finance approach to the same criticism that applies to empirical asset pricing. Can we measure investor expectations? How should we proxy the unobservable market portfolio?

Many authors continue to interpret significant autocorrelation in unadjusted returns as evidence against market efficiency (see Lo, 2004; Ito and Sugiyama, 2009). However, Anderson et al. (2012) lists four sources of return autocorrelation: partial price adjustment, time-varying risk premia, nonsynchronous trading, and bid-ask bounce. Of these explanations, only partial price adjustment implies pricing inefficiency.

What causes departures from perfect price adjustment? The neoclassical approach assumes that unboundedly rational investors optimize their expected utility, while operating in efficiently functioning financial markets. In this ideal world, prices adjust to the arrival of new information quickly and accurately. Lo (2004) notes that behavioral biases in human decision-making in our non-ideal world lead to departures from the neoclassical assumptions about investor behavior. These biases include overconfidence, overreaction, loss aversion, herding, psychological accounting, misscalibration of probabilities, and hyperbolic discounting. Most of us are willing to agree that at least some of these biases characterize human behavior. This, however, does not imply that the neoclassical approach should be abandoned. It is not the behavior of separate individuals, but the average rationality of financial markets that matters when considering how prices adjust to new information. An obvious drawback of behavioral finance is that we can easily pick a story that explains some puzzling phenomenon by choosing a suitable bias afterwards. Thus, if we are interested in explaining future returns, the neoclassical approach (with some obvious, but necessary, simplifications of investor behavior) may still offer the superior analysis.

The choice between neoclassical and behavioral finance analysis is often treated as an either-or proposition. However, Shiller (2006) argues that both approaches can be advantageously applied together in describing interactions in real-life financial markets. For example, while time-varying risk premia and market microstructure may induce at least part of the autocorrelation in stock returns, Anderson et al. (2012) find that partial price adjustment is an important source of autocorrelation. This implies that behavioral finance may be useful in explaining the mixed risk-return trade-off results and the appearance of autocorrelation in returns; i.e., neoclassical efficient markets and rational investors cannot in themselves describe fully stock returns.

As Campbell et al. (1997) point out, perfect market efficiency rarely holds in practice. Grossman and Stiglitz (1980) show that, while markets can be relatively efficient, small abnormal returns must exist to compensate investors for the costs of gathering and processing information.[4] In other words, certain small abnormal returns that are ultimately paid by noise traders are needed to generate market equilibrium and relatively efficient markets. It is difficult to augment equilibrium pricing models to observe these inefficiencies without knowing the exact trading strategies of the various investors. Moreover, several studies suggest that market efficiency varies over time (see survey of Lim and Brooks, 2011), and hence, the degree of partial price adjustment induced autocorrelation is unlikely to be stable over time.

1.2. Objectives

This doctoral thesis investigates a relation between the mixed evidence on the intertemporal risk-return trade-off and the appearance of autocorrelation in stock returns. Set within the above-described framework, the thesis consists of four essays. Essays 1 and 2 augment the ICAPM to take into account autocorrelation induced by partial price adjustment. The conditions when pricing inefficiencies exist are specified, and the time-varying degree of autocorrelation is modeled along an equilibrium model. This approach requires no exact

[4] After these expenses are taken account, the returns are no longer abnormal.

specification of investor type or the market friction inducing the autocorrelation. Essay 3 notes the risk-return trade-off and autocorrelation using a heterogeneous agent model with two investor types.[5] This approach provides a formal description for autocorrelation by making a strict assumption on the investor type that induces autocorrelation. Essay 4 models dynamic cross-autocorrelation in stock returns on statistical bases. The essays have the following objectives:

Essay 1 [*Risk-return trade-off and serial correlation: Do volume and volatility matter?*] investigates whether the relative contribution of the risk-return trade-off and autocorrelation in explaining the US aggregate stock returns varies over time, possibly causing inconclusive results for the sign of the risk-return trade-off. The essay tests an empirical model that builds on the ICAPM theory and the insight that the relevance of the risk-return explanation and autocorrelation may fluctuate with information flow (approximated by volatility and volume). The changing relevance of the risk-return explanation is economically motivated by the adaptive market hypothesis (AMH) proposed by Lo (2004). The AMH posits that investors with bounded rationality adapt to constantly changing market conditions with satisfactory behavior attained through heuristics and a process of evolution. Under the AMH, the degree of market efficiency is dynamic and can exhibit cyclical behavior due to changing market conditions.

Essay 2 [*Dynamic return predictability in the Russian stock market*] applies the model proposed in Essay 1 to the Russian stock market, one of the world's largest emerging stock markets. This allows testing of the model insights in a drastically different market environment. Unlike the US stock market, which can be assumed to be fairly efficient and stable, the Russian stock market, like many emerging financial markets, is characterized by poor corporate governance (Black et al., 2006) and liquidity risk (Bekaert et al., 2007). In addition, the Russian stock market has seen its share of colorful economic and political events (Goriaev and Zabotkin, 2006). Harvey (1995a, 1995b) further reports that the levels of return predictability and autocorrelation in emerging stock market returns are higher than those observed in developed markets.

Essay 3 [*Feedback trading and international portfolio allocation*] explores the effect of feedback trading on expected returns and portfolio allocation between the US and Latin American stock markets. The Sentana-Wadhwani feedback-trading model (Shiller, 1984; Sentana and Wadhwani, 1992) suggests that both a conditional risk-return trade-off and dynamic autocorrelation drive expected return. The model assumes two investor types, and indirectly agrees with the model in the first two essays. Earlier studies on feedback trading (e.g., Sentana and Wadhwani, 1992; Koutmos, 1997; Bohl and Siklos, 2008) do not compare performance of the feedback-trading model against traditional equilibrium models or

[5] For a survey on heterogeneous agent models in finance, see Hommes (2006).

alternative models with time-varying autocorrelation. This is essential, however, if we want to evaluate how well the feedback-trading model performs in modeling expected returns. In addition, the paper is the first to explore the effect of taking feedback traders into account in portfolio optimization.

Essay 4 [*Dynamic cross-autocorrelation in stock returns*] investigates whether the cross-autocorrelation pattern of small- and large-firm returns in the US changes with the variance of returns. This is accomplished by an exponential vector autoregressive (EVAR) model with volatility. The EVAR model has similarities with the logistic vector smooth transition autoregressive model (LVSTAR) (e.g., He et al., 2009), but the approach is novel. Dynamic autocorrelation in stock returns has been studied by several authors (Chen et al., 2008, McKenzie and Faff, 2003; Campbell et al., 1993), but time-varying cross-autocorrelation between stock returns has received far less attention. Essay 4 complements the findings in the first three essays and extends the discussion of cross-autocorrelation in stock returns of previous studies in time-invariant settings (Berhardt and Mahani, 2007; Hou, 2007; Chordia and Swaminathan, 2000).

1.3. Contribution

The essays of this doctoral thesis make the following contributions to the literature on asset pricing and autocorrelation:

Essay 1 establishes the existence of a positive relation between the conditional mean and variance of the US aggregate stock return; i.e., investors are compensated for bearing conditional market risk. This result comports with the work of Ghysels et al. (2005) and Nyberg (2012), among others. However, the relative contribution of the risk-return trade-off and autocorrelation in explaining the US aggregate stock return fluctuates with market conditions (measured by volatility). Since volatility serves as a proxy for information flow (e.g., Andersen, 1996), this offers a plausible explanation as to why it has been difficult to document a positive risk-return trade-off. During periods of low amounts of new information, market-wide persistence in returns increases, leading to failure of the equilibrium model in explaining aggregate return.

The tested empirical model notes the low-volatility (or low-information) shortcoming of the risk-return explanation. The model summarizes the effect of autocorrelation in one coefficient and time-varying weight that shows the relative contribution of the risk-return trade-off and autocorrelation in explaining the aggregate return. The underlying economic intuition builds on the AMH, where prices reflect both information and the prevailing market ecology. The degree of market efficiency can exhibit cyclical behavior due to changing market conditions.

Essay 1 assumes that these changes can be modeled by concentrating on the level of new information available to be subsumed in prices. Intuitively, during low-information periods, those investors incapable to process new information and trading strategies relying on past prices survive due to a relatively low degree of misspricing and the steady state of financial markets. During high-information periods, the dominant investor type resembles a rational expected utility maximizer.

The model outperforms its traditional alternatives and two heterogeneous agent models: the Shiller-Sentana-Wadhwani feedback-trading model and the model of Campbell et al. (1993). The time-varying relevance of the autoregressive component is in line with Kim et al. (2011), who find support for the AMH by testing a relation between time-varying return predictability and changing market conditions. However, the results show that the conditional risk-return trade-off is also important in the US stock market, especially during high-information (or high-volatility) periods. It is important to pay attention to the risk-return trade-off in market efficiency studies as market efficiency can only be tested in conjunction with an equilibrium model for expected returns. Otherwise, autocorrelation can simply reflect the documented significant relation between the conditional mean and variance of the aggregate return (for details, see Section 3.1).

Essay 2 confirms the findings of Essay 1 in an emerging market context. A conditional risk-return trade-off and autocorrelation are both relevant in explaining the Russian aggregate stock return. However, the relevance of the two components fluctuates considerably more than for the US stock market. This comports with the underlying economic intuition on the degree of market efficiency and changing market conditions. Emerging market conditions change rapidly and unpredictably. Partly due to the opacity of publicly available information, investors are forced to rely more on heuristics in their decision-making than in developed markets.

Essay 2 documents a high degree of return predictability. This finding is consistent with previous emerging market studies (e.g., Harvey, 1995a). If volatility is interpreted as a proxy for information flow, when the amount of new information is high, almost all predictability in the Russian aggregate return is explainable by a conditional asset pricing model. During low-information periods, market-wide persistence in returns increases, while an asset pricing model explanation becomes practically irrelevant. This demonstrates the inadequacy of a pure equilibrium model explanation for stock returns, especially in emerging stock markets. In developing stock markets such as Russia, an asset-pricing model for expected returns alone can lead to wrong conclusion in practical applications (e.g., performance evaluation of portfolio managers) if the time-varying contribution of autocorrelation is ignored.

Consistent with Essay 1, the tested model performs better than traditional models or the heterogeneous agent models of Campbell et al. (1993) and Sentana and Wadhwani (1992). The out-of-sample analysis on the economic significance of the results indicates that the model can be used to form profitable trading strategies before transaction costs. A simple short-selling strategy based on the models one-step-ahead forecasts outperforms a passive benchmark model and a traditional technical analysis tool, which underperforms the passive benchmark model. The poor performance of the traditional technical analysis tool (a rolling historical average) indicates that use of naïve forecasting models is not economically beneficial, even in emerging stock markets.

Essay 3, which explores the US and Latin American stock markets, finds indirect support for Essays 1 and 2 in that the degree of autocorrelation is shown to vary with volatility. However, the underlying economic intuition is different; the result suggests some investors implement feedback trading strategies. Essay 3 documents that the first-lag autocorrelation is mostly positive in both stock markets – usually at a higher level in the Latin America aggregate return than in the US aggregate return. This is in line with Essays 1 and 2, and more generally, with the view that return autocorrelation is more important in emerging than developed stock markets (Harvey, 1995b). Contrary to previous feedback trading studies, the results are controlled against the increased influence of global factors (see Roll and Pukthuanthong, 2009). Lagged return on the global aggregate stock market and changes in the oil price as additional explanatory variables do not help forecasting future returns.

The feedback trading model fits the data better than a conditional version of the zero-beta CAPM. This implies that heterogeneous agent models offer a more realistic description for stock returns than a single-investor models that assume efficiently functioning and frictionless markets. This interpretation comports with the results in Essay 1 and 2. However, differences in performance in explaining monthly returns between the Shiller-Sentana-Wadhwani feedback-trading model and alternative models with a first-order autoregressive term are modest.

Taking time-varying autocorrelation into consideration can improve an investor's portfolio allocation between emerging and developed stock markets. Using the feedback trading model and its alternatives to model expected returns, Essay 3 constructs period by period both the global minimum variance portfolio and the tangency portfolio with the risk-free return and a shorting constraint. Based on the average performance of different portfolios, taking autocorrelation into consideration is found to be important in portfolio optimization as it can influence portfolio choice indirectly via the effect of forecasting errors on the covariance matrix estimates and directly through expected returns. The most drastic effect on portfolio performance comes not from allowing time-varying autocorrelation, but simply realizing that stock returns are autocorrelated, especially in emerging markets.

