Essays on asset allocation and diversification

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Essays on Asset Allocation and Diversification

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Est modus in rebus, sunt certi denique fines, quos ultra citraque nequit consistere rectum.
Horace

I honestly admit that I have never read a Ph.D. thesis before starting to write my own. Therefore I recall well that, as the first copies of graduating colleagues' theses were delivered to my pigeon-hole, I was bemused by the elaborate acknowledgement sections they contained. Having embarked rather light-heartedly on this voyage by hastily sending a research proposal from an antiquated PC in a Parisian Internet cafe, I was not quite aware that it would require 'enduring support' or involve 'profound gratitude', to name just two recurrent phrases.

Six years later I have a better understanding of these words. While many scholars have come up with appealing metaphors for their pursuits, the one that comes to my mind actually has a military background. In his treatise *On War* the Prussian general von Clausewitz writes: *'Der Krieg ist das Gebiet der Ungewißheit: drei Vierteile derjenigen Dinge, worauf das Handeln im Krieg gebaut wird, liegen im Nebel einer mehr oder weniger großen Ungewißheit.'* I think something similar holds for writing a thesis, three quarters being a somewhat conservative estimate. And even for those accustomed to murky lowlands weather, a lengthy trip through the fog may put some strain on body and mind.

Let me first, then, thank those who were my pilots through the mist. I am grateful to Robert Lensink for his gentle guidance, especially at times when I had gone quite far astray from the road to successful completion. Robert also made sure that my preoccupation with statistical methods did not fully eclipse the economic interpretation of their results.

I thank Laura Spierdijk for her thorough involvement, and in particular for the efforts she put into the second chapter of this thesis. Each time I left her office, I felt I had not only learned something about economic modelling, but also had gained confidence as to my ideas and the enthusiasm required to carry them out.

I am also very much indebted to the members of the reading committee for

studying the manuscript. I received many comments valuable both from the perspective of conceptual clarification and general readability. I would also like to thank -without implicating- Jan Jacobs, Siep Kroonenberg and Sascha de Haan for their help in improving the layout of this thesis. For the latter purpose, the thesis package created by Ward Romp was also very helpful.

To compensate for the somewhat greyish landscapes sketched above, I must say that I was fortunate to share my university office with bright and colourful individuals. Already in the first week together with Rients Galema, some colleagues came by to jokingly complain about the loud bursts of laughter emanating from our office. We managed to keep this spirit up, fuelling it by occasional, yet not uneventful, dashes into the Groningen nightlife. I also very much enjoyed the company of Jacob Bosma, especially his enthusiasm for sharing research ideas and discussing philosophical issues. These discussions would typically reach their zenith only after Bernard Boonstra joined in, which is hereby duly noted.

The regular three 'o clock meetings at the coffee machine, with Lammertjan Dam, Peter Dijkstra, Remco van Eijkel, Pim Heijnen, Allard van der Made, Aljar Meesters, Bastiaan Overvest and Eelco Zandberg were not only a pleasant distraction, but a valuable opportunity to learn first-hand about the vicissitudes of academic research.

Although the University of Groningen provided me with spacious offices all along, a substantial part of this thesis has been written in a small annex at my parents' home, counting less than five square metres. It was in this refuge that I could work in complete tranquillity. Once I obtain my coveted VINEX house, I will ensure to construct one on top of it.

While my Ph.D. journey was quite demanding in terms of time, I'm glad that I was able to reserve some of it to join a number of other, more epic, trips over the last couple of years. Diederik, Kris, Jamie, Jasper en Vincent, here's to another decade of 'pilgrimages'!

I am also thankful to Karin for being a very understanding housemate, even if our housing conditions were initially suboptimal. Sincere thanks go out to Wybren and Roman, for being great friends I can always rely on.

To those I love most I would just like to say, wishing, in the end, to avoid the superfluous 'profound gratitude' and 'enduring support', that I realize this thesis took its toll. I promise not to write any again.

Tomasz Katzur

Contents

Chapter 1

Introduction

The concept of diversification is firmly embedded in the field of investment theory by the seminal work of Markowitz (1952, 1959). In spite of its conceptual appeal, the translation of his portfolio theory into practical investment decisions has proved to be a challenging task. This has sparked an academic debate that continues even sixty years after Markowitz' first paper was published.

This debate has developed along three main lines. The first line of research addresses the issue of parameter estimation. Markowitz himself recognized that the implementation of his mean-variance approach would require procedures that '[...] combine statistical techniques and the judgement of practical men' (see Markowitz (1952), p. 91). Subsequent empirical research has demonstrated that the use of sample estimates of expected returns and covariances leads to extreme portfolio weights, that fluctuate considerably over time. Consequently a wide range of methods has been brought to bear on the portfolio selection problem. Bayesian shrinkage approaches have been proposed to mitigate the error in estimating expected returns (Jorion (1986), Pástor and Stambaugh (2000)). MacKinlay and Pástor (2000) developed a factor model of returns that implies moment restrictions that allow for more precise estimation of expected returns and covariances. Kan and Zhou (2007) and Garlappi et al. (2007) have worked out the idea of diversifying away estimation risk alongside with investment risk. However, DeMiguel et al. (2009) show that, in spite of these methodological advances, the simple allocation rule that prescribes an equal allocation of wealth over all available assets remains very hard to outperform.

The second line of research seeks to extend the static mean-variance optimization approach to a dynamic, intertemporal setting, allowing for differences in optimal portfolio choice between short-term and long-term investors. Here the main focus is on modelling and quantifying the diversification properties of asset classes across time horizons. The theoretical foundations of this approach have been laid in the late 1960s and early 1970s (Merton (1969, 1973)). However, due to difficulties in solving Merton's intertemporal model, the empirical link with long-term asset allocation decisions has been forged much more recently, as more powerful numerical methods and approximate solutions have become available (see e.g., Campbell and Viceira (2002) for an overview). This literature has provided an empirical foundation for differences between short-term and long-term portfolio choice using the statistical phenomena of return predictability (e.g., Barberis (2000)), mean reversion (e.g., Brennan et al. (1997)) and regime switching (e.g., Guidolin and Timmermann (2005)). The debate about these empirical phenomena is far from settled, however (Goyal and Welch (2008)). Moreover, little attention has been devoted to financial return data outside the United States.

The third line of research focuses on the diversification benefits that can be derived from adding a specific asset, or asset class, to the investment opportunity set. There is a particularly long tradition of studying international portfolio diversification (Levy and Sarnat (1970), French and Poterba (1991), Ang and Bekaert (2002), De Roon et al. (2001)). Likewise attention has been devoted to the diversifying potential of 'alternative' asset classes like real estate, commodities and hedge funds (Hoevenaars et al. (2008)), microfinance (Galema et al. (2011)) or timberland investments (Scholtens and Spierdijk (2010)).

This thesis consists of a collection of papers that contribute to these three strands of literature on asset allocation and diversification. Rather than working out a common theme we have chosen to explore various topics that can be tackled using the tools developed in the field of modern portfolio theory. The methodological diversity of the field has allowed us to venture from studying the inflation exposure of U.S. stocks (Chapter 2), through the determinants of government bond demand in India (Chapter 3), all the way to optimal group lending contracts in microfinance (Chapter 6). From a statistical point of view we have studied asset allocation decisions using both a frequentist approach (chapters 3 and 4) and the Bayesian perspective (chapters 2 and 5). This variety notwithstanding, the larger part of this thesis is devoted to the study of asset allocation decisions in an emerging market context (Chapters 3-5). This is motivated by the observation that, while contractual savings in these markets are growing rapidly, there is but little research on long-term portfolio choice that takes into account the characteristics of asset returns in these markets. In the remainder of this introduction we will provide a brief outline of our contributions.

Chapter 2: New perspectives on stock returns and inflation risk.

One of the main concerns for long-term investors is inflation risk. Long-term investors prefer to invest in assets that provide some protection against an increase in the general price level – especially pension funds, whose liabilities usually rise with inflation. Inflation-hedging entails identifying asset classes that offset fluctuations in long-term real liabilities and thus boils down to a way of diversification.

The relationship between asset returns and inflation levels has been studied extensively in the finance literature, starting in the early 1970s when the U.S. inflation rate rose in the aftermath of the Oil Crisis. At the time, investors sought to diversify away the inflation risk embedded in their nominal bond holdings by allocating a larger proportion of their wealth to asset classes less affected by the inflation rate increase. Stocks were commonly thought to be suitable 'inflation hedges' as, contrary to bonds, they represent claims on real assets. This suggests that stock returns should not be affected by inflation rate fluctuations. On the other hand there are reasons to believe that inflation rates negatively affect stock returns due to e.g., money illusion (Modigliani and Cohn (1979)) or informational frictions (Barnes et al. (1999)). The competing hypotheses have been put to the test in several empirical studies (e.g., Fama and Schwert (1977), Barnes et al. (1999), Bekaert and Wang (2010)), with mixed results. Statistically significant relationships proved to be hard to establish due to the high volatility of stock returns as compared to inflation rate fluctuations.

In our contribution we apply both parameter estimation techniques and investment horizon analysis methods developed in the portfolio selection literature (Barberis (2000)) to offer a new perspective on the relationship between stock returns and inflation. We adopt an approach that differs in two ways from previous literature on this topic. First, we propose to study the link between stock returns and inflation from the perspective of long-term inflation exposure rather than inflation hedging. This is motivated by the fact that, as the availability of inflation-linked instruments increases, investors are less likely to use stocks as inflation hedges and may rather be concerned about the long-run impact of inflation risk on their stock portfolio. Second, in view of the statistical difficulties mentioned above, we consider economic measures of the impact of inflation on stock returns. Our results suggest that, in spite of the fact that the impact of inflation on stock returns cannot be measured precisely, a long-horizon investor who disregards this relationship may suffer an annual certainty-equivalent loss of several percentage points, even in an environment where inflation is stable.

Chapters 3-5: Case studies on asset allocation in emerging markets

Background

The growth of contractual savings is arguably one of the most important developments in the financial landscape worldwide. A relatively new phenomenon is the growth of such savings in economies that are classified in the World Bank's 'middle income' category. While in these economies the joint assets of pension funds, insurance firms and mutual funds amounted to but a small fraction of Gross Domestic Product at the beginning of the nineties, their volume has increased substantially over the last two decades. This development can be attributed to several factors. Macroeconomic conditions conducive to long-term saving are increasingly being realized. Income levels in major developing countries are rising to a level that justifies interest for pension and insurance products. In the first decade of the twenty-first century numerous countries, most notably in Latin America, have successfully stabilized inflation. The financial markets in South-east Asia have made a credible recovery from the 1997 crisis. On the institutional level, pension system reforms have played an important role. Traditional public defined-benefit funds that increasingly failed to deliver on their social objectives have been replaced or supplemented by funded systems in many middle income economies.

Pension funding and asset allocation

In the design of a funded pension system, the regulation of institutional investors' asset allocation decisions plays a key role. Reformers have traditionally faced a trade-off between stimulating the development of local capital markets and ensuring adequate financial performance and risk diversification (Roldos (2004)). In the early stages of pension reform, regulation typically involves strict quantitative investment limits on domestic equity and foreign assets, restricting the allocation of institutional investors to domestic bonds.

Although clearly suboptimal from the point of view of diversification, this strategy is endorsed for a number of reasons (cf. Srinivas et al. (2000), Chan-Lau (2005), Holzmann and Hinz (2005)). Regarding risk management, it is believed to counter the relative inexperience of fund managers at the early stage of the reform process.

It offers safeguards against early failures stemming from performance-hunting and excessive risk-taking in local markets that lack liquidity and transparency. This is especially important as pension benefits are often guaranteed by the government to foster confidence in reform. From the perspective of capital market development, channelling assets into the government bond market can be justified by the fact that these markets serve as a benchmark for pricing other securities like corporate bonds. Stimulating a liquid government bond market is considered to be a prerequisite for the development of other markets.

The literature on pension fund design agrees, however, that easing quantitative restrictions on domestic equity and foreign investments is a necessary step once the assets under management by domestic pension funds rise beyond a certain threshold and a basic bond market infrastructure is in place. Davis (2002) provides a general overview of the drawbacks of quantitative investment limits. From the perspective of portfolio management, such limits distort managers' decisions, as they base their decisions on compliance to legal restrictions rather than achieving an optimal risk-return trade-off. For example, managers' allocations to risky assets under quantitative restrictions tend to be well below the limits, in order not to breach them when asset prices rise. Moreover, due to their inflexibility, quantitative limits reduce the possibility to react to business cycle fluctuations or structural changes in asset supply. At the level of the economy as a whole quantitative limits may induce an inefficient allocation of capital and hamper economic growth.

Roldos (2004) argues in favour of loosening restrictions on equity and foreign investments from the point of view of supply and demand distortions in local asset markets. He claims that, although the transition to a funded system has contributed significantly to the development of local markets, the assets under management by pension funds have outpaced domestic asset issuance in many cases. This entails the risk of price bubbles and liquidity problems, as funds command large shares of the markets they operate in (Srinivas et al. (2000)).

Overallocation to domestic debt has also been criticized from the perspective of long-term investors, or pension plan participants (Viceira (2010)). While bonds appear safe in the short run, their risk profile in the long run may be very different due to accruing inflation risk. Likewise, short-term debt instruments need to be reinvested at uncertain future interest rates.

Portfolio choice in emerging markets

As the consensus in the literature appears to be that institutional investors in emerging markets should be given more freedom in deciding on their optimal portfolio mix, or even move towards the self-regulatory 'prudent man rule' (Roldos (2004)), it is surprising that very little is known about portfolio choice from an emerging market perspective. Over the last twenty years important advances have been made in the study of long-term asset allocation decisions. In seminal contributions, Brennan et al. (1997) and Campbell and Viceira (1999,2001,2002) highlighted the differences between short-term investors and long-term investors by modelling the time series of returns on cash, bonds, and stocks in the United States. They attributed the difference in stock allocation to the empirical phenomenon of mean reversion in stock returns, which implies that the variance of stock returns increases less than linearly with the investment horizon, thus reducing their riskiness in the long run. The higher proportion of bonds in the portfolio of the long-term investor was in turn explained by the fact that bond returns are negatively related to interest rate fluctuations. This generates an additional hedging demand for bonds as compared to the one-period model. Cash holdings, on the other hand, are riskier in the long run than in a static setup, as they have to be reinvested at uncertain future interest rates.

While the methodology developed in this literature can be applied to emerging economies, the resulting portfolio implications depend on the statistical properties of asset returns in these markets. Several studies have documented how these properties differ from those of developed market returns, focusing mainly on equity. C. Harvey (1995) is the first contribution that comprehensively studies the characteristics of emerging market returns. He reports high expected returns, accompanied by high volatility and a low correlation with developed equity markets. Analysing the dynamic properties of emerging market returns, he finds that emerging market returns are predictable to a larger extent than returns in developed markets. Local variables like lagged returns on the domestic stock index, exchange rate fluctuations, dividend yields, and interest rates play an important role.

Subsequent studies show that, while expected returns in emerging markets have decreased since the financial liberalizations that took place around 1990, other return characteristics as high volatility and non-normality have persisted (Bekaert and Harvey (2003)). As for return predictability, there is quite some ambiguity in the literature. In a study of fifteen emerging markets, Karemera et al. (1999) found no evidence against the random walk model in either local or U.S. dollar returns.

Contrary to the findings of C. Harvey (1995) they found these markets to be weak-form efficient. However, Bekaert and Harvey (2007) identified market liquidity as an important driver of expected returns in emerging markets and found that this effect persists after financial liberalization. In turn, a recent study by Hjalmarsson (2010), using the most comprehensive dataset to date, reported very little evidence of emerging market return predictability. A similar level of ambiguity exists concerning mean reversion. Chaudhuri and Wu (2003) find that the null hypothesis that stock prices follow a random walk can be rejected for ten out of seventeen emerging markets in their study, while Malliaropulos and Priestley (1999) report mixed evidence for a sample of South-east Asian markets.

Due to limited data availability, bond markets have received little attention in the literature on emerging markets finance (Bekaert and Harvey (2003)). Burger and Warnock (2007) have recently addressed this issue and compiled a dataset on the size and composition of 49 local bond markets and analysed basic one-period return characteristics. Very little is known, however, about the long-run risk-return trade-offs implied by the risk premia, the real interest rate hedging potential and the inflation risk of local currency bonds.

Three case studies

We focus on three issues that play an important role in the debate on pension fund regulation: 1) the privileged position of domestic government bonds 2) foreign investment restrictions and 3) the impact of changes in economic regime on asset allocation decisions. While these issues have been addressed qualitatively in previous studies, our objective is to provide a quantitative analysis of their financial consequences for emerging market investors.

In each of the three cases mentioned above governments and regulatory authorities face a trade-off. Reducing mandatory investments to domestic bonds may complicate debt financing and require the issuance of costly foreign currency bonds. Allowing investors to allocate part of their assets abroad may slow down the growth of domestic capital stock and induce depreciation of the national currency. Adopting a 'prudent person rule' that allows portfolio managers to react to changing market circumstances requires an investment in governance and expertise in the pension fund sector. On the other hand, enhancing investors' opportunities to select a portfolio that matches their preferences in terms of risk and return contributes to the popularity of contractual savings programmes and channels additional funds to domestic capital markets. To assess the potential gains from any of these measures, a better understanding of portfolio choice in the emerging market context is required.

Chapter 3: Portfolio demand for long-term government bonds in India.

Chapter 3 addresses the relationship between contractual savings and the financing of government debt, which is hypothesized to be one of the reasons of enforcing high allocations to domestic bonds. Until the end of the previous century, borrowing for the long term in domestic currency was virtually impossible for most developing countries, both among foreign and local investors (e.g., Hausmann and Panizza (2003)). Thus developing countries were largely dependent on foreign-currency denominated bonds, carrying a high yield, and on a domestic 'captive investor' base of financial institutions. However, over the last decade local currency debt markets have grown dramatically, mainly due to inflation stabilization and improvements in creditor rights (Burger and Warnock (2006)). With the market infrastructure in place, and with an increasing proportion of the population at an income level sufficient to create interest in long-term savings products, a new source of long-term debt financing becomes available.

In our analysis, we focus on India, a major developing country that has a considerable potential to harness household savings, which are in the range of 400 billion dollars annually (Shah and Patnaik (2011)). The Indian government is actively trying to raise awareness about long-term bond investment under small institutional investors and the public. Under the recently launched New Pension System (NPS) each citizen is entitled to allocate his savings to mutual funds investing in the markets for domestic equity, government debt and corporate debt, respectively. Moreover, he can actively decide on his asset allocation, the only restriction being a cap of 50 % on equities.

This raises the question which role government bonds can play in the portfolio of an Indian investor. To answer this question we make use of the intertemporal asset allocation model proposed by Campbell and Viceira (2001). This model allows to disaggregate bond demand into components that stem from portfolio diversification along the lines of Markowitz (1952) and components that stem from the dynamic properties of long-term bond returns. Notably, long-term bond demand may differ significantly from short-term bond demand due do the fact that bond returns are negatively correlated to interest rate levels. Thus bonds can act as a hedge against fluctuations in investment opportunities over the business cycle, which makes them more attractive to long-term investors. On the other hand, long-term bonds have relatively high exposure to inflation risk, which is particularly relevant for investors with a long horizon.

Using data from capital markets in the United States, Campbell and Viceira (2001) found that the extension of the static diversification framework with these dynamic effects leads to a substantial increase in the bond component of the portfolio. Our results for India point towards a different composition of government bond demand. We use time series of benchmark bonds with maturities of one, five, and ten years, with a length of over fifteen years, to study optimal bond allocation for investors with various risk preferences. We find that, although Indian inflation has been relatively stable over the past two decades, the associated risk is still too large to induce risk-averse investors to buy long-term bonds. However, long-term bonds do play an important role in portfolios of moderately risk-averse investors who want to diversify away part of the market risk in their highly volatile domestic stock holdings and simultaneously earn a term premium over the short-term interest rate.

Chapter 4: International diversification benefits for investors in emerging markets: the role of horizon effects and model uncertainty.

Chapter 4 fits into the third line of literature discussed in our opening remarks, focusing on the diversification benefits stemming from adding new assets to the investment opportunity set. In this chapter we quantify the gains from foreign investment from the perspective of emerging market investors. While there is a voluminous literature on diversification benefits accruing to investors in developed markets, and particularly the U.S., when investing in emerging markets (e.g., Bekaert and Urias (1996), De Roon et al. (2001)), there are but few studies that take the opposite perspective. Given the costs associated with gaining the expertise and setting up the regulatory infrastructure necessary to invest abroad and the opposition to not re-investing domestic savings in the local economy it is important to assess the potential gains from diversification in emerging markets.

Three studies have recently addressed this topic. Driessen and Laeven (2007) find that the benefits of investing abroad are largest in developing countries, particularly those with high country risk. They argue in favour of further liberalization of financial markets and the introduction of globally oriented mutual funds in developing countries. However, they also note that diversification benefits decrease over time as country risk decreases and stock markets become integrated with the global market. Chiou (2008) arrives at a similar conclusion, singling out East Asian and Latin American investors as those with the highest potential benefits. Kumara and Pfau (2011) use a bootstrap approach to compare the full distribution of retirement wealth with and without foreign investment restrictions. They also report significant diversification benefits, with optimal foreign asset holdings amounting to more than 50 % of wealth, on average, for investors with moderate to high risk aversion levels.

In our contribution, we extend this literature by studying foreign diversification benefits using a dynamic vector autoregressive (VAR) model. In contrast to the papers mentioned above, which have focused on the one-period characteristics of asset returns, this allows us to study the benefits of foreign diversification in a setting where the risk-return characteristics of both domestic and foreign assets vary with the investment horizon. As has been shown by, amongst others, Barberis (2000), the dynamic properties of stock returns can induce very substantial differences between the optimal portfolios of short-term and long-term investors. At the same time it is well-known that these properties can differ considerably between international stock markets (C. Harvey (1995), Schrimpf (2010), Hjalmarsson (2010)). One of the implications could be that investors in an economy with a highly mean-reverting domestic stock market, which is safer in the long run than its one-period return characteristics suggest, benefit less from diversification than a static analysis suggests.

To capture the high degree of uncertainty about return dynamics in emerging markets, we use recent advances in Bayesian VAR modelling (Diris (2011)). An important feature of the model, in view of the relatively short time series of asset returns in emerging markets, is that it allows for parsimonious estimation of the VAR parameters.

Studying a sample of four major Asian economies, India, Malaysia, Pakistan and Thailand, we find that the impact of return dynamics on foreign diversification benefits is limited. From the perspective of an emerging market investor, there is but little predictability in both domestic and foreign equity returns. With some exceptions, the gains from investing abroad and the corresponding portfolio weights do not seem to depend on the investment horizon to any significant degree.

Chapter 5: Stock market crashes, inflation hikes and asset allocation: evidence from the Philippines

In Chapter 5 we focus on the impact of economic regimes on asset allocation decisions. One of the objections against the application of quantitative investment limits on institutional investors' portfolios is that this reduces their ability to adapt to changing economic regimes (Davis (2002)). The relationship between economic regimes and asset allocation decisions in U.S. and U.K. markets has been studied by, amongst others, Guidolin and Timmermann (2005, 2007), and Guidolin and Hyde (2008). Guidolin and Ria (2011) provided international evidence based on MSCI indices for five macro-regions. These papers contributed to generalizing static portfolio selection models to a dynamic setting (the second strand of literature mentioned in our opening remarks) by allowing asset return properties to vary over time, in line with e.g., 'bull' and 'bear' market conditions that are commonly encountered in practitioners' parlance. This generalization implies time diversification effects. For example, while short-term investors may decide to benefit from rising equity markets by increasing their equity allocation, long-term investors will do this to a lesser extent. This is due to the fact that they can expect a sequence of regime changes before their investment horizon expires and want to protect themselves against equity downturns in less favourable regimes. Importantly, the proposed approach allows for the regimes to be determined endogenously by market return data. Moreover, the regime that is in effect at any particular moment is unobservable; only a probabilistic inference can be made about it. This reflects the uncertainty involved in making investment decisions related to market timing.

In Chapter 5 we apply the regime-switching methodology advanced in this literature to an emerging market context. This methodology is well-suited to accommodate the empirical features of asset returns in emerging markets, which are often triggered by political events, regulatory changes or exchange rate fluctuations (Claessens et al. (1995), Bekaert et al. (1998)). The objective is to assess the impact of such events on long-horizon asset allocation decisions. This allows us to verify whether allowing for flexibility in determining asset class weights adds value in an emerging market context.

Using data from the Philippines, we find that the dynamics of the stock market and the market for short-term debt are adequately captured by a three-regime model, where stable periods are interrupted by 'crisis' and 'inflationary' regimes. The latter two regimes tend to alternate, so that an investor who is locked into the local market is deprived of the possibility to 'flee to quality' as soon as he finds himself in one of them. Still, the best strategy upon entering the inflationary or the crisis regime is to reduce the percentage of the portfolio allocated to stocks. This result holds not only for short-term investors, but across investment horizons of up to ten years, and confirms the disadvantages of imposing strict quantitative limits in the asset management industry.

Chapter 6: Group lending and diversification in microfinance

In chapter 6 we consider diversification in a very different setting. In this chapter we focus on microfinance, which has proved to be an increasingly important element in the financial landscape of developing countries over the last two decades. Among the distinctive features of microfinance are group lending contracts, where group members are jointly liable for the repayment of their peers' loans. Ghatak and Guinnane (1999) discuss how lending to groups of borrowers, instead of to individuals, can overcome the problems of adverse selection, moral hazard, costly state verification and enforcement of repayments when the borrowers possess no collateral.

Group lending essentially amounts to a diversification mechanism from the perspective of the lending institution, along the lines of Tirole (2005, p.158) and Diamond (1984). According to their theoretical results, giving borrowers the possibility to cross-pledge collateral (e.g., between different divisions of a firm) increases lending institutions' possibilities to distribute credit. The main limitation to this mechanism is the correlation level between the outcomes of the projects used for cross-pledging.

One of the critiques on theoretical microfinance models is that, with few exceptions (Laffont (2003), Ahlin and Townsend (2007)) they assume that the results of borrower's investment projects are uncorrelated. As the members of a microfinance group usually live close to each other and are exposed to similar shocks, this is not likely to be the case and positive correlation is to be expected. This is thought to be detrimental to the functioning of group lending contracts, as group members are less likely to pay joint liability for their peers if projects tend to either succeed or fail together (Ghatak (2000)).

In our contribution, we examine the role of correlations in borrowers' project outcomes more closely. We consider the setting of the classic adverse selection problem of Stiglitz and Weiss (1981). In this setting the presence of risky borrowers leads to an interest rate that discourages safe clients from borrowing at the break-even interest rate. We find that in this case positive correlations between project outcomes are not necessarily detrimental for the functioning of group lending contracts. In certain cases, the full information welfare outcome can be attained when project outcomes are positively correlated, while this is impossible in the case of independent contracts (Gangopadhyay et al. (2005)).

This result suggests that the benefits of group lending advanced in earlier literature need not be mitigated by the more realistic assumption of positive correlations between project outcomes. It thereby contributes to the recent debate on the advantages and disadvantages of group lending as compared to individual lending (Giné and Karlan (2009), Giné et al. (2010)).

Finally the main findings of our research are summarized in Chapter 7. Please note that, as this thesis is presented as a collection of papers, notation may differ between chapters and definitions may be repetitive. Chapter 2 is joint work with Laura Spierdijk (Katzur and Spierdijk (2013)) and Chapter 6 is joint work with Robert Lensink (Katzur and Lensink (2012)).

Chapter 2

Stock returns and inflation risk: economic versus statistical evidence

2.1 Introduction

Inflation risk represents one of the primary concerns of long-term investors. While inflation-linked instruments such as Treasury Inflation-Protected Securities (TIPS) provide a hedge against inflation, the real returns on such assets tend to be low. This makes it attractive for investors to extend their portfolio by investing in stocks to benefit from the equity premium. But stocks are potentially exposed to inflation risk.

A common view in the economic literature indicates that an asset is a good hedge against inflation if the Fisher hypothesis holds true (e.g., Fama and Schwert (1977), Boudoukh and Richardson (1993), Barnes et al. (1999), Bekaert and Wang (2010)). In the classic *Theory of Interest* (1930), Irving Fisher postulated that the anticipated rate of inflation is completely incorporated into the ex ante nominal interest rate. Yet he also precluded a relation between the expected real rate and expected inflation, emphasising the independence of real and monetary sectors. The proposition that ex ante nominal returns contain the market's perception of anticipated inflation rates applies to all assets, such that the expected nominal returns on any asset would move one-for-one with expected inflation. The marginal effect of a unit change in expected inflation on nominal returns is often referred to as the Fisher coefficient. Alternatively, the Fisher hypothesis describes real asset returns as statistically uncorrelated with expected inflation.

Because stocks represent claims on real assets, they were for long considered good inflation hedges. However, empirical studies produce ambiguous results with respect to the influence of inflation on stock returns; see e.g., Boudoukh and Richardson (1993), Solnik and Solnik (1997), Barnes et al. (1999), Bekaert and Wang (2010) and Schmeling and Schrimpf (2011). Possible explanations for the negative effect of inflation rates on stock returns are the proxy hypothesis (Fama (1981)), money illusion (Modigliani and Cohn (1979)) and informational frictions (Barnes et al. (1999)).

The difficulty of estimating the Fisher coefficient is that stock returns and inflation rates have very different time series properties; the former being much more volatile than the latter (Schotman and Schweitzer (2000)). Consequently, it is hard to accurately estimate the relation between stock returns and inflation, particularly for short samples. Estimated coefficients relating stock returns to inflation will be subject to a lot of parameter uncertainty. Consequently, we encounter situations in which the Fisher hypothesis cannot be rejected as an artefact of large parameter uncertainty, and not because of genuine evidence in favour of it. Furthermore, the Fisher coefficient is a purely statistical measure for the inflation-hedging ability of stocks; it is uninformative about the economic relevance of the influence of inflation on stock returns.

Where many studies view stocks as a potential hedge against the inflation risk in a portfolio consisting of nominally risk-free bonds, we take a different view. Nowadays, inflation-linked bonds are available in both developed and emerging economies (Swinkels (2012)). Consequently, inflation risk stemming from stock holdings seems a bigger concern than inflation risk associated with fixed-income securities. Therefore, we do not consider stocks as a potential hedge against inflation risk. Instead, we focus on the inflation risk exposure of long-term stock holdings and propose an economically based measure to assess this exposure. Our novel method reflects the economic influence of inflation rates on stock returns in a context of portfolio optimization and explicitly deals with parameter uncertainty.

The economic context we consider is as follows. A long-term investor divides her wealth between stocks and inflation-linked bonds that pay a risk-free real rate. The investor sets her portfolio weights to maximise the expected utility associated with its real wealth at the end of the investment horizon. The investor must make an important assumption about the relation between real stock returns and inflation: Assume *a priori* that real stock returns are uncorrelated with expected inflation or remain more agnostic by allowing for interaction between real returns and expected inflation. An investor who believes that the Fisher coefficient is equal to unity and who thereby ignores the information contained in the noisy estimate of Fisher coefficient is referred to as a 'Fisher' investor. An investor who acknowledges the influence of expected inflation on real stock returns is referred to as an 'agnostic' investor.