Essay 4 extends the exponential autoregressive model of LeBaron (1992) to the EVAR model with volatility. Returns on a large-firm portfolio are shown to lead returns on a small-firm portfolio. The lead-lag relation changes with conditional variance of the large-firm returns. Because the large-firm portfolio closely reflects market movements, this finding concurs with Chan (1993), who explains cross-autocorrelations among stock returns in a context where market makers observing noisy signals about their stocks cannot immediately condition prices on the signals of other stocks that contain market-wide information. If the signal quality is better for large firms than for small firms, large firm returns can lead small firm returns. The Chan model implies that both own- and cross-autocorrelations can vary with the size of market movement.

Dynamic cross-autocorrelation has been previously studied using the LVSTAR framework mainly in a macroeconomic context. For example, Rothman et al. (2001) investigate nonlinear Granger causality in the money-output relation. Camacho (2004) studies the nonlinear relation between US gross domestic product and the Conference Board's composite index of leading indicators. The EVAR model with volatility allows current values of dependent variables to depend on their own lagged values and lagged values of other variables with coefficients that change with the conditional second moments of the variables. To my best knowledge, this approach has not been previously used. The results show that time-invariant vector autoregressions (e.g., Boulatov et al., 2012; Hou, 2007; Chordia and Swaminathan, 2000) appear to be overly restrictive when testing lead-lag relations in stock markets.

Essay 4 complements the findings of the previous three essays, which investigate autocorrelation at the market level. First, as the autocorrelation in large-firm returns is found to be time-invariant, it seems that the time-varying autocorrelation in the US aggregate return is mainly induced by the dynamic own- and cross-autocorrelation in small-firm returns. Second, Kim et al. (2011) document a relation between changing market conditions and time-varying return predictability at the market-level, which is in line with the results in the previous essays. Essay 4 implies that most of the dynamic predictability is attributable to predictability in small-firm returns.

1.4. Structure

The rest of this introductory part of the thesis is organized as follows. Section 2 introduces the neoclassical approach to asset pricing via the stochastic discount factor, discusses the risk-return trade-off between the conditional mean and variance of the aggregate return implied by the ICAPM, and represents the modern view on return predictability and market efficiency. Section 3 presents four sources of autocorrelation in stock returns. Section 4 introduces an empirical model to assess the time-varying relevance of an equilibrium pricing model and autocorrelation in driving expected returns. The last section summarizes the main results.

2. RISK-RETURN TRADE-OFF

This section discusses the neoclassical approach to asset pricing. Section 2.1 presents the general consumption-based model in a stochastic discount form. Section 2.2 introduces the intertemporal CAPM, and discusses the intertemporal risk-return trade-off at the aggregate market level. Section 2.3 provides a brief summary of the modern view on market efficiency and return predictability (e.g., in the form of autocorrelation in returns).

2.1. Stochastic discount factor

The neoclassical approach to asset pricing is best characterized by a stochastic discount factor presentation for expected returns.[6] A simple example of how the stochastic discount factor can be introduced is to consider an investment-consumption choice problem of an investor (with Neumann-Morgenstern preferences) who can freely buy or sell asset i and who maximizes a time-separable additive expected utility function:

$$\max u(c_t) + \beta E_t\left[u(c_{t+1})\right], \tag{1}$$

where $E_t[\cdot]$ denotes the expectation conditional on time t information, and c_t and c_{t+1} denote the investor's consumption at time t and $t + 1$. $u(\cdot)$ is the period utility function of consumption with $u'(\cdot) > 0$ and $u''(\cdot) < 0$. The strictly increasing and strictly concave $u(\cdot)$ implies that the investor prefers more consumption over less, but the marginal value of additional consumption declines. $u''(\cdot) < 0$ induces aversion to both risk and substitution of consumption over time. β is the subjective discount factor (if the investor prefers consumption sooner rather than later, $\beta < 1$).

The investor must choose how much to consume today and how much to invest for future consumption. The first-order condition for an optimal consumption-portfolio choice is

$$u'(c_t) = \beta E_t\left[(1 + R_{it+1})u'(c_{t+1})\right], \tag{2}$$

where R_{it+1} is the net return on the asset i at time $t + 1$. At the optimum, the marginal utility loss of consuming one dollar less at time t must equal to the expected marginal utility gain from the extra payoff at time $t + 1$. Dividing eq. (2) by the marginal utility at time t, yields

[6] The discussion here follows the standard introduction to the topic (see Cochrane, 2005; Campbell et al. 1997).

(3) $$1=\beta E_t\left[\left(1+R_{it+1}\right)\frac{u'\left(c_{t+1}\right)}{u'\left(c_t\right)}\right]$$

or

(4) $$1=E_t\left[\left(1+R_{it+1}\right)M_{t+1}\right].$$

The variable $M_{t+1} = \beta u'(c_{t+1})/u'(c_t)$ is the stochastic discount factor. In the present context, it measures the intertemporal marginal rate of substitution. Eq. (4) states that the expected product of any asset return with the stochastic discount factor is equal to one.

The gross return for a risk-free asset is $(1 + R_{ft}) = E_t[(1 + R_{ft})] = 1/E_t[M_{t+1}]$.[7] Using the covariance decomposition and the expression for the risk-free return, eq. (4) suggests that the expected return on the asset *i* in excess to the risk-free return is

(5) $$E_t\left[R_{it+1}\right]-R_{ft}=-\left(1+R_{ft}\right)\mathrm{Cov}_t\left[R_{it+1},M_{t+1}\right].$$

Eq. (5) states that an asset's expected return depends on its covariance with the stochastic discount factor. Assets with payoffs that have negative covariance with M_{t+1} have positive expected risk premiums. An asset with negative covariance with the stochastic discount factor yields low returns when the marginal utility of consumption is high. During these periods, consumption is low and an extra dollar would be most valuable, so investors demand a risk premium to hold such an asset in their portfolios. An asset whose expected return has positive covariance with M_{t+1} tends to yield high returns when wealth is most valuable, and hence, investors are willing to pay a premium to hold it.

In empirical work, the consumption-based asset pricing model presented above commonly involves aggregating investors into a single representative investor. While the consumption-based model is theoretically appealing and most pricing models are merely special cases of this model, it has some unattractive features, especially at short intervals. Campbell et al. (1997) mention two potential problems facing the empirical researcher. First, it is difficult to measure aggregate consumption at a given point of time as available consumption data are time-aggregated and suffer from measurement errors. Second, aggregate consumption may be an inadequate measure for the consumption of stock market investors in the presence of constrained investors not operating in the stock market. The consumption of constrained investors may account for a substantial fraction of aggregate consumption, yet it is irrelevant

[7] Some authors use R_{ft+1} instead of R_{ft} to denote the return on the risk-free asset at time $t + 1$ (observed at time t).

in determining equilibrium prices. Mankiw and Zeldes (1991) find support for the view that the consumption of stockholders and non-stockholders differ in important ways.

Essay 3 considers a case where one investor group bases their demand on past price changes instead of risk-return considerations. The other equilibrium pricing models in this doctoral thesis, however, are linear factor models with wealth and other variables as proxies for aggregate marginal utility growth. In these models, the stochastic discount factor is linear (or approximately linear) such that

(6) $$M_{t+1} = a_t + \mathbf{b}_t{}'\mathbf{F}_{t+1},$$

where $\mathbf{F}_{t+1} = [f_{1t+1}, f_{2t+1}, \ldots, f_{Kt+1}]$ is a K x 1 vector of risk factors. In the CAPM, the sole factor is the return on the wealth portfolio. The ICAPM of Merton (1973) implies that innovations in state variables that forecast changes in future investment opportunities should be considered as additional variables.

In multi-period models, investors optimize their expected utility of lifetime consumption. For example, if the investor lasts T periods, eq. (1) becomes

(7) $$\max E_t\left[\sum_{j=0}^{T}\beta^j u\left(c_{t+j}\right)\right].$$

In the ICAPM, the optimal consumption is explained in terms of wealth and other state variables using the indirect utility function of the investor J_t. To illustrate how this works, let θ_{it} be the number of units of asset i held at time t and $\boldsymbol{\theta}_t = [\theta_{1t},\ldots,\theta_{Nt}]'$ denote the portfolio of the investor chosen at time t to be held for the next period. In addition to the wealth W_t at time t, which can be either invested or consumed, the indirect utility depends on the investor's remaining life, and hence, t will affect J_t.[8] If a state variable z_t contains information about future investment opportunities (the conditional distribution of asset returns the investor faces in the future), the indirect utility function of the investor at time t is

(8) $$J\left(W_t, z_t, t\right) = \max_{\{c_t,\ldots c_T,\boldsymbol{\theta}_t,\ldots,\boldsymbol{\theta}_T\}} E_t\left[\sum_{j=0}^{T}\beta^j u\left(c_{t+j}\right)\right],$$

with a terminal condition that $J(W_T,z_T,T) = u(c_T) = u(W_T)$. In other words, at the final date T, no portfolio is chosen (meaning that $\boldsymbol{\theta}_T = \mathbf{0}$) and consumption is equal to wealth at time T. The indirect utility function J_t denotes the maximum expected utility of current and future

[8] For simplicity, the investor is assumed to have no labor income.

consumption at time t, which depends on the consumption and investment decisions for the current period and all future periods.

The indirect utility has the dynamic programming property, so the multi-period maximization problem can be divided in the consumption-investment decisions for the current period and the decision for all future periods:

$$(9) \qquad J\left(W_t, z_t, t\right) = \max_{\{c_t, \boldsymbol{\theta}_t\}} \left\{ u\left(c_t\right) + \beta E_t\left[J\left(W_{t+1}, z_{t+1}, t+1\right)\right]\right\}.$$

The dynamic programming property of the indirect utility can be used to show that, at the optimum, the envelope condition holds

$$(10) \qquad u'\left(c_t\right) = J_W\left(W_t, z_t, t\right),$$

where J_W denotes the partial derivative of the indirect utility with respect to wealth. Eq. (10) allows writing the stochastic discount factor in terms of the indirect utility. This can be further used to derive a linear discrete-time approximation for M_{t+1} [see eq. (6)] by taking a Taylor expansion that can be used in eq. (4). Alternatively, we can derive an exact linearization for M_{t+1} in continuous time and use the continuous time result as a discrete-time approximation.

2.2. Intertemporal CAPM

A discrete-time approximation of the ICAPM implies that the expected excess return on asset i is

$$(11) \qquad E_{t-1}\left[r_{it}\right] = \frac{-W_t J_{WW}\left(W_t, z_t, t\right)}{J_W\left(W_t, z_t, t\right)} \mathrm{Cov}_{t-1}\left[r_{it}, r_{Wt}\right] + \frac{-J_{Wz}\left(W_t, z_t, t\right)}{J_W\left(W_t, z_t, t\right)} \mathrm{Cov}_{t-1}\left[r_{it}, \Delta z_t\right],$$

where $E_{t-1}[r_{it}] = E_{t-1}[R_{it}] - R_{ft-1}$ and Δz_t is the innovation to the state variable. Subscripts on J denote partial derivatives. Eq. (11) suggests that the representative investor is compensated for bearing the systematic market risk (the first term on the right hand side (RHS)) and the risk of unfavorable shifts in the investment opportunity set (the second term on the RHS). Eq. (11) can be written for the aggregate wealth (or market) portfolio as

$$(12) \qquad E_{t-1}\left[r_{Mt}\right] = \lambda \mathrm{Var}_{t-1}\left[r_{Mt}\right] + \gamma \mathrm{Cov}_{t-1}\left[r_{Mt}, \Delta z_t\right],$$

where $\lambda = -WJ_{WW}/J_W$ and $\gamma = -J_{Wz}/J_W$ are now both assumed to be constant over time. The former measures the (constant) relative risk aversion of the representative investor. This should be positive under risk aversion, since $J_W > 0$ and $J_{WW} < 0$.

Eq. (12) suggests a positive partial relation between the conditional mean and variance of the market excess return. The sign of γ can be negative or positive depending on J_{Wz}. If both $J_{Wz} > 0$ and $\text{Cov}_{t-1}[r_{Mt}, \Delta z_t] > 0$ or $J_{Wz} < 0$ and $\text{Cov}_{t-1}[r_{Mt}, \Delta z_t] < 0$, the second term on the RHS will be negative. Thus, the expected return on the market portfolio is lower than the required compensation suggested by market risk alone. Recalling the discussion in the previous section and eq. (5), this can be seen as a reflection of the fact that the market portfolio tends to yield high returns when the marginal utility of wealth is high. If both $J_{Wz} > 0$ and $\text{Cov}_{t-1}[r_{Mt}, \Delta z_t] < 0$ or $J_{Wz} < 0$ and $\text{Cov}_{t-1}[r_{Mt}, \Delta z_t] > 0$, investors will demand a higher expected return as the market portfolio tends to deliver high returns when the marginal utility is low.

If there are no shifts in investment opportunities or the investor has logarithmic utility, eq. (12) reduces to the conditional CAPM,

$$(13) \qquad E_{t-1}\left[r_{Mt}\right] = \lambda \text{Var}_{t-1}\left[r_{Mt}\right],$$

suggesting a proportional relation between the conditional mean and variance of the aggregate market.[9] Here, λ is the ratio of the conditional expected excess market return and the conditional variance of the market return. The coefficient measures the compensation the representative investor demands for a one-unit increase in the variance of the market return. While λ strongly depends on the level of risk aversion, it is exactly equal to the relative risk aversion only under strong assumptions concerning the consumption process (for details, see Harvey, 1989).

Merton (1980) argues that, under certain milder conditions than those discussed above, eq. (13) offers a reasonable approximation for the expected market return. Specifically, either the variance of the change in wealth (approximated by the variance of the market return) is much larger than the variance of the change in the state variables or the optimal consumption function of the representative investor [descries the optimal consumption rule of the investor in terms of the wealth, time, and the additional state variable (see Merton, 1973)], is much less sensitive to the additional state variable than to wealth.

In empirical work, it is assumed that realized returns are investors' unbiased estimates for expected returns. In addition, eq. (13) and (12) are often augmented by a constant term,

9 The state variable does not affect the marginal utility of an investor with logarithmic utility. This makes the investor uninterested in hedging against changes in the state variable.

(14) $$r_{Mt} = \mu + \lambda \mathrm{Var}_{t-1}\left[r_{Mt}\right] + \gamma \mathrm{Cov}_{t-1}\left[r_{Mt}, \Delta z_t\right] + \varepsilon_{Mt},$$

where $r_{Mt} = E_{t-1}[r_{it}] + \varepsilon_{Mt}$. The coefficient, μ, captures the average effect of missing factors and takes account market imperfections such as taxes, preferred habitat, and transaction costs (e.g., Scruggs, 1998; Bollerslev et al., 1988). It can be also interpreted as Jensen's (1969) measure. In this case, $\mu > 0$ (< 0) implies that the market portfolio has performed better (worse) than expected given its exposure to the systematic market risk and investors' intertemporal hedging demands.

Eq. (12) and (13) have been extensively used as the theoretical motivation to test the relation between the conditional mean and variance of the aggregate return, which is often referred to as the intertemporal or conditional risk-return trade-off. Despite a huge body of research, the empirical results concerning the sign of λ remains mixed. Previous studies have struggled to document a positive risk-return relation, often detecting a negative or weak relation instead. Although Campbell and Hentschel (1992), French et al. (1987), and Baillie and DeGennaro (1990) do demonstrate a positive risk-return trade-off, it is largely insignificant. Statistically significant and positive risk-return trade-offs are identified by Bollerslev et al. (1988), Scruggs (1998), Ghysels et al. (2005), Nyberg (2012), and Lanne and Saikkonen (2006). In contrast, Nelson (1991), Campbell (1987), and Glosten et al. (1993) report a negative relation between the conditional mean and variance of the aggregate stock return. Detailed overviews on the empirical results concerning the risk-return trade-off can be found in Scruggs (1998), Ghysels et al. (2005), Guo and Whitelaw (2006), Brandt and Wang (2010), and Nyberg (2012).

These mixed results relate to an omitted-variable problem or differences in how the conditional mean and variance are modeled. The former may result if the hedging component of the ICAPM is omitted from an empirical specification. As Scruggs (1998) notes, when the true asset pricing model is a two-factor model such as eq. (14) and the econometrician estimates the model with $\gamma = 0$, the following bias arises:

(15) $$\hat{\lambda} - \lambda = \gamma \frac{\mathrm{Cov}\left[\mathrm{Var}_{t-1}\left[r_{Mt}\right], \mathrm{Cov}_{t-1}\left[r_{Mt}, \Delta z_t\right]\right]}{\mathrm{Var}\left[\mathrm{Var}_{t-1}\left[r_{Mt}\right]\right]},$$

where $\hat{\lambda}$ is the estimate obtained using eq. (14) with $\gamma = 0$. The sign of the bias depends on both the unconditional covariance between $\mathrm{Var}_{t-1}[r_{Mt}]$ and $\mathrm{Cov}_{t-1}[r_{Mt}, \Delta z_t]$ and the sign of J_{Wz}. Some studies suggest this explains (at least partially) the inconclusive results concerning λ (Scruggs, 1998; Gerard and Wu, 2006; Guo and Whitelaw, 2006; Brandt and Wang, 2010).

The ICAPM does not prescribe the exact variable that should be used in empirical work to proxy the state variable. In practice, this makes it difficult to distinguish between a two-factor model and the ICAPM. In addition, if K state variables are needed to describe the variations in investment opportunities, the result is a (K + 1)-factor model. After choosing K relevant factors, the hedge component can be modeled by specifying a model for the conditional covariance between the market return and the change (or innovation) in factor k. Scruggs (1998) and Gerard and Wu (2006), for example, use multivariate GARCH (MGARCH) models. This doctoral thesis follows Ghysels et al. (2005) and Guo and Whitelaw (2006) and models the hedge component as a linear function

$$\sum_{k=1}^{K} \gamma_k \mathrm{Cov}_{t-1}\left[r_{Mt}, f_{kt}\right] = \boldsymbol{\tau}'\mathbf{X}_{t-1}, \tag{16}$$

where $\boldsymbol{\tau}$ is a vector of coefficients and $\mathbf{X}_{t-1}$ is a vector of predetermined information variables known at time $t - 1$.[10] As Gerard et al. (2003) point out, this approach can be used to control for the influence of additional factors, but cannot be taken as direct evidence as to whether or not a particular factor is priced. Note that eq. (16) is written for K factors instead of K state variables to highlight the fact that it is difficult to distinguish between a multifactor model and the ICAPM in empirical work.

Given that the focus of this thesis lies in the risk-return trade-off between the conditional mean and variance of the aggregate market return, eq. (16) is included in empirical models mainly for control purposes. So what variables should we include? As a rule, ICAPM-motivated factors should help forecasting future expected returns and variances. For example, Scruggs (1998) and Gerard and Wu (2006) consider long-term bond rates following Merton's (1973) suggestions. Ghysels et al. (2005) use predetermined macro variables such as the US default spread and the dividend-price ratio. On the other hand, there might be important control variables not necessarily directly related to the ICAPM approach that bear on the empirical question of whether the representative agent is a local or global investor. For example, since the degree of financial integration between world capital markets has increased for most countries (see, e.g., Roll and Pukthuanthong, 2009), the return on the global market portfolio is potentially an important control variable. This has been demonstrated in such works as Harvey (1991) and De Santis and Gerard (1997), who test a conditional version of the world CAPM. International asset pricing theories also predict that, under certain conditions, exchange rate risk is priced (for details, see Dumas and Solnik, 1995). De Santis and Gerard (1998) and De Santis et al. (2003), for example, find support for the pricing of the currency risk in selected markets. Therefore, changes in exchange rates are potentially important factors to be noted.

[10] Similarly, time-varying λ_t can be modeled using a linear function of lagged information variables (λ can be restricted to be positive using an exponential function).

The above discussion implies a second reason for the inconclusive results: none of the conditional moments is directly observable, so the modeling assumptions shape the obtained result. Indeed, Campbell (1987) reports that results are sensitive to the chosen set of information variables. In addition, several econometric methods can be used to empirically model $E_{t-1}[r_{it}]$, $\mathrm{Var}_{t-1}[r_{Mt}]$, and $\mathrm{Cov}_{t-1}[r_{Mt}, f_t]$. The most typical approaches are a multivariate or univariate GARCH-M framework (e.g., Bollerslev et al., 1988; Scruggs, 1998; Nyberg, 2012), generalized methods of moments (GMM) (e.g., Campbell, 1987; Brandt and Wang, 2010), and the mixed data sampling (MIDAS) approach of Ghysels et al. (2005). An interesting exception here is Pastor et al. (2008), who model the dynamics of the expected return using implied cost of capital computed from analyst forecasts. While the various econometric approaches have their own pros and cons, they all share a common feature – it is essential to test whether the obtained results are sensitive to the used variance specification and the chosen set of information variables.

2.3. Return predictability and market efficiency

Eq. (14) (with or without the hedging component) is often augmented by a time-invariant autoregressive term in empirical work. An autoregressive component is included to control for nonsynchronous trading (e.g., Nelson, 1991; De Santis and Imrohoroglu, 1997) or to test whether the lagged return helps forecasting the future return along the risk-return explanation (e.g., Bollerslev et al., 1988; Ghysels et al., 2005). The latter practice closely relates to the market efficiency literature, which is next discussed in relevant depth to elucidate the conditions under which autocorrelation in stock returns implies pricing inefficiency.

Before the theoretical foundations were laid by LeRoy (1973), Rubinstein (1976), and Lucas (1978) and others, a violation of the random walk hypothesis was seen as evidence against market efficiency. The common view was that if prices fully reflect all information, price changes must be unforecastable in an informationally efficient market (see Samuelson, 1965; Fama, 1970). In contrast, the modern view on return predictability states that price changes should be unpredictable after controlling for dividends and weighting by the stochastic discount factor, while unadjusted returns can be time-varying and predictable.

Let p_{it+1} and d_{it+1} denote the price and dividend of an asset i at time $t + 1$. Since the gross return on an asset i is $(p_{it+1} + d_{it+1})/p_{it}$, eq. (2) can be written as

$$p_{it}u'(c_t) = E_t\left[\beta u'(c_{t+1})(p_{it+1} + d_{it+1})\right]. \tag{17}$$

Cochrane (2005) lists the conditions under which prices follow a random walk: If the asset does not pay dividends during the next period ($d_{it+1} = 0$), investors are indifferent for delay in consumption ($\beta = 1$), and investors are risk neutral [$u(\cdot)$ is a linear function, implying $u'(c_{t+1})/u'(c_t) = 1$] or consumption does not vary, eq. (17) reduces to

(18) $$p_{it+1} = p_{it} + \varepsilon_{it+1},$$

where $p_{it+1} = E_t[p_{it+t}] + \varepsilon_{it+1}$. If ε_{it+1} is independently and identically distributed with zero mean and constant variance, the price follows a random walk process and returns are unpredictable.

Campbell et al. (1997) argue that the assumption of identically distributed increments is implausible for financial assets over longer time periods because the environment where stock prices are determined changes over time. For example, few would expect that the variance of ε_{it+1} remained the same before and during the recent financial crisis. Campbell et al. (1997) categorize eq. (18) with an independent but not identical distribution as a more general random walk hypothesis that still contains the idea of unforecastable price changes and has the random walk as its special case. They also discuss a one-step more general random walk hypothesis with dependent, but uncorrelated, increments. For example, Cov[ε_{it}, ε_{it-k}] =0 $\forall\, k\neq0$, while Cov[$\varepsilon_{it}^2, \varepsilon_{it-k}^2$] $\neq 0$ for some $k \neq 0$.

The ICAPM [eq. (11)] suggest that if conditional second moments of returns or risk preferences vary over time, excess returns can be time-varying and predictable. This implies the joint hypothesis encountered in empirical work. Only if an equilibrium model is correct and the market is efficient should past returns (or other additional variables) not be helpful in forecasting future returns. Market efficiency as such cannot be rejected. Said simply, autocorrelation in unadjusted returns is not evidence against market efficiency. While this doctoral thesis does not try to directly relate autocorrelation (in adjusted or unadjusted) returns to market efficiency in empirical work, it uses GARCH models in which squared error terms are autocorrelated. Therefore, in empirical work, a relation between random walk models and market efficiency is related to the last definition of the random walk hypothesis with dependent but uncorrelated increments.

Many researchers continue to interpret autocorrelation in unadjusted stock returns as evidence against market efficiency (e.g., Lo, 2004; Ito and Sugiyama, 2009). This may lead to false conclusions since, in addition to time-varying expected returns, autocorrelation may simply reflect market frictions. Anderson et al. (2012) lists four sources of autocorrelation in stock returns: partial price adjustment, time-varying risk premia, nonsynchronous trading, and bid-ask bounce. Of these explanations, partial price adjustment alone implies pricing inefficiency.

3. AUTOCORRELATION

This section discusses four sources of return autocorrelation: time-varying risk premia, nonsynchronous trading, bid-ask-bounce, and partial price adjustment. The first source is an example of autocorrelation in unadjusted returns induced by time-varying expected returns. The next two sources of autocorrelation are related to market microstructure. The final source is the only one that implies pricing inefficiency.