Our approach is based on recent stock return predictability literature, such as Barberis (2000), which has used Bayesian methods to deal with the problem of parameter uncertainty in investment decisions. The idea of the Bayesian approach is to consider a range of values for each model parameter and to determine the probability of observing certain parameter values given the data. Subsequently, optimal portfolio holdings are obtained while taking into account all possible parameter values and the associated probability of observing these parameters given the data. By adopting such a Bayesian approach, we obtain optimal asset allocations in the presence of parameter uncertainty for the agnostic and Fisher investors. In a world where nominal stock returns move in parallel with expected inflation, the Fisher and agnostic investors have the same optimal portfolio weights. But if real stock returns and expected inflation are correlated, an investor ignoring this correlation will hold non-optimal stock holdings, resulting in a loss of expected utility. The loss in expected utility (as measured by the difference in certainty equivalent returns) reflects the economic effect of ignoring the influence of expected inflation on real stock returns and explicitly accounts for parameter uncertainty. We use it as a novel measure for the inflation risk exposure of stock returns.

The setup of the remainder of this chapter proceeds as follows: We describe the asset allocation framework in Section 2.2. After outlining the data for the empirical study in Section 2.3, we discuss the empirical results in Section 2.4. Finally, we conclude in Section 2.5.

2.2 Asset allocation framework

2.2.1 Notation

This section outlines the asset allocation framework for assessing the inflation risk exposure of stock returns. We start with some notation. We assume a k-period investment horizon and focus on k-period stock returns and inflation rates, where k is measured in quarters. We denote nominal k-period continuously compounded stock returns from time t to time $t+k$ by $r_{\text{nom},t}(k) = \log\left(S_{t+k}/S_t\right)$, where S_t is the nominal price of the stock at time t. The inflation rate from time t to $t+k$ is written as $\pi_t(k) = \log(\mathrm{CPI}_{t+k}/\mathrm{CPI}_t)$, where CPI_t denotes the value of the consumer price index at time t. Continuously compounded k-period real stock returns are then given by $r_t(k) = r_{\mathrm{nom},t}(k) - \pi_t(k)$.

The continuously compounded k-period risk-free real rate is denoted by $r_{f,t}(k)$. One-year rolling window dividends are obtained by aggregating the dividends paid in the four quarters prior to time t and dividing by the value of the stock index at time t:

$$D_t^4 = [D_t + D_{t-1} + D_{t-2} + D_{t-3}]/S_t.$$

The log dividend yield is then denoted by $d_t = \log D_t^4$ (see Ang and Bekaert (2007)). Finally, the one-period conditional inflation rates, nominal, and real stock returns are represented by π_{t+1}, $r_{\mathrm{nom},t+1}$, and r_{t+1}, respectively.

2.2.2 Investment problem

We use a standard asset allocation framework, similar to Barberis (2000). We consider an investor with initial nominal wealth $W_{\mathrm{nom},t} = 1$ at time t, at which the price level is normalized at $\mathrm{CPI}_t = 1$. The investor seeks to maximise utility over real-term wealth $W_{t+k} = W_{\mathrm{nom},t+k}/\mathrm{CPI}_{t+k}$ by time $t+k$. We assume power utility over real term wealth; that is

$$u(W_{t+k}) = \frac{W_{t+k}^{1-\gamma}}{1-\gamma}, \tag{2.1}$$

where $\gamma > 1$ is the coefficient of relative risk aversion. At time t the investor determines the proportion of wealth ω to be allocated to a stock index; the other investment option is a risk-free inflation-linked bond with a maturity of k time units. We assume the investor holds these investments until time $t+k$ (i.e., buy and hold). Although the inflation-linked bond provides a hedge against inflation, its real return is usually low. Therefore it can be attractive for the investor to extend the portfolio with an investment in a stock index and benefit from the equity risk premium.

Rather than considering an exhaustive asset menu, our objective is to isolate inflation risk inherent in equity investments. We therefore consider two asset classes only: inflation-linked bonds and a stock index. Moreover, we assume a buy-and-hold investment strategy, so that the inflation-linked bond investment is truly risk-free in real terms. In this setting, the utility of terminal wealth W_{t+k} is given by

$$u(W_{t+k}) = \frac{\left[\omega e^{r_t(k)} + (1-\omega) e^{r_{f,t}(k)}\right]^{1-\gamma}}{1-\gamma}. \tag{2.2}$$

2.2.3 Model for stock return and inflation dynamics

As a starting point for modelling the relationship between stock returns and inflation we use a specification proposed by Fama and Schwert (1977):

$$R_{\text{nom},t+1} = \alpha + \beta \Pi_t^e + \zeta \Pi_t^u + \varepsilon_{t+1}. \tag{2.3}$$

This equation relates nominal stock returns to expected and unexpected inflation. As the latter variables are unobserved, a proxy of $\Pi_t^e = E_t[\Pi_{t+1}]$ is used for empirical estimation.[1] Unexpected inflation is then defined as $\Pi_t^u = \Pi_{t+1} - E_t[\Pi_{t+1}]$.

Fama and Schwert (1977) defined an asset to be a complete hedge against inflation if $\beta = \zeta = 1$. In this case, one-period real returns are uncorrelated with inflation, and nominal asset returns move in step with inflation. Likewise, they defined an asset as a complete hedge against *expected* inflation if its nominal returns move only in step with inflation *expectations*, that is, $\beta = 1$ but $\zeta \neq 1$. This application of Fisher's (1930) hypothesis to stock returns has been studied empirically by e.g., Boudoukh and Richardson (1993), Solnik and Solnik (1997) and Bekaert and Wang (2010).

We apply a model that is based on this specification, yet differs in three respects. First, we directly model real instead of nominal stock returns. Second, we formulate an AR(1) model for inflation expectations. Third, we include the dividend yield as an additional variable in the return equation. The dividend yield is commonly considered as a predictor of excess stock returns (see, e.g., the overview article of Ang and Bekaert (2007)), although its predictive power is not undisputed (Boudoukh et al. (2008)).

These elements are combined into a reduced-form vector autoregressive (VAR) model that captures the dynamics between real stock returns (r_t), expected inflation (π_t^e), unexpected inflation (π_t^u) and rolling-window log dividend yield (d_t). This VAR model is given by

[1] This proxy often stems from a dynamic model (e.g., a state-space model) for inflation. In this paper we choose a different approach based on survey data of inflation expectations, see section 2.3.

$$\begin{aligned} r_{t+1} &= \alpha_1 + \beta_1 \pi_t^e + \beta_2 d_t + \varepsilon_{1,t+1}; \\ \pi_{t+1}^e &= \alpha_2 + \beta_3 \pi_t^e + \varepsilon_{2,t+1}; \\ \pi_{t+1}^u &= \varepsilon_{3,t+1}; \\ d_{t+1} &= \alpha_3 + \beta_4 d_t + \varepsilon_{4,t+1}. \end{aligned} \tag{2.4}$$

where $\boldsymbol{\varepsilon}_t = (\varepsilon_{1,t}, \varepsilon_{2,t}, \varepsilon_{3,t}, \varepsilon_{4,t})'$ is a series of independent, multivariate normally distributed disturbances, with mean 0 and covariance matrix Σ. Σ has diagonal elements σ_i^2 for $i = 1, 2, 3, 4$ and off-diagonal elements $\sigma_{ij} = \sigma_{ji}$ for $i \neq j$. The corresponding correlation coefficients are denoted by $\rho_{ij} = \sigma_{ij} / (\sigma_i \sigma_j)$ for $i \neq j$.

The first equation in model (2.4) directly relates real stock returns to expected inflation through the Fisher coefficient β_1. Because we use real returns instead of nominal returns in the VAR model, the Fisher hypothesis that real stock returns are uncorrelated with expected inflation corresponds to the parameter restriction $\beta_1 = 0$. Moreover, the log dividend yield affects the stock return through the coefficient β_2. The second equation specifies expected inflation as an AR(1) process. In the third equation of model (2.4), unexpected inflation is a white noise process with variance σ_3^2. The fourth equation specifies the log dividend yield as an autoregressive process. The correlation between $\varepsilon_{1,t}$ and $\varepsilon_{3,t}$ captures the influence of unexpected inflation on (innovations in) stock returns.

The hypothesis that real stock returns are uncorrelated with unexpected inflation corresponds to the parameter constraint $\rho_{13} = 0$. The VAR model also allows for correlation between innovations in real stock returns and shocks in expected inflation through ρ_{12}. Furthermore, ρ_{14}, ρ_{24} and ρ_{34} are the correlations between innovations in log dividend yield and – respectively – innovations in real stock returns, expected inflation and unexpected inflation.

2.2.4 Estimation

As noted in the introduction, accurate parameter estimates for the return equation of model (2.4) are difficult to obtain. The time-series properties of asset returns, which are highly volatile, differ considerably from those of the inflation process, which tends to be slowly moving and persistent. Consequently, estimates of β_1 are usually characterised by large standard deviations. For example, suppose that our (OLS) estimate of β_1 in equation (2.4) equals $\hat{\beta}_1 = 2.3$ with standard deviation 1.5. In this case, we cannot reject the null hypothesis $\beta_1 = 0$ on the basis of a two-sided

t-test, despite a lack of convincing evidence in favour of this hypothesis.

As in the above example, the lack of evidence against the Fisher hypothesis usually stems from the large amount of parameter uncertainty, caused by the different time series properties of stock returns and inflation rates (Schotman and Schweitzer (2000)). Barberis (2000) sketches three alternative ways of dealing with regressions characterised by low significance levels: (1) assume that insignificant coefficients are equal to 0, (2) ignore the parameter uncertainty in the estimated coefficients and treat them as if they were exactly known, or (3) account for parameter uncertainty. We implement the last option by adopting a Bayesian approach to solve the investor's optimization problem.

The idea of the Bayesian approach is to consider a range of values for each model parameter and to determine the probability of observing certain parameter values given the data ('posterior distribution'). Subsequently, we calculate optimal portfolio holdings, taking into account all possible parameter values and the associated probability of observing these parameters given the data. The Bayesian approach also solves the aforementioned controversy regarding the predictive power of the dividend yield. Even if dividend yields do not significantly affect stock returns, the Bayesian approach ensures that we take into account all information contained in the relation between stock returns and dividend yields.

Suppose that at time $t = T$, the investor estimates the parameters of model (2.4) using all available information about real returns and inflation. The estimated parameters $\hat{\boldsymbol{\theta}}$ and the information set $\mathcal{I}_T$ available at time T determine the conditional k-period return density $p(r_T(k)|\mathcal{I}_T, \hat{\boldsymbol{\theta}})$. For an investor who treats the estimated parameters as fixed, the optimization problem boils down to

$$\max_{\omega} E_T\left[u(W_{T+k})\right] = \max_{\omega} \int u(W_{T+k}) p(r_T(k)|\mathcal{I}_T, \widehat{\boldsymbol{\theta}}) dr_T(k). \tag{2.5}$$

Instead of using fixed parameter values, the Bayesian approach applies a posterior distribution $p(\boldsymbol{\theta}|\mathcal{I}_T)$ to summarise uncertainty about the parameters, given the information set $\mathcal{I}_T$. This posterior distribution weights the conditional return distributions $p(r_T(k)|\mathcal{I}_T, \boldsymbol{\theta})$ in an objective function of the form:

$$\max_{\omega} \int \int u(W_{T+k}) p(r_T(k)|\mathcal{I}_T, \boldsymbol{\theta}) p(\boldsymbol{\theta}|\mathcal{I}_T) dr_T(k) d\boldsymbol{\theta}. \tag{2.6}$$

Appendix 2.A provides the technical details on the Bayesian approach used to obtain the optimal stock allocations. For an overview of Bayesian estimation methods for VAR models, see Kadiyala and Karlsson (1997) and Koop and Korobilis (2009).

2.2.5 Inflation risk exposure of stocks

Our objective is to assess the economic significance of the influence of inflation rates on stock returns. Now that we have defined the investor's portfolio optimization problem, we turn to our economically motivated measure for the inflation risk exposure of stocks.

We consider two investors, with different beliefs about the relation between real stock returns and expected inflation. We will call them the 'Fisher' investor and the 'agnostic' investor. The Fisher investor believes that stock returns are a complete hedge against expected inflation. The Fisher investor's VAR model is specified as in equation (2.4), with the additional parameter restriction $\beta_1 = 0$. The Fisher investor precludes a relation between real stock returns and expected inflation ($\beta_1 = 0$), but acknowledges that innovations in real stock returns can be correlated with shocks in expected and unexpected inflation ($\rho_{12} \neq 0, \rho_{13} \neq 0$). By contrast, the agnostic investor does not impose any restrictions in the parameters in equation (2.3) and thus allows for interaction between real stock returns and expected inflation. The beliefs of the agnostic and Fisher investors about the role of the log dividend yield are the same.

In a world where nominal stock returns move in parallel with expected inflation, the Fisher and agnostic investors have the same optimal portfolio weights. But if real stock returns and expected inflation are correlated, an investor ignoring this correlation will hold non-optimal stock holdings, resulting in a loss of expected utility. The loss in expected utility reflects the economic influence of ignoring the influence of expected inflation on real stock returns. Following Kandel and Stambaugh (1996), we calculate the loss in expected utility as the difference in certainty equivalent returns (CERs). We first calculate the agnostic investor's expected utility based on the optimal stock holdings, as well as the agnostic investor's expected utility based on the suboptimal Fisher stock holdings. Subsequently, we obtain the agnostic investor's CERs for these two expected utilities.[2] The corresponding difference in CERs reflects the economic impact of ignoring the influence of expected inflation on real stock returns. We use this difference as a novel measure for the inflation risk exposure of stock returns. This definition acknowledges that the portfolio allocations of the agnostic and Fisher investors would be the same in a world where real stock returns are uncorrelated with expected inflation. The underlying Bayesian approach ensures that this measure explicitly accounts for parameter un-

[2] The CER corresponding to a certain asset allocation is defined is the annual rate of return on wealth that, if earned with certainty, would result in utility equal to the expected utility of the given asset allocation.

certainty. In this way, we deal with the large amount of parameter uncertainty usually involved with the Fisher coefficient.

2.3 Data

2.3.1 Sources

Obtaining optimal portfolios using the Bayesian methods of Section 2.2.4 requires data about real stock returns, (proxies of) expected and unexpected inflation and a risk-free real rate. We focus on the United States and take the S&P 500 Total Return Index, as provided by Thomson Datastream, as our stock index. Ang et al. (2007) show that surveys provide the best out-of-sample inflation forecasts. We therefore opt for quarterly data and use one-quarter-ahead inflation forecasts, available from the *Survey of Professional Forecasters*, as a proxy for expected inflation.[3] We also take realised inflation from this source. To obtain the unexpected inflation rates, we subtract expected inflation from realised inflation rates. Furthermore, we use total inflation to convert nominal stock returns to real returns. For the risk-free real rate, we employ the real yield curve, provided by the US Department of the Treasury, with maturities equal to 5, 7 and 10 years.[4]

The final input required to estimate our model is the coefficient of relative risk aversion $\gamma > 1$. In a review article, Meyer and Meyer (2005) compare and synchronise relevant empirical evidence. Using studies by Friend and Blume (1975) and Blake (1996), they report risk aversion coefficients for wealth outcome variables between 2 and 5. In line with the finance literature (e.g., Barberis (2000), Guidolin and Timmermann (2007)), we select a risk aversion coefficient $\gamma = 5$.[5]

[3] The results of this survey are published at `http://www.phil.frb.org/research-and-data/real-time-center/survey-of-professional-forecasters/`. The inflation time series used in this chapter are taken from the Forecast Error Statistics file provided on this page. These forecasts relate to the seasonally adjusted U.S. Consumer Price Index, CPI-U, all-urban, provided by the Bureau of Labor Statistics.

[4] This yield curve is available at `http://www.treasury.gov/resource-center/data-chart-center/interest-rates/Pages/default.aspx`.

[5] The corresponding risk profile is best illustrated by the investor's optimal decision in a standard static one-period model. Assuming an average interest rate of 4.3% and average quarterly excess equity returns of 1.4%, as observed over our sample period, an investor with $\gamma = 5$ invests 55% in equity and the rest in the risk-free asset. For $\gamma = 1$ this is 275% (i.e. the investor borrows almost twice his wealth and invests it in equities). For $\gamma = 10$ the optimal equity allocation is 28% and for $\gamma = 20$ it decreases to 14%.

2.3.2 Expanding window

Although the economic literature has shown that it is reasonable to model inflation as a mean-reverting process, both the average level of inflation and the volatility of the inflation process differ considerably over sub-periods. The differences between the Great Moderation (starting in the mid-1980s) and the previous inflationary period are particularly large (see Stock and Watson (2006)). To avoid structural breaks, we therefore opt for a relatively homogeneous period that starts in the first quarter of 1985 and runs until the first quarter of 2011.

There is evidence that the sample period affects the estimated sign of the Fisher coefficient β_1. For example, several studies show that sustained periods of high (expected) inflation adversely affect real activity and lower stock returns (e.g., Barnes et al. (1999)). If a period of stagflation appears in the sample, we might capture this effect. In a relatively stable inflationary environment though, high expected inflation can reflect positive demand shocks, which would lead to higher company profits and stock returns. Although we have opted for a relatively homogeneous sample period with respect to inflationary regimes, we will use an expanding window to deal with any remaining parameter instability in Section 2.4. The choice for the year 2003 as the earliest end date of the expanding window is motivated by the availability of the risk free yield curve. We particularly expect parameter instability as of 2008, when stock markets were severely hit by the bankruptcy of Lehman Brothers.

2.3.3 Timing of expected inflation and stock returns

The deadline for forecast submissions to the Survey of Professional Forecasters is typically in the second month of each quarter, and forecasters predict the average quarter-to-quarter annualised inflation rate.[6] To match the inflation forecasts with the appropriate stock returns, we observe that during our sample period, the average quarterly inflation rate correlates highly with the inflation rate obtained from dividing the mid-quarter CPI levels (during our sample period, this correlation equals 0.98). Therefore, we associate with each quarterly inflation forecast the return on the stock index from the 15th of the second month of that quarter until the 15th of the second month in the next quarter.

[6] The deadline was usually the third week of the second month of the quarter during 1990 – 1998, the end of the second week in 1999 – 2004 and the middle or the start of the second week thereafter.

2.3.4 Sample statistics

During the sample period, the average quarterly real returns on the S&P 500 Total Return Index equalled 1.87%, with a standard errors (SE) of 7.75% (Table 2.1). The inflation rate had a quarterly average value of 0.70% (SE = 0.58%). Forecasted quarterly inflation, our proxy for expected inflation, was equal to 0.72% on average (SE = 0.24%). The difference between realised and forecasted inflation, our proxy for unexpected inflation, averaged -0.01% (SE = 0.49%), with expectation not significantly different from zero.

Figure 2.1 displays the quarterly stock index returns during the 1985 – 2010 period, together with expected and unexpected inflation rates over time. The different time-series properties of stock returns and inflation rates become apparent immediately, as the return series is very volatile in comparison with the slowly moving processes of expected and unexpected inflation.

Table 2.1. **Sample statistics.**

	returns	**exp. infl.**	**unexp. infl.**	**total infl.**	**div. yield**
mean	1.87	0.72	−0.01	0.70	2.39
median	2.49	0.70	0.00	0.74	2.09
std.dev.	7.75	0.24	0.49	0.58	0.86
skewness	−1.90	0.45	−2.38	−2.21	0.44
kurtosis	7.37	0.02	13.18	12.30	−0.93
0.5% quantile	−33.70	0.20	−2.11	−1.68	1.13
5% quantile	−7.85	0.38	−0.69	−0.33	1.22
10% quantile	−5.97	0.43	−0.44	0.24	1.36
90% quantile	9.45	1.08	0.49	1.27	3.61
95% quantile	11.36	1.20	0.67	1.52	3.81
99.5% quantile	15.01	1.30	0.88	1.93	4.27

This table displays sample statistics for quarterly real stock returns, expected inflation, unexpected inflation, total inflation and one-year rolling-window dividend yields (all measured in %) for the period 1985Q1 – 2011Q1.

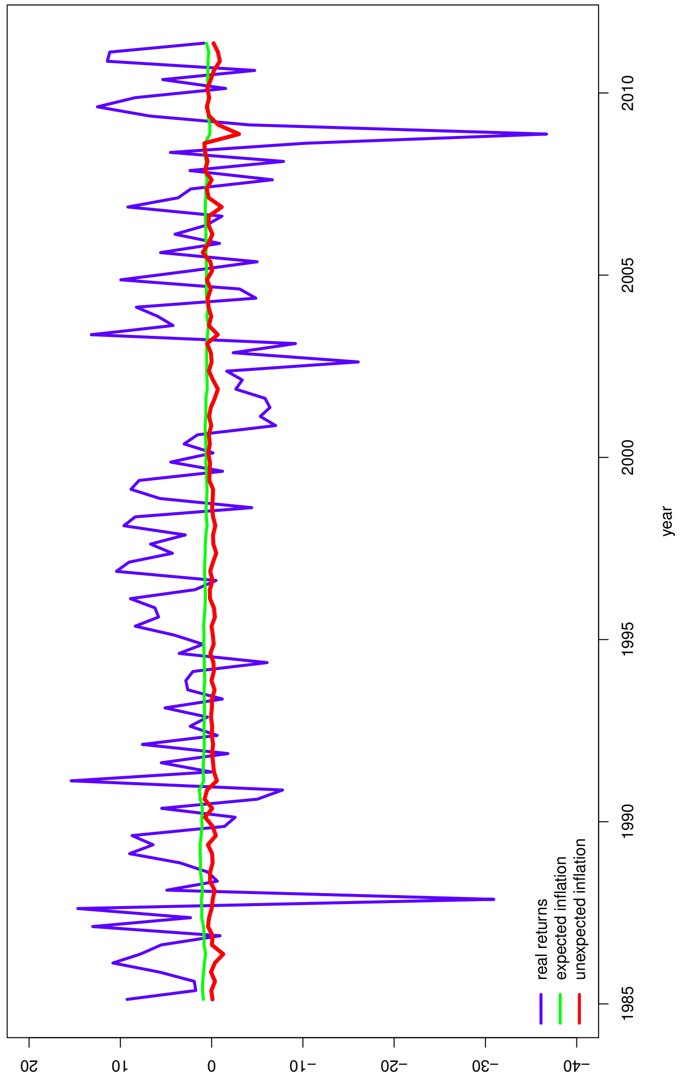


Figure 2.1. **Quarterly real returns and expected and unexpected inflation (in %) during the 1985 – 2010 period.**

2.4 Empirical results

In this section we present the posterior distributions of the model parameters of the agnostic investor and the Fisher investor. We then compare the optimal stock holdings of the two investors, which enables us to quantify the inflation risk exposure of stock returns.

2.4.1 Posterior distributions

We take $N = 1,000,000$ draws from the posterior parameter distribution corresponding to the agnostic investor's VAR model in equation (2.4). We do the same for the Fisher investor, who additionally imposes the parameter restriction $\beta_1 = 0$. The means and standard deviations of the parameters' posterior distributions appear in Table 2.2 (agnostic investor) and Table 2.3 (Fisher investor), for an expanding window starting in 1985 and ending in the first quarter of the years 2003 – 2011.

For all samples that end by 2008, the posterior means and standard deviations of the model parameters are fairly constant. On average, expected inflation negatively affects stock returns ($\beta_1 < 0$), whereas the average effect of the log dividend yield on real stock returns is positive ($\beta_2 > 0$). Return innovations correlate negatively with unexpected inflation ($\rho_{13} < 0$), on average. Furthermore, on average return innovations correlate negatively with unexpected changes in expected inflation ($\rho_{12} < 0$). Changes in unexpected inflation are on average positively correlated with unexpected changes in expected inflation ($\rho_{23} > 0$).

The relation between stock returns and unexpected inflation changes considerably after 2008. When the sample's end date is 2009 or later, the posterior means of β_1, ρ_{12} and ρ_{13} are positive. Also the correlations ρ_{24} and ρ_{34} change signs as of 2009. The parameters' sign changes as of 2009 likely reflect the impact of the global financial crisis. The bankruptcy of Lehman Brothers in September 2008 was followed by a stock market collapse, accompanied by a drop in expected and unexpected inflation.[7]

We are mainly interested in the Fisher coefficient β_1 in Table 2.2 and the correlation ρ_{13} in Tables 2.2 and 2.3. The large standard deviations of the Fisher coefficients β_1 in Table 2.2 illustrate the magnitude of the parameter uncertainty problem.

[7] The average values of β_3 and β_4 are close to unity, which reflects strong persistence in expected inflation rates and dividend yields. Sims et al. (1990) explain that unit roots are not a problem in a Bayesian setting; thus, we do not worry about the possibility of a unit root in the autoregressive model for expected inflation rates and dividend yields.

Table 2.2. **Means and standard deviations of the posterior parameter distributions (unrestricted VAR model).**

	2003		2004		2005		2006		2007		2008		2009		2010		2011	
	mean	SD	mean	SD	mean	SD	mean	SD	mean	SD	mean	SD	mean	SD	mean	SD	mean	SD
α_1	0.226	0.089	0.253	0.087	0.273	0.084	0.277	0.083	0.267	0.082	0.259	0.082	0.154	0.092	0.117	0.090	0.136	0.090
β_1	−1.043	2.231	−3.000	2.161	−3.613	2.018	−3.686	1.954	−3.563	1.959	−3.364	1.905	1.584	1.914	3.562	1.933	2.294	1.889
β_2	0.053	0.021	0.055	0.021	0.059	0.020	0.060	0.020	0.057	0.020	0.056	0.020	0.040	0.023	0.034	0.022	0.035	0.022
α_2	0.001	0.000	0.001	0.000	0.001	0.000	0.001	0.000	0.001	0.000	0.001	0.000	0.001	0.000	0.000	0.000	0.001	0.000
β_3	0.917	0.044	0.930	0.044	0.927	0.042	0.931	0.041	0.928	0.041	0.929	0.042	0.928	0.042	0.933	0.039	0.927	0.037
α_3	−0.125	0.074	−0.103	0.073	−0.114	0.072	−0.120	0.070	−0.115	0.069	−0.114	0.069	−0.142	0.080	−0.164	0.081	−0.155	0.082
β_4	0.969	0.020	0.975	0.019	0.972	0.019	0.971	0.019	0.972	0.018	0.972	0.018	0.964	0.021	0.959	0.021	0.961	0.021
ρ_{12}	−0.334	0.107	−0.353	0.102	−0.364	0.099	−0.359	0.096	−0.358	0.094	−0.296	0.097	0.080	0.103	0.070	0.101	0.060	0.099
ρ_{13}	−0.196	0.116	−0.203	0.112	−0.192	0.109	−0.172	0.107	−0.201	0.104	−0.206	0.101	0.201	0.099	0.210	0.097	0.171	0.096
ρ_{14}	−0.937	0.015	−0.926	0.017	−0.931	0.015	−0.932	0.015	−0.930	0.015	−0.931	0.014	−0.933	0.014	−0.905	0.019	−0.898	0.020
ρ_{23}	0.562	0.082	0.493	0.089	0.495	0.086	0.471	0.086	0.434	0.088	0.418	0.087	0.592	0.067	0.571	0.068	0.574	0.067
ρ_{24}	0.297	0.109	0.277	0.108	0.300	0.103	0.297	0.101	0.297	0.099	0.225	0.100	−0.091	0.102	−0.108	0.100	−0.112	0.098
ρ_{34}	0.195	0.116	0.224	0.111	0.221	0.108	0.201	0.106	0.236	0.102	0.229	0.100	−0.148	0.101	−0.173	0.098	−0.143	0.097
σ_1^2	4.861	0.851	4.806	0.820	4.750	0.786	4.594	0.742	4.465	0.701	4.432	0.682	6.141	0.924	6.018	0.883	5.973	0.860
σ_2^2	0.001	0.000	0.001	0.000	0.001	0.000	0.001	0.000	0.001	0.000	0.001	0.000	0.001	0.000	0.001	0.000	0.001	0.000
σ_3^2	0.011	0.002	0.011	0.002	0.011	0.002	0.012	0.002	0.013	0.002	0.014	0.002	0.025	0.004	0.025	0.004	0.025	0.004
σ_4^2	4.959	0.868	4.946	0.843	4.864	0.807	4.686	0.756	4.589	0.721	4.564	0.702	5.988	0.901	6.335	0.930	6.323	0.912

This table displays the means and standard deviations of the posterior distributions for the parameters of the unrestricted VAR model of Equations (2.4). The parameters σ_2^2 and σ_3^2 have been multiplied by a factor of 10,000. Estimation results are for samples starting in 1985 and ending in the first quarter of the years 2003 – 2010.

Table 2.3. **Means and standard deviations of the posterior parameter distributions (restricted VAR model).**

	2003		2004		2005		2006		2007		2008		2009		2010		2011	
	mean	**SD**	**mean**	**SD**	**mean**	**SD**	**mean**	**SD**	**mean**	**SD**	**mean**	**SD**	**mean**	**SD**	**mean**	**SD**	**mean**	**SD**
α_1	0.196	0.073	0.177	0.072	0.183	0.071	0.186	0.070	0.178	0.068	0.174	0.068	0.190	0.080	0.199	0.079	0.186	0.079
β_2	0.048	0.020	0.041	0.019	0.043	0.019	0.044	0.018	0.041	0.018	0.041	0.018	0.046	0.021	0.048	0.021	0.044	0.021
α_2	0.001	0.000	0.001	0.000	0.001	0.000	0.001	0.000	0.001	0.000	0.001	0.000	0.001	0.000	0.000	0.000	0.000	0.000
β_3	0.916	0.043	0.924	0.044	0.919	0.041	0.923	0.040	0.920	0.040	0.922	0.041	0.932	0.041	0.943	0.039	0.934	0.036
α_3	−0.125	0.074	−0.105	0.073	−0.117	0.071	−0.123	0.070	−0.117	0.068	−0.115	0.068	−0.142	0.079	−0.165	0.081	−0.155	0.081
β_4	0.969	0.020	0.975	0.019	0.972	0.019	0.970	0.018	0.972	0.018	0.972	0.018	0.964	0.021	0.958	0.021	0.961	0.021
ρ_{12}	−0.314	0.108	−0.320	0.105	−0.334	0.101	−0.329	0.099	−0.329	0.096	−0.265	0.099	0.086	0.103	0.084	0.101	0.077	0.099
ρ_{13}	−0.205	0.114	−0.213	0.111	−0.194	0.109	−0.169	0.107	−0.198	0.104	−0.197	0.102	0.197	0.099	0.212	0.097	0.165	0.097
ρ_{14}	−0.944	0.013	−0.940	0.014	−0.938	0.014	−0.938	0.014	−0.936	0.014	−0.937	0.013	−0.939	0.013	−0.925	0.015	−0.925	0.015
ρ_{23}	0.561	0.083	0.493	0.089	0.495	0.086	0.472	0.086	0.434	0.088	0.418	0.087	0.591	0.068	0.572	0.069	0.574	0.067
ρ_{24}	0.297	0.109	0.278	0.108	0.300	0.104	0.298	0.101	0.297	0.099	0.226	0.101	−0.090	0.103	−0.108	0.100	−0.111	0.098
ρ_{34}	0.196	0.115	0.224	0.110	0.221	0.108	0.201	0.106	0.237	0.102	0.229	0.100	−0.148	0.101	−0.173	0.098	−0.143	0.098
σ_1^2	4.919	0.863	4.961	0.845	4.865	0.805	4.703	0.759	4.561	0.715	4.527	0.695	6.162	0.925	6.100	0.897	6.107	0.878
σ_2^2	0.001	0.000	0.001	0.000	0.001	0.000	0.001	0.000	0.001	0.000	0.001	0.000	0.001	0.000	0.001	0.000	0.001	0.000
σ_3^2	0.011	0.002	0.011	0.002	0.011	0.002	0.012	0.002	0.013	0.002	0.014	0.002	0.025	0.004	0.025	0.004	0.025	0.004
σ_4^2	4.959	0.870	4.948	0.844	4.862	0.808	4.687	0.755	4.587	0.720	4.565	0.701	5.987	0.899	6.336	0.931	6.327	0.907

This table displays the means and standard deviations of the posterior distributions for the parameters of the VAR model of Equations (2.4) with the additional restriction $\beta_1 = 0$. The parameters σ_2^2 and σ_3^2 have been multiplied by a factor of 10,000. Estimation results are for samples starting in 1985 and ending in the first quarter of the years 2003 – 2010.