3.1. Time-varying risk premia

The ICAPM suggests that risk-averse investors demand compensation for holding risky assets. As discussed in the previous section, expected returns can be time-varying and predictable due to the time-varying risk premium. This offers a natural explanation for autocorrelation in unadjusted returns: autocorrelation can simply reflect time-varying risk premia (Anderson, 2011). To illustrate more specifically, assume that the conditional CAPM [eq. (13)] is the true asset pricing model and that the variance of the aggregate return follows a GARCH(1,1) process. These assumptions are both widely used in empirical research and imply that the aggregate market return follows the GARCH(1,1)-in-mean (GARCH-M) process:

(19)
$$\begin{gathered} r_{Mt} = \lambda h_{Mt} + \varepsilon_{Mt}, \\ h_{Mt} = \omega + \alpha \varepsilon_{Mt-1}^2 + \beta h_{Mt-1}, \\ \varepsilon_{Mt} \big| \Omega_{t-1} \sim N\left(0, h_{Mt}\right), \end{gathered}$$

where Ω_{t-1} denotes the complete information set available at time $t-1$, and $\omega > 0$, $\alpha > 0$, and $\beta \geq 0$. The condition for covariance-stationary and an existence of the fourth moment are $\alpha + \beta < 1$ and $3\alpha^2 + 2\alpha\beta + \beta^2 < 1$, respectively. The error term is assumed here to be conditional normally distributed, but other symmetric distributions can be assumed instead. Hong (1991) shows that the autocorrelation structure for r_{Mt} is

(20)
$$\rho_1 = \frac{\left(\alpha+\beta\right)\left(2\alpha^2\lambda^2\omega\right)}{\left(2\alpha^2\lambda^2\omega\right)+\left(1-\alpha-\beta\right)\left(1-\beta^2-2\alpha\beta-3\alpha^2\right)}$$

and, for the higher-order lags $L > 1$,

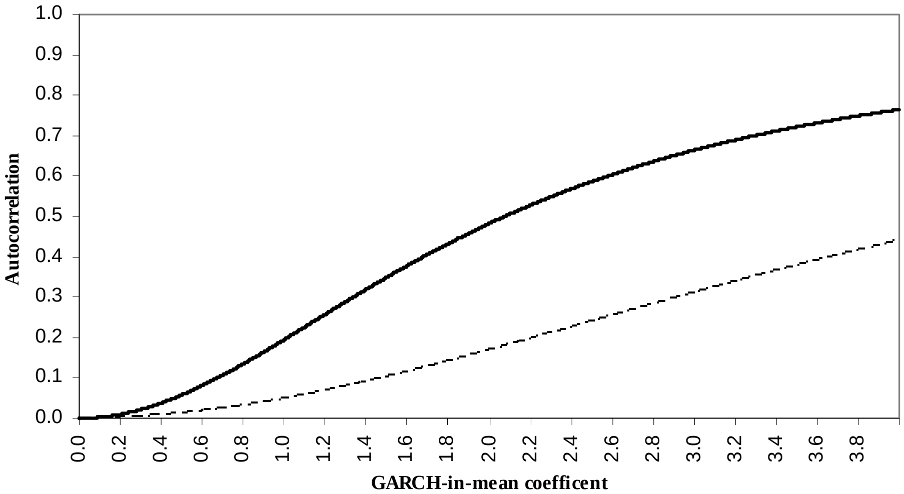

Figure 1. Autocorrelation. This figure shows the first-order autocorrelation implied by the GARCH-M(1,1) process [eq. (19)] with different λ. The first-lag autocorrelation is given as in eq. (20). The solid line results when $\omega = 0.05$, $\alpha = 0.10$, and $\beta = 0.85$. The dashed line is obtained when $\omega = 0.05$, $\alpha = 0.05$, and $\beta = 0.90$.

(21)
$$\begin{aligned}\rho_L &= (\alpha+\beta)\,\rho_{L-1} \\ &= (\alpha+\beta)^{L-1}\,\rho_1.\end{aligned}$$

Since the GARCH parameters are restricted to be positive, $\rho_L \geq 0 \ \ \forall L \geq 1$. There will be positive autocorrelation if investors are not risk neutral ($\lambda \neq 0$).[11, 12]

Figure 1 plots the first-order autocorrelation with different levels of λ when ω, α, and β are set equal to two different set of typical values obtained in empirical research. The dashed line shows the degree of autocorrelation for a relative persistence variance process ($\alpha + \beta = 0.95$) in which the GARCH term dominates. In other words, the conditional variance is mainly driven by the past conditional variance, while the effect of lagged squared innovations is low. The solid line is obtained for a variance process (with the same ω and $\alpha + \beta = 0.95$) in which the GARCH term still dominates, but the ARCH term has slightly more influence on the conditional variance. The degree of autocorrelation depends drastically on the type of the variance process and the absolute value of λ. If the representative investor is risk averse, a higher risk-premium implies a higher degree of positive autocorrelation. Similarly, in case of $\lambda < 0$, a smaller risk-premium induces a higher degree of positive autocorrelation.

[11] Eq. (13) implies that the expected return is related to the conditional variance of the aggregate return, R_{Mt}. In equation (19), the conditional variance of the error term, ε_{Mt}, enters into the conditional mean equation instead. However, it holds that $\mathrm{Var}[R_{Mt}|R_{Mt-1}, R_{Mt-2}\ldots] = \mathrm{Var}[\varepsilon_{Mt}|\varepsilon_{Mt-1}, \varepsilon_{Mt-2}\ldots]$.

[12] Note that $\alpha \geq 0$ (with the rest of the GARCH parameter restrictions) would guarantee positive h_{Mt}, while $\alpha > 0$ is required for β to be identified. If α is allowed to be zero, in theory, ρ_L can be zero even if $\lambda \neq 0$.

While the same is generally true without specifying the variance process and equilibrium model, the GARCH-M example above formally illustrates the importance of taking into consideration the time-varying risk premium(s) that can cause autocorrelation in stock returns. The conditional CAPM itself imposes no restrictions on the conditional second moments, and GARCH models are widely claimed to capture typical features found in financial data (e.g., volatility clustering and heavy tails).[13] A researcher using unadjusted returns could mistakenly interpret autocorrelation as a sign against market efficiency, even if the equilibrium model still holds in practice (see Section 2.3). The hedging component of the ICAPM may command a time-varying risk premium in an exactly similar fashion. Therefore, it is important to control for the additional pricing factors, not only because it may affect the evidence concerning the risk-return trade-off (see Section 2.2), but also if one wants to argue that autocorrelation is not simply a sign of time-varying risk premia.

3.2. Nonsynchronous trading and bid-ask bounce

The equilibrium models in the previous sections assume frictionless markets. Of course, most securities trading does not take place continuously and bid and ask prices of assets can sometimes differ significantly. Nonsynchronous trading (e.g., Lo and MacKinlay, 1990) and bid-ask bounce (e.g., Roll, 1984) can cause autocorrelation in individual security and portfolio returns that arises from market microstructure. Often asset pricing studies (see Nelson, 1991; De Santis and Imrohoroglu, 1997) include a time-invariant autoregressive term along the conditional risk-return trade-off to control for spurious autocorrelation that is neither evidence against market efficiency nor a reflection of time-varying risk premia. In other words, market microstructure can induce autocorrelation in observed returns even if the underlying true price process is a random walk (with or without a drift induced by risk premia).

Campbell et al. (1997) offer a detailed discussion of autocorrelation induced by non-trading and the bid-ask spread. The latter arises as randomly arriving buy and sell orders cause asset prices to bounce between ask and bid prices, thereby inducing autocorrelation in the observed returns. Such autocorrelation is spurious in the sense that it is caused by market microstructure, not by changes in economic value of an asset. Roll (1984) proposes a simple model in which the bid-ask bounce induces negative autocorrelation in security returns.

[13] Specifically, financial markets are not continuously open. New information may arrive when markets are closed, resulting a jump in an asset's price when markets reopen. This discontinuity causes larger negative or positive returns than one would expect if markets were continuously open. The result is a leptokurtic distribution with fat tails and excess peakedness. Volatility clustering, on the other hand, refers to a tendency of large (small) price changes to be followed by large (small) price changes of either sign. This was first noted by Mandelbrot (1963). For a survey on use of GARCH models in applied econometrics, see Engle (2001). For surveys on multivariate GARCH models, see Bauwens et al. (2006) and Silvennoinen and Teräsvirta (2009).

Nonsynchronous trading refers to an effect that arises from the assuming that returns are measurable with an exact equally long frequency. Assume, for example, that stock A is traded less frequently than stock B and we calculate returns using the end-of-day prices. If new information arrives just before the market closes, it may be that this information is incorporated in stock B's end-of-day price but not in A's price, simply because no trades were executed with stock A before the closing of the market. Eventually, stock A's price will respond to the information with a lag, and this causes both spurious cross-autocorrelation between the returns of A and B and spurious negative own-autocorrelation in the returns on stock A. As a rule, nonsynchronous trading induces positive (negative) autocorrelation in portfolio (individual security) returns.

Anderson et al. (2012) argue that the consensus among researchers is that bid-ask bounce unlikely causes significant autocorrelation in returns on well-diversified stock portfolios, while it may induce slightly negative autocorrelation in portfolio returns. Note that there is no bid and ask price for a stock portfolio; its price is an average of prices of assets in the portfolio. Since this study concentrates on the market-level analysis, it is unlikely that bid-ask bounce would be a significant source of autocorrelation. In addition, while infrequent trading of some of the stocks in market indices may result autocorrelation in studied index returns, markets would have to be unrealistically thin if nonsynchronous trading could solely produce the observed autocorrelation patterns (see Lo and MacKinlay, 1990). Boudoukh et al. (1994), however, report that when the underlying assumptions of Lo and MacKinlay (1990) are loosened, nonsynchronous trading can explain a significant fraction of autocorrelation in weekly returns on a small-stock portfolio.

3.3. Partial price adjustment

In addition to time-varying risk premia and market microstructure induced autocorrelation, a common interpretation for autocorrelation is partial price adjustment that implies pricing inefficiency, i.e., asset prices do not fully reflect the information investors possess. In general, if investors under-react to new information, prices fail to reflect their true values after arrival of new information.[14] This implies persistence in returns as prices slowly adjust to their true values. Over-reaction to new information, in contrast, implies mean reversion: prices reverse after first overshooting. Anderson et al. (2012) find that partial price adjustment is a major source of autocorrelation in daily individual stock and portfolio returns in the US stock market.

[14] Market frictions such as transaction costs can induce partial price adjustment. Specifically, as Koutmos (1998) points out, transaction costs may prevent investors to exploit deviations from true asset values until the expected gains outweigh the resulting transaction costs.

Heterogeneous agent models can explain variety of stylized facts in financial data, including several different autocorrelation patterns.[15] In these models, a typical approach is to assume that there are specific types of rational (informed) and limited rational (uninformed) traders in the economy. Llorente et al. (2002) and Boulatov et al. (2012), among others, consider the relation between partial price adjustment and autocorrelation. In their models, informed traders use their information slowly. On the other hand, the feedback-trading model (Shiller, 1984; Sentana and Wadhwani, 1992) suggests that autocorrelation changes with conditional variance in the presence of feedback traders and smart money investors. Feedback traders simply base their demand on past prices, inducing autocorrelation, while smart investors base their demand on risk-return considerations.[16] Campbell et al. (1993) propose a model with market makers and non-informational traders. In their model, an unusual high trading volume is a signal of selling pressures of non-informational traders. Their volume-autocorrelation model suggests that autocorrelation can change with trading volume.

Whatever the exact underlying reason, autocorrelation induced by partial price adjustment implies pricing inefficiency with respect to the stochastic discount factor presentation for expected returns on financial assets (see Section 2.1). It is difficult to modify the general consumption-based model to accommodate partial price adjustment effects without first having detailed information on the investment strategies of various market participants. Heterogeneous agent models offer a solution that allows for a formal explanation of expected returns and autocorrelation as the result of interactions between a few strictly specified investor types. Another approach is to consider the conditions under which the consumption-based model fails and the relevance of autocorrelation induced by partial price adjustment increases, and then augment the consumption-based model to accommodate its empirical failure without specifying the exact investor or type of interaction that causes the failure. The latter approach is illustrated in the next section.

[15] For a survey on heterogeneous agent models in finance, see Hommes (2006).

[16] A negative feedback strategy implies that investors buy (sell) after price declines (increases). In contrast, a positive feedback strategy means that investors buy (sell) after price increases (decreases). Such behavior agrees with portfolio insurers and those using stop-loss orders. As Sentana and Wadhwani (1992) discuss, a portfolio insurance strategy can be perfectly rational behavior under risk aversion that declines with wealth.