As we noted in Section 2.2.4, the conventional approach uses point estimates of β_1 and ρ_{13} to test the Fisher hypothesis. Figure 2.2(a) displays the posterior means of β_1 for sample periods ending between 2003 and 2011, together with the 95% highest posterior density interval. The approach of the Fisher investor, who assumes that $\beta_1 = 0$, seems reasonable. Figure 2.2(b) displays the posterior means of ρ_{13} and the corresponding 95% highest posterior density interval. Also the assumption that stocks are a perfect hedge against unexpected inflation does not seem unreasonable.

Finally, we compare the estimated parameters with those in existing studies. The sign of the estimated coefficient of expected inflation differs widely across studies (see Schotman and Schweitzer (2000), Bekaert and Wang (2010)). Despite mixed evidence regarding the sign, many studies establish a lot of parameter uncertainty in the estimate. The negative correlation between innovations in real stock returns and unexpected inflation that we establish prior to 2009 ($\rho_{13} < 0$) matches the findings in previous literature (Schotman and Schweitzer (2000)).

2.4.2 Optimal stock allocations

We obtain the agnostic and Fisher investors' optimal stock allocations for holding periods of 5, 7 and 10 years after the last day of the sample period. To obtain these allocations, we need an initial value of the expected inflation and the dividend yield, which we set equal to their values at the end date of the sample period. The first panel part of Table 2.4 displays the optimal stock holdings for the agnostic investor, whereas the second panel contains the results for the Fisher investor. For both investors, we report the optimal stock allocations for an expanding window that ends between 2003 – 2011.

We observe certain differences in the investors' optimal stock allocations across sample periods, which are due to changes in the risk-free rate and the model parameters over time. The changes in the model parameters prompt changes in the mean and variance of stock returns, which affect optimal portfolio holdings. For example, in comparison with 2008, the optimal stock allocations for the agnostic investor are much lower in 2009 and 2010.

Figure 2.2. **Posterior distributions of β_1 and ρ_{13}.**

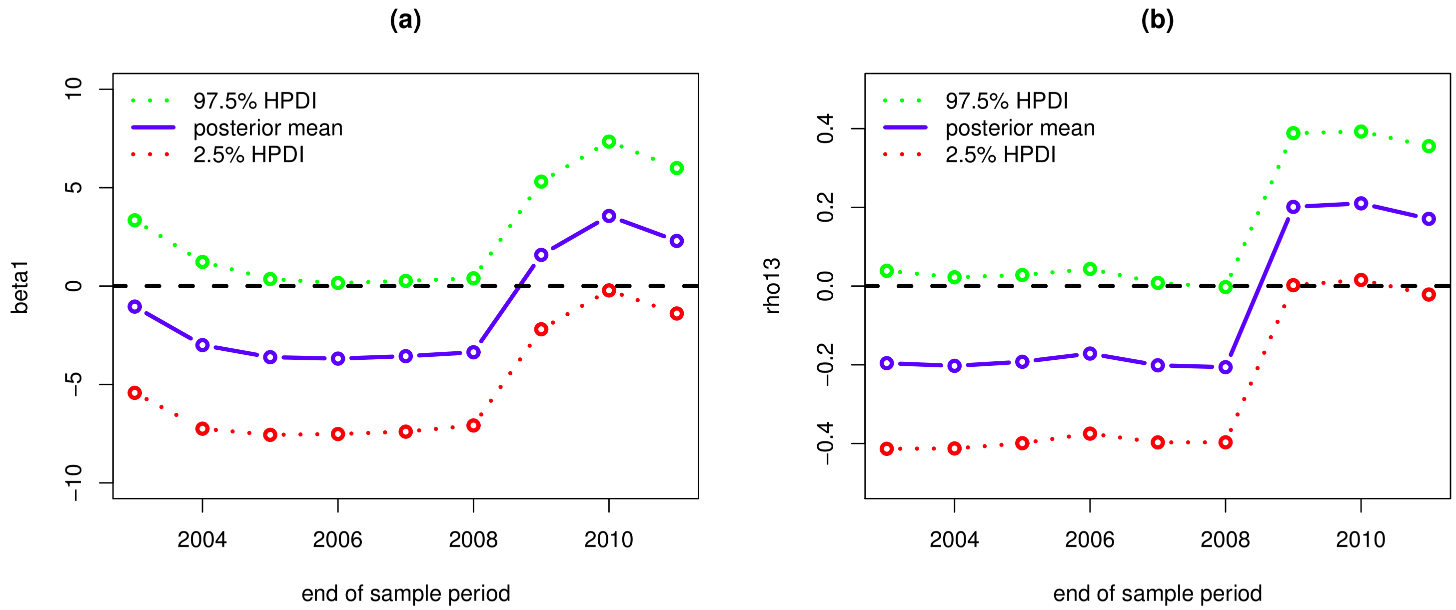


Figure (a) displays the posterior means of β_1 in the agnostic investor's VAR model, whereas Figure (b) shows the posterior means of ρ_{13} in the same model. In addition to the posterior means, we indicate the 95% highest posterior density interval (HPDI). The year of the final observation appears on the horizontal axis.

In response to changes in the optimal portfolio weights over time, investors may want to change the composition of their asset portfolio before the end of the holding period. If they do so, the real yield on the inflation-linked bond is no longer guaranteed. As mentioned in Section 2.2.2, we therefore assume throughout that investors complete the full holding period of 5, 7, or 10 years.

Several other results emerge from Table 2.4. The agnostic investor's optimal stock holdings decrease with the investment horizon, regardless of the end date of the sample. This means that we observe certain horizon effects, which deserve further attention.

2.4.3 Horizon effects

Assuming normality of logarithmic portfolio returns, Campbell and Viceira (2002, p. 25-30) show that the optimal share of wealth invested in a stock by a power utility investor increases with expected stock return and decreases with return variance. To gain insight into the risk-return trade-off in relation to the investment horizon, it is thus useful to derive from the VAR model of equation (2.4) the expected value and the variance of k-period real stock returns; see Appendix 2.B. From equation (2.B.1), it becomes clear that the initial levels of expected inflation and dividend yield affect the conditional mean and thereby the optimal stock holdings. If the highly persistent processes of expected inflation is below its expected value, it slowly increases over time. For $\beta_1 > 0$, expected stock returns will therefore increase over time (*ceteris paribus*), which makes stocks a more attractive investment in the long run. The initial level of the highly persistent dividend affects the expected stock return in a similar way.

The predictability of stock returns from expected inflation and dividend yields can also give rise to negative (positive) autocorrelation in stock returns – a phenomenon known as mean reversion (aversion). Because the persistence parameters have values close to unity, it becomes apparent from equation (2.B.1) that stock returns exhibit negative (positive) autocorrelation for sufficiently negative (positive) values of $\beta_1\sigma_{12}$, $\beta_2\sigma_{14}$ or $\beta_1\beta_2\sigma_{24}$. In this case the variance of the k-period stock return grows less (faster) than proportionally over time. Consequently, the agnostic investor considers stocks less (more) risky in the long run and allocates a relatively large (small) share of wealth to stocks for longer investment horizons.

A third reason for horizon effects is the fact that the risk-free rate increases with maturity, so the inflation-linked bond becomes a more attractive investment opportunity in the long run.

Table 2.4. **Optimal stock allocations for agnostic and Fisher investors.**

	2003	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**
					weights VAR				
5	18.6	32.5	36.3	42.2	25.6	62.8	48.0	14.6	33.7
7	11.1	22.2	27.9	35.4	21.8	50.8	42.3	12.8	29.8
10	6.2	11.7	17.9	26.3	17.5	37.8	35.4	10.4	27.0
					weights Fisher				
5	20.1	36.9	47.6	51.8	46.2	87.2	90.6	55.1	58.6
7	13.9	32.2	48.1	55.3	49.1	87.0	83.3	53.3	56.2
10	10.0	24.5	45.6	58.7	52.8	86.4	73.0	48.4	55.0
					ΔCER				
5	0.00	0.00	0.06	0.04	0.17	0.25	2.06	0.93	0.31
7	0.00	0.04	0.16	0.15	0.29	0.79	2.11	0.99	0.33
10	0.00	0.08	0.35	0.51	0.56	2.14	1.70	0.91	0.39
					$E[r_p]$				
5	1.55	1.86	2.26	3.58	2.95	3.72	4.68	0.65	1.67
7	1.89	1.87	2.14	3.31	2.89	3.42	4.31	1.11	2.03
10	2.09	2.08	2.13	3.04	2.79	3.13	3.95	1.63	2.27
					ΔCER$/E[r_p]$				
5	0.0	0.0	2.5	1.0	5.8	6.6	43.9	142.8	18.9
7	0.0	2.4	7.4	4.5	10.2	23.1	48.8	89.5	16.5
10	0.0	4.1	16.6	16.7	20.0	68.4	43.1	55.7	17.4

The first part of this table ('weights VAR') displays the optimal stock allocations (in % of initial real-term wealth) for the agnostic investor who bases her optimal stock allocations of the VAR model of equation (2.4). The second part of the table ('weights Fisher') shows the optimal stock allocations for the Fisher investor who bases her stock allocations on the same VAR model, with the additional restriction that $\beta_1 = 0$. The third part of the table ('ΔCER') reports the corresponding difference in certainty equivalent returns (in percentage points), whereas the fourth part ('$E[r_p]$') displays the expected annual real return (in %) on the optimal portfolio. The last part of the table ('ΔCER$/E[r_p]$') reports the difference in CERs as a percentage of the expected real return on the optimal portfolio. Throughout, we consider investment horizons equal to 5, 7 and 10 years, as indicated in the first column. The allocations are based on samples starting in 1985 and ending in the first quarter of the years 2003 – 2011.

The final source of horizon effects is parameter uncertainty, due to which the variance of the multi-period real returns grows faster than linear over time, making stocks less attractive in the long run (Barberis (2000)).

The agnostic investor's optimal stock allocations in Table 2.4 make clear that the overall result of the four horizon effects is a reduction of the allocation to stocks at longer holding periods. The Fisher investor's optimal stock allocation also tends to decrease with the investment horizon, but not for all end dates.

2.4.4 Inflation risk exposure of stocks

The third panel of Table 2.4 (captioned 'ΔCER') reports the loss in expected utility incurred by the Fisher investor if she ignores the influence of expected inflation on real stock returns. To assess its magnitude, we compare the difference in CERs with the expected real return on the optimal portfolio Kandel and Stambaugh (1996); see the fourth and fifth panel of Table 2.4 (captioned '$E[r_p]$' and '$\Delta\text{CER}/E[r_p]$'). The differences in CERs in Table 2.4 reveal a considerable exposure of stock returns to inflation risk. For the sample ending in 2010 and a holding period of 5 years the difference in CERs is almost 150% of the expected return on the optimal portfolio. Up to 2008, we observe the highest inflation risk exposure for longer investment horizons.

We can explain our findings as follows. The agnostic investor, who acknowledges that expected inflation affects real stock returns, believes that stocks are more risky than does the Fisher investor. The predictability of stock returns from expected inflation makes stock riskier in the view of the agnostic investor.[8] The agnostic investor therefore consistently allocates a substantially smaller fraction of wealth to stocks than does the Fisher investor. Consequently, ignoring the inflation risk exposure of real stock returns results in an over-allocation to stocks, implying a loss of expected utility for the Fisher investor.

Where some studies based on the Fisher coefficient claim that stocks are a better hedge against inflation for longer investment horizons (see e.g., Boudoukh and Richardson (1993)), we identify sample periods during which the inflation risk exposure of stocks increases with the investment horizon.

[8] The agnostic investor takes into account the influence of expected inflation on stock returns. Because the posterior distribution of $\beta_1\sigma_{12}$ has most probability mass in the range of positive values, stocks become riskier when the influence of expected inflation on real stock returns is accounted for.

2.4.5 Discussion

The numerical results for the inflation risk exposure of stocks depend on the asset allocation framework, the degree of risk aversion, the specification of the VAR model and the selected predictor variables. Our analysis provides some important insights. We have provided an example of a situation with little traditional evidence against the Fisher hypothesis. Nevertheless, our economically based inflation measure makes clear that the economic significance of the influence of expected inflation on stock returns is substantial.

Often, the Fisher hypothesis cannot be rejected as an artefact of large parameter uncertainty, and not because of genuine evidence in favour of it. The large parameter uncertainty stems from the different time series properties of stock returns and inflation rates; the former being much more volatile than the latter (Schotman and Schweitzer (2000)). An attractive feature of our new measure is that it accounts for the parameter uncertainty associated with the estimated model coefficients, thereby circumventing this problem.

2.5 Conclusion

A widespread assumption in the economic literature is that an asset is a good hedge against inflation if the Fisher hypothesis holds, that is, if nominal asset returns move in parallel with expected inflation. However, the Fisher coefficient is a purely statistical measure for the inflation-hedging ability of stocks; it is uninformative about the economic relevance of the influence of inflation rates on stock returns. Furthermore, in a regression of volatile stock returns on slowly moving inflation rates, the estimated Fisher coefficient often involves large standard deviations, due to which the Fisher hypothesis cannot be rejected.

Our economically based inflation measure has illustrated that the economic relevance of the influence of expected inflation on stock returns can be substantial, despite a lack of traditional evidence against the Fisher hypothesis. The new measure for inflation risk proposed in this study reflects the economic influence of inflation rates on stock returns in a context of portfolio optimization and explicitly accounts for parameter uncertainty due to estimating model coefficients.

The economic context determines the type of economic measure that is needed to sensibly assess inflation risk. This chapter has focused on a framework of portfolio optimization, but other applications are possible. We leave this as a direction for future research.

2.A Bayesian estimation

In this Appendix we describe the estimation method used to obtain parameter estimates in model (2.4), used by the agnostic investor. We define

$$\begin{aligned}
\boldsymbol{y}_t &= \left(r_{t+1}, \pi^e_{t+1}, \pi^u_{t+1}, d_{t+1}\right)' \\
\boldsymbol{\theta} &= \left(\alpha_1, \beta_1, \beta_2, \alpha_2, \beta_3, \alpha_3, \beta_4\right)' \\
Z_t &= \begin{pmatrix} 1 & \pi^e_t & d_t & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & \pi^e_t & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & d_t \end{pmatrix}.
\end{aligned}$$

We write the agnostic investor's VAR model as $\boldsymbol{y}_t = Z_t\boldsymbol{\theta} + \boldsymbol{\varepsilon}_t$, where the disturbance vector $\varepsilon_t = (\varepsilon_{1,t}, \varepsilon_{2,t}, \varepsilon_{3,t}, \varepsilon_{4,t})$ follows a multivariate normal distribution, with mean 0 and covariance matrix Σ and is independent over time t. We stack the observations for all T time periods in the information set, so that $\boldsymbol{y}$ and $\boldsymbol{\varepsilon}$ are $(4T \times 1)$ vectors, and Z is a $(4T \times 4)$ matrix and we can write $\boldsymbol{y} = Z\boldsymbol{\theta} + \boldsymbol{\varepsilon}$. In this setting we can use an independent normal-Wishart prior to arrive at conditional posterior distributions, $\boldsymbol{\theta} \mid \boldsymbol{y}, \Sigma^{-1} \sim N(\overline{\boldsymbol{\theta}}, \overline{V}_{\boldsymbol{\theta}})$ and $\Sigma^{-1} \mid \boldsymbol{y}, \boldsymbol{\theta} \sim \text{Wish}(\bar{S}^{-1}, \overline{v})$. Here

$$\overline{V}_{\boldsymbol{\theta}} = \left(\sum_{t=1}^{T} Z_t'\Sigma^{-1}Z_t\right)^{-1}, \quad \overline{\boldsymbol{\theta}} = \overline{V}_{\boldsymbol{\theta}} \sum_{t=1}^{T} Z_t'\Sigma^{-1}\boldsymbol{y}_t;$$

with

$$\overline{v} = T, \quad \overline{S} = \sum_{t=1}^{T} (\boldsymbol{y}_t - Z_t\boldsymbol{\theta})(\boldsymbol{y}_t - Z_t\boldsymbol{\theta})'.$$

A Gibbs sampling algorithm is used to draw sequentially from $p(\boldsymbol{\theta} \mid \boldsymbol{y}, \boldsymbol{\Sigma}^{-1})$ and $p(\boldsymbol{\Sigma}^{-1} \mid \boldsymbol{y}, \boldsymbol{\theta})$. To obtain a sample $r_T(k)^{(1)}, \ldots, r_T(k)^{(N)}$ from the predictive k-period return distribution , we exploit the distribution of the k-period return, which is normal given $\boldsymbol{\theta}$ and Σ. The resulting sample from the predictive distribution is used to estimate the expected utility for different stock allocations ω; the integral in equation (2.6) is approximated by

$$\int\int u(W_{T+k})p(r_T(k)|\mathcal{I}_T,\theta)p(\theta|\mathcal{I}_T)dr_T(k)d\theta \approx \frac{1}{N}\sum_{i=1}^{N} u\left[W_{T+k}(r_T(k)^{(i)})\right].$$

The optimal value of ω can be obtained using a numerical optimization routine.

For the Fisher investor, who believes that stocks are a perfect hedge against expected but not against unexpected inflation, we adopt a similar approach, with

$$
\begin{aligned}
\boldsymbol{\theta} &= (\alpha_1, \beta_2, \alpha_2, \beta_3, \alpha_3, \beta_4)' \\
Z_t &= \begin{pmatrix} 1 & d_t & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & \pi_t^e & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & d_t \end{pmatrix}
\end{aligned}
$$

2.B Mean reversion due to predictability

In this Appendix we provide the expressions for expected k-period returns $E_t[r_t(k)]$, and their variance $\mathrm{Var}_t[r_t(k)]$, in terms of the parameters in model (2.4).

$$
\begin{aligned}
E_t[r_t(k)] &= E_t[r_{t+1} + \ldots + r_{t+k}] \\
&= k\alpha_1 + \sum_{n=2}^{k} \sum_{j=1}^{n-1} \left\{ \beta_1 \beta_3^{j-1} \alpha_2 + \beta_4^{j-1} \beta_2 \alpha_3 \right\} \\
&\quad + \sum_{n=1}^{k} \left\{ \beta_1 \beta_3^{n-1} \pi_t^e + \beta_4^{n-1} \beta_2 d_t \right\},
\end{aligned}
$$

$$
\begin{aligned}
\mathrm{Var}_t[r_t(k)] &= \mathrm{Var}_t[r_{t+1} + \ldots + r_{t+k}] = \sum_{n=1}^{k} \mathrm{Var}_t[r_{t+n}] \\
&\quad +2 \sum_{i>j} \mathrm{Cov}_t[r_{t+i}, r_{t+j}],
\end{aligned}
$$

where the following definitions apply:

$$
\begin{aligned}
\sum_{n=1}^{k} \mathrm{Var}_t[r_{t+n}] &= k\sigma_1^2 + \sum_{n=2}^{k} \sum_{j=1}^{n-1} \Big\{ \beta_1 \beta_3^{j-1} \left(\beta_1 \beta_3^{j-1} \sigma_2^2 + \beta_4^{j-1} \beta_2 \sigma_{24} \right) \\
&\quad + \beta_4^{j-1} \beta_2 \left(\beta_1 \beta_3^{j-1} \sigma_{24} + \beta_4^{j-1} \beta_2 \sigma_4^2 \right) \Big\},
\end{aligned}
$$

and, for $i > j$,

$$
\begin{aligned}
\mathrm{Cov}_t[r_{t+i}, r_{t+j}] &= \sum_{n=1}^{j-1} \Big\{ \beta_1 \beta_3^{n-1} \left(\beta_1 \beta_3^{i-j+n-1} \sigma_2^2 + \beta_4^{i+j-n-1} \beta_2 \sigma_{24} \right) + \\
&\quad + \beta_4^{n-1} \beta_2 \left(\beta_1 \beta_3^{i-j+n-1} \sigma_{24} + \beta_4^{i+j+n-1} \beta_2 \sigma_4^2 \right) \Big\} + \\
&\quad + \beta_1 \beta_3^{i-j-1} \sigma_{12} + \beta_4^{i-j-1} \beta_2 \sigma_{14}.
\end{aligned}
$$

2.C Real yield data

The table below displays the real rate for various investment period starting dates (February 15, 2003 to 2011) at maturities of 5, 7 and 10 years. For example, at the end date of our sample, February 15, 2011, the yearly real yields were equal to 0.44%, 1% and 1.33% for maturities of 5, 7 and 10 years, respectively.

Table 2.C.1. **Term structure of real interest rates.**

	maturity (years)		
start	**5**	**7**	**10**
2003	1.29	1.78	2.03
2004	0.85	1.28	1.74
2005	1.06	1.30	1.61
2006	2.03	2.06	2.08
2007	2.38	2.41	2.38
2008	0.68	1.15	1.48
2009	1.21	1.40	1.68
2010	0.37	0.87	1.42
2011	0.44	1.00	1.33

This table displays the real yield (% per year) as provided by the U.S. Department of the Treasury. The starting date of the real yield is February 15 of the year in the first column. The data are sourced from the website `http://www.treasury.gov/resource-center/data-chart-center/interest-rates/Pages/default.aspx`.

Chapter 3

Who should buy long-term bonds? The case of India

3.1 Introduction

The Indian economy has gone through a period of fast economic growth in the last decade. Between 1999 and 2009 Indian GDP more than trebled in dollar terms. At the same time, the domestic savings rate increased from 24.1 to 34.7 percent. Annual household savings are currently in the range of 400 billion dollars a year (Shah and Patnaik (2011)). An increasing number of households has the opportunity to decide independently about the allocation of their savings, either directly through mutual funds or through the framework of the New Pension System (NPS).

But what is an appropriate investment strategy for an Indian household? This question is important not only for individuals who want to select a portfolio mix that matches their risk preferences. It also has implications for the financial market reforms the Indian government is undertaking to efficiently process the growing savings inflow.

In this chapter we will address this question using results from the strategic asset allocation literature. Using a fifteen-year sample of benchmark government bond yields and domestic stock index returns, we apply the methodology proposed by Campbell and Viceira (2001) to obtain optimal allocations to various government bonds and to the stock index. We distinguish between different investor types by allowing for a range of risk aversion levels and for different investment horizons.

We are particularly interested in the optimal allocation to government bonds. This is for two reasons. First, recent literature on investment plan design in developing economies highlights overallocation to government debt instruments as a major problem Viceira (2010). One of the reasons for this overallocation may be the conventional wisdom that bonds are safe financial instruments, as they provide a stable stream of income. This would make them suitable for conservative investors. But in the face of inflation risk, the safety of nominal bonds can be elusive (Campbell et al. (2003), Bekaert and Wang (2010), Brière and Signori (2011)). In this chapter we will quantify the trade-off between the inflation risk exposure of nominal bonds and their role as a hedge against real interest rate fluctuations. Thus we will assess whether the portfolio of a conservative investor should contain long-term bonds, or rather consist of cash only.

The second reason for our focus on the bond market is the recent Indian debate on financial reform (see e.g., the report of the Committee for Financial Reform of the Planning Commission and Shah and Patnaik (2011)). The Indian government securities market is generally considered a success story when it comes to modernizing the transaction settlement infrastructure, removing trading frictions and facilitating price discovery by active market makers (Reddy (2002), Report of the Committee for Financial Reform, p. 117). The investor base, however, still largely consists of 'captive' investors, like public financial institutions, employee's provident funds and insurance companies. Such institutions are currently required to allocate at least 23 % of their assets to liquid instruments, predominantly cash and government bonds. Shah and Patnaik (2011) forcefully argue against this 'financial repression', claiming that only 15 % of government bond holdings with these institutions are voluntary. In our analysis, we will shed additional light on this issue from the perspective of retail investors. Specifically, we will show that while investing in long-term bonds may not be in the best interest of agents who prioritize safety over return, a long position in bonds can be optimal for moderately risk-averse investors if they are restricted to investing in domestic assets.

While the case of a rapidly growing economy like India is interesting by and of itself, overallocation to domestic bonds is an issue in many developing countries (e.g., Roldos (2004), Viceira (2010)). Unfortunately, an analysis like the one in this study is often infeasible due to the lack of sufficiently long time series of bond market data. Nonetheless we believe that quantifying the benefits and risks of holding long-term bonds can contribute to the broader discussion on investment restrictions in emerging markets, which has been largely qualitative this far. Moreover, the results of this study can be compared to those obtained for U.S. markets, which is helpful for determining which elements of long-term investment theory can be translated to an emerging market setting.

The remainder of this chapter is structured as follows. In section 2, we describe recent developments in the Indian bond market and in the asset management industry. In section 3, we briefly discuss the main elements of the econometric methodology used to extract optimal portfolio weights from bond yields and stock returns. We present our empirical results in section 4. Section 5 concludes.

3.2 Institutional context

3.2.1 Government bond market

The development of a well-functioning government bond market has been a key policy objective of the Reserve Bank of India (RBI) since the early 1990s, when the country abandoned its system of government-administered interest rates. To achieve this objective, RBI chose a strategy of promoting companies working to improve the market microstructure. These companies were obliged to place bids in the primary auctions of government paper and to provide two-way quotes in the secondary market, thus facilitating the emergence of a benchmark yield curve.

With the basic structures in place, further technological innovations were implemented to increase transaction efficiency and transparency. Notably, in 2002, RBI introduced the Negotiated Dealing System (NDS) for electronic trading in government securities, with the Clearing Corporation of India (CCIL) acting as central counterparty for all trades. Next to the clearing role, CCIL also takes an active part in facilitating the price discovery process. For example, it disseminates daily zero coupon yield curves, benchmark bond indices and similar information products (Reddy (2002)).

These efforts have ensured a substantial growth of the government bond market. In the period March 1995-March 2010 the share of government debt financed by market loans increased from 49.1% to 74.2%. The absolute amount of loans outstanding on the market grew from 130,908 crore Rupees to 1,734,505 crore Rupees (41.5 to 359.3 billion USD) marking an average annual growth rate of 11.3% in real terms.

In Table 3.1 we put several features of the Indian domestic bond market in a comparative perspective. We use a group of countries at a similar stage of development (i.e. in the World Bank's 'Middle Income' category) as a reference. The first column of this table shows that the size of the Indian market as a percentage of GDP (35.2%) is typical for a middle-income country. This naturally makes it one of the bigger markets in absolute size (column two). Columns three and four show the importance of long-term debt. In India, the percentage of short-term debt (maturity up to one year) is very low at 4.4 % while the average maturity of total debt outstanding is very high at nearly ten years. Moreover, the vast majority of domestic debt (85.8 %) is issued by the government, reflecting the relatively low state of development of the corporate debt market.

Table 3.1. **The Indian domestic bond market, 2010.**

	Relative Size	Absolute Size	Maturity < 1 Year (%)	Average Maturity	Government Share (%)
Malaysia	53.8	128.0	1.1	4.5	53.3
Thailand	52.1	166.1	55.4	6.0	73.6
Brazil	39.7	829.4	36.9	3.4	62.0
Morocco	36.7	33.5	-	-	-
Egypt	35.7	78.1	60.5	-	-
India	**35.2**	**608.3**	**4.4**	**9.8**	**85.8**
Turkey	31.0	227.6	2.7	2.5	99.0
Philippines	30.9	58.4	26.8	5.4	96.4
China	27.6	2,156.7	45.9	-	53.5
Colombia	24.4	70.3	-	-	-
Peru	14.6	22.4	38.1	15.0	79.1
Argentina	13.4	49.4	36.1	9.5	83.9
Indonesia	11.6	98.2	20.4	0.9	87.6
Chile	11.1	22.6	15.8	13.5	37.6

The relative size of the bond market is expressed as a percentage of GDP. The absolute size is in billions of United States dollars. The percentage of bonds with a maturity below one year is expressed in terms of their total value divided by the value of all outstanding bonds. The average maturity is value weighted. The percentage of government bonds is in terms of their total value, divided by the total value of all domestic debt instruments outstanding. The figures were retrieved from Tables 16 and 17 of the Bank for International Settlements' statistics at http://www.bis.org/statistics/secstats.htm. The ratio of outstanding debt to GDP was obtained by using the GDP data provided in the World Bank's World Development Indicators database at http://data.worldbank.org/data-catalog/world-development-indicators.

The liquidity of the Indian government bond market has been assessed favourably in the recent report by the Committee on Financial Sector Reforms of the Planning Commission of the Government of India. This committee considered three liquidity criteria: immediacy (i.e. the impact cost of small trades), depth (the impact cost of large trades) and resilience (adjustment of the market after large trades). The market for on-the-run government bonds scored positively on the first two counts, making it the second most liquid market after equity.

Overall we can conclude that Indian bonds are quite liquid, and in considerable supply. These are important prerequisites for attracting individual investors. Even in developed countries, however, most individuals don't operate directly on the bond market, but rather invest in mutual funds with fixed income positions. Before turning to the analysis of investor bond demand, we will therefore briefly dwell on the Indian asset management industry.

3.2.2 Asset management industry

The scope of investment opportunities for Indian citizens has improved considerably after the entry of privately owned asset management companies on the market in 1993. As of 2010, a total of 47 mutual funds running 590 investment schemes are registered with the Securities and Exchange Board of India (SEBI).[1] Over the period 2000-2010 the average annual growth of net assets under management by mutual funds amounted to 12.1 percent in real terms. The ratio of assets to GDP increased from 5.5% to 9.9%, with their end-of-fiscal-year value in March 2010 amounting to 613,979 crore Rupees (USD 137 billion). This figure ensures a high ranking of India's asset management industry among middle income countries, in terms of both its absolute and relative size (Table 3.2).

Individual investors command a share of about 51% of total assets under management, the remainder belonging to corporate entities, banks and foreign institutional investors. This share can be divided in a part contributed by high net worth individuals investing 5 lakh Rupees (approx. USD 10,000) and above and a part contributed by retail investors. The former hold folios with an average worth of USD 40,500, amounting to 47% of individual investments. The retail segment contributes 53%; here the average folio is worth USD 785.

[1] The data on assets under management by mutual funds that are used in this section are disseminated by the Association of Mutual Funds in India and have been accessed at http://www.amfiindia.com.

Table 3.2. **Size of the Indian mutual fund industry**.

	Relative Size (%)	Absolute Size
Brazil	29.2	784.0
Chile	20.9	34.2
India	9.9	130.3
Mexico	9.3	81.6
China	7.6	381.2
Costa Rica	4.5	1.3
Turkey	3.2	19.4
Argentina	1.5	4.5
Pakistan	1.4	2.2
Philippines	0.9	1.5

The relative size is the value of net assets under management (AUM) by mutual funds divided by GDP. The absolute size is the value of AUM in billions United States dollars. Data on net assets of mutual funds are from Table 102 of the Handbook of Statistics on the Indian Securities Market 2010 (Securities and Exchange Board of India (2010), available from www.sebi.gov.in). GDP data are from the World Bank's World Development Indicators, available at http://data.worldbank.org/data-catalog/world-development-indicators.

Exact figures of the number of individuals investing in mutual funds are hard to determine. The average folio worth in the retail branch and the fact that there are over 46 million folios outstanding strongly suggest that investment is not restricted to the wealthiest citizens only. Individual investment can be expected to grow further due to the recent introduction of the National Pension System (NPS). This system, accessible to all citizens of India, consists of a mandatory pension contribution and a voluntary investment account, which allows adding or withdrawing funds at all times. The account holders can decide on their preferred mix of equity- and debt-based mutual funds. To participate, one must provide an initial sum of 1000 Rupees (about USD 25) and a minimum annual contribution of 250 Rupees.

3.3 Modelling the government bond market

3.3.1 Choice of econometric model

Our objective is to analyse investor demand for Indian government bonds. These bonds come at a wide range of maturities. They have different degrees of exposure to, for example, inflation and interest rate shocks, and hence different redemption yields. Therefore our analysis requires an econometric model for the relationship between the maturity of a bond and its yield, i.e. for the term structure of interest rates.

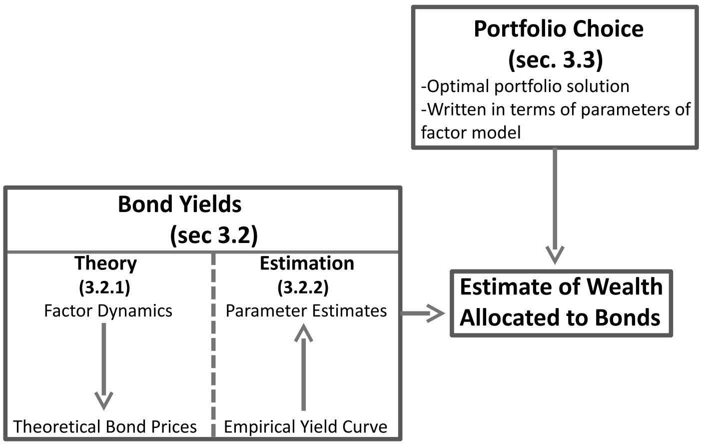
There is a long research tradition in the field of term structure modelling (e.g., Modigliani and Shiller (1973), Vasicek (1977), Cox et al. (1985)). The link between realistic, arbitrage-free term structure models and long-term portfolio choice has been forged much more recently, however. Sørensen (1999) studied a model explaining differences in bond yields from variation in the short-term real interest rate. Campbell and Viceira (2001) allowed both the real interest rate and inflation expectations to affect the term structure of interest rates. They studied the portfolio choice problem of an infinitely-lived agent who invests his financial wealth to finance a stream of income. A similar two-factor model was proposed by Brennan and Xia (2002) for the case of an investor interested in the return on his investments at one specific moment in the future.

Over the last decade, joint term structure-portfolio selection models have been extended to allow for more factors driving yield spreads and for time variation in the risk premia underlying these spreads (e.g., Sangvinatsos and Wachter (2005)). While it is tempting to use a comprehensive multi-factor model, the relatively short history of the Indian benchmark yield curve makes parsimony the main model selection criterion.[2] In the class of two-factor models, the approach of Campbell and Viceira (2001) (henceforth CV (2001)) stands out. It allows for a clear interpretation of the two factors as the real interest rate and expected inflation.

In the sections to come we will briefly introduce the methodology developed in CV (2001). This methodology follows a partial equilibrium approach. It takes the perspective of a small investor, who treats security prices as given and whose choices are assumed not to affect these prices. Its components are summarized in Figure 3.1. First, a time series model is formulated for the dynamics of the two factors. This model results in theoretical bond prices/yields (section 3.3.2). The parameters of this model can be estimated from empirical data on bond yields at different maturities (section 3.3.2). Second, the investor's optimal allocation to bonds is expressed in terms of the parameter of the time series model (section 3.3.3). Using the model estimates, we obtain investors' demand for bonds, which is our penultimate objective.

[2] It has been noted in the literature that, even in the case of U.S. yield curve data spanning half a century, the estimation of three-factor models is computationally difficult and gives rise to overfitting concerns (e.g., Duffee (2002), p. 418, Sangvinatsos and Wachter (2005), p. 194).

Figure 3.1. **Schematic depiction of the CV (2001) model.**



3.3.2 Nominal bond prices

Theoretical model

It is assumed that bond price fluctuations are related to the movements of two unobserved factors: the real short-term interest rate and expected inflation.[3] These processes can be linked to the stochastic discount factor which prices all assets in the economy. Specifically, the natural logarithms of the real short-term interest rate r_r, the real stochastic discount factor m_r, the inflation rate π and its conditional expectation π^e follow the vector autoregressive process (VAR):

$$\begin{pmatrix} r_{r,t+1} \\ -m_{r,t+1} \\ \pi^e_{t+1} \\ \pi_{t+1} \end{pmatrix} = \begin{pmatrix} \mu_r(1-\phi_r) \\ c \\ \mu_{\pi^e}(1-\phi_{\pi^e}) \\ 0 \end{pmatrix} + \begin{pmatrix} \phi_r & 0 \\ 1 & 0 \\ 0 & \phi_{\pi^e} \\ 0 & 1 \end{pmatrix} \begin{pmatrix} r_{r,t} \\ \pi^e_t \end{pmatrix} + \begin{pmatrix} \varepsilon_{r,t+1} \\ \varepsilon_{m,t+1} \\ \varepsilon_{\pi^e,t+1} \\ \varepsilon_{\pi,t+1} \end{pmatrix}, \tag{3.1}$$

with multivariate normal innovations $\boldsymbol{\varepsilon} \sim N(\mathbf{0}, V)$.[4]

[3] Throughout this chapter the real short-term interest rate is defined as the time-t interest rate on a hypothetical inflation-indexed bill maturing at time $t+1$.

[4] The relationship between the nominal stochastic discount factor and the real stochastic discount factor is given by $m_{t+1} = m_{r,t+1} - \pi_{t+1}$.

In this model the log real interest rate follows an AR(1)-process with mean μ_r and persistence parameter ϕ_r. The log real-term stochastic discount factor is inversely related to the current real interest rate. The dynamics of expected and realized inflation rates are modelled in a similar way. The covariance matrix of the innovations is parametrized as $V = QDQ'$ with

$$Q = \begin{pmatrix} 1 & 0 & 0 & 0 \\ \beta_{mr} & 1 & 0 & 0 \\ \beta_{\pi^e r} & \beta_{\pi^e m} & 1 & 0 \\ \beta_{\pi r} & \beta_{\pi m} & \beta_{\pi\pi^e} & 1 \end{pmatrix}; D = \mathrm{diag}(\sigma_r^2, \sigma_m^2, \sigma_{\pi^e}^2, \sigma_\pi^2)$$

It can be derived that under the dynamics in (3.1), the log price of a zero-coupon bond with k periods to maturity is linearly related to r_t and π_t^e :[5]

$$-p_{k,t} = a_k + b_{1,k} r_t + b_{2,k} \pi_t^e. \tag{3.2}$$

The elasticities of the bond price with respect to the real rate ($b_{1,k}$) and to inflation expectations ($b_{2,k}$) are determined by the persistence of the corresponding AR-processes in equation (3.1):

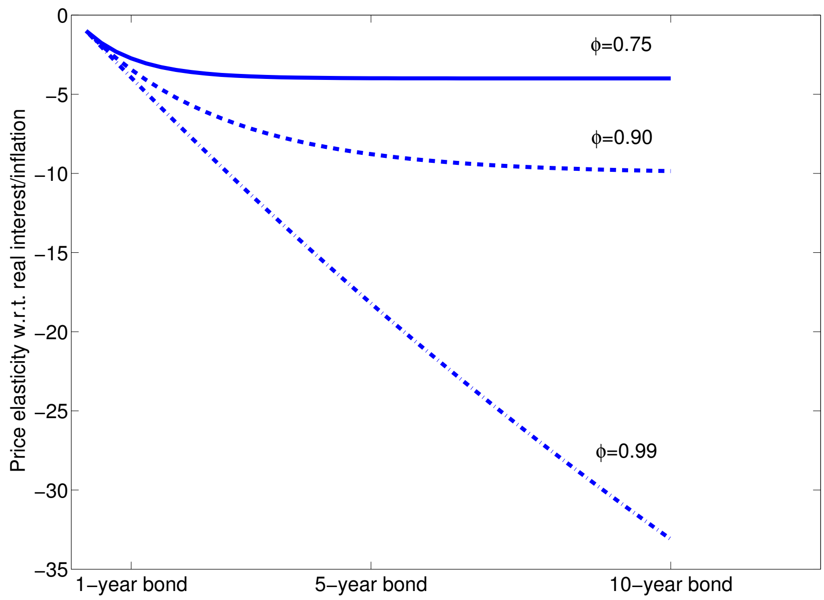
$$b_{1,k} = \frac{1 - \phi_r^k}{1 - \phi_r}; \quad b_{2,k} = \frac{1 - \phi_s^k}{1 - \phi_s}. \tag{3.3}$$

In Figure 3.2 we display bond price elasticity at different maturities, for varying values of the persistence parameter. Remark that for any given maturity, the elasticity increases with persistence. The higher the persistence parameter, the longer the effects of an expected real rate or inflation shock can be expected to last, and the more pronounced the bond price response. Also, for any given persistence level, the elasticity increases with bond maturity.

The increase in bond price in response to an unexpected decrease of the interest rate, which determines the bond's interest rate hedging potential, thus depends crucially on the persistence of the real rate process ϕ_r. Likewise, the bond price decrease following a positive inflation shock, which determines its exposure to inflation risk, depends on ϕ_{π^e}.

[5] The details of this derivation, and the exact expression for a_k in terms of the parameters in equation (3.1), are presented in the online Appendix to the article 'Who Should Buy Long-Term Bonds?' available from the site of John Campbell: http://scholar.harvard.edu/campbell/publications. Backus et al. (1998) present more general derivation techniques for bond prices in discrete-time factor models.

Figure 3.2. **Illustration of bond price elasticity.**



In absolute terms, the elasticity is increasing in bond maturity given any persistence parameter $\phi \in (0,1)$. Also, the larger the persistence, the larger the absolute bond price elasticity at all maturities.

Parameter estimation

The parameters of system (3.1) can be estimated by maximum likelihood, using state-space methods to construct the likelihood function (see e.g., A. Harvey (1989)). The real interest rate and expected inflation act as the state variables. They can be related to the (realized) inflation rate and to market prices/yields of benchmark zero-coupon bonds at different maturities. The state-space model can also be extended by including equity returns, which allows for an analysis of the role of bonds in mixed stock-bond portfolios.

3.3.3 Nominal bond demand

It is assumed that investors possess a certain endowment of financial wealth and intend to use it to finance a stream of future consumption. Their preferences are summarized by the Epstein-Zin (1989) recursive utility function

$$U_t(C_t, E_t[U_{t+1}]) = \left\{ (1-\delta) C_t^{\frac{\psi-1}{\psi}} + \delta \left(E_t[U_{t+1}^{1-\gamma}] \right)^{\frac{\psi-1}{\psi(1-\gamma)}} \right\}^{\frac{\psi}{\psi-1}}. \tag{3.4}$$

At time t, the investor derives utility from time-t consumption C_t and from expected utility at time $t+1$, $E_t[U_{t+1}]$. The parameter $\delta < 1$ is the investor's time discount factor, weighting the utility from current consumption and from expected utility in the future. The parameter γ controls the risk aversion of the investor, while ψ captures his elasticity of intertemporal substitution.

The investor maximizes utility function (3.4) subject to the budget constraint

$$W_{t+1} = (1 + R_{p,t+1})(W_t - C_t). \tag{3.5}$$

In this constraint, W_t stands for the investors' wealth at time t and $R_{p,t+1}$ denotes the gross return on his portfolio. The latter can be expressed as

$$R_{p,t+1} = \boldsymbol{\omega}_t' \boldsymbol{R}_{t+1} + R_{0,t+1},$$

where $R_{0,t+1}$ is the one-period return on a benchmark asset and $\boldsymbol{R}_{t+1}$ is a $n \times 1$ vector of excess returns on the other assets. Utility maximization takes place with respect to the investors' consumption path $\{C_t\}$ and his portfolio weight path $\{\boldsymbol{\omega}_t\}$.

CV (2001) present a solution of the investor's portfolio problem in an economy with bond price dynamics as in equations (3.1) and (3.2). If the asset space consists of a nominal one-period bill and n bonds with maturities $k_1, k_2, ..., k_n$ periods into the future, let's define the one-period nominal interest rate at time t by $r_{\text{nom},t+1}$. The one-period return on a bond maturing k_i periods ahead, $i \in \{1, \ldots, n\}$, is written as $r^{(k_i)}_{\text{nom},t+1}$. The optimal portfolio in terms of long-term bond weights is then equal to[6]

$$\boldsymbol{\omega} = \frac{1}{\gamma} \Sigma^{-1} \left(\boldsymbol{m} + (1-\gamma)\boldsymbol{c} + \frac{(1-\gamma)\delta}{1-\delta\phi_r} \boldsymbol{h} \right). \tag{3.6}$$

[6] The solution presented here holds for $\psi = 1$. For $\psi \neq 1$ this solution depends on a log-linear approximation of the investor's budget constraint. Moreover, the parameter δ is replaced by a function of the log consumption-wealth ratio $c_t - w_t$ in (3.5) and hence of other model parameters. Portfolio weights then have to be obtained using a numerical recursive procedure. Our primary interest is in portfolio weights, rather than in the consumption path. CV (2001, p. 113) find that, in general, ψ has a very small effect on optimal portfolio policies. Therefore we will henceforth assume that $\psi = 1$.

In this equation, the i-th elements of the $n \times 1$ vectors $\boldsymbol{m}$, $\boldsymbol{c}$ and $\boldsymbol{h}$ are defined as

$$\begin{aligned}
\boldsymbol{m}_i &= E_t\left[r^{(k_i)}_{\mathrm{nom},t+1} - r_{\mathrm{nom},t+1}\right] + \frac{1}{2}\mathrm{Var}_t\left[r^{(k_i)}_{\mathrm{nom},t+1} - r_{\mathrm{nom},t+1}\right] \\
\boldsymbol{c}_i &= \mathrm{Cov}_t\left[\left(r^{(k_i)}_{\mathrm{nom},t+1} - r_{\mathrm{nom},t+1}\right), \pi_{t+1}\right] \\
\boldsymbol{h}_i &= \mathrm{Cov}_t\left[\left(r^{(k_i)}_{\mathrm{nom},t+1} - r_{\mathrm{nom},t+1}\right), r_{r,t+1}\right],
\end{aligned} \tag{3.7}$$

and element (i, j) of the $k \times k$ matrix Σ is given by

$$\Sigma_{ij} = \mathrm{Cov}_t\left[\left(r^{(k_i)}_{\mathrm{nom},t+1} - r_{\mathrm{nom},t+1}\right), \left(r^{(k_j)}_{\mathrm{nom},t+1} - r_{\mathrm{nom},t+1}\right)\right].$$

Note that the optimal portfolio can be interpreted as a mix of three distinct portfolios. The first two of them correspond to optimal choices of investors who are only interested in one-period returns ($\delta = 0$). The portfolio $\Sigma^{-1}\boldsymbol{m}$ is the optimal strategy for a risk-neutral one-period investor ($\gamma = 1, \delta = 0$). This investor cares only about the ratio of expected excess returns m to their conditional one-period variance. The portfolio $-\Sigma^{-1}\boldsymbol{c}$ is the choice of his infinitely risk-averse counterpart ($\gamma = \infty, \delta = 0$). This investor only wants to minimize portfolio variance. He is interested in risky assets that covary negatively with inflation. This is due tot the fact that he dislikes the inflation risk in the real T-Bill return. The optimal portfolios of one-period investors with intermediate risk aversion levels ($1 < \gamma < \infty$) can be seen as a division of their wealth between these two boundary portfolios.

The optimal portfolio of an investor who does look beyond one period in the future ($\delta > 0$) consists of an additional third component. This investor needs to take into account that real interest rates vary over time and can be quite persistent. Therefore he takes an additional hedging position in assets that pay off when the real rate falls. The more negative the covariance with the real rate, the more suitable bonds become for this purpose. The magnitude of the hedging position is positively related to real rate persistence ϕ_r, to risk aversion γ, and to δ, the value the investor attaches to future as compared to current consumption.

In our subsequent empirical analysis we will apply the result in (3.6) to assess which investor types should be interested in Indian government bonds, and for what reason. We can use the bond price expression (3.2) to express all optimal portfolio components in (3.8) in terms of the parameters in system (3.1). For future reference, the expressions are given in Table 3.3.

Table 3.3. **Expressions for σ_k^2 h, c and m**

h_k	$-(b_{1,k-1} + \beta_{\pi^e r} b_{2,k-1})\sigma_r^2$
c_k	$\beta_{\pi r} h_k - \beta_{\pi m} \beta_{\pi^e m} b_{2,k-1} \sigma_m^2 - \beta_{\pi \pi^e} b_{2,k-1} \sigma_{\pi^e}^2.$
m_k	$\beta_{mr} h_k + c_k - \beta_{\pi^e m} b_{2,k-1} \sigma_m^2$
σ_k^2	$(b_{1,k-1} + \beta_{\pi^e r} b_{2,k-1})^2 \sigma_r^2 + (\beta_{\pi^e m} b_{2,k-1})^2 \sigma_m^2 + b_{2,k-1}^2 \sigma_{\pi^e}^2$

In this table we provide the expression for the variance σ_k^2 of an k-period bond, as well as its covariance with, respectively, the real interest rate (h_k), the inflation rate (c_k) and the stochastic discount factor (m_k), in terms of the parameters of system (3.1).

3.4 Empirical analysis

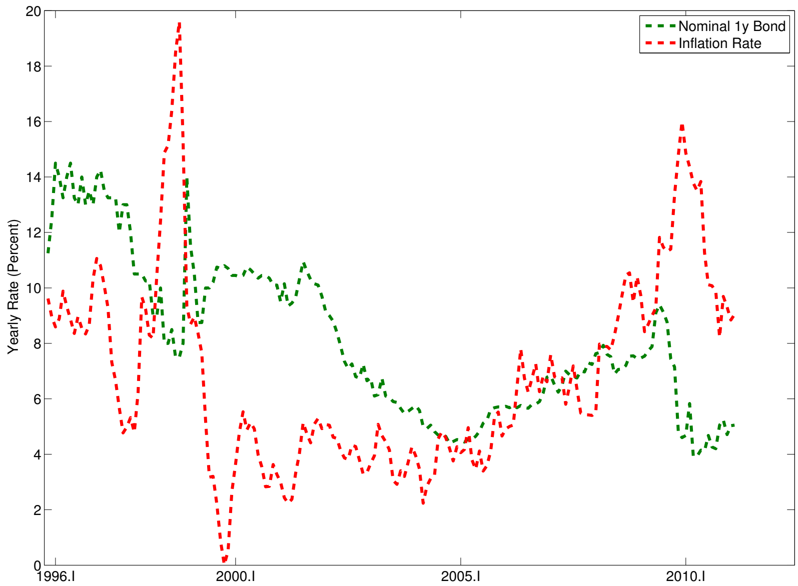
3.4.1 Data and summary statistics

To obtain parameter estimates for the model presented above we require time series of bond yields, inflation rates and real equity returns. Yields on Indian government bonds with maturities of one, five and ten years have been retrieved from Thomson Datastream. The starting date of these series is November 1994. For the sake of comparison with the results found by CV(2001) for the United States, we use quarterly data in our main analysis. The sample starts in the first quarter of 1995 and ends in the second quarter of 2011. We take the Indian Government 91-day Treasury Bill as our benchmark asset. We obtain quarterly inflation rates from the difference in logs of the Indian Consumer Price Index, which we adjust for seasonality using the X-12-ARIMA methodology (Findley et al. (1998)). Finally, real log equity returns are constructed from log differences of the India BSE National 100 Index, subtracting the inflation rate as computed above.[7]

Figure 3.3 presents the year-on-year inflation rate, along with the corresponding interest rate on the one-year zero-coupon bond. From this figure we see that nominal bond yields have exceeded the inflation rate on average, but the difference between the two series is highly variable over time. Except for the inflation hike in the second part of 1998, it has been positive throughout the 1996-2005 period. However, from 2006 onwards the CPI inflation rate has generally outpaced nominal interest rates, the difference becoming particularly striking from the beginning of 2010.

[7] The Datastream Mnemonic codes for these series are INTB91D (T-bill), INBD1YR, INBD5YR INBD10Y, (Bonds), IBOMBSE (Equity Index) and INCONPRCF (Consumer Price Index). Results based on monthly data are very similar and available from the author upon request. The same holds for results obtained using inflation rates that are not seasonally adjusted.

Figure 3.3. **Inflation and nominal interest rate.**

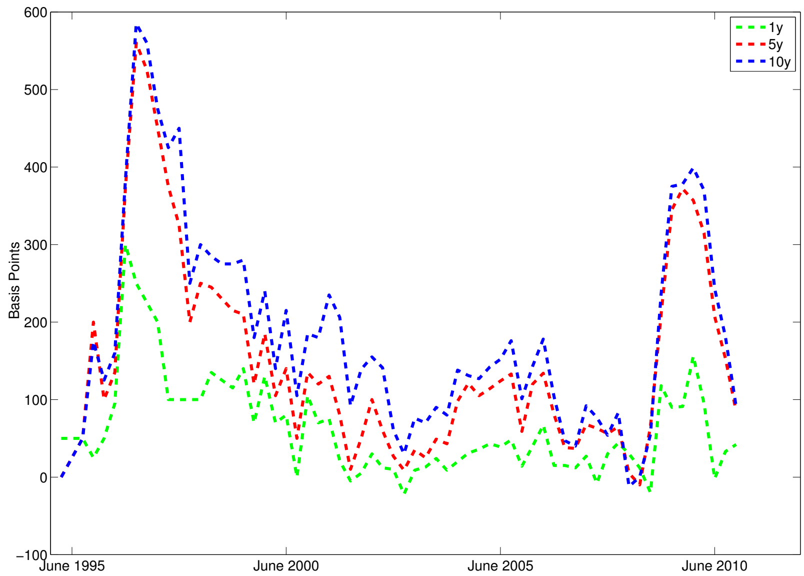


This figure shows the year-on-year inflation rate and the corresponding nominal return from holding a one-year zero-coupon bond. For example, the values for 2000.1 correspond to the inflation rate over the period 1999.1-2000.1 and to the redemption yield obtained from the one-year zero-coupon bond bought in 1999.1 and redeemed in 2000.1.

This increase of the inflation rate was caused by rising and volatile commodity and food prices in the world market. The Reserve Bank of India initially responded with a restrictive monetary policy. This policy was discontinued by mid-2008 however. In the midst of the global financial crisis. the policy objectives changed and an expansionary policy was followed so as not to jeopardize the rate of economic growth as the influx of foreign capital slowed. Combined with persistently high food prices, this led to double-digit CPI inflation starting in the second quarter of 2009. With economic recovery setting in, the policy rates were raised again and inflation has been brought back to 9.2 percent over the last quarter of 2010 and the first quarter of 2011. Still, this is 2.5 percent in excess of the average in our sample period.

Figure 3.4 displays the evolution of the yield spreads between the one-year bond and the three-month bill and the ten-year bond and the three-month bill. The corresponding average yields are given in Table 3.4. A distinctive feature in this figure is the considerable rise in long-term bond yield spreads during the recent inflationary period. This suggests that investors believe that the current inflation shocks may have persistent, long-term effects. For a detailed analysis, we now turn to estimating the CV (2001) two-factor model using these data.

Figure 3.4. **Yield spreads**



This figure shows the difference in annualized yield between the benchmark 91-day Bill and, respectively, 1 year, 5 year and 10 year government bonds over the last fifteen years.

Table 3.4. **Average yields on Indian bonds**

Maturity	3 months	1 year	5 years	10 years	**Inflation**
	7.52	8.11	8.95	9.32	6.77
	(2.67)	(2.81)	(2.82)	(2.81)	

The average yields are given in percentage terms. The sample period is 1995.I-2010.IV. Standard deviations are in parentheses.

3.4.2 Risk-averse investors: the trade-off between interest rate risk and inflation risk

The estimates of system (3.1) for Indian bonds are presented in Table 3.5.[8] Let us first consider the means and persistence parameters of the processes for the real interest rate and for expected inflation. The real interest rate process has unconditional mean $\mu_r = 0.001$. This implies a rather low mean real rate of 43 basis points per annum over the sample period.[9] This rate is quite persistent, with $\phi_r = 0.699$. This suggests that, at least on the part of risk-averse investors, there should be a considerable demand to hedge interest rate risk.

Looking at the persistence $\phi_{\pi^e} = 0.997$ of the expected inflation process, however, it immediately becomes doubtful whether long-term bonds are the appropriate instrument to do this. On the one hand, the covariance of bond returns with the real rate is negatively related to ϕ_{π^e}. This is due to our positive estimate of $\beta_{\pi^e r}$. This estimate implies that a decrease (increase) of the real rate tends to coincide with a decrease (increase) of the inflation rate.[10] Consequently, the bond price reaction in response to real rate shock is augmented through the inflation channel. This is beneficial from the perspective of hedging real interest rate fluctuations.

On the other hand, however, the covariance of bond returns with inflation is also negatively related to inflation persistence. The longer the effects of an upward inflation shock can be expected to last, the more pronounced is the bond price decrease resulting from it. This trade-off between the desire to hedge interest rate variation and the reluctance to take inflation risk is the main driver of the portfolio decision of an infinitely risk-averse investor ($\gamma = \infty$) whose portfolio weights, by equation (3.6), equal

$$\boldsymbol{\omega} = \Sigma^{-1}\left(\boldsymbol{c} - \frac{\delta}{1-\delta\phi_r}\boldsymbol{h}\right). \tag{3.8}$$

[8] In order to reduce overfitting concerns, and for the sake of comparison with the analysis in CV (2001), we fix μ_{π^e} at the sample mean of the inflation rate. Moreover, we restrict the model parameters so that the mean nominal short rate implied by the model equals the mean short rate in the sample. All estimates are in original, i.e. quarterly, terms.

[9] Note that we have to multiply by 400 to obtain this rate from the parameter estimate, which is based on quarterly data. For comparison, the average real rate found in CV (2001) for the United States over the period 1952-1996 was equal to 139 basis points.

[10] In terms of the expression for h_k in Table 3.3, h_k is decreasing in $b_{2,k-1}$ (and hence in ϕ_{π^e}) given that $\beta_{\pi^e r} > 0$.

Table 3.5. **Estimates of the factor model parameters**.

	India		United States	
Parameters	Estimate	Std. Error	Estimate	Std. Error
Process Means				
μ_r	0.0011	0.1277	0.0034	0.0298
μ_{π^e}	0.0169		0.0094	
Persistence				
ϕ_r	0.6999***	0.0309	0.8688***	0.0057
ϕ_{π^e}	0.9974***	0.0026	0.9992***	0.0012
D-matrix				
σ_r	0.0019***	0.0002	0.0025***	0.0001
σ_m	0.2302	0.1747	0.2694***	0.0927
σ_{π^e}	0.0015***	0.0002	0.0013***	0.0001
σ_π	0.0135***	0.0013	0.0071***	0.0004
Q-matrix				
β_{mr}	−321.74**	127.66	−74.980*	41.695
$\beta_{\pi^e r}$	0.0976	0.1616	0.0752	0.0516
$\beta_{\pi^e m}$	0.0003	0.0014	−0.0012**	0.0006
$\beta_{\pi r}$	0.5703	1.1951	0.5198*	0.3050
$\beta_{\pi m}$	−0.0039	0.0097	−0.0088***	0.0034
$\beta_{\pi\pi^e}$	1.8908	2.0113	1.4320***	0.2940
Equity				
β_{ex}	−10.315	14.584	−3.4957	3.4123
β_{em}	0.6417	0.4798	0.3013***	0.0979
Loglik.	24.3575		26.3327	

The standard errors are valid asymptotically. Note that μ_{π^e} has no standard error, as it is fixed in our estimation. For comparison, the results of Campbell and Viceira (2001) are also presented. The reported log-likelihood is obtained from the model log-likelihood, divided by the number of estimation periods.

The estimates of h_k, c_k and σ_k for our three bonds with maturities one, five and ten years are given in Table 3.6. The covariance between bond returns and the real rate is negative and significant, as was to be expected. It is negatively related to bond maturity. However, the ratio of covariance to bond volatility drops in absolute terms. This means that short-term bonds provide a better interest rate hedge-volatility trade-off than long-term bonds. The covariance of bond returns with the inflation rate is also negative, although statistical significance cannot be established, as some of the components of c_k cannot be measured very precisely from our data.

In Table 3.7 we present the resulting allocation for an infinitely risk-averse investor who can invest in the Treasury Bill and a single bond. From the first column, an investor with a reasonably high discount factor ($\delta > 0.9$) will invest between 12 and 31 percent of his wealth in the one-year bond, and the remainder in the bill. He is not at all interested, however, in longer-term bonds. The exposure to inflation risk outweighs the interest rate hedging potential of these bonds. As compared to the one-year bond, they have to bear the long-run effects of a persistent inflation shock for a longer period; hence their price falls more in response to such shocks. Indeed, if it were possible, the investor would prefer to short long-term bonds in order to hedge against the short-term inflation risk contained in the Treasury Bill.

Considering portfolios consisting of the Treasury Bill and multiple bonds, we find the results in Table 3.8. The investor's optimal strategy in this case is to short the instruments which are most exposed to interest rate risk and inflation risk (i.e. borrow money at the T-bill rate and short the long-term bond) and invest the proceeds from this operation, along with all his wealth, in the one-year bond. This underlines the importance of the one-year bond as a middle ground in the trade-off between interest rate risk and inflation risk.

This optimality of short positions in long-term bonds should of course be treated as an illustrative result, that unveils the relative magnitude of the three bond demand factors, rather than an actually feasible strategy. The latter would require borrowing money at the T-bill rate and finding a counterparty willing to lend the underlying bond. Both are typically impossible for an individual investor; neither does the National Pension System allow for short positions in bonds. We will address strategies that take these restrictions into account in section 3.4.3.[11]

[11] Taking these restrictions into account, the analytical decomposition of the portfolio components in equation 3.6 is lost. This is an important reason for discussing the unrestricted results as a starting point.

Table 3.6. **Estimates of the components of the optimal portfolio.**

Component		1y	5y	10y	Equity
h	model	-0.004^{***}	-0.008^{***}	-0.011^{*}	-0.015
	s.e.	0.001	0.003	0.006	0.022
c	sample	-0.009	-0.039	-0.082	-0.074
	model	-0.007	-0.036	-0.068	0.014
	s.e.	0.008	0.041	0.080	0.118
m	sample	0.789	2.611	5.223	16.01
	model	1.189^{**}	2.359	3.091	18.31^{**}
	s.e.	0.466	1.758	3.363	8.131
σ	sample	1.617	6.958	12.33	30.39
	model	1.321^{***}	5.923^{***}	11.47^{***}	29.74^{***}
	s.e.	0.169	0.585	1.11	3.266
$\text{SR} = m/\sigma$		0.900	0.398	0.269	0.616

Columns 3-5 correspond to excess returns on bonds with maturities of one, five and ten years. Column five corresponds to excess equity returns. Rows 1-2 concern the covariance of returns with the real rate, denoted h. The model estimate is in row 1. Its asymptotic standard error, obtained by the delta method, is in row 2. Rows 3-5 concern the covariance with inflation. Here, we also provide the sample value in row 3. Rows 6-8 are about the expected excess return m and rows 7-9 contain its standard deviation. The estimates are reported in annual percentage terms. For example, the entry 5.223 for the risk premium on the 10-year bond indicates an expected yearly return of 5.223% over the Treasury Bill rate.

Table 3.7. **Single bond portfolios of the infinitely risk-averse investor.**

Discount factor δ	1-year bond	5-year bond	10-year bond
0.50	-24	-8	-5
0.75	-7	-7	-4
0.90	12	-5	-3
0.96	22	-4	-3
0.99	29	-3	-3
1.00	31	-3	-3

The second column shows the percentage of wealth invested in a one-year bond, if the investor has to divide his wealth between the T-Bill and this bond. Columns three and four do the same for five- and ten-year bonds.