4. RISK-RETURN TRADE-OFF AND AUTOCORRELATION

This section introduces an empirical model that allows investigation of whether the relevance of the consumption-based asset pricing model and autocorrelation fluctuates over time. The time-varying relevance of an equilibrium model and autocorrelation in driving returns can be motivated by bounded investor rationality and changes in market conditions. The section ends with a discussion of the model's empirical estimation and practical implications.

4.1. A model with autocorrelation: economic motivation

Essays 1 and 2 investigate the time-varying relevance of the consumption-based model and autocorrelation in explaining expected returns in the following setting. First, the stochastic discount factor is assumed to be linear with wealth and other variables as proxies for aggregate marginal utility growth [see eq. (6)], implying a linear factor model for expected returns.[17] Second, the complete information set is replaced by a subset of information $Z_{t-1} \subset \Omega_{t-1}$ available to an econometrician. A model for N risky assets and the aggregate market is written from the perspective of the econometrician as

$$
\begin{aligned}
&E_{t-1}[r_{1t}] = \mu_1 + \varphi_{t-1}\left(\lambda_{t-1}\mathrm{Cov}_{t-1}[r_{1t}, r_{Mt}] + \sum_{k=1}^{K}\gamma_{kt-1}\mathrm{Cov}_{t-1}[r_{1t}, f_{kt}]\right) + (1-\varphi_{t-1})\rho_1 r_{1t-1} \\
&\quad\vdots \qquad\qquad\qquad\qquad \vdots \\
&E_{t-1}[r_{Nt}] = \mu_N + \varphi_{t-1}\left(\lambda_{t-1}\mathrm{Cov}_{t-1}[r_{Nt}, r_{Mt}] + \sum_{k=1}^{K}\gamma_{kt-1}\mathrm{Cov}_{t-1}[r_{Nt}, f_{kt}]\right) + (1-\varphi_{t-1})\rho_N r_{Nt-1} \\
&E_{t-1}[r_{Mt}] = \mu_M + \varphi_{t-1}\left(\lambda_{t-1}\mathrm{Var}_{t-1}[r_{Mt}] + \sum_{k=1}^{K}\gamma_{kt-1}\mathrm{Cov}_{t-1}[r_{Mt}, f_{kt}]\right) + (1-\varphi_{t-1})\rho_M r_{Mt-1},
\end{aligned}
\tag{22}
$$

where $\varphi_{t-1} \in [0, 1]$ measures the time-varying relative weight of a linear factor model. If an equilibrium model fully explains the expected returns, $\varphi_{t-1} = 1$ and intercepts are zero. If an equilibrium explanation is completely irrelevant, the expected returns follow autoregressive processes of order one. The model allows the econometrician to assess the time-varying relevance of the autoregressive components through φ_{t-1}. In practice, autocorrelation may to some extent reflect market microstructure effects such as nonsynchronous trading and bid-ask spread, but the main motivation is autocorrelation induced by partial price adjustment that potentially is caused by changing market conditions.

[17] As Cochrane (2005) stresses, linear factor models (e.g., CAPM, ICAPM) are special cases of the general consumption-based model. However, a linear consumption-based factor model can be replaced by some other equilibrium model in interest (e.g., by a nonlinear model or a production-based asset pricing model).

An economic explanation for the changing relevance of an equilibrium model and autocorrelation is offered by the adaptive market hypothesis (AMH) of Lo (2004). The AMH builds on bounded investor rationality (Simon, 1955) and evolutionary principles. Lo argues that investors adapt to the constantly changing market environment with satisfactory rather than optimal behavior as predicted by the traditional view with unboundedly rational investors. The satisfactory outcome is reach via heuristics and an evolutionary process. The process of natural selection ultimately determines the number and composition of the market participants and trading strategies at a given time. Under the AMH, prices reflect both information and the prevailing market structure. The AMH implies that the degree of market efficiency is dynamic and dependent on market conditions. Rather than always increasing, it may exhibit trends or cyclical behavior. An important implication of the AMH is that different trading strategies can yield cyclical performance in response to a changing market environment.

Unlike the neoclassical approach, behavioral biases under the AMH are present and their origins are heuristics used to adapt to changing market conditions. The impact of these biases depends on the size of the population with particular biases compared to the size of the competing investor populations with different heuristics. The above model can be interpreted such that when φ_{t-1} is close to one, the typical investor resembles a rational investor who maximizes his or her expected utility. The market is close being in equilibrium, and relatively efficient. Perfect efficiency is unlikely to hold, as Grossman and Stiglitz (1980) show, simply because certain abnormal returns must exist to compensate investors for costs related to gathering and processing information (after these expenses are taken account, returns are not abnormal). In other words, small abnormal returns, ultimately paid by noise traders, are needed to generate market equilibrium.

Similarly, as φ_{t-1} moves toward zero, prices reflect information only partially, inducing autocorrelation as prices slowly adjust to their true values. A high degree of market inefficiency should attract arbitragers to exploit profit opportunities. The traditional view on market efficiency assumes that arbitrage opportunities should disappear almost instantaneously due to the actions of rational investors. Lo (2004), however, points out that history has shown that an aggregate market irrationality can dominate aggregate rationality, even if unsustainable, for certain time periods. This is demonstrated by behavior during certain speculative bubbles, panics, and crashes in financial markets seen over past centuries. Moreover, the complexity of modern financial markets and human interactions make it possible that pricing anomalies do not disappear immediately. Without taking a stand on whether momentum anomalies actually exist, it is sufficient here to note that momentum-type strategies have gained enormous interest among scholars and practioners. According to the classic view on market efficiency, if momentum anomalies are true pricing anomalies, they should disappear upon their discovery. In any case, an extremely low level of φ_{t-1} is unlikely to last as the high degree of inefficiency should attract investors to exploit the arbitrage opportunities.

4.2. Changing market conditions: information flow

Aggregate volatility and trading volume reflect changes in market conditions, and hence, these variables can be used in empirical work to model time variation in $\varphi_{t\text{-}1}$. In this case, the model indirectly agrees with the Shiller-Sentana-Wadhwani feedback-trading model and the model of Campbell et al. (1993), suggesting that autocorrelation can change with volatility or volume, respectively. As these heterogeneous agent models suggest that volume and volatility provide a signal or pricing information, one can adopt a broad view that both variables serve as proxies for information flow (see, e.g., Andersen, 1996). This interpretation agrees with the AMH motivation as changing market conditions are closely linked to type and amount of new information and the ways various market participants process and use information.

The AMH refers to market conditions as a multidimensional and complex construct. In practice, this leaves it up to the researcher to determine which features to focus on in their empirical work. The level of information flow is a natural candidate as a key market condition. It is self-evident that survival of market participants and trading strategies that rely on past prices depend on the level of new information needed to be subsumed in prices. The same applies to investors incapable of processing new pricing information. When the level of new information is high, price fluctuation usually strengthens, breaking historical price patterns. This indicates poor performance for momentum-type strategies and technical analysis. At the same time, investors unable to process information face more severe problems in adjusting their expectations. While occasional information peaks may have little effect on the composition of market participants, longer lasting shifts in the level and types of information can reshape the pool of market participants. Such long term shifts can be driven by such factors as adoption of new technologies that change the pace or scope of information processing, changes in the aggregate economy, and financial bubbles and crises.

While there is no attempt here at specifying the exact mechanism behind the changing relevance of the consumption-based model and autocorrelation, it is useful to consider how things might work. For example, if there is a longer sustained increase in the level of new pricing information, the population of investors and number of trading strategies that rely on past prices may start to decrease as investors better at processing new information exploit profit opportunities move first in adjusting their strategies. At sufficiently low levels of new information, profit opportunities may be relatively modest as the amount of information needed to be processed is low, and hence, may not cause enough misspricing to cover transaction and information gathering costs. This prevents sophisticated investors from eliminating all misspricing through exploiting arbitrage opportunities. Above a certain level of new information, the rate of misspricing may accelerate, implying significant profit opportunities for investors capable of processing information. At this point, the typical investor starts to resemble a rational investor maximizing his or her expected utility.

Assume a market that is close to equilibrium and relatively efficient. At first glance, it seems unlikely that the size of the population with neoclassical-type of heuristics could start to decrease. However, in practice, after a period of sustained success, investors may become overconfident or adopt some other behavioral bias. There might be a change in technology or a financial crisis or bubble that causes changes in the type of new information that a population with different heuristics starts to succeed. The next generation of rational investors may embrace a different view of market efficiency and expected returns. This new group of investors may process and use information more efficiently, and old rational investors may resemble noise traders from their perspective. For example, as discussed in Section 2.3, departures from the random walk hypothesis were long seen as a violation of market efficiency, while the modern view states that returns can be time-varying and predictable. Moreover, ways to process information are constantly changing. For example, rapid algorithm trading could take profits from rational investors who are too slow at processing information. On the other hand, discovery of new pricing anomalies might cause rational investors to change their trading strategies.

All events discussed above can take place more or less simultaneously. The point is that in a highly dynamic investment environment, the degree of market efficiency is likely to be time-varying and exhibit cyclical behavior with changing market conditions. These changes are directly reflected in the type and amount of available pricing information, as well as in the ways market participants process and use information. To illustrate how complex real-life human interactions in financial markets can be, note that momentum-type investors may believe that they are exploiting a pricing anomaly, when in fact autocorrelation in returns can reflect time-varying risk premia as discussed in Section 3.1. In this case, prices can be in equilibrium from the perspective of rational investors, while the behavior of market participants is still drastically different. It is further possible that the behavior of noise traders under certain market conditions is too random for risk-averse investors to be willing or able to exploit all profit opportunities.

4.3. A model with autocorrelation: empirical issues

An empirically testable version of the system of equations (22) can be written as

(23)

$$r_{1t} = \mu_1 + \varphi_{t-1}\left(\lambda_{t-1}\mathrm{Cov}_{t-1}\left[r_{1t}, r_{Mt}\right] + \sum_{k=1}^{K}\gamma_{kt-1}\mathrm{Cov}_{t-1}\left[r_{1t}, f_{kt}\right]\right) + \left(1-\varphi_{t-1}\right)\rho_1 r_{1t-1} + \varepsilon_{1t}$$

$$\begin{array}{ll} \bullet & \bullet \\ \bullet & \bullet \\ \bullet & \bullet \end{array}$$

$$r_{N-1t} = \mu_{N-1} + \varphi_{t-1}\left(\lambda_{t-1}\mathrm{Cov}_{t-1}\left[r_{N-1t}, r_{Mt}\right] + \sum_{k=1}^{K}\gamma_{kt-1}\mathrm{Cov}_{t-1}\left[r_{N-1t}, f_{kt}\right]\right) + \left(1-\varphi_{t-1}\right)\rho_{N-1} r_{N-1t-1} + \varepsilon_{N-1t}$$

$$r_{Mt} = \mu_M + \varphi_{t-1}\left(\lambda_{t-1}\mathrm{Var}_{t-1}\left[r_{Mt}\right] + \sum_{k=1}^{K}\gamma_{kt-1}\mathrm{Cov}_{t-1}\left[r_{Mt}, f_{kt}\right]\right) + \left(1-\varphi_{t-1}\right)\rho_M r_{Mt-1} + \varepsilon_{Mt}.$$

In empirical work, $N-1$ risky assets and the market portfolio can be included in the system of equations to avoid redundancies. If all N risky assets are included, the equation for the market return is a combination of the rest of the equations. While the model could be tested simultaneously for multiple risky assets, the work at hand deals with the aggregate level, and therefore, concentrates on the equation for the aggregate market. By estimating the model for the market portfolio, we essentially test the model for all N assets.

The main motivation here for including the autoregressive terms is autocorrelation induced by partial price adjustment. However, this doctoral thesis does not try to attribute autocorrelation directly to market efficiency in empirical work. While Kim et al. (2011) find support for the AMH and a number of studies suggest market efficiency varies over time (see survey of Lim and Brooks, 2011), autocorrelation may also partly reflect time-varying risk premia. In other words, as discussed in Section 2.3, even if the financial market is efficient, we may obtain significant autocorrelation if our pricing model is incorrect. In addition, the autoregressive coefficients may to some extent reflect microstructure effects such as nonsynchronous trading and bid-ask bounce. It is also worth noting that return predictability using past prices does not necessarily indicate market inefficiency as it may not be economically exploitable due to transaction costs. Therefore, the work at hand concentrates on the empirically testable implication of the model: the relevance of the consumption-based model and autocorrelation may change with market conditions.