Table 3.8. **Multiple bond portfolios of the infinitely risk-averse investor.**

δ	1y	5y	1y	10y
0.50	43	−17	28	−7
0.75	92	−25	70	−11
0.90	144	−33	115	−14
0.96	174	−38	141	−16
0.99	192	−41	156	−18
1.00	198	−42	162	−18

The second and third columns contain the optimal allocation, in percentage terms, of an investor with time preference δ when the investment opportunity set consists of cash, a one-year bond and a five-year bond. The fourth and fifth columns contain the optimal allocation if the investment opportunity set consists of a one-year bond and a ten-year bond.

A second purpose of these results is comparison with previous studies conducted in developed markets. There are quite some similarities to the findings of CV (2001) for the 1952-1996 period in the United States. They report a very similar multiple bond strategy for a risk-averse investor, which involves a long position of 184 percent in a 3-year bond and a short position of 57 percent in the long bond (p. 117). This is not surprising, as the inflation persistence parameter they estimate is even larger than in our case, at 0.999. However, contrary to our results, they do find a positive (yet modest) demand of 9 percent for 10-year bonds when the available assets are the bill and the 10-year bond. This difference can be attributed to the fact that they also estimate a higher persistence of the real interest rate process ($\phi_r = 0.869$), which leads to higher hedging demand.

We can conclude that the safest fixed income strategy in India consists of short-term instruments only. It is not in the interest of conservative investors, who put absolute priority on a stable income stream, to participate in the market for long-term bonds. As we will see in the next section, such bonds are more likely to be found in the portfolios of investors who are willing to benefit from the risk premia in bond and stock markets.

3.4.3 Speculative investors: earning the term premium and diversifying equity holdings

For investors with a lower degree of risk aversion the term premium offered for investing in bonds comes into play. In the last row of Table 3.6 we can see that the trade-off between return and risk, as summarized by the Sharpe ratio SR $= \frac{m}{\sigma}$, is quite favourable for Indian bonds.[12] Still, it is unlikely that speculative investors will invest in bonds only. Therefore we will focus on the demand for bonds in a portfolio containing both equity and fixed income instruments.

The characteristics of equity returns are given in the last column of Table 3.6. The annual equity risk premium is very substantial at 18.31 percent. This is not surprising, given the annual return volatility of nearly 30 percent. It can therefore be expected that all but the completely risk-neutral investors will be willing to diversify their portfolios by including other assets. The question is whether long-term bonds can play a role here.

We have obtained optimal allocations to stocks and bonds using equation (3.6) and subsequently imposing both borrowing and short-sale constraints.[13] The results presented in Table 3.9 show that the answer to our question is a definite 'yes'. Most importantly, bonds of all three maturities under study are in positive demand with investors in the conventional risk aversion range (i.e. $1 \leq \gamma < 20$). Their weight in the portfolio as a function of the risk aversion level follows a hump-shaped pattern. Investors with a very low level of risk aversion want to benefit maximally from the risk premium on equity and hence are not interested in bonds. For the others, long-term bonds are an attractive diversifying possibility due to their high Sharpe Ratio and their low correlation with equity returns. This is especially true for investors with moderate levels of risk aversion. Indeed, for risk aversion levels between 5 and 20 the majority of the investor's portfolio consists of bonds. With increasing risk aversion bond volatility becomes more and more important. Consequently bond demand declines towards zero. This decline sets in earliest for the ten-year bond, which is the most volatile. Note, however, that exactly this ten-year bond is demanded the most by investors with low risk aversion. For them the magnitude of its risk premium is most important, alongside its diversifying capabilities.

[12] For example, the Sharpe ratios for the one-year and the ten-year bonds found by CV are 0.34 and 0.17.

[13] The focus of this chapter is on individual investors who want to allocate a certain endowment of financial wealth. Such investors are not likely to leverage their portfolios and are typically restricted from short-selling assets (see e.g., the rules of the NPS saving scheme). Optimal constrained portfolios can be obtained from unconstrained portfolios by applying the methods in Teplá (2000).

Table 3.9. **Allocation to bonds and equity in a mixed portfolio, as a function of risk aversion γ.**

γ	1y	Eq	5y	Eq	10y	Eq
1	0	100	0	100	0	100
2	2	98	9	91	12	88
5	61	39	61	39	49	43
10	80	20	66	21	23	21
20	90	10	31	11	10	11
100	88	2	3	2	0	2
∞	22	0	0	0	0	0

Column 2 contains the allocation to a one-year bond if the asset menu consist of this bond, equity and the treasury bill. Column 3 contains the allocation to equity for this case. Likewise, the remaining columns provide the allocation when the available bond has a maturity of five years (columns 4-5) and ten years (columns 6-7). All numbers are in percentage terms. The discount factor δ is set to 0.96 throughout.

A similar, but much less pronounced pattern has been found by CV (2001) in their 1952-1996 U.S. sample (see Table 3.10). Here also bond demand peaks at a risk aversion level of $\gamma = 5$, but now bonds constitute only 12 percent of the investor's portfolio. This can be attributed to the lower bond term premium in their sample, and to the fact that U.S. equity is less risky and hence more attractive for moderately risk-averse investors. Moreover, CV (2001) show that demand stems primarily from the interest rate hedging motive here, rather than from equity diversification or speculative purposes, as in our case.

Table 3.10 also shows that Indian long-term bond demand is not nearly as high as in the short sample of CV (2001) from the 'Great Moderation' period (1983-1996). Once again, the difference stems from the absence of hedging demand in the case of India. Opposite to what we saw in our Indian data, the persistence of the real rate in the Great Moderation era has been very high ($\phi_r = 0.986$), while inflation has been contained at a low level. This combination ensures that interest rate hedging by means of bonds is particularly relevant and effective.

Although the reasons for holding long-term bonds may be different for Indian investors, this does not necessarily mean that bond positions are suboptimal for them. Even if the traditional view of bonds as safe instruments for conservative investors is not valid in the Indian case, they do have value for more aggressive investors who seek a diversified portfolio with a relatively high rate of return.

Table 3.10. **Comparison of bond-equity allocations in India and the United States.**

	India		U.S. 1952-1996		U.S. 1983-1996	
γ	10y	Eq	10y	Eq	10y	Eq
1	0	100	0	100	4	96
2	12	88	0	100	48	52
5	49	43	12	69	75	25
10	23	21	11	33	84	16
∞	0	0	10	0	92	3

Columns two and three contain the optimal allocation to the ten-year bond and to equity, in percentage terms, for the Indian investor, as a function of risk aversion γ in the first column. The remainder is invested in short-term bills. The remaining columns reproduce the corresponding results of Campbell and Viceira (2001) for two distinct periods in the United States.

3.5 Conclusion

The rapid growth of savings in the Indian economy requires a thorough analysis of their optimal allocation. In this chapter we have analysed the allocation decision of a small Indian investor who divides his wealth between domestic equity and government bonds. Our primary focus was on the bond market, in view of the recent debate surrounding the effects of compulsory investment in government securities.

We have found that there is considerable demand for long-term bonds from moderately risk-averse investors. They can use bonds to counterbalance the considerable risk incurred in the domestic stock market, while still earning a term premium in excess of the three-month interest rate. This source of bond demand is naturally related to future developments in both the equity risk premium and the volatility in the Indian stock market. It may also depend on the Indian government's future decisions considering financial liberalization, as allowing investment in foreign markets will give access to plenty of alternative hedging instruments.

However, the long-term bond market has, up to now, largely failed to cater to the needs of very risk-averse investors who wish to minimize their exposure to interest rate or equity market fluctuations and are only interested in a stable stream of real income over time. This is a missed opportunity for three reasons. First of all this means that an important class of investors, like for example pensioners, lacks an instrument to hedge against interest rate fluctuations. If they participate in a compulsory savings plan, where they cannot decide on the maturity of their bond portfolio, they are exposed to substantial inflation risk. Second, the absence of hedging demand is detrimental for the heterogeneity of the bond market and may limit its liquidity. Third, the Indian government is deprived of a potential source of voluntary funding, which is likely to grow over time. The best way out of this situation, particularly after the recent inflationary episode, is to stabilize inflation and to anchor inflation expectations, thus decreasing the inflation risk of long-term bonds. Alternatively, the Indian government can follow the path taken before by developing countries like Chile, and consider the introduction of inflation-indexed bonds.

Chapter 4

International diversification benefits in developing economies

4.1 Introduction

Should developing countries allow their pension funds to invest abroad? This question has recently received a lot of attention as the asset management industry has grown considerably across emerging markets. A clear trade-off exists between portfolio diversification on one side and enhancement of domestic capital stock and financial markets on the other. In practice, most developing country governments impose stringent restrictions on foreign investment.[1] This chapter contributes to the discussion on such restrictions by quantifying international diversification benefits for investors in four major emerging markets: India, Pakistan, Malaysia and Thailand.

Three studies have recently addressed the issue of international portfolio diversification from a developing country perspective. Driessen and Laeven (2007) investigated a sample of 52 countries, including 23 developed and 29 developing markets, over the period 1985-2002. Using a mean-variance spanning approach (Huberman and Kandel (1987), De Roon et al. (2001)) they found that diversification benefits for developing countries are substantial, and significantly larger than

[1] Viceira (2010) and Kumara and Pfau (2011) provide comprehensive overviews of investment restrictions per country.

for developed countries. Their results indicate that the average Sharpe ratio increase for developing country investors who gain access to global equity markets amounts to 13.5%, as opposed to 7.8% for investors in developed countries.

Chiou (2008) confirmed these results using both risk-adjusted performance gains and volatility reduction measures in a similar mean-variance framework. He considered a sample consisting of 21 developed and 13 developing countries over the period 1988-2004. According to his findings, the average risk-adjusted performance increase of a globally diversified portfolio amounts to 70% in emerging markets, as opposed to 46% in developed countries. Moreover, investors in emerging markets can reduce portfolio volatility by 65% by investing abroad. These results hold in spite of increasing global market integration over the sample period.

Kumara and Pfau (2011) focused exclusively on investors in emerging markets. They used a bootstrap approach to simulate the retirement wealth distribution of pension fund participants who can invest in both local and global equity and fixed income assets. Their results suggest that the wealth distribution resulting from internationally diversified portfolios dominates that of strictly domestic portfolios in 22 out of the 25 emerging markets considered in their analysis.

Our study contributes to this literature in two ways. First, we analyse diversification benefits for emerging market investors using a dynamic, rather than a static model of asset returns. It is well known that dynamic features of asset returns, most notably return predictability and mean reversion, can lead to significant timing and investment horizon effects in optimal portfolio decisions (e.g., Brennan et al. (1997), Barberis (2000)). Risk-averse long-term investors are willing to allocate a larger part of their wealth to assets with mean-reverting returns, as their volatility increases more slowly over time. Such dynamic features of the return process may render diversification benefits dependent on an investor's asset horizon. For instance, investing in a mean-reverting foreign stock market yields higher diversification benefits for a long-term institutional investor than for a short-term investment fund with a similar risk appetite. To the best of our knowledge, our study is the first to map diversification benefits as a function of the investment horizon in an emerging market context.

While predictability and mean reversion have been analysed assiduously for developed markets,[2] few studies have addressed these statistical features in an emerging market context. C. Harvey (1995), Bekaert and Harvey (2007) and Hjalmarsson (2010) are among the few studies that analyse return predictability, while Malli-

[2] See e.g., Goyal and Welch (2008) for a recent overview of the return predictability literature with a focus on the U.S. market.

aropulos and Priestley (1999) and Chaudhuri and Wu (2003) present results on mean reversion in emerging equity markets. Consequently investors in such markets face uncertainty about both the extent of return predictability, and the relevant predictor variables. This introduces model risk in their asset allocation problem. In addition to this model risk, emerging market investors are subject to a relatively large amount of estimation risk, as model parameters have to be obtained from relatively short and volatile return time series.

The second contribution of this study, therefore, is the analysis of diversification benefits in a framework that explicitly takes these risk factors into account. To this end we apply recent advances in Bayesian vector autoregressive (VAR) modelling. We take the perspective of an investor who considers various candidate predictor variables for asset returns. He uses the Bayesian posterior probability of the resulting models to assign 'inclusion probabilities' to each of the predictors. An important advantage of this approach is that, while many candidate predictors can be taken into account, not all of them have to be included in each and every model considered by the investor. This reduces the parameter proliferation problem typical of the standard unrestricted VAR approach, an important advantage in view of the fact that the time series of emerging market asset returns are relatively short.

Our empirical focus on India, Malaysia, Pakistan and Thailand stems from two considerations. First, these countries have a long financial market history, with at least twenty years of data available for both asset returns and predictor variables. Second, these markets have a high capitalization relative to domestic savings. Thus gains from international diversification are not obvious *a priori* in these markets, contrary to developing economies with financial markets that are too small to absorb domestic savings. For each of these four countries, we consider four local and three global predictor variables for asset returns.

Our main findings can be summarized as follows. In the four countries considered, there is little evidence of stock return predictability once model and parameter uncertainty are taken into account. While the inclusion probabilities for all candidate predictors are relatively low, their magnitude is non-negligible, which confirms the relevance of an approach that incorporates model uncertainty. We find that, from the perspective of emerging market investors, there is no indication for horizon effects in the optimal allocation to either domestic or global stock returns. However, we do find strong evidence of mean-aversion in the returns on the other assets we consider, as both short-term domestic debt and foreign bonds become riskier for investors with a longer horizon. As for the gains from foreign investment, we find that diversification benefits vary considerably across countries, mainly due to differences in the return properties of domestic assets and in exchange rate fluctuations. Moderately risk-averse investors would be willing to pay a fee ranging from 3.63% of the annual expected return on their optimal domestic portfolio (Thailand) to nearly 39.20% of this return (Pakistan). In Malaysia and Thailand horizons effects are small, whereas they are more substantial in India and Pakistan. Moreover, there are considerable differences in horizon effects across investors' risk preferences.

The remainder of this chapter is structured as follows. In section 2 we introduce the dynamic model for asset returns, formulate the investor's problem and introduce the empirical strategy used to obtain parameter estimates. Section 3 contains the empirical estimates and section 4 concludes.

4.2 The model

4.2.1 Assets, return dynamics and portfolio problem

We assume that investors can allocate their wealth to $n_D + 1$ domestic assets and n_F foreign assets. We select one of the domestic assets as the benchmark asset and denote the logarithmic real return on this asset at time t by $r_{0,t}$.[3] We denote excess returns on domestic assets by the $n_D \times 1$ vector $\boldsymbol{r}_{D,t}$ and those on foreign assets by the $n_F \times 1$ vector $\boldsymbol{r}_{F,t}$.[4] Furthermore, we assume that there are n_S state variables that are potentially relevant for modelling these returns. Their values at time t are given by the $n_S \times 1$ vector $\boldsymbol{s_t}$.

The model thus consists of $n = n_D + n_F + n_S + 1$ variables, which we collect in the vector $\boldsymbol{y}_t = (r_{0,t}, \boldsymbol{r}'_{D,t}, \boldsymbol{r}'_{F,t}, \boldsymbol{s}'_t)$. We assume that their dynamics can be captured by a first-order vector autoregression (VAR) (cf. Barberis (2000), Campbell and Viceira (2002, 2005), Hoevenaars et al. (2008)):

$$\boldsymbol{y}_{t+1} = \boldsymbol{a} + B\boldsymbol{y}_t + \boldsymbol{\varepsilon}_{t+1}. \tag{4.1}$$

In this equation $\boldsymbol{a}$ is an $n \times 1$ vector, B is an $n \times n$ matrix and $\boldsymbol{\varepsilon}_t \sim N(\boldsymbol{0}, \Sigma)$.

The investor has a conventional power utility function over wealth W_{t+k} at a

[3] By convention, short-term domestic government debt is the benchmark asset in our empirical implementation. Logarithmic real returns are obtained by subtracting the logarithm of inflation from the logarithm of nominal asset return, i.e., if the benchmark asset price at time t is $P_{0,t}$ and the value of the price index is PI_t, then $r_{0,t} = \ln(P_{0,t}/P_{t-1}) - \ln(\mathrm{PI}_t/\mathrm{PI}_{t-1})$.

[4] Excess returns on asset i are defined as $r_{i,t} = \ln(P_{i,t}/P_{i,t-1}) - \ln(P_{0,t}/P_{0,t-1})$.

moment k periods in the future

$$u(W_{t+k}) = \frac{W_{t+k}^{1-\gamma}}{1-\gamma}, \tag{4.2}$$

where $\gamma > 1$ parametrizes the level of risk aversion. At time $t = T$, she selects an $(n_D + n_F) \times 1$ vector of portfolio weights $\boldsymbol{\omega} = (\boldsymbol{\omega}_D', \boldsymbol{\omega}_F')$ for the non-benchmark assets. The balance $1 - \iota'\boldsymbol{\omega}$ is invested in the benchmark asset. If the investor is allowed to invest in both domestic and foreign assets, her investment problem can consequently be written as[5]

$$\begin{aligned} \max_{\boldsymbol{\omega}} \quad & E_T\left[\frac{W_{T+k}^{1-\gamma}}{1-\gamma}\right] \\ \text{s.t.} \quad & W_{T+k} = W_T\left(\boldsymbol{\omega}'\boldsymbol{R}_T(k) + (1-\boldsymbol{\omega}'\boldsymbol{\iota})R_{0,T}(k)\right). \end{aligned} \tag{4.3}$$

In this problem, the $(n_D + n_F) \times 1$ vector $\boldsymbol{R}_T(k) = (\boldsymbol{R}_{D,T}(k)', \boldsymbol{R}_{F,T}(k)')'$ represents the simple k-period returns on the non-benchmark assets over the period between T and $T+k$ and $R_{0,T}(k)$ is defined likewise for the benchmark asset.[6] The problem of an investor who is constrained to domestic assets is obtained by adding the constraint $\omega_F = \mathbf{0}_{n_F}$.

4.2.2 Solution method

The portfolio problem presented in section 4.2.1 has an approximate analytical solution once the relevant state variables and the VAR parameters are known.[7] However, the empirical evidence on return predictability is mixed, even in U.S. markets which have received most attention in the literature (e.g., Goyal and Welch (2008)

[5] As our main interest goes out to the strategic asset allocation of institutional investors, which typically remains unchanged for several years, we opt for a buy-and-hold setting. In our emerging market context this has the additional advantages of minimizing transaction costs and the effects of illiquidity. Hoevenaars et al. (2008) follow a similar approach, the difference being that in their paper the portfolio is rebalanced to the initial weights at the end of every trading period.

[6] Note that simple returns on the non-benchmark assets are related to log returns by the relationship $R_{i,t}(k) = e^{\left(\sum_{j=1}^{k}(r_{i,t+j}+r_{0,t+j})\right)}$.

[7] In this case the vector of optimal weights on the non-benchmark assets is given by

$$\boldsymbol{\omega}^* = (1/\gamma)\Sigma_k^{-1}\left(\boldsymbol{\mu}_k - \mu_{0,k}\iota + \boldsymbol{\sigma}_k^2/2\right) + (1-1/\gamma)\left(-\Sigma_k\boldsymbol{\sigma}_{0,k}\right).$$

where μ_k stands for k-period expected log returns and Σ_k for their covariance matrix. The k-period expected log return on the benchmark asset is written as $\mu_{0,k}$ and the vector of excess return covariances with the benchmark asset as $\boldsymbol{\sigma}_{0,k}$. Given a vector of initial values $\boldsymbol{y}_0$, these elements can be obtained using standard VAR results. The solution relies on a log-linear approximation of portfolio returns. See Campbell and Viceira (2002, 2005) for details.

are sceptical about return predictability while Campbell and Thompson (2008) argue in favour of it). In an international context, Schrimpf (2010) shows that return predictability is neither a uniform, nor a universal feature across capital markets.

Avramov (2002) was the first to propose a statistical framework to incorporate uncertainty about the relevant predictors (i.e. model uncertainty). A limitation of his approach, however, is that the set of predictors is constrained to be identical for each asset. Recent methodological advances (George et al. (2008), Korobilis (2013), Diris (2011)) tackle this problem and allow for different explanatory variables across the various VAR equations. In our subsequent analysis we will apply the method proposed by Diris (2011), which is best adapted to a setting where (candidate) predictors are highly correlated, as is typically the case in financial applications. The advantage of this approach is that the exclusion of predictors that are irrelevant in certain return equations leads to a more parsimonious model and reduces efficiency loss due to inclusion of irrelevant variables.

In this approach the key to solving asset allocation problem (4.3) is to obtain $p(\boldsymbol{r}_T(k)|\mathcal{I}_T)$, the investor's *predictive density* of k-period log asset returns, conditional on the information set observed up until the start of investment horizon $\mathcal{I}_T = (\boldsymbol{y}_1, \ldots, \boldsymbol{y}_T)$. This predictive density allows us to calculate the expectation in equation (4.3). We assume that, in forming this predictive density, investors use the VAR model (4.1). However, taking into account the debate on return predictability, they are not certain which variables (if any) influence specific asset returns and state variables. In terms of model (4.1) this means that they are not certain which elements of the matrix B differ from zero. This leads to model uncertainty. Moreover, they are aware of the fact that even if they would know the relevant variables, the corresponding model parameters would still have to be estimated from available data, and hence would be subject to parameter uncertainty.

These two sources of uncertainty can be made explicit by writing the predictive density as

$$p(\boldsymbol{r}_T(k)|\mathcal{I}_T) = \sum_{j=1}^{2^{n^2}} p(M_j|\mathcal{I}_T) \int_{\Theta_j} p(\boldsymbol{r}_T(k)|M_j, \Theta_j, \mathcal{I}_T) p(\Theta_j|M_j, \mathcal{I}_T) d\Theta_j. \tag{4.4}$$

In this expression $j \in \{1, \ldots, 2^{n^2}\}$ indexes all models that can be obtained by in/excluding right-hand side variables in any of the equations of the $n \times n$ vector autoregression in (4.1).[8] The parameters corresponding to model j are collected

[8] All constant terms in $\boldsymbol{a}$ are always included.

in $\Theta_j = (\boldsymbol{\beta}_j, \Sigma)$. The integral in (4.4) captures parameter uncertainty conditional on a given VAR model, as in, for example, Barberis (2000). Model uncertainty is taken into account by weighting the 2^{n^2} possible models by their posterior probabilities $p(M_j|\mathcal{I}_T)$.

The predictive density $p(\boldsymbol{r}_T(k)|\mathcal{I}_T)$ in equation (4.4) can be approximated using a four-step procedure.[9] In the first step, one of the n^2 possible combinations of explanatory variables in matrix B is selected. Conditional on this selection, one can draw a set of parameters for $\boldsymbol{a}$ and B and subsequently for the covariance matrix Σ. Conditional on these model parameters, a vector $\boldsymbol{r}_T(k)$ of log asset returns k periods ahead can be drawn from the multivariate normal distribution. Repeating this procedure a large number of times N we can use the return draws $\boldsymbol{r}^i_T(k)$, $i \in \{1, \ldots, N\}$ to approximate the predictive density and, consequently, the expectation in equation (4.3) for any given allocation vector $\boldsymbol{\omega}$. The optimal allocation is then obtained by numerical maximization.

4.2.3 Measuring the gains from investing abroad

In order to assess the benefits of adding foreign assets to the investment opportunity set, we follow the Certainty Equivalent Return (CER) approach (cf. Kandel and Stambaugh (1996)). For an investor with utility function $u(.)$ and horizon k, the CER of an investment strategy $\boldsymbol{\omega}$ is defined implicitly by the relationship

$$u\Big(W_T(1+\mathrm{CER}_\omega)^k\Big) = E_T\left[u(W_{T+k}(\boldsymbol{\omega}))\right]. \tag{4.5}$$

It amounts to the certain (riskless) per-period rate of return an investor would accept as a substitute for the proceeds from portfolio $\boldsymbol{\omega}$. Alternatively, it can be interpreted as the maximum per-period fee (in percentage terms) that she would be willing to pay to participate in an investment scheme following strategy $\boldsymbol{\omega}$. Our measure of diversification benefits is the CER difference between the optimal unrestricted portfolio $\boldsymbol{\omega}^*$ and the optimal domestic portfolio $\boldsymbol{\omega}^*_D$, scaled by $E_T(R^*_{D,T}(k))$, the expected return on the latter portfolio:

$$\Delta\mathrm{CER}_k = \frac{\mathrm{CER}_{\boldsymbol{\omega}^*} - \mathrm{CER}_{\boldsymbol{\omega}^*_D}}{E_T(R^*_{D,T}(k))}. \tag{4.6}$$

Apart from its straightforward economic interpretation, this measure offers an important additional advantage from the perspective of asset allocation decisions and

[9] For completeness, the details of this procedure are presented in Appendix A.

investment regulation. It allows us to compare benefits from foreign investment along the whole range of risk aversion levels γ. For a policy-maker it may be important to distinguish between investor types, as benefits for highly speculative investors may be valued differently than those for more risk-averse investors.

4.3 Empirical analysis

4.3.1 Data and summary statistics

Assets

We assume that the domestic asset menu available to investors consists of short-term government debt and an equity index. For Malaysia, Pakistan and Thailand we use Treasury Bills to model short-term debt. In the case of India, we use the discount rate charged by the central bank to commercial banks, for reasons of data availability. For equity returns, we use the Datastream Total Market Indices.

The foreign asset menu consists of equity and long-term bonds. For equity returns, we use the Datastream World Market Total Return Index and for bond returns the Barclays Capital Aggregate U.S. Bond index. Foreign currency returns are converted into domestic currency returns using market exchange rates from International Financial Statistics (IFS) sources, as we assume that investors are interested in wealth denominated in local currency.

Predictor variables

The vector of state variables includes both local and global variables. As an advantage of our approach lies in its ability to identify relevant predictors from a large set without compromising efficiency we can allow for many 'candidate' variables. Our choice is based on three prominent studies of emerging market return predictability: C. Harvey (1995), Bekaert and Harvey (2007) and Hjalmarsson (2010).

C. Harvey (1995) uses the most comprehensive set of predictors, and is the only one to include global variables. His global predictors include lagged values of returns on the MSCI World Index, the dividend yield on the S&P 500 index, the difference in return between 3-month and 1-month U.S. bills and the credit spread between Baa and Aaa rated bonds. We follow this choice with some minor adjustments: 1) we use the Datastream World Market Index and corresponding dividend yields 2) in line with more recent predictability literature we use the nominal U.S. short rate instead of the bill return difference (e.g., Ang and Bekaert (2007)) 3) we use the term spread (the difference between ten-year U.S. bonds and one-year bills) instead of the credit spread, for reasons of data availability.

As for local predictors, the dividend yield of the domestic stock index is used in all three studies mentioned above. Bekaert and Harvey (2007) focus specifically on (proxies of) domestic stock market liquidity and find that these indeed have predictive power. For this reason we include the turnover ratio and the percentage of stale trading days in the local market in our model, except for India and Pakistan, where these proxies are non-stationary as market liquidity increases considerably over time.

Furthermore, both C. Harvey (1995) and Hjalmarsson (2010) consider local short-term interest rates. Both studies warn, however, that the relationship between asset returns and these interest rates may be hard to model. Regulatory measures typically affect the extent to which this rate reflects financial market conditions, while uncontrolled inflation, financial crises, or monetary policy changes can lead to non-stationary behaviour. The latter is particularly troublesome in a dynamic model. In our sample this is the case for Malaysia and Thailand, where monetary policy in the aftermath of the Asian crisis focused on lowering an stabilizing the interest rate. Consequently we do not include the nominal interest rate as a predictor for these countries.

An issue that warrants special attention is the role of the exchange rate in the VAR model. Note that in our specification exchange rate fluctuations are implicitly included in foreign asset excess returns $\boldsymbol{r_F}$, which are measured in domestic currency. This is the conventional approach in international asset allocation models (see C. Harvey (1995) De Roon et al. (2001), Ang and Bekaert (2002)).[10] It is in line with the observation that most exchange rate models tend not to outperform naïve random walk forecasts.[11] As emphasized by Diris (2011), if the exchange rate itself cannot be predicted, it will also be of little use as long-term predictor of asset returns. It can simply be included as an additional random component of asset returns.

This does not necessarily hold in an emerging market context, but here the exchange rate poses difficulties similar to those discussed above for the short rate. This also holds for the four countries in our sample. India had a pegged exchange rate until July 1991 and transitioned to a nominally floating regime by March 1993. However, significant evidence of exchange rate stabilisation by the central bank

[10] As these papers take the perspective of the U.S. investor, the reverse transformation is applied there, i.e. from the emerging market currency to U.S. dollars, but the principle is identical.
[11] See Killian and Taylor (2003) and Wright (2008) for a recent discussion of this topic.

has been found well into the 2000's; exchange rate volatility increased only in the second half of the decade. In Malaysia, the Ringgit was pegged to the dollar between December 1998 and June 2005, in the aftermath of its depreciation starting in mid-1997. Likewise, in the case of Thailand, the exchange rate between the U.S. Dollar and the Baht was closely controlled by an equalization fund until July 1997; after the financial crisis a much less rigid, though still managed, floating regime was adopted.

Due to the difficulty of capturing such regime changes in a VAR specification, and in the absence of strong evidence of return predictability from the exchange rate, we have chosen not to explicitly incorporate the exchange rate in the model.

Sample period and data construction

All time series data are obtained from Datastream. They are measured at a monthly frequency, with the sample period starting in January 1986 for Malaysia, January 1987 for Thailand, January 1990 for India and August 1992 for Pakistan. The sample period ends in January 2012 for all countries. Details on Datastream mnemonic codes and the data processing procedure are given in Appendix B.

Summary statistics

We provide summary statistics of our return data in Table 4.1.There are considerable differences between similar assets across the four countries. In India, Malaysia and Thailand the Sharpe ratios for domestic equity are high, in excess of 0.35, while this ratio is only 0.20 for Pakistan. Foreign stocks have both lower expected returns and volatilities in all four countries. A comparison of Sharpe ratios yields mixed results. Foreign stocks provide a better one-period risk-return trade-off than domestic ones in Malaysia and Pakistan and a worse one in the other countries.[12] In all cases, returns on foreign and domestic stocks are positively correlated, indicating that the local stock markets are integrated with the global stock market. Finally, foreign bonds are characterized by low or even negative Sharpe ratios. However, their returns are negatively correlated with domestic equity and, to a lesser extent, with domestic short-term debt. Therefore such bonds are potentially useful for investors who want to hedge their domestic asset exposure.

[12] Note that expected excess returns on foreign assets may differ between countries due to the fact that they are measured in excess of different short-term interest rates and are adjusted to domestic currency.

Table 4.1. **Return moments.**

	Asset	Av. Ret.	SR	Volatilities and Correlations				Skew	Kurt
				Bill	DS	FS	FB		
IN	Bill	0.08	–	3.04				−0.04	0.03
	DS	13.88	0.39	0.09	34.84			−0.31	0.42
	FS	4.90	0.30	0.00	0.35	16.42		−0.22	0.20
	FB	0.19	0.02	−0.07	−0.18	0.22	8.48	−0.06	0.19
MAL	Bill	1.45	–	1.34				−0.04	0.01
	DS	10.81	0.42	−0.09	25.34			−0.50	0.27
	FS	7.16	0.44	−0.02	0.29	16.39		−0.24	0.14
	FB	0.60	0.07	0.09	−0.38	0.18	8.02	−0.15	0.17
PAK	Bill	1.25	–	2.65				−0.02	0.02
	DS	7.50	0.21	−0.06	35.16			−0.44	0.34
	FS	5.61	0.34	−0.04	0.24	16.27		−0.23	0.14
	FB	−0.79	−0.13	−0.13	−0.17	0.07	5.95	−0.05	0.07
THA	Bill	3.10	–	2.19				−0.02	0.04
	DS	12.15	0.36	−0.02	33.76			−0.38	0.37
	FS	3.71	0.22	−0.14	0.31	16.49		−0.26	0.19
	FB	−1.50	−0.16	−0.04	−0.25	0.24	9.39	−0.16	0.18

This table contains summary statistics on the risk-return characteristics of domestic short-term debt (Bill), domestic stocks (DS), foreign stocks (FS) and foreign bonds (FB) for India (IN), Malaysia (MAL), Pakistan (PAK) and Thailand (THA). The first column lists average real returns on short-term domestic bills and average excess returns on the other asset classes, measured in domestic currency. The second column contains annual Sharpe Ratios. The correlation matrix is given in columns 3-6. In this matrix, the diagonal elements represent annual return volatilities. The final two columns contain skewness and excess kurtosis of log returns.The sample periods are 1990.I-2012.I (India), 1986.I-2012.I (Malaysia), 1987.I-2012.I (Thailand) and 1992.VIII-2012.I (Pakistan).

4.3.2 VAR estimation results

Return predictability

As a first step in our analysis of investment decisions and diversification benefits at longer horizons, we estimate the VAR model in equation (4.1).[13] We focus on

[13] Details about prior choice, burn-in draws and retained draws used in this estimation procedure are provided in Appendix A.

the dynamics of the asset return equations. These are given in Tables 4.2-4.5 for real returns on short term debt, domestic equity, foreign stocks and foreign bonds, respectively. The columns of these tables correspond to first lags of asset returns and to our predictor variables. The rows contain, for the four countries, the inclusion probabilities of each of the potential predictors in the VAR model, and the posterior mean and standard deviation of the corresponding model parameter.

Let us first consider the inclusion probabilities of the predictor variables. Table 4.2 contains the results for the short-term debt equation of the VAR model. The main finding from this table is that short-term debt returns are positively autocorrelated. Their first lag is included with probability close to unity in all four countries in the sample and the mean of the posterior distribution for the corresponding parameter is positive on all occasions. Turning to the excess returns on domestic stocks, which are given in Table 4.3, we find that the data do not provide much evidence in favour of return predictability. The highest inclusion probability is that of the liquidity proxy for the Malaysian stock market at 0.38. The domestic dividend yield enters the excess return equation with probability 0.29 in the case of Malaysia and the domestic short rate enters with probability 0.25 for Pakistan. All these inclusion probabilities are lower than the prior inclusion probability, which is set to 0.5.[14] This means that an investor who believes a priori that there is a 50 percent chance that a variable is relevant for predicting domestic stock returns would adjust this probability downward upon observing the return data.

These results contrast sharply with the findings of Diris (2011) for the United States stock market. Using a set of nine commonly used predictor variables of U.S. stock returns, he found that there are two predictors with an inclusion probability of over 0.80: the dividend yield and the spread between corporate and government bonds. These two predictors are, in turn, related to the remaining seven, so that ultimately all nine variables play a role in equity premium prediction in the long run. We have calculated similar long-run (five-year) inclusion probabilities and included them in the rows labelled '5y' in Tables 4.2-4.5. However, due to the fact that none of the predictors enters with high probability in the short run, as we learned above, there is also little room for 'indirect' predictability in the long run.

[14] This is the standard choice in the financial model uncertainty literature, see e.g., the seminal paper of Avramov (2002). Schrimpf (2010) takes an alternative approach, based on expected model size. The main results presented in his paper are based on an inclusion probability of 0.2, which implies an a-priori down weighting of larger model specifications. The author motivates this choice by the principle of parsimony prevailing in econometrics (p. 1266). As the literature on return predictability from the emerging market perspective is, in our opinion, too scarce to motivate a non-standard prior belief on the inclusion probability, we have opted for the default approach. We refer the interested reader to the Appendix of this chapter for further details on prior choice.

Table 4.2. **Estimates of the real Treasury Bill return equation.**

		Bill	DS	FS	FB	DIVD	SRD	TURN	NTD	DIVW	SRW	YSW
	1m	1.0000	0.0171	0.0193	0.0118	0.0157	0.0571			0.0748	0.0145	0.0171
IN	5y	1.0000	0.0215	0.0401	0.0203	0.0223	0.0620			0.0896	0.0252	0.0291
	Mean	0.3414	−0.0001	0.0003	−0.0002	0.0000	0.0290			−0.0004	0.0041	−0.0008
	Std. Dev	0.0602	0.0011	0.0025	0.0028	0.0002	0.1339			0.0015	0.0506	0.0091
	1m	0.9403	0.0123	0.0582	0.0073	0.0102			0.0354	0.0126	0.0603	0.0108
MAL	5y	0.9410	0.0210	0.0662	0.0208	0.0364			0.0484	0.0347	0.0645	0.0157
	Mean	0.2145	0.0000	−0.0005	0.0000	0.0000			0.0002	0.0000	0.0140	0.0000
	Std. Dev	0.0774	0.0004	0.0024	0.0009	0.0001			0.0011	0.0002	0.0630	0.0035
	1m	0.6813	0.0152	0.0234	0.0190	0.1458	0.7031			0.4240	0.1215	0.0803
PAK	5y	0.9436	0.1233	0.1728	0.7447	0.3894	0.7359			0.5914	0.2556	0.3574
	Mean	0.1582	0.0000	0.0002	−0.0002	0.0003	0.4347			−0.0029	0.0880	−0.0061
	Std. Dev	0.1250	0.0006	0.0021	0.0042	0.0007	0.3300			0.0037	0.2835	0.0286
	1m	1.0000	0.3366	0.1054	0.0272	0.0176		0.0199	0.0188	0.0099	0.0636	0.0226
THA	5y	1.0000	0.3922	0.2024	0.2793	0.1548		0.1053	0.1467	0.1286	0.1797	0.2284
	Mean	0.3770	−0.0029	−0.0015	−0.0004	0.0000		−0.0001	−0.0001	0.0000	0.0182	−0.0005
	Std. Dev	0.0566	0.0045	0.0048	0.0030	0.0001		0.0024	0.0010	0.0002	0.0816	0.0059

This table gives the estimates of the real Treasury Bill return equation in VAR model (4.1) for the four countries in our study. Apart from lagged values of real returns on short-term debt (Bill), domestic stocks (DS), foreign stocks (FS) and foreign bonds (FB), candidate predictors are domestic dividends (DIVD), the domestic short rate (SRD), equity market turnover (TURN), the percentage non-trading days (NTD), the dividend yield on the world equity market proxy (DIVW), the U.S. short rate (SRW) and the yield spread between a U.S. T-bill and an ten-year bond (YSW). The rows labelled '1m' report the inclusion probability of any given variable. The rows labelled '5y' give the long-term inclusion probability at a five-year horizon. The rows labelled 'Mean' and 'Std. Dev.' report the posterior mean and the posterior standard deviation of the distribution of the VAR parameter corresponding to the predictor in the column.

Table 4.3. **Estimates of the domestic stock excess return equation.**

		Bill	DS	FS	FB	DIVD	SRD	TURN	NTD	DIVW	SRW	YSW
IN	1m	0.0148	0.0199	0.0145	0.0115	0.0399	0.0134			0.0114	0.0096	0.0096
	5y	0.0191	0.0253	0.0147	0.0068	0.0443	0.0186			0.0235	0.0155	0.0186
	Mean	−0.0054	0.0013	−0.0010	−0.0013	0.0011	−0.0244			0.0001	0.0112	−0.0002
	Std. Dev	0.0653	0.0150	0.0124	0.0210	0.0061	0.3051			0.0020	0.2442	0.0331
MAL	1m	0.0184	0.0972	0.0078	0.0076	0.2859			0.3824	0.0132	0.0127	0.0080
	5y	0.0398	0.1306	0.0229	0.0269	0.3692			0.4128	0.0378	0.0405	0.0204
	Mean	−0.0091	0.0139	0.0001	0.0002	0.0080			0.0318	0.0001	−0.0089	−0.0002
	Std. Dev	0.0965	0.0465	0.0062	0.0085	0.0137			0.0440	0.0017	0.1436	0.0172
PAK	1m	0.0281	0.0396	0.0915	0.0164	0.0521	0.2491			0.0561	0.0796	0.0311
	5y	0.3280	0.1092	0.1059	0.3610	0.2697	0.3462			0.2960	0.1826	0.2340
	Mean	0.0200	0.0023	0.0164	−0.0014	0.0008	−1.0223			−0.0024	−0.5307	0.0147
	Std. Dev	0.1625	0.0147	0.0603	0.0366	0.0043	1.9657			0.0126	2.1919	0.1329
THAI	1m	0.0275	0.0240	0.0209	0.1254	0.0672		0.0347	0.0981	0.1025	0.0269	0.3489
	5y	0.2008	0.2195	0.1454	0.3169	0.1958		0.1278	0.1962	0.1871	0.1869	0.4247
	Mean	−0.0195	0.0008	0.0015	0.0434	0.0013		0.0074	0.0119	0.0049	0.0160	0.3507
	Std. Dev	0.1611	0.0082	0.0186	0.1278	0.0055		0.0577	0.0409	0.0162	0.5994	0.5292

This table gives the estimates of the domestic stock excess return equation in VAR model (4.1) for the four countries in our study. Apart from lagged values of real returns on short-term debt (Bill), domestic stocks (DS), foreign stocks (FS) and foreign bonds (FB), candidate predictors are domestic dividends (DIVD), the domestic short rate (SRD), equity market turnover (TURN), the percentage non-trading days (NTD), the dividend yield on the world equity market proxy (DIVW), the U.S. short rate (SRW) and the yield spread between a U.S. T-bill and an ten-year bond (YSW). The rows labelled '1m' report the inclusion probability of any given variable. The rows labelled '5y' give the long-term inclusion probability at a five-year horizon. The rows labelled 'Mean' and 'Std. Dev.' report the posterior mean and the posterior standard deviation of the distribution of the VAR parameter corresponding to the predictor in the column.

Table 4.4. **Estimates of the foreign stock excess return equation.**

		Bill	DS	FS	FB	DIVD	SRD	TURN	NTD	DIVW	SRW	YSW
	1m	0.0106	0.0088	0.0110	0.0557	0.0152	0.0217			0.0130	0.0187	0.0119
IN	5y	0.0155	0.0049	0.0364	0.0145	0.0213	0.0335			0.0327	0.0324	0.0270
	Mean	−0.0008	0.0000	0.0001	−0.0050	0.0000	−0.0168			0.0002	−0.0182	−0.0005
	Std. Dev	0.0198	0.0014	0.0028	0.0234	0.0004	0.1528			0.0018	0.1772	0.0180
	1m	0.0700	0.0294	0.0136	0.1073	0.0236			0.0091	0.0093	0.0121	0.0125
MAL	5y	0.0788	0.0187	0.0249	0.1066	0.0448			0.0337	0.0240	0.0259	0.0164
	Mean	−0.0349	−0.0007	0.0003	0.0138	0.0001			0.0000	0.0001	−0.0054	−0.0009
	Std. Dev	0.1553	0.0051	0.0036	0.0446	0.0008			0.0017	0.0015	0.0837	0.0157
	1m	0.2171	0.0186	0.0379	0.0321	0.1815	0.2276			0.0253	0.1362	0.1593
PAK	5y	0.4615	0.0919	0.1728	0.4439	0.3481	0.4195			0.3732	0.2439	0.3059
	Mean	−0.0910	0.0000	0.0012	0.0026	−0.0013	−0.2516			0.0003	−1.0056	−0.1365
	Std. Dev	0.1936	0.0018	0.0084	0.0213	0.0032	0.5240			0.0029	2.8477	0.3610
	1m	0.3985	0.0433	0.0182	0.8906	0.1571		0.0545	0.0589	0.0128	0.0212	0.0205
THA	5y	0.5368	0.3647	0.2678	0.9157	0.3374		0.2073	0.3163	0.2086	0.3072	0.3102
	Mean	−0.2233	−0.0009	0.0003	0.1918	0.0009		0.0042	−0.0017	0.0000	−0.0109	−0.0018
	Std. Dev	0.2984	0.0058	0.0039	0.0842	0.0023		0.0222	0.0084	0.0015	0.1266	0.0220

This table gives the estimates of the foreign stock excess return equation in VAR model (4.1) for the four countries in our study. Apart from lagged values of real returns on short-term debt (Bill), domestic stocks (DS), foreign stocks (FS) and foreign bonds (FB), candidate predictors are domestic dividends (DIVD), the domestic short rate (SRD), equity market turnover (TURN), the percentage non-trading days (NTD), the dividend yield on the world equity market proxy (DIVW), the U.S. short rate (SRW) and the yield spread between a U.S. T-bill and an ten-year bond (YSW). The rows labelled '1m' report the inclusion probability of any given variable. The rows labelled '5y' give the long-term inclusion probability at a five-year horizon.The rows labelled 'Mean' and 'Std. Dev.' report the posterior mean and the posterior standard deviation of the distribution of the VAR parameter corresponding to the predictor in the column.

Table 4.5. **Estimates of the foreign bond excess return equation.**

		Bill	DS	FS	FB	DIVD	SRD	TURN	NTD	DIVW	SRW	YSW
	1m	0.0302	0.0138	0.0114	0.1915	0.0100	0.1680			0.0152	0.1983	0.1571
IN	5y	0.0450	0.0160	0.1654	0.2097	0.0492	0.1776			0.1287	0.2112	0.1797
	Mean	−0.0056	−0.0001	−0.0001	0.0211	0.0000	0.2255			0.0001	0.6213	0.0776
	Std. Dev	0.0397	0.0014	0.0026	0.0472	0.0003	0.5510			0.0011	1.3954	0.1943
	1m	0.0268	0.0107	0.0177	0.6567	0.0100			0.0000	0.0093	0.0382	0.0074
MAL	5y	0.0379	0.0143	0.0184	0.6579	0.0289			0.0226	0.0243	0.0424	0.0108
	Mean	0.0098	0.0000	0.0005	0.0984	0.0000			−0.0001	0.0000	0.0359	0.0002
	Std. Dev	0.0744	0.0018	0.0047	0.0830	0.0003			0.0016	0.0006	0.2102	0.0120
	1m	0.0206	0.0469	0.0203	1.0000	0.0303	0.0280			0.0220	0.0688	0.0510
PAK	5y	0.1268	0.0711	0.0648	1.0000	0.1331	0.1171			0.1402	0.0979	0.1229
	Mean	0.0007	−0.0005	−0.0001	0.2906	0.0000	0.0040			0.0000	0.1491	0.0158
	Std. Dev	0.0230	0.0031	0.0031	0.0549	0.0004	0.0717			0.0008	0.7598	0.0971
	1m	0.0302	0.0332	0.0174	0.9843	0.0381		0.0459	0.2101	0.0194	0.0196	0.0225
THA	5y	0.1760	0.2043	0.1521	0.9868	0.1673		0.1286	0.2379	0.1290	0.2037	0.1856
	Mean	0.0067	−0.0008	−0.0001	0.2770	−0.0001		−0.0035	0.0084	−0.0001	0.0108	0.0012
	Std. Dev	0.0654	0.0056	0.0036	0.0691	0.0008		0.0195	0.0180	0.0013	0.1200	0.0198

This table gives the estimates of the foreign bond excess return equation in VAR model (4.1) for the four countries in our study. Apart from lagged values of real returns on short-term debt (Bill), domestic stocks (DS), foreign stocks (FS) and foreign bonds (FB), candidate predictors are domestic dividends (DIVD), the domestic short rate (SRD), equity market turnover (TURN), the percentage non-trading days (NTD), the dividend yield on the world equity market proxy (DIVW), the U.S. short rate (SRW) and the yield spread between a U.S. T-bill and an ten-year bond (YSW). The rows labelled '1m' report the inclusion probability of any given variable. The rows labelled '5y' give the long-term inclusion probability at a five-year horizon.The rows labelled 'Mean' and 'Std. Dev.' report the posterior mean and the posterior standard deviation of the distribution of the VAR parameter corresponding to the predictor in the column.

Our results are more in line with those of Schrimpf (2010). In his study of four major industrialized stock markets, he found the evidence for stock return predictability to be very weak for Germany, Japan and the United Kingdom. Our findings extend his suggestion that return predictability is not a stylized fact of international return data to emerging markets. However, at the same time, we obtain non-negligible inclusion probabilities for at least one predictor in three out of the four countries analysed in this study. This underlines the importance of an estimation approach that explicitly allows for model uncertainty in the study of long-term asset allocation decisions involving emerging market equities.

Moving on to Table 4.4, we find that excess returns on foreign stocks are also hard to predict from the perspective of local investors. Although the world market index contains a considerable U.S. component, which we would expect to be predictable based on previous literature, the results suggest that this is offset by fluctuations in the domestic short rate (the investor's benchmark) and the exchange rate. The only exception is the high inclusion probability of lagged returns on foreign bonds in Thailand, which equals 0.89. This is likely due to exchange rate effects. The exchange rate is an important driver of excess bond returns measured in domestic currency. It is highly autocorrelated. Thus, an increase in returns on foreign bonds is likely caused by a falling exchange rate. As this situation is likely to persist for more than one period, returns on foreign stocks are more likely to be high in the next period if current bond returns are high, which explains the positive coefficients on lagged bond returns. This effect also explains the high inclusion probability of an autoregressive component in bond returns, which, as can be seen in Table 4.5, is included with high probability for all countries except India.

Correlation between current return shocks and expected return shocks

In the next step of our analysis, we use the VAR model estimates to assess the correlation between *current* and *expected* return shocks. As observed by Barberis (2000) and Diris (2011), negative correlation between shocks to current returns and return expectations slows the growth of the cumulative return variance. Empirically, this is the main driver of the 'time diversification' effect which makes an asset more attractive at longer investment horizons.[15] Positive correlation, on the other hand,

[15] Note however that this effect can also occur in the absence of this feature. The predictability effect may be strong enough to lower the annualized variance of multi-period returns without inducing negative correlation between current return shocks and shocks to return expectations. See e.g., Barberis (2000), p. 243-246 for the construction of numerical examples that yield this result. As we observed only weak predictability effects in section 4.3.2, we do not consider this scenario here.

increases return variance growth and, in the absence of a high degree of return predictability, implies a lower optimal allocation to the asset at long horizons.

In a VAR specification the correlation between shocks to current and expected returns of an asset modelled in row i amounts to the correlation between $\varepsilon_{t,i}$ and $B_i\varepsilon_t$, where B_i is the i'th row of the B-matrix (Diris (2011)). The posterior distribution of this correlation can be readily obtained for the four asset classes under consideration. The key properties of these distributions are summarized in Table 4.6.

As was to be expected from our earlier VAR results, the correlation between current shocks to the returns on short-term debt and future return expectations is highly positive. This means that an investment strategy based on rolling over short-term bills becomes riskier as the investment horizon increases. As for excess returns on domestic stocks, the posterior means of the correlation distribution are close to zero in all cases. However, due to the fact that each predictor variable is included in at least some of the VAR models, there is also substantial probability mass at non-zero correlations, except for the case of India where the probability of zero correlation equals 0.85. Shocks to foreign stock returns also appear uncorrelated with shocks to future expectations, except for the case of Thailand. This can be explained from the positive association between foreign stock returns and lagged foreign bond returns found in the previous section. As can be seen in the rows labelled 'FB', the latter are mean-averting in all four countries. The posterior means of the correlation distribution vary considerably, though, ranging from 0.186 for India to 0.995 for Pakistan.

4.3.3 Term structure of risk

The implications of these findings for the riskiness of the four asset classes at different investment horizons are visualized in Figures 4.1 and 4.2. These figures display the annualized standard deviation of asset returns as a function of the investment horizon, mapping the term structure of risk (Campbell and Viceira (2005)).[16]

The upper panel of Figure 4.1 confirms that rolling over short-term debt becomes riskier in the long run, as expected from our earlier mean aversion results. The extent of this effect differs; it is particularly large for India and Pakistan and much less so for Malaysia and Thailand.

[16] We present the results conditional on all predictor variables being equal to their historical average, as is customary in the literature.

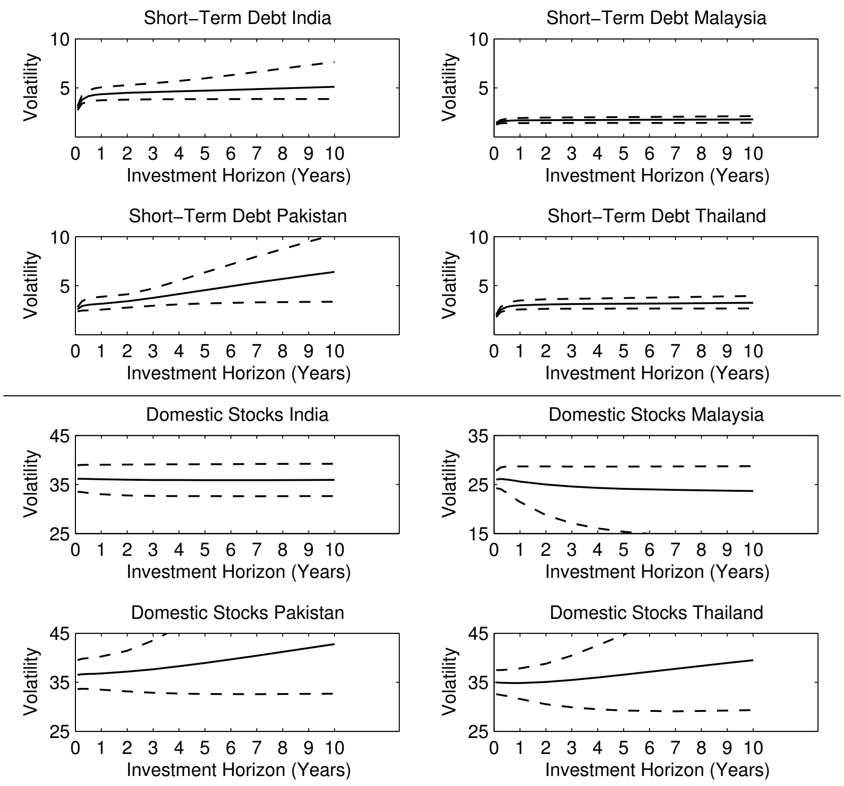
Table 4.6. **Correlation between current asset returns and return expectations.**

		Post. Mean	Post. Std. Dev.	$\Pr(\rho < 0)$	$\Pr(\rho = 0)$	$\Pr(\rho > 0)$
IN	Bill	0.9972	0.0132	0	0	1
	DS	−0.0267	0.2221	0.0871	0.8659	0.0469
	FS	−0.0169	0.1525	0.1068	0.8470	0.0460
	FB	0.1859	0.3905	0.1714	0.4516	0.3769
MAL	Bill	0.9277	0.2418	0.0084	0.0488	0.9427
	DS	−0.0747	0.4871	0.2826	0.3445	0.3728
	FS	0.0092	0.1564	0.0836	0.7473	0.1689
	FB	0.6546	0.4733	0.0201	0.2951	0.6846
PAK	Bill	0.6642	0.4513	0.1310	0.0012	0.8677
	DS	0.0565	0.2555	0.0985	0.5008	0.4006
	FS	0.0483	0.2096	0.2024	0.3936	0.4039
	FB	0.9949	0.0218	0.0000	0	0.9999
THA	Bill	0.9627	0.0570	0	0	1
	DS	−0.0600	0.2561	0.3216	0.3750	0.3033
	FS	0.1890	0.1082	0.0319	0.0371	0.9309
	FB	0.9680	0.1264	0.0018	0.0106	0.9874

This table contains statistics pertaining to the correlation between current asset returns and return expectations $\rho = \mathrm{Corr}(\varepsilon_{i,t}, B_i\varepsilon_t)$ implied by the vector autoregressive model in equation (4.1). Posterior means of the autocorrelation coefficient are given in the first column and posterior standard deviations in the second. The third to fifth columns give the posterior probability that there is, respectively, negative autocorrelation, no autocorrelation and positive autocorrelation.

As for domestic stocks, several factors play a role. In the case of India, the term structure of risk is flat, reflecting the high posterior probability of zero correlation between current and expected return shocks. In the other three countries there is substantial probability that this correlation is non-zero For the stock markets of Thailand and Pakistan, the result is an upward sloping term structure of risk. In both cases, the correlation distribution (not reported) is skewed to the right, with relatively high probability mass attributed to mean aversion.

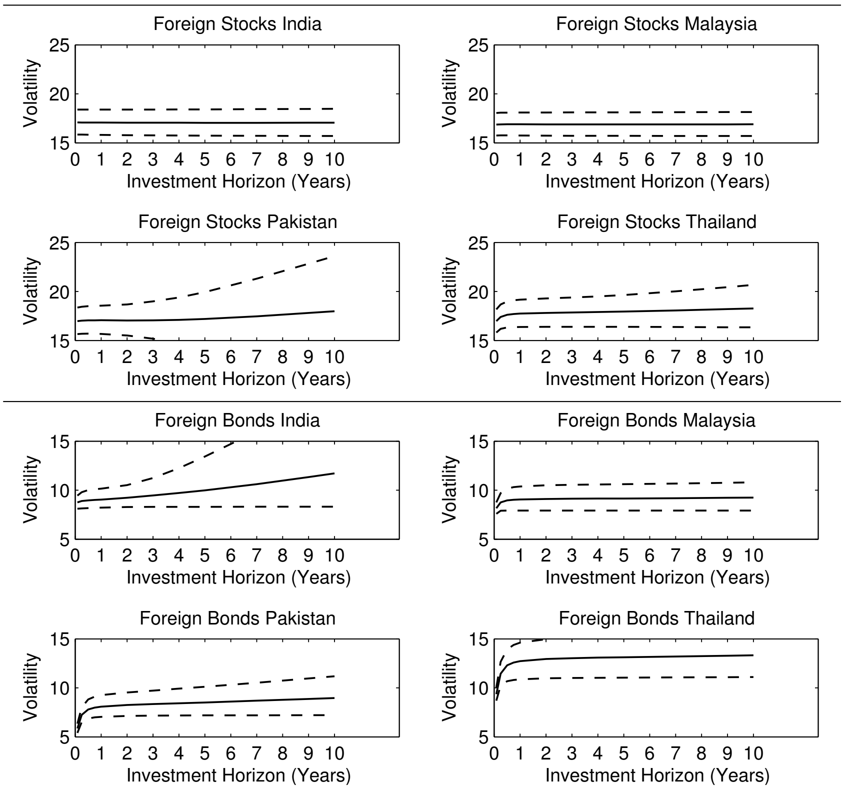
Figure 4.1. **Volatility versus investment horizon**



Annualized standard deviations of the predictive density of asset returns (solid, y-axis) are plotted against the investment horizon (x-axis). The dashed lines the bounds of the 95% highest posterior density interval (HPDI) of the posterior distribution of return variance. The upper panel is for short-term debt and the lower panel for domestic stocks.

The opposite holds for Malaysia, where domestic stocks become slightly less risky over time as there is a small probability that returns are strongly mean-reverting. In the upper panel of Figure 4.2 we see that the term structure of foreign stock risk is flat for India and Malaysia and increasing for Pakistan and Thailand. This reflects the substantial probability of mean aversion reported for these two countries in Table 4.6. Finally, the lower panel of Figure 4.2 shows the increasing riskiness of foreign bonds as a consequence of the positive autocorrelation that become evident from our VAR model.

Figure 4.2. **Volatility versus investment horizon**



Annualized standard deviations of the predictive density of asset returns (solid, y-axis) are plotted against the investment horizon (x-axis). The dashed lines the bounds of the 95% highest posterior density interval (HPDI) of the posterior distribution of return variance. The upper panel is for foreign stocks and the lower panel for foreign bonds.

4.3.4 Allocation to foreign assets and diversification benefits

Do the dynamic properties of asset returns, as captured by our VAR models, induce any horizon effects that might be important for institutional investors' decisions regarding foreign investment? Table 4.7 lists the optimal allocation to foreign stocks and bonds for three levels of risk aversion and horizons up to five years. The risk aversion level $\gamma = 1$ corresponds to a risk-neutral investor, $\gamma = 5$ is the benchmark risk aversion level used in the strategic asset allocation literature and $\gamma = 20$ corresponds to a relatively risk-averse investor. The relative differences in certainty equivalent return between domestic and diversified portfolios (equation (4.6)), are given in Table 4.8. As there are considerable differences between the four countries in our sample, we will discuss each of them separately.

India

Let us first consider the benchmark one-period situation. The results in the second column of Table 4.8 indicate that, in India, relatively conservative investors ($\gamma = 5$ and $\gamma = 20$) benefit most from diversifying their portfolio by including foreign assets. The certainty equivalent increase amounts to about 10% of the expected return on the optimal domestic portfolio in both cases. This can be attributed to the fact that Indian short-term debt has a low expected return and a high volatility, as we saw already from our summary statistics in Table 4.1. Conservative investors lack a domestic alternative for this benchmark asset, as the volatility of domestic equity is high. They benefit from adding safe foreign bonds and less volatile foreign equity to their portfolio. The allocation to foreign assets required to achieve these benefits amounts to 25-30% of the portfolio for moderately risk-averse investors and to less than 10% for highly risk averse investors. The gains for risk-neutral investors are very small relative to their expected portfolio return, although they would be willing to invest over 15% of their portfolio abroad.

Turning to horizon effects, the main finding is that, at long horizons, the diversification benefits for conservative investors decrease considerably. This can be attributed to two factors. First, as discussed in the previous sections, the riskiness of foreign bonds increases with the investment horizon due to mean aversion effects. The same holds for the benchmark asset, domestic short-term debt. This raises the overall risk level in the long run, even if the volatility of excess returns remains constant. As a consequence, long-term investors choose to allocate more to the benchmark asset and reduce their allocation to foreign assets, as can be seen in Table 4.7. The same is true for moderately risk-averse investors, though to a much lower extent. Diversification benefits in CER terms decrease from 9.84 % of expected annual return for a one-month horizon to 7.56% and optimal holdings of foreign assets decrease from 30% to 25% of the portfolio.

Malaysia

The pattern of diversification benefits in Malaysia is similar to that in India, with moderately and highly risk-averse investors benefiting most. For $\gamma = 5$ benefits from foreign diversification amount to a substantial 25% percent of expected returns on the domestic portfolio. The one-period allocations in the second column of Table 4.7 show that Malaysian investors' optimal portfolios contains much more foreign assets, though, than those of their Indian counterparts, amounting to up to 70% of the total portfolio value for a moderately risk-averse investor.

Table 4.7. **Optimal allocation to foreign stocks and foreign bonds.**

			Investment Horizon (months)						
	γ		1	6	12	24	36	48	60
	1	FS	0.15	0.15	0.15	0.16	0.17	0.17	0.18
		FB	0.00	0.00	0.00	0.00	0.00	0.00	0.00
IN	5	FS	0.19	0.19	0.19	0.18	0.18	0.17	0.17
		FB	0.11	0.12	0.11	0.10	0.09	0.08	0.08
	20	FS	0.05	0.05	0.05	0.04	0.03	0.01	0.00
		FB	0.03	0.03	0.03	0.03	0.03	0.05	0.01
	1	FS	0.25	0.26	0.25	0.25	0.25	0.25	0.26
		FB	0.00	0.00	0.00	0.00	0.00	0.00	0.00
MAL	5	FS	0.33	0.32	0.32	0.31	0.31	0.30	0.29
		FB	0.37	0.37	0.36	0.34	0.31	0.30	0.29
	20	FS	0.08	0.08	0.08	0.08	0.08	0.08	0.07
		FB	0.10	0.09	0.08	0.08	0.07	0.07	0.06
	1	FS	0.73	0.73	0.73	0.72	0.71	0.70	0.70
		FB	0.00	0.00	0.00	0.00	0.00	0.00	0.00
PAK	5	FS	0.35	0.34	0.33	0.30	0.28	0.25	0.23
		FB	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	20	FS	0.09	0.08	0.07	0.05	0.03	0.00	0.00
		FB	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	1	FS	0.15	0.17	0.18	0.19	0.21	0.22	0.23
		FB	0.00	0.00	0.00	0.00	0.00	0.00	0.00
THA	5	FS	0.16	0.18	0.18	0.19	0.19	0.19	0.19
		FB	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	20	FS	0.05	0.07	0.07	0.07	0.07	0.07	0.07
		FB	0.00	0.00	0.00	0.00	0.00	0.00	0.00

This table contains the optimal allocation to foreign stocks (FS) and foreign bonds (FB) for risk aversion levels $\gamma = 1, 5, 20$ and investment horizons of up to five years (sixty months). The allocations are expressed as a fraction of the total portfolio.