The key market condition is assumed to be the level of new information, measured by aggregate volatility and trading volume. Dynamics of φ_{t-1} can be modeled, for example, using a logistic function,

(24) $$\varphi_{t-1} = \frac{1}{1+\exp\left(-\boldsymbol{\beta}'\mathbf{s}_{t-1}\right)},$$

where $\boldsymbol{\beta}$ is a vector of parameters and $\mathbf{s}_{t\text{-}1}$ is a vector of the predetermined variables: volatility and volume. If we use both variables simultaneously and want to analyze individual effects of volume and volatility on the relevance of the consumption-based model and autocorrelation, we must notice that, as Schwert (1989) mentions, three theories predict a positive relation between volatility and volume. First, if market participants hold heterogeneous beliefs, arrival of new information can induce movements in prices and trading volume. Second, if some market participants use price changes as information on which they base their decisions to trade, large price changes will induce large trading volumes. Third, in sufficiently illiquid secondary markets, large trading volume that is mainly either sell or buy orders will induce price movements. Lamoureux and Lastrapes (1990) and Gallant et al. (1992) empirically document a positive relation between volume and volatility.

In the empirical work, the component for K additional factors [modeled as in eq. (16)] is included mainly for control purposes. The conditional covariances between the asset returns and the aggregate market return in (23) can be modeled using a multivariate GARCH-M model. Let $\boldsymbol{\varepsilon}_t$ = $[\varepsilon_{1t},\ldots,\varepsilon_{N\text{-}1t},\varepsilon_{Mt}]'$ be an N x 1 vector of error terms, here assumed to be conditionally normally distributed,

(25) $$\boldsymbol{\varepsilon}_t \left| \mathbf{Z}_{t-1} \sim N\left(\mathbf{0}, \mathbf{H}_t\right)\right..$$

The conditional covariance matrix of the error terms $\mathbf{H}_t = [h_{ijt}]$ can be assumed to follow, for example, the BEKK parameterization of Engle and Kroner (1995),

(26) $$\mathbf{H}_t = \mathbf{C}'\mathbf{C} + \mathbf{A}'\boldsymbol{\varepsilon}_{t-1}\boldsymbol{\varepsilon}'_{t-1}\mathbf{A} + \mathbf{B}'\mathbf{H}_{t-1}\mathbf{B},$$

where $\mathbf{C} = [c_{ij}]$ is an N x N upper triangular matrix, and $\mathbf{A} = [a_{ij}]$ and $\mathbf{B} = [b_{ij}]$ are N x N parameter matrices. The conditional covariances and variance in the system of mean equations are then modeled as $\mathrm{Cov}_{t-1}[r_{it}, r_{Mt}] = h_{iMt}$ and $\mathrm{Var}_{t-1}[r_{Mt}] = h_{MMt}$. The BEKK model guarantees the positive definiteness of $\mathbf{H}_t$ by construction. The covariance-stationary condition for the BEKK model is that the eigenvalues of $\mathbf{A}\otimes\mathbf{A}$ + $\mathbf{B}\otimes\mathbf{B}$ are less than one in modulus (where $\otimes$ denotes the Kronecker product of two matrices). To reduce the number of model parameters, it is common to restrict $\mathbf{A}$ and $\mathbf{B}$ to be diagonal matrices. If $N = 1$, eq. (26) with $c_{11}^2 = \omega$, $a_{11}^2 = \alpha$, and $b_{11}^2 = \beta$ can be interpreted as equal to the univariate GARCH(1,1) parameterization in eq. (19).

The model [eqs. (23) – (26)] can be estimated via maximum likelihood.[18] Let **Θ** be the vector of the parameters of the model, under the assumption of the conditional normality, the log-likelihood function for the model for N assets:

$$\ln L(\boldsymbol{\Theta}) = -\frac{TN}{2}\ln 2\pi - \frac{1}{2}\sum_{t=1}^{T}\ln\left|\mathbf{H}_t\right| - \frac{1}{2}\sum_{t=1}^{T}\boldsymbol{\varepsilon}'_{t-1}\mathbf{H}_t^{-1}\boldsymbol{\varepsilon}_{t-1}. \tag{27}$$

Because financial time series often violate the normality assumption, the standard practice is to estimate the model using the quasi-maximum likelihood (QML) approach proposed by Bollerslev and Wooldridge (1992). When the first two conditional moments are correctly specified, the QML estimator is consistent and statistical inferences can be made using robust standard errors, often referred as Bollerslev-Wooldridge standard errors in the ARCH literature.

The parameterization (26) treats effects of positive and negative shocks on volatility symmetrically. Since asymmetric effects of shocks can be important in asset pricing applications (see, e.g., Bekaert and Wu, 2000), the symmetric BEKK model can be extended to allow asymmetric effects following Kroner and Ng (1998):

$$\mathbf{H}_t = \mathbf{C}'\mathbf{C} + \mathbf{A}'\boldsymbol{\varepsilon}_{t-1}\boldsymbol{\varepsilon}'_{t-1}\mathbf{A} + \mathbf{B}'\mathbf{H}_{t-1}\mathbf{B} + \mathbf{D}'\boldsymbol{\eta}_{t-1}\boldsymbol{\eta}'_{t-1}\mathbf{D}, \tag{28}$$

where **D** is an N x N parameter matrix and $\boldsymbol{\eta}_{t-1}$ is a vector where $\eta_{it-1} = \varepsilon_{it-1}$ if $\varepsilon_{it-1} < 0$ and zero otherwise. Eq. (28) can be seen as a multivariate extension of Glosten et al. (1993). Asymmetric effects are usually related to leverage effects after Black (1976) or the volatility feedback hypothesis (Campbell and Hentschel, 1992).[19] In the former case, a decline in the stock price of a firm decreases (increases) the relative proportion of equity (debt) value to the firm value, making the firm's stock riskier (more leveraged) and, as a result, increasing its volatility. The latter case states that negative (positive) changes in expected returns tend to be intensified (dampened), generating the asymmetric volatility effect. Kroner and Ng (1998) and Bekaert and Wu (2000) discuss these asymmetry explanations in a multivariate context.

The symmetric and asymmetric BEKK models above do not discriminate between large and small shocks. A multivariate GARCH parameterization could be further extended to allow for size effects (see Herwartz and Lütkepohl, 2000). However, in practice, the full model

[18] The positive definiteness of $\mathbf{H}_t$ is important from a statistical perspective ($\mathbf{H}_t$ is a variance-covariance matrix) and from a computational perspective (a negative definite $\mathbf{H}_t$ implies that $|\mathbf{H}_t| < 0$, meaning that $\ln|\mathbf{H}_t|$ will not exist in the log-likelihood function).

[19] The volatility feedback hypothesis implies a positive relation between the conditional mean and variance and a negative relation between realized returns and conditional volatility. Koutmos et al. (2008) argue that the latter can make it difficult to document the conditional risk-return trade-off. In general, as González-Rivera (1996) discuss, it is important to allow a rich parameterization for $\mathbf{H}_t$ as the consistency of the GARCH-in-mean coefficient depends on a well-specified volatility process.

(consisting of a system of mean equations and a GARCH model), especially with time-varying $\varphi_{t\text{-}1}$, will be highly nonlinear, and numerical algorithms are needed to maximize the log-likelihood function.[20] This imposes a limit on a number of assets that can be included simultaneously in the system in addition to the aggregate market, as well as the complexity of GARCH parameterizations that can be considered in empirical work. In addition as the standard GARCH-in-mean term, h_{MMt} could be used simultaneously in the logistic function as a predetermined transition variable. However, this would further increase the nonlinearity of the model, and hence, it is recommended that other proxies for volatility are used instead in eq. (24) to ease the numerical estimation of the model.

As discussed in Section 3.1, asset pricing models such as the conditional CAPM do not in themselves impose restrictions on the dynamics of the conditional second moments. The GARCH parameterizations (26) and (28) are in line with the recommendation of Bollerslev et al. (1988); any correctly specified intertemporal asset-pricing model should notice the heteroscedastic nature of asset returns. An interesting alternative for the GARCH models is the MIDAS approach of Ghysels et al. (2005), who test the ICAPM at the aggregate market level. MIDAS uses high-frequency observations to model low-frequency variables. For example, the weighted average of lagged daily squared returns is used to model expected monthly variance. The MIDAS approach has been used to model conditional covariances in a cross-sectional asset-pricing context by González et al. (2012), who test selected linear factor models in a beta form. A special case of the MIDAS approach is to use a lagged sum of squared daily returns over a month as a (non-parametric) measure of variance (see French et al., 1987; Kim et al., 2011). This approach has been used to model daily variance using intraday returns by Andersen et al. (2001). Similarly, a sum of cross-product of lagged daily returns can be used to model the covariances in eq. (23). In all above cases, parameters of the model can be estimated via maximum likelihood after specifying a distribution for the error terms. For example, the latter case with the non-parametric measures for $\mathrm{Var}_{t-1}[r_{Mt}]$ and $\mathrm{Cov}_{t-1}[r_{it}, r_{Mt}]$ can be estimated assuming constant $\mathbf{H}_t = \mathbf{H}$ by setting $\mathbf{A} = \mathbf{B} = \mathbf{D} = \mathbf{0}$ in (26) and (28) or, alternatively, by allowing GARCH errors.

[20] When estimating nonlinear models, it is important to be aware that the log-likelihood function may contain a number of local maxima. Different initial values for the model parameters may yield different outcomes (see Brooks et al., 2001), so the researcher should try a number of different initial values to ensure the global maxima.

4.4. A model with autocorrelation: practical implications

In addition to allowing modeling the time-varying relevance of an equilibrium pricing model and autocorrelation in driving expected returns, the model has several important implications for practical applications. For example, a linear factor model with local and global pricing factors is commonly estimated in an international setting to investigate whether a particular stock market is integrated with the world capital market (see Carrieri et al., 2007; Chamber and Gibson, 2008). If expected returns in a particular country are driven by different factors than those affecting expected returns on an investor's global portfolio, the country is assumed to be at least partially segmented and offer diversification opportunities. This approach is based on an assumption that an equilibrium model describes expected returns. However, if the relevance of an asset-pricing model in driving expected returns changes with market conditions, diversification opportunities should be measured based on an asset-pricing explanation only when φ_{t-1} is close to one. When the relevance of an asset-pricing model explanation is low, diversification benefits should be analyzed by considering correlation structure between individual asset returns.

Similarly, a common approach to measuring performance of a risky asset or portfolio of assets is to estimate intercepts for realized excess returns using a variant of eq. (23) with φ_{t-1} set to one. If an equilibrium model explains excess returns, the resulting intercepts should be zero. If a particular asset or portfolio has positive (negative) intercept, it has performed better (worse) than expected based on its exposure to pricing factor(s). If the intercept is used to measure the risk-corrected performance of an investment, a pure asset-pricing model will lead to false conclusions if the asset-pricing model explanation for expected returns is irrelevant, i.e., during periods when φ_{t-1} is low. This could have drastic implications, for example, in evaluating the performance of fund managers. It would also be important to consider when analyzing pricing anomalies.

A pricing anomaly is often measured by positive or negative intercepts [obtained using a variant of eq. (23) with φ_{t-1} set to one] of portfolios sorted by certain asset-specific characteristics. It is thus an anomaly with respect to the tested equilibrium model.[21] While this doctoral thesis concentrates on the market-level risk-return relation and autocorrelation in a time-series context, the same framework can be applied to provide insights into cross-sectional questions and a wide range of trading strategies. For example, momentum anomalies (winners beat losers) continue to confound asset-pricing studies (see Jegadeesh and Titman, 1993; 2001). While momentum is a cross-sectional result, it can be related to autocorrelation in returns and cross-autocorrelation among stocks (Lewellen, 2002). The system of equations (23) can be estimated for stock portfolios sorted by past performance to explore whether the relevance of a linear factor model and autocorrelation (and cross-autocorrelation) in driving

[21] For an overview on cross-sectional pricing anomalies, see Fama and French (2008).

returns changes with general market conditions or portfolio-specific features by allowing for asset-specific weights $\varphi_{it\text{-}1}$.

Dynamic weighting of an equilibrium model and autocorrelation can be important for other applications such as derivatives pricing. For example, stock options are usually priced assuming risk-neutral preferences (in which case the expected return on an underlying asset is equal to the risk-free rate) and that stock prices follow a geometric Brownian motion. If stock returns exhibit autocorrelation, standard pricing formulas have to be adjusted (see Jokivuolle, 1998). If the degree of autocorrelation in returns also changes with market conditions, one could potentially identify interesting option trading strategies.