Table 4.8. **Gains in from foreign diversification.**

		Investment Horizon (months)						
	γ	1	6	12	24	36	48	60
	1	0.89	0.94	1.00	1.14	1.29	1.43	1.62
IN	5	9.84	9.85	9.40	9.14	8.55	7.99	7.56
	20	10.66	10.62	9.95	9.10	6.12	3.86	0.12
	1	1.85	1.96	1.90	1.93	1.95	2.04	2.14
MAL	5	24.92	24.53	23.53	22.69	21.50	20.48	19.71
	20	12.79	12.62	12.19	11.77	11.34	10.76	10.33
	1	41.64	39.97	38.72	36.38	33.63	31.08	28.34
PAK	5	39.20	36.52	33.94	29.59	25.57	21.84	18.51
	20	14.51	12.42	9.72	5.47	1.90	0.06	0.00
	1	0.87	1.17	1.40	1.80	2.16	2.53	2.76
THA	5	3.63	5.02	5.57	6.22	6.53	6.91	6.92
	20	2.70	4.80	5.58	6.09	6.60	7.01	6.73

This table contains the gains in Certainty Equivalent Return (CER) from foreign diversification, as a fraction of the expected return on the optimal domestic portfolio. We consider risk aversion levels of $\gamma = 1, 5, 20$ and investment horizons of up to five years (sixty months).

This can be explained from the more favourable Sharpe ratios on both assets as compared to the Indian case. Also, foreign stocks and bonds have a somewhat lower correlation with domestic equity. Horizon effects are limited in the Malaysian case. The certainty equivalent gain decreases by about 20% at the five-year horizon, but substantial diversification benefits remain, as the increase in riskiness of short-term debt and foreign bonds is less pronounced than in the Indian case.

Pakistan

In the case of Pakistan, diversification benefits stem from investing in foreign stocks. In view of the low Sharpe ratio of domestic equity, these benefits are substantial. In the one-period situation the increase in certainty equivalent return amounts to over 40% of the expected return on the domestic portfolio for short-term risk-neutral investors, who optimally allocate almost 75% of their portfolio to foreign stocks. Moderately risk-averse investors can achieve similar gains, requiring an investment of only 35% of their portfolio in foreign equity. However, here also we find adverse horizon effects, which are most pronounced for conservative investors. This is related to the volatility increase of the benchmark asset, which is most pronounced in the case of Pakistan. This increases the overall risk level for long-run investors, which causes conservative investors to lower their allocation to risky assets.

Thailand

Thailand has the lowest diversification benefits of the four countries considered, which can be explained from the low Sharpe ratio of foreign equity found in Table 4.1, as well as the negative expected returns on foreign bonds. Still, foreign stocks amount to up to 20% of the optimal portfolio for moderately risk-averse investors. The proportion of foreign stocks in the portfolio increases slightly over time, in line with the observation that annualized volatility of domestic stocks increases faster than that of foreign stocks (Figures 4.1- 4.2). However, these horizon effects are relatively small.

4.3.5 Conclusion

This chapter has investigated foreign diversification benefits for emerging market investors. We have followed an approach that differs from previous literature on this topic by allowing for horizon effects in portfolio decisions. Moreover we incorporated both model and parameter uncertainty inherent in the decision problem of emerging market investors in our analysis.

Contrary to previous studies in emerging markets, we found that, in our sample of four large markets, there is little evidence for domestic stock return predictability. These results confirm recent research suggesting that such predictability is a particular feature of the U.S. market, rather than a stylized fact in international stock markets. Returns on a global stock portfolio are also not predictable from the perspective of emerging market investors. The main dynamic effects we encountered were positive autocorrelations in returns on short-term domestic debt and long-term foreign bonds.

Turning back to the main research question of this study, we can conclude that the four countries in our sample differ considerably when it comes to the magnitude of diversification benefits or the investor type that benefits most from investing abroad. For a 5-year investment horizon, the diversification benefits in terms of certainty equivalent return range between 0.12% (India, risk-averse investor) and

28.34% (Pakistan, risk-neutral investor) of the expected return on the optimal domestic portfolio. In many cases the differences in certainty equivalent returns can be attributed to properties of single-period asset returns that also become apparent in a static portfolio model. However, in the cases of Indian and Pakistani investors, the use of a static single-period model would imply a significant overestimation of certainty equivalent returns and an overallocation to foreign securities.

It is well-known that financial markets are subject to structural change, which is particularly relevant for emerging markets and developing economies. Hence, one particularly relevant extension of our approach would be to allow for time-varying or regime-dependent model parameters. We leave this as a direction for further research.

4.A Estimation method

In this Appendix we summarize the approach of Diris (2011) for estimation of VAR models under uncertainty about the relevant predictor variables, accounting for the possibility that predictors differ between VAR equations. A description of the corresponding algorithm is given in Table 4.A.1.

A generic model M_j is obtained by selecting subsets $\boldsymbol{y}^{(i,j)}$ of $\boldsymbol{y}$ as right-hand side variables in the i'th VAR equation, $i \in \{1, \ldots, n\}$. The corresponding parameters are denoted by $\boldsymbol{\beta}^{(i,j)}$. Stacking these parameters in a vector $\boldsymbol{\beta}^{(j)}$ the model can be rewritten in a standard Seemingly Unrelated Regression (SUR) form (Zellner (1962)) which allows for the use of GLS estimators.

Prior choice is required at two levels. At the level of model choice, q is the inclusion probability of a typical right-hand side variable. Setting a high value of q corresponds to the *a priori* belief that there are many predictive relationships in model (4.1). At the level of the autoregressive coefficients, it is necessary to specify prior means $\boldsymbol{m}^j$. Their prior covariance matrix is based on the empirical Bayes approach. It is equal to the covariance matrix of the GLS estimator of $\boldsymbol{\beta}^{(j)}$ weighted by a constant g. This constant specifies the strength of prior beliefs as compared to data-based inference. As is immediately clear from the conditional posterior of $\boldsymbol{\beta}^{(j)}$, a higher value of g implies a smaller role of prior beliefs.

The MCMC sampling procedure consists of four iterative steps. In the first step, a new model is proposed by randomly adding or deleting an explanatory variable from the current model. The acceptance probability of the candidate model is determined by its conditional marginal likelihood $p(\mathcal{I}_T|M_j, \Sigma_j)$. In the second step, the slope coefficients of the model are drawn according to their conditional posterior, which is analytically available. The conditional posterior of the covariance matrix is not, and, in the third step, its distribution is approximated with a Metropolis-Hastings procedure, drawing candidate matrices from the inverse-Wishart distribution. Finally, standard VAR results show that the distribution $p(\boldsymbol{r}_T(k)|M_j, \Theta_j, \mathcal{I}_T)$ in (4.4) is multivariate normal. Thus we arrive at a draw from the predictive distribution $p(\boldsymbol{r}_T(k)|\mathcal{I}_T)$.

The results reported in this chapter are for $q = 0.5$ and $g = T$. Setting $q = 0.5$ implies that, a priori, every element of the VAR matrix B is as likely to be included as it is to be excluded. Setting $g = T$ implies that prior means and covariance matrices on the slope coefficients have as much 'weight' as a single observation. Furthermore, our results are based on 200.000 retained draws of k-period ahead log returns, after discarding 100.000 draws in a burn-in phase.

Models	$M_j: \quad y_{i,t+1}$	$=$	$(1,\boldsymbol{y}_t^{(i,j)'})\boldsymbol{\beta}^{(i,j)} + \varepsilon_{i,t+1},\ i \in \{1,\dots,n\}$
	$\boldsymbol{\beta}^{(j)}$	$=$	$\left(\boldsymbol{\beta}^{(1,j)'},\dots,\boldsymbol{\beta}^{(n,j)'}\right)'$
Priors			
Model	$p(M_j)$	$\propto$	$q^{\lvert M_j\rvert}(1-q)^{n^2-\lvert M_j\rvert}$
Covariances	$p(\Sigma^{(j)}\lvert M_j)$	$\propto$	$\lvert\Sigma^{(j)}\rvert^{-\frac{n+1}{2}}$
AR-coeff.	$p(\beta^{(j)}\lvert\Sigma^{(j)}, M_j)$	$\sim$	$N\left(\boldsymbol{m}^{(j)}, gV(\hat{\boldsymbol{\beta}}_{GLS}^{(j)})\right)$
Posterior			
AR-coeff.	$p(\boldsymbol{\beta}^{(j)}\lvert\mathcal{I}_T, M_j, \Sigma^{(j)})$	$\sim$	$N\left(\frac{(\boldsymbol{m}^{(j)}+g\hat{\boldsymbol{\beta}}_{GLS}^{(j)})}{1+g}, \frac{g}{1+g}V(\hat{\boldsymbol{\beta}}_{GLS}^{(j)})\right)$

Algorithm

Step-s model: M_s

Step-s Cov. : $\Sigma^{(s)}$

1. Select proposal model M_{s+1}^* by randomly adding or deleting an explanatory variable in one of the VAR equations

-Set $M_{s+1} = M_{s+1}^*$ with probability $\alpha = \min\left\{1, \frac{p(M_{s+1}^*)p(\mathcal{I}_T|M_{s+1}^*,\Sigma^{(s)})}{p(M_s)p(\mathcal{I}_T|M_s,\Sigma^{(s)})}\right\}$

-Otherwise set $M_{s+1} = M_s$

2. Draw $\beta^{(s+1)}$ from $p(\beta^{(s+1)}|\mathcal{I}_T, M_s, \Sigma^{(s)})$

3. Draw $\Sigma^{(s+1)*}$ from iWishart$(E^{(s+1)'}E^{(s+1)} + \frac{1}{g}H^{(s+1)}, T+n+1)$

-Accept with probability $\alpha = \min\left\{1, \frac{|V(\hat{\beta}_{GLS}^{(s+1)})|^{\frac{1}{2}}|\Sigma^{(s+1)*}|^{\frac{n+1}{2}}}{|V(\hat{\beta}_{GLS}^{(s+1)})|^{\frac{1}{2}}|\Sigma^{(s)*}|^{\frac{n+1}{2}}}\right\}$

-Otherwise set $\Sigma^{(s+1)} = \Sigma^{(s)}$

Table 4.A.1. Diris (2011) MCMC approach.

4.B Data sources and data construction

This Appendix describes the time series construction procedure for the elements of the vector $\boldsymbol{y}$ in equation (4.1). The Datastream mnemonic codes of the basic input data are given in Table 4.B.1. All data are sampled at a monthly frequency.

Table 4.B.1. **Datastream mnemonic codes.**

	Equity	Short-term debt	Inflation	Exchange rate
India	TOTMKIN	INI60...	INI64...F	INI..AE.
Malaysia	TOTXTMY	MYI60C..	MYI64...F	MYI..RF.
Pakistan	TOTMKPK	PKI64..F	PKI60C..	PKI..RF.
Thailand	TOTMKTH	THI64..F	THI60C.	THI..RF.
World	TOTMKWD	FRTBS3M	—	—

Datastream mnemonic codes used to construct time series of benchmark short-term debt returns, equity excess returns and predictor variables. The equity index attributes used are RI (total return index), DY (dividend yield), VA (turnover by value), MV (market capitalization), FS (the number of stocks that fell on a given trading day), RS (the number of stocks that rose on a given trading day) and UC (the number of stocks that did not change in value on a given trading day). The sample periods are 1990.I-2012.I (India), 1986.I-2012.I (Malaysia), 1987.I-2012.I (Thailand) and 1992.VIII-2012.I (Pakistan).

1. **Returns on short-term domestic debt**: We use the Datastream series in the 'short-term debt' column as proxies for the nominal domestic short rates. We denote the short rate at the beginning of month t by $r_{N,t}$. The value of the inflation index at this moment is denoted by PI_t. The log short term debt return over the course of month t is obtained from the equation

$$r_{0,t+1} = \ln\left(1 + r_{N,t}/100\right)/12 - \ln\left(\mathrm{PI}_{t+1}/\mathrm{PI}_t\right).$$

2. **Excess returns on domestic stocks**: We denote the Total Return Index for the domestic stock market at the beginning of month t (in the column 'Equity') by $S_{DS,t}$. Excess returns on domestic stocks are obtained from

$$r_{DS,t+1} = \ln\left(S_{DS,t+1}/S_{DS,t}\right) - \ln\left(1 + r_{N,t}/100\right)/12.$$

3. **Excess returns on foreign stocks and bonds**: We denote the Total Return Index for the global stock market at the beginning of month t (in the fifth row of the 'Equity' column) by $S_{FS,t}$. The market exchange rate, in domestic currency

units per dollar (in the column 'Exchange rate'), is denoted by EX_t. Excess returns on foreign stocks are obtained from

$$r_{FS,t+1} = \ln\left(S_{FS,t+1}/S_{FS,t}\right) + \ln\left(\mathrm{EX}_{t+1}/\mathrm{EX}_t\right) - \ln\left(1 + r_{N,t}/100\right)/12.$$

Excess returns on foreign bonds are obtained analogously, using the Barclays Capital total world bond return index with mnemonic code LHGOVBD.

4. **Dividend Yields** are obtained by dividing the DY attribute of the series listed in the 'Equity' column by 100 and taking the natural logarithm of the result.

5. **Nominal interest rates** are obtained from the nominal short rate $r_{N,t}$ by calculating $\ln\left(1 + r_{N,t}/100\right)/12$.

6. **Turnover ratios** are obtained by dividing the VA attribute (turnover by value) by the MV attribute (market capitalization) for the series listed in the 'Equity' column.

7. **Non-trading days**: The Datastream return index attributes FS, RS and UC give the number of index constituents that respectively, decreased in value, rose in value or remained at the same value during a trading day. Our liquidity proxy is constructed by summing these figures over the course of month t and computing the ratio $\mathrm{UC}_t/\left(\mathrm{FS}_t + \mathrm{RS}_t + \mathrm{UC}_t\right)$.

Chapter 5

Inflation, stock market crashes and asset allocation in the Philippines

5.1 Introduction

The provision of old age income support is a key challenge across the developing world. In recent years the World Bank has been involved in pension reforms in over eighty countries. The consensus view on pension reform emphasizes the advantages of a funded pillar whenever financial and institutional development permits. Moreover it underlines the importance of well-diversified investment of participants' contributions, instead of a strong reliance on domestic government bonds (Holzmann and Hinz (2005, p. 12, 44-52)).

This approach entails the need for investment strategies that distribute the collected funds over various asset classes. A vast academic literature on long-term asset allocation has emerged in the course of the last two decades (see e.g., Campbell and Viceira (2002) for an overview). While the concepts advanced in this literature can provide guidelines for pension fund design in developing economies (Viceira (2010)), its empirical focus has been on developed countries.

Asset returns in developing economies differ in several important ways. Stock markets are typically much more volatile. Political events, regulatory changes and currency devaluations lead to shocks standard finance models cannot account for (Claessens et al. (1995), Bekaert et al. (1998)). The perceived safety of government bonds is relative at best, due to high inflation risk (Viceira (2010)).

The objective of this chapter is to study asset allocation decisions in a framework that captures these empirical features of developing stock and bond markets. To this end we apply the multivariate regime-switching approach proposed recently by Guidolin and Timmermann (2005, 2006a, 2007). This approach recovers distinct financial market regimes from time series of asset returns. Each of the regimes is characterized by different return expectations, volatilities and correlations.

It has three features which make it particularly suitable for the analysis of developing financial markets. First, it has been shown to perform well at assessing downside risk stemming from extreme events (Guidolin and Timmermann (2006b)). Second, it can take into account return predictability, which, in the case of developing markets, has been documented by e.g., C. Harvey (1995) and Bekaert and Harvey (2007). Third, it offers the possibility to study regimes in stock and bond markets simultaneously. In this way we can not only assess the mutual hedging potential of these asset classes, but also the signalling effects of regime changes in either market.

We use the regime-switching methodology to address two core questions from the long-term asset allocation literature in a developing country context. First, is there evidence of time-varying investment opportunities, or is the optimal distribution of wealth to stocks and bonds virtually constant over time? Second, does this distribution depend on the investment horizon, or is it similar for both short-term and long-term investment?

In our empirical analysis we opt for a country case study. This is motivated by two considerations. First, the background of financial market regimes, and most notably of crisis episodes, is country-specific (e.g., the Mexican crisis of 1994, the Asian crisis of 1997, the Argentine crisis of 1999-2002). Second, financial infrastructure differs vastly between developing countries. Equity market size, regulatory investment restrictions and trading costs necessarily play a major role in asset allocation decisions (Holzmann and Hinz (2005)). The purpose of this chapter is to discuss the asset allocation insights that can be gained from regime-switching models in a developing market context, rather than to propose general asset allocation strategies for such markets.

We have chosen the Philippines as an illustrative example. The Philippines are a lower-middle-income economy with a funded pension system. There are two main funds, aimed at employees in the private and public sectors, respectively. They have a relatively high coverage of 74% of the formally employed population, although their assets under management are limited, at around 10% of GDP. Importantly, the Philippine stock market is relatively large, its capitalization averaging just below 50% of GDP. Regulation allows for investments of up to 30% of total funds to domestic stocks (Dela Rama (2009)). Thus pension fund investment in the equity market is curtailed by neither its size, nor by regulatory constraints. With foreign investment limited to just 7.5%, the primary trade-off is between investment in domestic stocks and bonds.

Our estimation results show that the returns on these assets are adequately described by a three-regime model. Periods of stable stock market growth (regime 1) are interrupted by crashes (regime 2), which last for several months. Interest rates rise in such crash episodes, as lending becomes riskier. Such periods of stock market turmoil are often preceded and succeeded by an increase in bond market volatility (regime 3), which can be related to inflation shocks.

Consequently market timing turns out to be important. At a three-month horizon, the optimal allocation to stocks ranges between thirty-five percent and zero percent, depending on the regime. The severity of stock market crashes is such that even investors with a ten-year horizon reduce their stock allocation by more than 50% if the crash regime is imminent. Even in periods of financial market stability this allocation decreases considerably with the investment horizon, as the probability of going through a crisis episode increases with holding time.

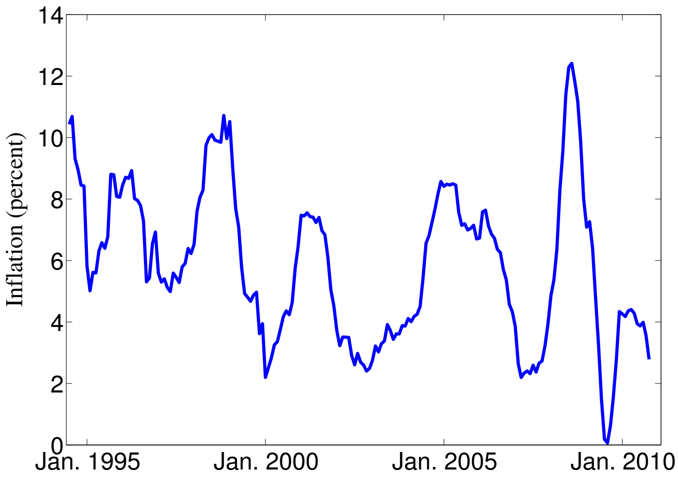
The remainder of this chapter is structured as follows. Section 5.2 gives a brief description of the main features of the Philippine stock and bond markets over the last two decades. Section 5.3 introduces the regime-switching methodology. Our empirical results are presented in section 5.4. Section 5.5 concludes.

5.2 Financial markets in the Philippines

5.2.1 Interest rates and inflation

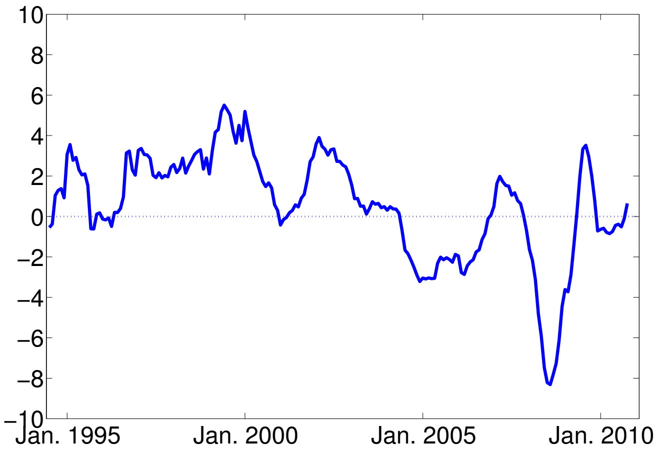
Asset allocation studies for developed financial markets typically assume a constant risk-free interest rate, set to the mean or end-value of the interest rate proxy in the sample period (e.g., Barberis (2000)). This assumption is not appropriate for developing economies, where unexpected inflation shocks can be considerable even in the short run. The evolution of CPI inflation in the Philippines in the period 1995-2010 is graphed in Figure 5.1.

Figure 5.1. **Year-on-year CPI inflation rate in the Philippines, July 1994-October 2010.**



Source: Datastream CPI series (PHCONPRCF).

Figure 5.2. **Year-on-year real return on short-term bills in the Philippines, July 1994-October 2010.**



Source: Datastream, 30-60 day middle rate series (PHTMEDP) and CPI series (PHCONPRCF).

Although annual inflation mostly remains in the single-digit range throughout this period, four large swings are visible. During the first swing, CPI inflation rises from 6.5% in 1997 to 10.5% over 1998, then drops to only 2.2% over 1999. This is related to the depreciation of the peso during the Asian crisis and the economic slowdown that followed. The following three spikes can be attributed to the exposure of the Philippine economy to rising global commodity prices and to weather-related supply shocks in domestic agriculture (Bangko Sentral ng Pilipinas Annual Reports 2000-2010). As these two factors are hardly predictable, unexpected short-term inflation is likely to play a role in the investment decisions of Philippine investors.

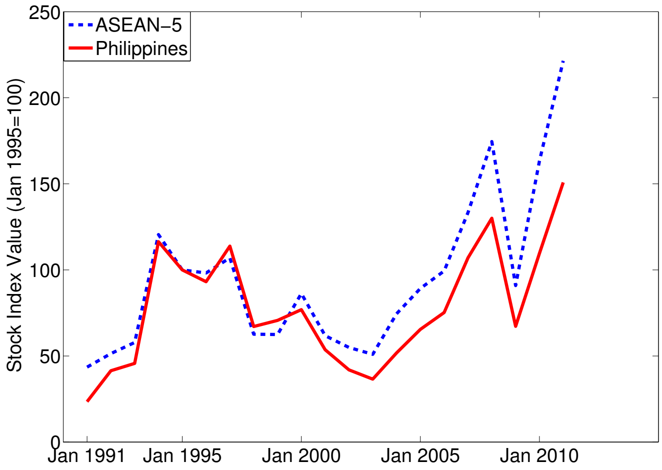
Figure 5.2 illustrates the effects of unexpected inflation on the real returns on short-term bills. In this figure we graph the return that results from rolling over a short-term bill during a one-year period. The real return moves inversely to the inflation rate. The two most recent inflationary episodes even lead to negative real returns. Based on these considerations, we will treat the investor's returns on short-term bills as a stochastic process in our subsequent analysis.

5.2.2 Stock market

Figures 5.3 and 5.4 show the evolution of the Philippine PSE Composite index and its capitalization relative to GDP. The major stock price movements closely resemble those of other East Asian indices. The early nineties were characterized by high returns, driven by foreign investment streams. By the end of 1996 stock market capitalization peaked at USD 80.5 billion, amounting to 97.4% percent of GDP. The Asian crisis led to a 41% drop in the PSE Composite index in the course of 1997. Levels comparable to the 1997 high were reached only after a decade, with a capitalization of USD 102.9 billion (71.7% of GDP) by the end of 2007. This recovery was checked by a fall of 48.3% percent amidst the global financial downturn of 2008. Subsequently, however, stock prices rebounded and by December 2010 the index was 16% above the end-2007 level.

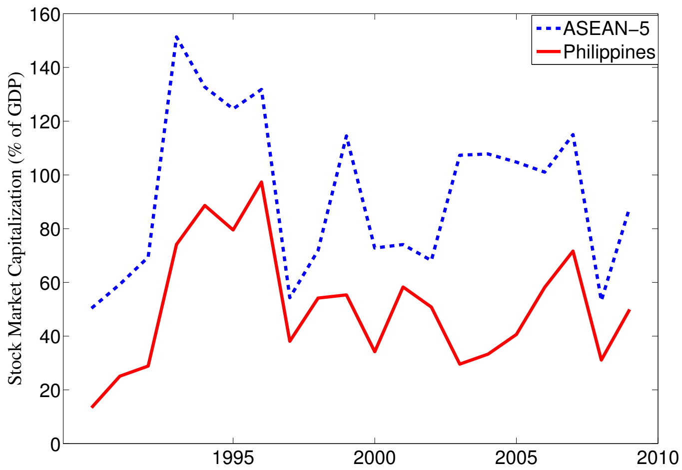
In terms of market liquidity, the Philippine stock market lags behind other markets in the region (Table 5.1). The average annual turnover ratio over the period 2001-2010 was only 18.5%. In addition, over half of the trades were in shares of the largest ten listed companies. This lack of liquidity can be attributed to several factors. First, governance and disclosure standards are far from perfect, hampering the price discovery process. Second, transaction costs are high, reducing incentives for frequent trading (Ghosh (2006, p. 107), Hsieh and Nieh (2010, p. 27). Third, the development of equity mutual funds, which tend to trade actively, has remained marginal. This is due to both outdated legislation and crowding out by the defined-benefit schemes offered by the two large provident funds (Ghosh (2006), Purfield et al. (2006)).

Figure 5.3. **The Philippine PSE Composite Index 1991-2011.**



The graph connects beginning-of-the-year values. The average of the main stock market indices of the ASEAN-5 countries is plotted for comparison. Both series are benchmarked so that their value in January 1995 equals 100. Source: World Federation of Exchanges, accessed at http://www.world-exchanges.org/statistics/time-series/indexes.

Figure 5.4. **Philippine stock market capitalization as a percentage of GDP.**



The ASEAN-5 average is plotted for comparison. Source: World Bank, accessed at http://data.worldbank.org/.

Table 5.1. **The Philippine stock market in a regional perspective.**

	Capitalization		Turnover		Transaction
	USD billions	% of GDP	Ratio	Concen-tration	Costs
Indonesia	125.0	30.0	53.2	52.2	68.1
Malaysia	219.8	140.3	31.4	26.1	55.9
Philippines	**63.4**	**48.3**	**18.5**	**58.1**	**94.1**
Singapore	253.3	182.4	69.5	40.5	14.5
Thailand	130.1	62.1	94.0	35.0	56.9

The first column contains the average stock market capitalization, in billions U.S. dollars, calculated from year-end values over the period 2001-2010. The second column contains capitalization as a percentage of GDP and is calculated likewise. The data were retrieved from the World Bank database accessible at http://data.worldbank.org. The third column contains annual turnover ratios as a percentage of market capitalization. These are defined as twelve times the average ratio of monthly domestic share trading value to month-end capitalization. The fourth column contains the share of the ten largest listed companies in total annual value traded, in percentage terms. The values in both the third and the fourth column are averages over 2001-2010. The data were compiled by the World Federation of Exchanges and retrieved from http://www.world-exchanges.org/statistics. The final column contains transaction costs, measured in basis points, and is taken from Ghosh (2006, p.107).

These features of the Philippine stock market necessitate prudent model choice for the analysis of asset allocation strategies. Linear time series models are unlikely to fit the vehement fluctuations of a developing stock market in times of crisis. Regime-switching models are a reasonable alternative. They perform well at modelling higher-order moments of return distributions, yet do not require predictor variables to capture the business cycle dynamics relevant for asset allocation (cf. Guidolin and Hyde (2011)).

5.3 Methodology

Asset allocation problems are generally modelled by specifying a stochastic process for the returns on a number of assets and an objective function for the agent who considers investing in them. For the sake of comparison with influential papers in the literature (Barberis (2000), Guidolin and Timmermann (2005,2007)) we use a power utility objective function. At time $t \in \{0, 1, 2, \ldots\}$ an investor with an investment horizon of k periods and constant relative risk aversion $\gamma > 1$ has the following utility over real-term wealth W_{t+k} at time $t+k$:

$$u(W_{t+k}) = \frac{W_{t+k}^{1-\gamma}}{1-\gamma}. \tag{5.1}$$

We study a basic investment opportunity set, consisting of short-term bills and a stock index. Short-term bills are considered as the benchmark asset. We write $r_{0,t+1}$ for the continuously compounded real-term return on these bills between t and $t+1$. Likewise, continuously compounded excess stock returns are written as $r_{S,t+1}$. The fraction of an investor's wealth allocated to stocks is denoted by ω. The remainder is invested in bills. In view of the relatively low liquidity of the Philippine stock market and the considerable transaction costs of stock trading, we limit our analysis to buy-and-hold strategies. Furthermore, we restrict ω to be in the interval $(0,1)$, thus precluding short sales.

Under these assumptions, the decision problem of an investor who maximizes the expected value of the utility function in (5.1) at $t = T$ for a k-period horizon becomes

$$\begin{aligned} &\max_{\omega} E_T\Big[\frac{\big((1-\omega)e^{r_{0,T}(k)} + \omega e^{(r_{0,T}(k)+r_{S,T}(k))}\big)^{1-\gamma}}{1-\gamma}\Big] \\ &\text{s.t.} \quad \omega \in (0,1), \end{aligned} \tag{5.2}$$

where we have defined $r_{i,T}(k) = \sum_{j=1}^{k} r_{i,T+j}$, $i \in \{0, S\}$.

We model real interest rates and excess stock returns by means of a bivariate Markov-Switching Vector Autoregressive (MS-VAR) process (Hamilton (1989,1990), Krolzig (1997)). We assume that at time t, the financial markets are in one of L possible regimes, $\Lambda_t \in \{1,\ldots,L\}$. These regimes are not observable by investors. However, investors can use past returns to assess the probability that the market is in a certain regime. The 2×1 vector of returns $\boldsymbol{r_t} = (r_{0,t}, r_{S,t})'$ evolves according to

$$\boldsymbol{r}_t = \begin{cases} \boldsymbol{a}_1 + B_{11}\boldsymbol{r}_{t-1} + \ldots + B_{p1}\boldsymbol{r}_{t-p} + \boldsymbol{\varepsilon}_{1,t} & \text{if } \Lambda_t = 1 \\ \vdots & \\ \boldsymbol{a}_L + B_{1L}\boldsymbol{r}_{t-1} + \ldots + B_{pL}\boldsymbol{r}_{t-p} + \boldsymbol{\varepsilon}_{L,t} & \text{if } \Lambda_t = L \end{cases}, \tag{5.3}$$

where for $l \in \{1,\ldots,L\}$ and $p \in \{1,2,\ldots\}$ $\boldsymbol{a}_l$ is a 2×1 vector of intercepts, A_{pl} is a 2×2 matrix of autoregressive coefficients, $\boldsymbol{\varepsilon}_{l,t} \sim N(\boldsymbol{0}_{2\times 1}, \Sigma_l)$ and Σ_l is a 2×2 covariance matrix. Conditional on being in regime l, the return process is a standard vector autoregression (VAR) of order p. The VAR parameters differ across the regimes, which allows for flexible modelling of regime-dependent return expectations and volatilities. The regimes themselves are governed by a discrete, irreducible, ergodic first-order Markov process. The probability of entering regime l at time t depends only on the regime which is in effect at time $t-1$:

$$\begin{aligned}\Pr\left(\Lambda_t = l|\left(\Lambda_s\right)_{s=0}^{t-1}, \left(\boldsymbol{r_s}\right)_{s=0}^{t-1}\right) &= \Pr(\Lambda_t = l|\Lambda_{t-1} = m) \\ &= p_{ml}, \end{aligned} \tag{5.4}$$

with $\sum_{l=1}^{L} p_{ml} = 1, \forall m \in \{1, \ldots, L\}$. These probabilities can be collected in a $L \times L$ matrix P, with rows summing to unity.