The insight of the model and its practical applicability are likely to be highlighted in emerging stock markets. As Harvey (1995b) mentions, autocorrelation levels observed in emerging stock markets are generally higher than those observed in developed stock markets. Emerging stock markets can be assumed to be less efficient and stable than developed markets. Emerging markets often suffer from such problems as poor corporate governance (Black et al., 2006) and weak investor protections. In these markets, economic and political conditions often change rapidly and unpredictable compared to developed markets. These features support a view that investors in emerging markets must rely more heavily on heuristics in their decision-making than in developed stock markets. Decisions are further based on less quality information and greater opacity than in developed markets. This implies that the relevance of an equilibrium presentation for expected returns and autocorrelation fluctuate more drastically in emerging stock markets than in developed stock markets.

5. RESULTS

This doctoral thesis finds a positive relation between the conditional mean and variance of the aggregate return, as implied by the intertemporal CAPM of Merton (1973). However, the relevance of an intertemporal equilibrium model and autocorrelation in explaining expected aggregate stock returns fluctuates with volatility, especially in developing stock markets. Traditional equilibrium models by themselves appear to be inadequate for providing a rich and full description of expected stock returns. The significant autocorrelation can reflect omitted time-varying risk premia or market microstructure effects such as nonsynchronous trading and bid-ask bounce. A further source of autocorrelation is partial price adjustment, which implies a departure from the standard neoclassical view on equilibrium pricing with unboundedly rational investors and perfect market efficiency.

The changing relevance of an equilibrium model and autocorrelation may reflect interactions between heterogeneous investors. More generally, however, it can be seen as a departure from the neoclassical view toward behavioral explanations for investor behavior. For example, if investors with bounded rationality adapt to constantly changing market conditions with satisfactory (rather than optimal) behavior that is attained through heuristics and evolutionary process, asset prices will reflect both information and the prevailing market ecology. Prices do not necessarily adjust immediately and correctly to arrival of new information, and the degree of market efficiency can be dynamic and exhibit cyclical behavior due to changing market conditions, reflected in variables such as aggregate volatility. Since volatility serves as a proxy for information flow, the empirical results support a view that during low-information (low-volatility) periods, market-wide persistence in returns increases, leading to a failure of the neoclassical view on asset pricing. During high-information (high-volatility) periods, expected returns can be described using rational (intertemporal) investors acting to maximize their expected utility. This offers a plausible explanation as to why detection of a positive risk-return trade-off has been so challenging in earlier studies, while autocorrelation in stock returns has been a robust finding.

While this doctoral thesis finds support for the changing relevance of the risk-return trade-off and autocorrelation, it would be unwise to attribute autocorrelation solely to the degree of market efficiency. Market efficiency is always tested in conjunction with an equilibrium model for expected returns. Autocorrelation can reflect, at least to a minor extent, omitted time-varying risk premia. In addition, there is no attempt here to control the results for the effect of transaction and information gathering costs that could make it difficult to exploit autocorrelation in returns in an economically profitable way. A significant risk-return trade-off, on the other hand, implies that autocorrelation in unadjusted returns is not as such evidence against market efficiency. While many researchers interpret autocorrelation as a departure from the neoclassical doctrine, it can directly reflect the conditional risk-return trade-off. Besides offering an explanation for the mixed evidence concerning the sign of the risk-return trade-off, the results clearly show that it is important to take both the risk-return trade-off and autocorrelation into account in all applications that require estimates for expected returns, especially when operating in emerging stock markets.

In addition to providing a more realistic description of expected stock returns, the changing relevance of an equilibrium model and autocorrelation can influence empirical findings when evaluating diversification opportunities based on equilibrium models. When the relevance of an asset-pricing model explanation for expected returns is low, instead of an equilibrium model, diversification benefits should be evaluated by investigating correlation structures between individual assets. Similarly, a common practice to measure performance of risky assets is to compare their realized returns, corrected for risk using an equilibrium model. This can lead to incorrect conclusions during periods when the relevance of autocorrelation is high, which should be kept in mind when evaluating performance of portfolio managers and trading strategies. Moreover, the time-varying importance of an equilibrium model and autocorrelation can be potentially used to identify several new trading strategies.

The framework of this thesis could be applied to gain new insights on the issues discussed above. Furthermore, while this doctoral thesis concentrates on the market-level analysis in a time-series context, its models could help provide insight on several cross-sectional issues. For example, momentum strategies remain as a puzzling pricing anomaly. Although momentum is a cross-sectional result, it can be caused by return autocorrelation, cross-autocorrelation among stocks, or cross-sectional differences in unconditional means. With few modifications, the model used in Essay 1 and 2 could be estimated for momentum portfolios to explore whether the relevance of an equilibrium model and own- and cross-autocorrelation in driving expected returns changes with market conditions or portfolio-specific features. These questions are left for future research.

REFERENCES

Acharya, V.V., Pedersen, L.H., 2005. Asset pricing with liquidity risk. Journal of Financial Economics 77, 375-410.

Andersen, T.G., 1996. Return volatility and trading volume: An information flow interpretation of stochastic volatility. Journal of Finance 51, 169-204.

Andersen, T.G., Bollerslev, T., Diebold, F.X., Labys, P., 2003. Modeling and forecasting realized volatility. Econometrica 71, 579-625.

Anderson, R.M., 2011. Time-varying risk premia. Journal of Mathematical Economics 47, 253-259.

Anderson, R.M., Eom, K.S., Hahn, S.B., Park, J.-H., 2012. Sources of stock return autocorrelation. Working paper. http://emlab.berkeley.edu/~anderson/Sources-042212.pdf

Baillie, R.T., DeGennaro, R.P., 1990. Stock returns and volatility. Journal of Financial and Quantitative Analysis 25, 203-214.

Barberis, N., Thaler, R., 2003. A survey of behavioral finance. In Constantinides, G., Harris, M., Stulz, R. (eds.), Handbook of the Economics of Finance, Amsterdam: Elsevier North Holland.

Bauwens, L., Laurent, S., Rombouts, J.V.K., 2006. Multivariate GARCH models: A survey. Journal of Applied Econometrics 21, 79-109.

Bekaert, G., Wu, G., 2000. Asymmetric volatility and risk in equity markets. Review of Financial Studies 13, 1-42.

Bekaert, G., Harvey, C.R., Lundblad, C., 2007. Liquidity and expected returns: Lessons from emerging markets. Review of Financial Studies 17, 1783-1831.

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

Black, F., 1976. Studies of stock price volatility changes. Proceedings of the 1976 Meetings of the American Statistical Association, Business and Economics Section, 177-181.

Black, B.S., Love, I., Rachinsky, A., 2006. Corporate governance indices and firms' market values: Time series evidence from Russia. Emerging Markets Review 7, 361-379.

Bohl, M.T., Siklos, P.L., 2008. Empirical evidence on feedback trading in mature and emerging stock markets. Applied Financial Economics 18, 1379-1389.

Bollerslev, T., Engle, R.F., Wooldridge, J.M., 1988. A capital asset pricing model with time-varying covariances. Journal of Political Economy 96, 116-131.

Bollerslev, T., Wooldridge, J., 1992. Quasi-maximum likelihood estimation and inference in dynamic models with time-varying covariances. Econometric Reviews 11, 143-172.

Boudoukh, J., Richardson, M.P., Whitelaw, R.F., 1994. A tale of three schools: Insights on autocorrelations of short-horizon stock returns. Review of Financial Studies 7, 539-573.

Boulatov, A., Hendershott, T., Livdan, D., 2012. Informed trading and portfolio returns. Review of Economic Studies, forthcoming.

Brandt, M.W., Wang, L., 2010. Measuring the time-varying risk-return relation from the cross-section of equity returns. Working Paper, Duke University.

Brennan, M. J., 1970. Taxes, market valuation and financial policy. National Tax Journal 23, 417-429.

Brooks, C., Burke, S.P., Persand, G., 2001. Benchmarks and the accuracy of GARCH model estimation. International Journal of Forecasting 17, 45-56.

Camacho, M., 2004. Vector smooth transition regression models for US GDP and the composite index of leading indicators. Journal of Forecasting 23, 173-196.

Campbell, J.Y., 1987. Stock returns and the term structure. Journal of Financial Economics 18, 373-399.

Campbell, J.Y., Grossman, S.J., Wang, J., 1993. Trading volume and serial correlation in stock returns. Quarterly Journal of Economics 108, 905-939.

Campbell, J.Y., Hentschel, L., 1992. No news is good news: an asymmetric model of changing volatility in stock returns. Journal of Financial Economics 31, 281-318.

Campbell, J.Y, Lo, A.W., MacKinlay, A.C., 1997. The Econometrics of Financial Markets. Princeton University Press, Princeton.

Carrieri, F., Errunza, V., Hogan, K., 2007. Characterizing world market integration through time. Journal of Financial and Quantitative Analysis 42, 915-940.

Chambet, A., Gibson, R., 2008. Financial integration, economic instability, and trade structure in emerging markets. Journal of International Money and Finance 27, 654-675.

Chan, K., 1993. Imperfect information and cross-autocorrelation among stock prices. Journal of Finance 48, 1211-1230.

Chen, C.R., Su, Y., Huang, Y., 2008. Hourly index return autocorrelation and conditional volatility in an EAR-GJR-GARCH model with generalized error distribution. Journal of Empirical Finance 15, 789-798.

Chordia, T., Swaminathan, B., 2000. Trading volume and cross-autocorrelations in stock returns. Journal of Finance 55, 913-936.

Cochrane, J., 2005. Asset Pricing (revised edition). Princeton University Press, Princeton.

De Santis, G., Gerard, B., 1997. International asset pricing and portfolio diversification with time-varying risk. Journal of Finance 52, 1881-1912.

De Santis, G., Imrohoroglu, S., 1997. Stock returns and volatility in emerging financial markets. Journal of International Money and Finance 16, 561-579.

De Santis, G., Gerard, B., 1998. How big is the premium for currency risk? Journal of Financial Economics 49, 375-412.

De Santis, G., Gerard, B, Hillion, P., 2003. The relevance of currency risk in the EMU. Journal of Economics and Business 55, 427-462.

Dumas, B., Solnik, B., 1995. The world price of foreign exchange risk. Journal of Finance 50, 445-479.

Engle, R.F., 2001. GARCH 101: The use of ARCH/GARCH models in applied econometrics. Journal of Economic Perspectives 15, 157-168.

Engle, R.F., Kroner, K.F., 1995. Multivariate simultaneous generalized ARCH. Econometric Theory 11, 122-150.

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

Fama, E.F., 1970. Efficient capital markets: a review of theory and empirical work. Journal of Finance 25, 383-417.

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, 1653-1678.

French, K.R., Schwert, W., Stambaugh, R.F., 1987. Expected stock returns and volatility. Journal of Financial Economics 19, 3-29.

Gallant, A.R., Rossi, P.E., Tauchen, G., 1992. Stock prices and volume. Review of Financial Studies 5, 199-242.

Gerard, B., Thanyalakpark, K., Batten, J.A., 2003. Are the East Asian markets integrated? Evidence from the ICAPM. Journal of Economics and Business 55, 585-607.

Gerard, B., Wu, G., 2006. How important is intertemporal risk for asset allocation? Journal of Business 79, 2203-2241.

Ghysels, E., Santa-Clara, P., Valkanov, R., 2005. There is a risk-return trade-off after all. Journal of Financial Economics 76, 509-548.

Glosten, L.R., Jagannathan, R., Runkle, D.E., 1993. On the relation between the expected value and the volatility of the nominal excess return on stocks. Journal of Finance 48, 1779-1801.

González-Rivera, G., 1996. Time-varying risk The case of the American computer industry. Journal of Empirical Finance 2, 333-342.

González, M., Nave, J., Rubio, G., 2012. The cross section of expected returns with MIDAS betas. Journal of Financial and Quantitative Analysis 47, 115-135.

Goriaev, A., Zabotkin, A., 2006. Risks of investing in the Russian stock market: Lessons of the first decade. Emerging Markets Review 7, 380-397.

Grossman, S., Stiglitz, J., 1980. On the impossibility of informationally efficient markets. American Economic Review 70, 393-408.

Guo, H., Whitelaw, R.F., 2006. Uncovering the risk-return relation in the stock market. Journal of Finance 61, 1433–1463.

Harvey, C.R., 1989. Time-varying conditional covariances in tests of asset pricing models. Journal of Financial Economics 24, 289-317.

Harvey, C.R., 1991. The world price of covariance risk. Journal of Finance 46, 111-157.

Harvey, C. R., 1995a. Predictable risk and returns in emerging markets. Review of Financial Studies 8, 773-816.

Harvey, C.R., 1995b. The cross-section of volatility and autocorrelation in emerging markets. Finanzmarkt und Portfolio Management 9, 12-34.

He, C., Teräsvirta, T., González, A., 2009. Testing parameter constancy in stationary vector autoregressive models against continuous change. Econometric Reviews 28, 224-245.

Herwartz, H., Lütkepohl, H., 2000. Multivariate volatility analysis of VW stock prices. International Journal of Intelligent Systems in Accounting, Finance and Management 3, 35-54.

Hommes, C.H., 2006. Heterogeneous agent models in economics and finance. In Tesfatsion, L., Judd K.L., (eds.), Handbook of Computational Economics. Volume 2: Agent-Based Computational Economics, Elsevier Science B.V., chapter 23.

Hong, E.P., 1991. The autocorrelation structure for the GARCH-M process. Economics Letters 37, 129-132.

Hou, K., 2007. Industry information diffusion and the lead-lag effect in stock returns. Review of Financial Studies 20, 1113-1138.

Ito, M., Sugiyama, S., 2009. Measuring the degree of time varying market inefficiency. Economics Letters 103, 62-64.

Jegadeesh, N., Titman, S., 1993. Returns to buying winners and selling losers: Implications for market efficiency. Journal of Finance 48, 64-91.

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

Jensen, M.C., 1969. Risk, the pricing of capital assets, and the valuation of investment portfolios. Journal of Business 42, 167-247.

Jokivuolle, E., 1998. Pricing European options on autocorrelated indexes. Journal of Derivatives 6, 39-52.

Kim, J.H., Shamsuddin, A., Kian-Ping, L., 2011. Stock return predictability and the adaptive markets hypothesis: Evidence from century-long U.S. data. Journal of Empirical Finance 18, 868-879.

Koutmos, G., 1997. Feedback trading and the autocorrelation pattern of stock returns: Further empirical evidence. Journal of International Money and Finance 16, 625-636.

Koutmos, G., 1998. Asymmetries in the conditional mean and the conditional Variance: evidence from nine stock markets. Journal of Economics and Business 50, 277-290.

Koutmos, G., Knif, J., Philippatos, G., 2008. Modeling common volatility characteristics and dynamic risk premia in European equity markets. The Quarterly Review of Economics and Finance 48, 567-578.

Kroner, K.F., Ng, V.K., 1998. Modeling asymmetric comovements of asset returns. Review of Financial Studies 11, 817-844.

Lamoureux, C.G., Lastrapes, W.D., 1991. Heteroskedasticity in stock return data: Volume versus GARCH effects. Journal of Finance 45, 221-229.

Lanne, M., Saikkonen, P., 2006. Why it is so difficult to uncover the risk-return tradeoff in stock returns? Economic Letters 92, 118-125.

LeBaron, B., 1992. Some relations between volatility and serial correlation in stock market returns. Journal of Business 65, 199-219.

LeRoy, S., 1973. Risk aversion and the martingale property of stock returns. International Economic Review 14, 436-446.

Levy, H., 1978. Equilibrium in an imperfect market: A constraint on the number of securities in the portfolio. American Economic Review 68, 643-658.

Lewellen, J., 2002. Momentum and autocorrelation in stock returns. Review of Financial Studies 15, 553-563.

Lim, K.P., Brooks, R.D., 2011. The evolution of stock market efficiency over time: A survey of the empirical literature. Journal of Economic Surveys 25, 69-108.

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

Llorente, G., Michaely, R., Saar, G., Wang, J., 2002. Dynamic volume-return relation of individual stocks. Review of Financial Studies 15, 1005-1047.

Lo, A.W., 2004. The adaptive markets hypothesis: market efficiency from an evolutionary perspective. Journal of Portfolio Management 30, 15-29.

Lo, A.W., MacKinlay, A.C., 1990. An econometric analysis of nonsynchronous trading. Journal of Econometrics 45, 181-211.

Lucas, R., 1978. Asset prices in an exchange economy. Econometrica 46, 1429-1446.

Mandelbrot, B., 1963. The variation of certain speculative prices. Journal of Business 36, 394-419.

Mankiw, N.G., Zeldes, S., 1991. The consumption of stockholders and non-stockholders. Journal of Financial Economics 29, 97-112.

Markowitz, H., 1952. Portfolio selection. Journal of Finance 7, 77-91.

Mayers, D., 1972. Nonmarketable assets and capital market equilibrium under uncertainty. In M. Jensen (ed.), Studies in the Theory of Capital Markets, New York: Praeger, 223-248.

McKenzie, M.D., Faff, R.W., 2003. The determinants of conditional autocorrelation in stock returns. Journal of Financial Research 26, 259-274.

Merton, R.C., 1973. An intertemporal capital asset pricing model. Econometrica 41, 867-887.

Merton, R.C., 1980. On estimating the expected return on the market: An exploratory investigation. Journal of Financial Economics 8, 323-361.

Merton, R.C., 1987. A simple model of capital market equilibrium with incomplete information. Journal of Finance 42, 483-510.

Nelson, D.B., 1991. Conditional heteroskedasticity in asset returns: A new approach. Econometrica 59, 347-370.

Nyberg, H., 2012. Risk-return tradeoff in U.S. stock returns over the business cycle. Journal of Financial and Quantitative Analysis 47, 137-158.

Pastor, L, Meenakshi, S., Swaminathan, B., 2008. Estimating the intertemporal risk-return tradeoff using the implied cost of capital. Journal of Finance 63, 2859-2897.

Roll, R., 1984. A simple implicit measure of the effective bid-ask spread in an efficient market. Journal of Finance 39, 1127-1140.

Roll, R., Pukthuanthong, K., 2009. Global market integration: An alternative measure and its application. Journal of Financial Economics 94, 214-232.

Rothman, P., van Dijk, D., Franses, P.H., 2001. A multivariate STAR analysis of the relationship between money and output. Macroeconomic Dynamics 5, 506-532.

Ross, S.A., 1976. The Arbitrage Theory of Capital Asset Pricing. Journal of Economic Theory 13, 341-360.

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

Samuelson, P., 1965. Proof that properly anticipated prices fluctuate randomly. Industrial Management Review 6, 41-49.

Schwert, G.W., 1989. Why does stock volatility change over time? Journal of Finance 44, 1115-1153.

Sentana, E., Wadhwani, S., 1992. Feedback traders and stock return autocorrelations: Evidence from a century of daily data. Economic Journal 102, 415-425.

Scruggs, J.T., 1998. Resolving the puzzling intertemporal relation between the market risk premium and conditional market variance: A two-factor approach. Journal of Finance 53, 575-603.

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

Shiller, R.J., 1984. Stock prices and social dynamics. Brookings Papers on Economic Activity 2, 457-498.

Shiller, R.J., 2006. Tools for financial innovation: Neoclassical versus behavioral finance. Financial Review 41, 1-8.

Simon, H.A., 1955. A behavioral model of rational choice. Quarterly Journal of Economics 69, 99-118.

Silvennoinen, A., Teräsvirta, T., 2009. Multivariate GARCH models. In Andersen, T.G., Davis, R.A., Kreiß, J-P., Mikosch, J-P. (eds.) , Handbook of Financial Time Series, Springer, New York, 201-229.

Solnik, B., 1974. An equilibrium model of the international capital market. Journal of Economic Theory 8, 500-524.

Stulz, R.M., 1981. A model of international asset pricing. Journal of Financial Economics 9, 383-406.

PART B: ARTICLES

ACTA UNIVERSITATIS LAPPEENRANTAENSIS

510. RYYNÄNEN, HARRI. From network pictures to network insight in solution business – the role of internal communication. 2013. Diss.

511. JÄRVI, KATI. Ecosystem architecture design: endogenous and exogenous structural properties. 2013. Diss.

512. PIILI, HEIDI. Characterisation of laser beam and paper material interaction. 2013. Diss.

513. MONTO, SARI. Towards inter-organizational working capital management. 2013. Diss.

514. PIRINEN, MARKKU. The effects of welding heat input usability of high strength steels in welded structures. 2013. Diss.

515. SARKKINEN, MINNA. Strategic innovation management based on three dimensions diagnosing innovation development needs in a peripheral region. 2013. Diss.

516. MAGLYAS, ANDREY. Overcoming the complexity of software product management. 2013. Diss.

517. MOISIO, SAMI. A soft contact collision method for real-time simulation of triangularized geometries in multibody dynamics. 2013. Diss.

518. IMMONEN, PAULA. Energy efficiency of a diesel-electric mobile working machine. 2013. Diss.

519. ELORANTA, LEENA. Innovation in a non-formal adult education organisation – multi-case study in four education centres. 2013. Diss.

520. ZAKHARCHUK, IVAN. Manifestation of the pairing symmetry in the vortex core structure in iron-based superconductors. 2013. Diss.

521. KÄÄRIÄINEN, MARJA-LEENA. Atomic layer deposited titanium and zinc oxides; structure and doping effects on their photoactivity, photocatalytic activity and bioactivity. 2013. Diss.

522. KURONEN, JUHANI. Jatkuvan äänitehojakautuman algoritmi pitkien käytävien äänikenttien mallintamiseen. 2013. Diss.

523. HÄMÄLÄINEN, HENRY. Identification of some additional loss components in high-power low-voltage permanent magnet generators. 2013. Diss.

524. SÄRKKÄ, HEIKKI. Electro-oxidation treatment of pulp and paper mill circulating waters and wastewaters. 2013. Diss.

525. HEIKKINEN, JANI. Virtual technology and haptic interface solutions for design and control of mobile working machines. 2013. Diss.

526. SOININEN, JUHA. Entrepreneurial orientation in small and medium-sized enterprises during economic crisis. 2013. Diss.

527. JÄPPINEN, EERO. The effects of location, feedstock availability, and supply-chain logistics on the greenhouse gas emissions of forest-biomass energy utilization in Finland. 2013. Diss.

528. SÖDERHOLM, KRISTIINA. Licensing model development for small modular reactors (SMRs) – focusing on the Finnish regulatory framework. 2013. Diss.

529. LAISI, MILLA. Deregulation's impact on the railway freight transport sector's future in the Baltic Sea region. 2013. Diss.

530. VORONIN, SERGEY. Price spike forecasting in a competitive day-ahead energy market. 2013. Diss.

531. PONOMAREV, PAVEL. Tooth-coil permanent magnet synchronous machine design for special applications. 2013. Diss.

532. HIETANEN, TOMI. Magnesium hydroxide-based peroxide bleaching of high-brightness mechanical pulps. 2013. Diss.

533. TYKKÄLÄ, TOMMI M. Real-time image-based RGB-D camera motion tracking and environment mapping. 2013. Diss.

534. PEKKOLA, SANNA. Performance measurement and management in a collaborative network. 2013. Diss.

535. PANOREL, IRIS CHERRY. Pulsed corona discharge as an advanced oxidation process for the degradation of organic compounds in water. 2013. Diss.

536. TORKKELI, LASSE. The influence of network competence of internationalization of SMEs. 2013. Diss.

537. MOLANDER, SOLE. Productivity and services – safety telephone services for the elderly. 2013. Diss.

538. SITARZ, ROBERT. Identification of research trends in the field of separation processes. Application of epidemiological model, citation analysis, text mining, and technical analysis of the financial markets. 2013. Diss.

539. KATTEDEN, KAMIEV. Design and testing of an armature-reaction-compensated permanent magnet synchronous generator for island operation. 2013. Diss.

540. HÄMÄLÄINEN, HARRI. Integration of learning supportive applications to development of e-portfolio construction process. 2013. Diss.

541. RATCHANANUSORN, WARIN. Development of a process for the direct synthesis of hydrogen peroxide in a novel microstructured reactor. 2013. Diss.

542. PERFILEV, DANIIL. Methodology for wind turbine blade geometry optimization. 2013. Diss.

543. STROKINA, NATALIYA. Machine vision methods for process measurements in pulping. 2013. Diss.

544. MARTTONEN, SALLA. Modelling flexible asset management in industrial maintenance companies and networks. 2013. Diss.

545. HAKKARAINEN, JANNE. On state and parameter estimation in chaotic systems. 2013. Diss.

546. HYYPIÄ, MIRVA. Roles of leadership in complex environments
Enhancing knowledge flows in organisational constellations through practice-based innovation processes. 2013. Diss.

547. HAAKANA, JUHA. Impact of reliability of supply on long-term development approaches to electricity distribution networks. 2013. Diss.

548. TUOMINEN, TERHI. Accumulation of financial and social capital as means to achieve a sustained competitive advantage of consumer co-operatives. 2013. Diss.

549. VOLCHEK, DARIA. Internationalization of small and medium-sized enterprises and impact of institutions on international entrepreneurship in emerging economies: the case of Russia. 2013. Diss.

550. PEKKARINEN, OLLI. Industrial solution business – transition from product to solution offering. 2013. Diss.