We assume that the investor observes the return process between $t = 0$ and $t = T$ and uses the corresponding information set $\mathcal{I}_T$ for parameter estimation. The parameters of the MS-VAR model can be estimated by maximum likelihood methods, using the expectation maximization (EM) algorithm. Krolzig (1997) provides an excellent treatment of estimation and inference procedures for a wide range of model specifications. The estimation procedure also yields an $L \times 1$ vector of inferred regime probabilities. This allows us to relate model-implied regimes to historical events in the financial markets.

The investor's decision problem is then solved numerically using Monte Carlo methods (Guidolin and Timmermann (2005, 2007)). Conditional on estimated values of the model parameters in (5.3) and (5.4), we draw $N = 100,000$ simulated paths of the return process. We then approximate the investors' expected utility by

$$N^{-1}\sum_{j=1}^{N}\left\{\frac{\left((1-\omega)e^{r_{0,T}^{(j)}(k)} + \omega e^{\left(r_{0,T}^{(j)}(k)+r_{S,T}^{(j)}(k)\right)}\right)^{1-\gamma}}{1-\gamma}\right\} \tag{5.5}$$

where $r_{i,T}^{(j)}(k)$, $i \in \{0, S\}$, is the sum of continuously compounded returns over the n'th path. The value of ω that maximizes this expression is determined by means of a grid search on the interval $(0, 1)$.

5.4 Empirical analysis

5.4.1 Data

The input for our model consists of three time series with a monthly frequency. We use the natural logarithm of the 30-60 day deposit middle rate as a proxy for the continuously compounded return on short-term government bills. This nominal return is converted to real terms by subtracting the log change in the Philippine Consumer Price Index (CPI). We adjust the CPI series for seasonality using the Census-X12 methodology as implemented in the statistical package EViews. Continuously compounded stock returns, including dividend payouts, are calculated from the Philippine Composite Index time series. Excess returns are obtained by subtracting the nominal interest rate. Our sample spans the period between July 1993 (the first date for which the interest rate proxy is available) and October 2010. All data are obtained from Thomson Datastream.[1] Table 5.2 presents the summary statistics of monthly real returns on short-term bills and of excess returns on the stock index.

Table 5.2. **Summary statistics of returns.**

	Monthly Returns, cont. comp				Annual Returns	
	Mean ($\times 10^2$)	Std. Dev.	Min.	Max.	Mean	Std. Dev.
Bills	0.025	0.004	-0.022	0.011	0.31	1.51
Equity	0.160	0.082	-0.300	0.233	5.92	28.28

This table contains summary statistics of real returns on Philippine short-term bills and of excess equity returns on the Philippine Composite Index. The sample is 1993:07-2010:10. The first four columns contain statistics on continuously compounded monthly returns, while the last two contain annualized simple returns, adjusted for Jensen's inequality and in percentage terms.

5.4.2 Model selection

An empirical application of the regime-switching model in equation (5.3) involves a number of modelling choices. These choices concern the number of regimes, the autoregressive order, and the selection of switching and non-switching model parameters. Previous literature shows that, in developed markets as the United States and the United Kingdom, models with three or four regimes, with switching means and covariance matrices, and without autoregressive terms, provide a good fit to stock and bond return data (see Guidolin and Timmermann (2005, 2006a, 2006b, 2007)).

Taking such models as a starting point, we have estimated a wide range of specifications, varying the number of regimes, the switching components and the autoregressive order. In the Appendix we provide a detailed analysis of the characteristics of the estimated models. The results are generated using the Time Series Modelling package, Version 4.33 (Davidson (2011)), which runs under Ox 5.10 (see

[1] The Datastream mnemonic codes for the three series are PHTMEDP, PHCONPRCF, and MANCOMZ.

Doornik (2007)). In addition to a statistical model comparison, based on information criteria, we include tests of the return densities forecast by the models, in view of their importance for asset allocation decisions (Berkowitz (2001)). As a result of this analysis, we select a three-regime model with switching intercepts and covariance matrices, and non-switching first-order autoregressive terms.

5.4.3 Estimation results

The estimates of the selected model are presented in Table 5.3. Let us first consider the estimated transition probability matrix P at the bottom of this table. From this matrix we can derive the steady-state probabilities of each of the regimes and their expected durations.[2] The first regime turns out to be most prevalent. Its steady-state probability is 73.5% and it has an expected duration of 27.2 months. It can therefore be considered as a benchmark or 'normal' regime. Expected monthly real returns on short-term bills amount to 0.04%, while stocks offer a monthly excess return of 0.60%. The corresponding monthly volatilities are 0.26% and 7.11%.

The second regime picks up turmoil on the stock market. Figure 5.5 shows the model-implied probability that the financial markets are in this regime at any given moment in our sample period. This probability is close to one between July 1997 and January 1998, and again between June and October 1998. During these months the Philippine Composite Index suffered considerable losses due to the withdrawal of foreign investment as a consequence of the Asian financial crisis. The other occurrence of this regime is around ten years later and coincides with the global financial downturn in the fall of 2008.

In this regime, expected excess returns on stocks are highly negative at -7.13%, a significant difference as compared to the benchmark regime. Volatility is also higher at 14.11%, though this difference is not statistically significant. This implies that the 'crash' regime may occasionally include months in which equity markets rebound after substantial losses and show positive returns. From the second diagonal element of the transition probability matrix we estimate its duration at just over four months. Expected returns on bills are significantly higher in this regime as compared to normal times. A possible explanation is that stock market uncertainty raises the risk premium on lending money in order to compensate for higher default probabilities.

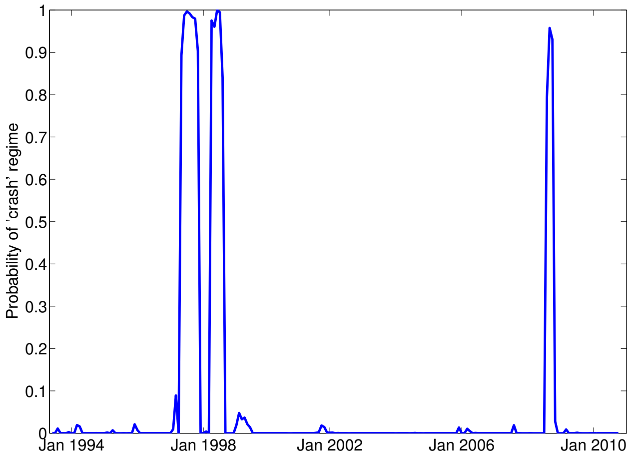
[2] The steady-state probability is obtained from the eigenvector of P that corresponds to its unity eigenvalue. It can be interpreted as the fraction of time the system would be in the given regime, if we would observe it indefinitely. The expected duration of regime l equals $1/(1 - p_{ll})$.

Table 5.3. **Parameter estimates for a switching model with three regimes.**

	Bills		Excess Stock	
Expected Returns				
Normal Regime	0.042	(0.051)	0.600	(0.690)
Crash Regime	0.433^{***}	(0.072)	-7.128^{*}	(4.506)
Inflationary Regime	-0.209	(0.241)	1.003	(2.210)
Volatilities and Correlations				
Normal Regime				
Bills	0.258	(0.020)		
Stocks	0.083	(0.081)	7.108	(0.470)
Crash Regime				
Bills	0.069^{***}	(0.020)		
Stocks	0.229	(0.389)	11.411	(2.790)
Inflationary Regime				
Bills	0.757^{***}	(0.130)		
Stocks	-0.329^{**}	(0.150)	8.814	(1.380)
Autoregressive Terms				
Bills	0.403^{***}	(0.081)	0.000	(0.003)
Stocks	1.381	(1.367)	0.052	(0.082)
Transition Probabilities	To			
From	Normal	Crash	Infl.	
Normal	0.967	0.000	0.033	
Crash	0.000	0.769	0.231	
Infl.	0.127	0.090	0.783	

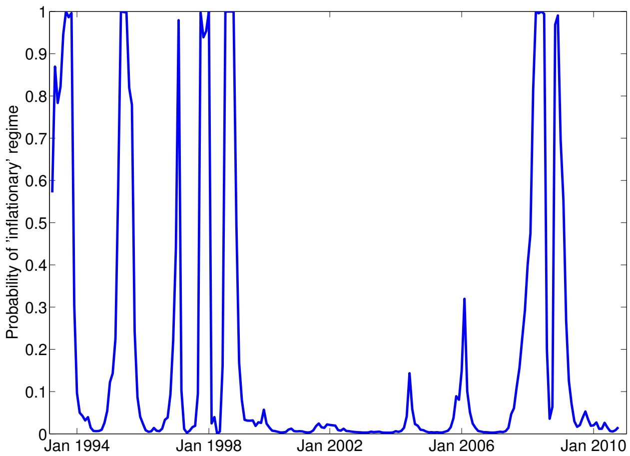
This table reports the parameter estimates for the regime-switching model in equation (5.3). The 2×1 return vector $\boldsymbol{r}_t$ consists of real returns on short-term bills, which we proxy by the 30-60 day deposit middle rate less the CPI inflation rate, and of excess returns on the PSE Composite index. The number of regimes is $L = 3$ and the autoregressive order is $p = 1$. The intercepts $\boldsymbol{a}_l$ and the covariance matrices Σ_l are assumed to differ between regimes, while the elements of the autoregressive matrices A_{1l} are equal in all regimes. The reported estimates are for monthly data in the sample period 1993:07-2010:10. Expected returns are obtained from the relationship $\boldsymbol{\mu}_l = (I - A_{1l})^{-1}\boldsymbol{a}_l$. The diagonal entries of the covariance matrices contain monthly return standard deviations, while the off-diagonal entries contain correlations. Both expected returns and their standard deviations are given in percentage terms, e.g., expected excess stock returns in the normal state are 0.600% per month, with a volatility of 7.108%. Standard errors are given in parentheses. For expected returns and volatilities in the crash and inflationary regimes, we test for differences from the normal regime. * denotes significance at 10%, ** at 5% and *** at 1%. For autoregressive terms and correlations these symbols refer to differences from zero.

Figure 5.5. **Model-implied probabilities of the 'crash' regime.**



This figure shows the probability that the financial markets are in the 'crash' regime identified by the model in Table 5.3, at any moment in our sample period 1994:7-2010:10.

Figure 5.6. **Model-implied probabilities of the 'inflationary' regime.**



This figure shows the probability that the financial markets are in the 'inflationary' regime identified by the model in Table 5.3, at any moment in our sample period 1994:7-2010:10.

Low and highly volatile returns on short-term bills are the main feature of the third regime in our model; see Figure 5.6. Apart from two episodes of rapidly changing inflation rates in the first part of the nineties, this regime seems to be coupled with the crash regime. This finding is not surprising given the fact that the Philippine peso depreciated by over 30% between July 1997 and January 1999. Likewise, the stock market slump in the fall of 2008 took place in a period of rising food and oil prices in the global market, which caused a severe inflation shock in the Philippines. Our model suggests that stock returns are not affected adversely by this uncertainty, with a point estimate that is higher than in the benchmark regime.

The transition probability matrix yields additional insights about the relationship between the three regimes. Starting from the normal regime, the model rules out the possibility of going directly to the crash regime. Rather, the financial markets first enter the inflationary regime, whence they either revert to their regular state, or tumble into crisis. Once in the inflationary regime, which has an expected duration of 4.6 months, the conditional probability of eventual exit into the crisis regime 41.5%. On the other hand, the only way out of the crash regime is also via the inflationary regime.

As turmoil episodes are rare events, we should exercise caution when interpreting these results. Nevertheless, our findings do reflect the multifaceted nature of financial setbacks in developing countries, which affect both debt and equity markets. For investors, it is valuable to know that inflationary episodes have some signalling value for stock market crashes and that interest rates tend to increase once the crash takes place. In the next section we will discuss the consequences of these features for asset allocation decisions.

At this stage, our results bear some resemblance to those obtained by Guidolin and Timmermann (2005) for the United Kingdom. In their study of excess stock and long-term bond returns, they also estimated a three-regime model consisting of a benchmark regime, a 'crash' or 'bear' regime and a 'bull' regime. Their benchmark regime has an expected excess stock return of 0.61% per month, which is comparable to our findings, though return volatility is much lower at 3.75%. Their 'bear' regime has even lower expected stock returns than our 'crash' regime, equal to −11.06%. In their case, however, this regime has a much shorter duration of about 1.3 months and captures sudden and brief declines rather than prolonged crisis periods. Moreover, in their analysis the 'bear' regime is nearly always succeeded by a 'bull' regime, which features an equity Sharpe Ratio twice as high as the normal regime and is expected to last about seven months. Guidolin and Timmermann (2007) also find good post-crash prospects for the United States. Their model unveils a 'recovery' regime with high, albeit volatile, expected returns on both stocks and bonds. The distinguishing features of our model for the Philippines are the severity and long duration of equity market crashes, their close relationship with periods of high inflation volatility, and the absence of quick recovery perspectives.

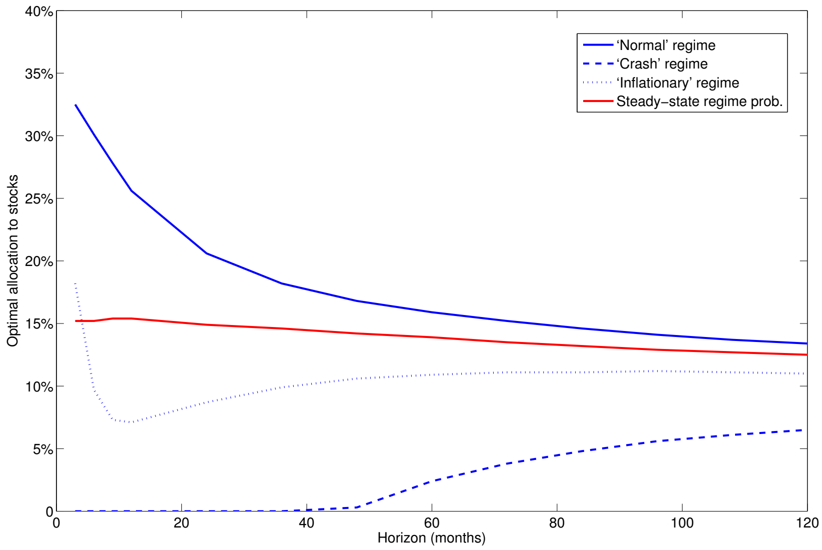
5.4.4 Implications for asset allocation

We use our estimation results to generate $N = 100,000$ return paths and we approximate investors' expected utility for stock allocations $0 < \omega < 1$ by means of equation (5.5). In line with previous literature, we use a risk aversion coefficient of $\gamma = 5$. Figure 5.7 displays the resulting optimal allocation to stocks for investment horizons between one month and ten years. This allocation is highest in the normal regime, given by the solid blue line in the figure. Starting from this regime, an investor with a three-month horizon allocates about one third of his wealth to stocks. This allocation falls to one fourth for a one-year horizon and to only one sixth for five years. This is due to the fact that the probability of going through a crisis episode increases with the investment horizon if one starts out from the benchmark regime.

Not surprisingly, optimal allocation to stocks is lowest in the crash regime, as an investor expects several months of negative and very volatile returns starting from there. In the longer run the financial markets are expected to get back into the normal regime again. The associated returns are sufficiently high to allocate a small fraction of wealth to stocks even in the crash regime, provided the investment horizon is long enough. Nevertheless, the impact of the crash regime is visible even at the ten-year horizon.

The investment schedule for the inflationary regime is the only one that is not monotonous. Although expected stock returns are relatively high in such periods, the high probability of getting into a crash regime in the near future leads to a lower stock allocation as compared to the benchmark regime. This allocation is decreasing for horizons up to one year, from 18.2% at the three-month horizon to 7.1% at the one-year horizon. It then increases to 11.0% for a horizon of ten years. This pattern can be explained from the expected duration of the inflationary regime, which we estimated at 4.6 months. With an investment horizon of just a few months, one has a larger probability of selling the stocks before a stock market crash occurs (if it does) than with a one-year horizon. For long-term investors, allocating to stocks is safer as they have more time left to compensate losses from a possible crash. This explains the upward slope of the allocation scheme beyond the one-year horizon.

Figure 5.7. **Market timing and horizon effects in asset allocation.**



This figure shows the optimal fraction of wealth allocated to stocks for investors with different horizons (the remainder being held in short-term bills). Investors have power utility as in equation (5.1) with risk aversion coefficient $\gamma = 5$. The investor's horizon is given on the horizontal axis. The solid blue line shows the optimal fraction allocated to stocks given that the benchmark regime identified by the model in Table 5.3 is in effect at the moment of investing. The dashed and dotted lines correspond to the crash and the inflationary regimes, respectively. The solid red line corresponds to the situation when the investor is uncertain about the regime and uses the steady-state probabilities implied by the model. These equal 0.7347 for the benchmark regime, 0.0744 for the crash regime and 0.1909 for the inflationary regime.

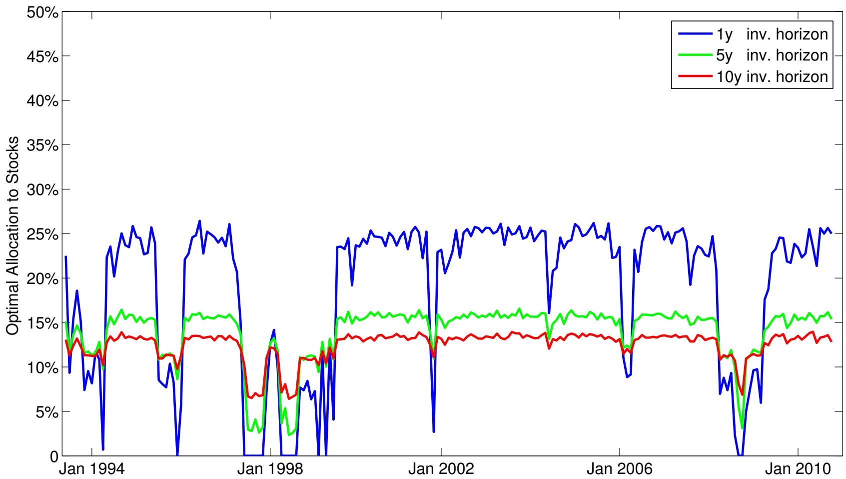
In practice investors cannot observe regimes directly at any moment in time. It is interesting to consider the optimal allocation schedule when, at the moment of investing, the model-implied steady-state probabilities apply.[3] This set-up corresponds to the hypothetical case of an investor who uses the model in Table 5.3 but does not observe recent asset returns and hence cannot make an inference about the current regime. The corresponding strategy is given by the red line in Figure 5.7. It turns out that, in this situation, the allocation patterns implied by the various regimes virtually cancel out against each other. The resulting stock allocation ranges from 15.2% at the three-month horizon to 12.5% at the ten-year horizon.

This finding underlines that conditioning the asset allocation decision on the initial regime and/or the investment horizon is only sensible when it's possible to

[3] These are 0.7347 (normal regime) 0.0744 (crash regime) and 0.1909 (inflationary regime).

extract information about this regime from asset returns. In Figure 5.8 we display stock allocations that result from combining the model estimates in Table 5.3 with the model-implied regime probabilities for each month in our sample. The moment of investing is given on the horizontal axis. We consider three different investment horizons: one year, five years and ten years. We assume that the full-sample parameter estimates of the regime-switching model are known by investors, but that they can only use return information up to the moment of investing to determine the regime that is in effect at that moment. From this figure we can deduce that, even when regimes are inferred rather than observed, optimal allocations vary considerably over time. Most notably, there is a clear decrease in the equity allocation during the Asian financial crisis and the 2008 crisis. But we can also see a clear reaction (stock allocation decrease) to the two inflationary regimes in the middle of the 1990s and to a brief period of high inflation volatility at the beginning of 2006. Short-term investors react more strongly to changes in the perceived regime probabilities than long-term investors. This is because for them the difference between allocations in the three regimes is largest, as we already saw in Figure 5.7.

Figure 5.8. **Optimal allocation to stocks in the 1994:07-2010:10 sample.**



This figure displays the optimal allocation to stocks for the investment date given on the horizontal axis. The blue, green and red lines correspond to horizons of one, five and ten years, respectively. It is assumed that investors base their investment decisions on the regime-switching model estimates in Table 5.3. They use asset returns up to the investment date on the horizontal axis to make inferences about the regime that is in effect when they start investing.

An important difference as compared to results obtained for developed countries is the overall level of allocation to stocks. For horizons in excess of one year Guidolin and Timmermann (2005, 2007) found steady-state equity allocations of 40% in the United Kingdom and 70% in the United States, as opposed to only 15% in the Philippines. This can partly be attributed to the severity of stock market crises in the Philippines. In Figure 5.7 we already saw that, starting from the crisis regime, the equity allocation remains at zero for horizons up to four years, before rising slowly to 6.5% at the ten-year horizon. In stark contrast, Guidolin and Timmermann (2005) report that in the U.K., starting from the crash regime, the two-year allocation is already close to the steady-state value of 40%. In the United States, the ten-year crash regime allocation does remain far below the steady-state result at around 30%, but here also the allocation of an investor with a one-year horizon is already around 20%.

On the other hand, also in non-crisis regimes the risk-return trade-off of Philippine stocks is less favourable. Both in the U.K. and in the U.S. data, the one-month allocation to equity in these regimes is close to 100%, while in our case it is always below 35%. This is due to a relatively high ratio of volatility to expected returns in our non-crisis regimes. It explains why the optimal portfolio strategies in Figure 5.8 are rather stable, in contrast to the rapidly changing strategies reported in Guidolin and Timmermann (2005, 2007). In the U.K. and U.S. markets the optimal strategy for a short-term investor is to allocate his entire wealth to stocks in all non-crash regimes. The Philippine market is too risky for such a strategy even in stable periods. This also helps explain the flat shape of the steady-state investment schedule in our study, as opposed to the findings of Guidolin and Timmermann (2005, 2007), where the schedule is strongly decreasing for horizons up to six months, and stabilizes afterwards. In the absence of strong momentum effects in the non-crisis regimes, the short-term steady-state allocation is not fundamentally different from its long-term counterpart.

5.5 Conclusion

Adequate portfolio management is an important prerequisite for the success of funded pension plans in developing economies. In this chapter we have studied how to deal with time-varying investment opportunities and with different investment horizons. Using returns on stocks and short-term bills in the Philippines we have found statistical evidence of three distinct financial market regimes, with economically significant implications for the optimal asset mix. We have established that stock market crash episodes play an important role in asset allocation decisions. Since they tend to persist for several months, the optimal strategy is to reduce the allocation to stocks once this regime is encountered, even if the investment horizon is as long as ten years. In times of stability in the stock and bond markets, the possibility of encountering a crash episode in the future still has a big impact. At a typical risk aversion level, it reduces the ten-year stock allocation to only one half of the one-year allocation. We have also identified a pivotal inflationary regime, which alternates with, and has some predictive power for, the crash regime. Upon entering this regime, the best strategy is also to reduce the allocation to stocks, though the effect is much less pronounced.

These results highlight the impact of episodes of financial turmoil on asset allocation decisions in developing economies. Naturally, such events are rare and their nature and causes differ vastly between developing economies. This makes the asset allocation implications in our study hard to generalize. Additional country studies using a similar methodology can provide a more complete picture of these important phenomena.

5.A Model selection

In our model selection procedure we follow a specific-to-general approach. As Markov switching models without autoregressive terms have received most attention in the literature, we take such models as a starting point. To avoid overfitting, we restrict ourselves to models with a maximum of three regimes. In the literature on non-linear time series models, a commonly applied rule of thumb is to adhere to a saturation ratio (number of observations divided by number of model parameters) in excess of 20 (Guidolin and Ono (2006), Guidolin and Ria (2011)). This mitigates estimation uncertainty and prevents instability of the maximization routine. In our case, a four-regime model with switching intercepts and covariance matrices would require estimation of 32 parameters and would have a saturation ratio of 13.[4] A similar three-regime model has a saturation ratio of 19.8. This is still rather low, yet the small dimension of the model, which consists of only two time series, and the possibility to directly relate the parameters to asset returns, somewhat reduces the concerns mentioned above. Due to similar considerations, we restrict ourselves to models of autoregressive order smaller than or equal to one.

For each number of regimes we estimate three benchmark models without autoregressive terms: a model with switching means, a model with switching variances and a model where both means and variances are switching. Subsequently we extend each of these models with a matrix of non-switching autoregressive coefficients and re-estimate. Finally, we also make the autoregressive coefficients regime-dependent.

In Table 5.A.1 we compare the estimated models based on the Akaike Information Criterion (AIC). We also provide likelihood ratio tests to compare nested models. Comparing the first and second columns of the table, we find that two-regime models benefit considerably from the inclusion of non-switching autoregressive terms. The corresponding p-values of the LR-tests are all significant at the ten percent level. This is mainly due to a strong autoregressive component in the real interest rate series. Expanding these models by making the autoregressive terms regime-dependent, we cannot reject the null of non-switching AR components. We find that the best-fitting two-regime model has switching covariance matrices and non-switching intercepts and autoregressive terms.

[4] This model would require 4×2 intercept parameters, 4×3 covariance matrix parameters and 4×3 free transition matrix parameters. The total number of monthly observations is $208 \times 2 = 416$.

Table 5.A.1. **Model Comparison.**

Linear	biv. normal	VAR(1)	
AIC	−10.175	−10.324	
LR-test	—	0.001	
Two-regime	MSI(2)	MSI(2)-VAR(1)	MSIA(2)
AIC	−10.420	−10.469	−10.498
LR-test	—	0.059	0.135
	MSH(2)	MSH(2)-VAR(1)	MSAH(2)
AIC	−10.440	−10.613	−10.600
LR-test	—	0.000	0.613
	MSIH(2)	MSIH(2)-VAR(1)	MSIAH(2)
AIC	−10.464	−10.597	−10.584
LR-test	—	0.001	0.616
LR-test 2	0.105	0.835	0.844
Three-regime	MSI(3)	MSI(3)-VAR(1)	MSIA(3)
AIC	−10.534	−10.528	−10.567
LR-test	—	0.495	0.149
	MSH(3)	MSH(3)-VAR(1)	MSAH(3)
AIC	−10.472	−10.611	−10.591
LR-test	—	0.001	0.661
	MSIH(3)	MSIH(3)-VAR(1)	MSIAH(3)
AIC	−10.597	−10.651	−10.677
LR-test	—	0.048	0.219
LR-test 2	0.052	0.089	0.012

This table compares various specifications of the regime-switching model in (5.3). We consider two- and three-regime models. In both cases we estimate nine different model specifications. We start with three benchmark models without autoregressive terms in column 1. We follow the notation in Krolzig (1997) for naming them. The MSI(k) model has Markov-Switching Intercepts, the MSH(k) model has Markov-Switching covariances (Heteroskedasticity) and in the MSIH(k) model both Intercepts and covariances switch. In the second column a non-switching first-order autoregressive matrix is added, which is denoted by the extension -VAR(1). In the third column, the coefficients of the autoregressive matrix are also made regime-dependent, which is denoted by adding an 'A' to the model name. We compare the models by means of the Akaike Information Criterion $AIC = (-2l + 2k)/n$, where l is the log-likelihood of the fitted model, k is the number of parameters and n is the number of observations. Low values indicate more adequate models. Additionally, we report the results of Likelihood Ratio (LR) tests for nested models. The rows labelled 'LR-test' contain the p-value of the likelihood ratio test of a model against the null of the simpler model in the preceding column. A low p-value indicates that the model extension is useful. For models with both switching intercepts and covariance matrices the rows labelled 'LR-test 2' contain a similar p-value, but here the benchmark model is the best-fitting equivalent without either switching intercepts or switching covariances (i.e. the best model from the two preceding rows).

Autoregressive terms are also important in the three-regime case, except for the model with non-switching covariance matrix. This model, however, has a much poorer fit than regimes with switching covariances. Once again, the likelihood ratio tests fail to reject the null of non-switching autoregressive terms against the switching specification, even if the resulting AIC improves in two out of three cases. As we can see from the final row of the table, the LR tests reject the null of non-switching intercepts and covariances at the 10 percent level. Therefore the preferred three-regime model has switching intercepts and covariances and constant autoregressive terms.

While, according to the AIC values, the three-regime model provides a better trade-off between model fit and the number of parameters than the two-regime model, it does require an additional 11 parameters. To assess whether this fit improvement is relevant for asset allocation decisions, we conduct further specification tests by applying a procedure suggested by Berkowitz (2001).[5] This procedure is based on a comparison of the one-step ahead forecast density produced by the model and actually realized returns $\tilde{\boldsymbol{r}}_t$, $1 \leq t \leq T$. We make use of the fact that, under the null hypothesis of a correctly specified model with parameter vector $\boldsymbol{\theta}$, the sequence $(z_{t,i})_{t=1}^{T}$, $i \in \{0, S\}$ with elements

$$z_{t,i} = \Pr\left(r_{t,i} \leq \tilde{r}_{t,i} | \left(\tilde{\boldsymbol{r}}_j\right)_{j=0}^{t-1}; \boldsymbol{\theta}\right),$$

consists of independent, uniformly distributed random variables. The sequence $\left(z'_{t,i}\right)_{t=1}^{T}$, with elements $z'_{t,i} = \Phi^{-1}(z_{t,i})$, then consists of independent elements that follow the standard normal distribution. This can be exploited to set up an LR-test for correct specification of the means and variances of the return process, and for remaining forecast error autocorrelation in levels and squares. Specifically, for both the real interest rate and the stock return forecasts, we compare the likelihood of the model

$$z'_{t+1,i} = \alpha + \beta_1 z'_{t,i} + \beta_2 (z'_{t,i})^2 + \sigma \varepsilon_{t+1}$$

to that of a restricted model with $\alpha = \beta_1 = \beta_2 = 0, \sigma = 1$. Furthermore, we assess misspecification of higher-order moments by a Jarque-Bera test on the sequence $\left(z'_{t,i}\right)_{t=1}^{T}$.

[5] A formal statistical test of a three-regime model against a two-regime model is complicated, as certain parameters of the two-regime model are not identified in the three-regime model (cf. Guidolin and Timmermann (2006a)). Therefore, an approach based on model fit criteria is generally adopted in the financial regime-switching literature.

Table 5.A.2. **Model Specification Tests.**

	Interest Rate		Excess Stock Returns	
Model	LR-test	J-B test	LR-test	JB-test
two-regime	1.90 (0.75)	10.30 (0.01)	0.14 (0.99)	2.88 (0.19)
three-regime	0.33 (0.99)	2.64 (0.22)	1.03 (0.91)	1.48 (0.43)

This table contains additional test statistics for the preferred two-regime and three-regime models resulting from the specification analysis in Table 5.A.1. The LR-test jointly tests for misspecification of the mean and the variance of returns, and for remaining autocorrelation in the model-implied one-step forecast errors. The resulting statistic has four degrees of freedom. The Jarque-Bera test checks for misspecification of the third and fourth moment of the return distribution. P-values are given in parentheses; low p-values point at the rejection of the null hypothesis that the model is correctly specified.

We report the test results for the two-regime model and the three-regime model in Table 5.A.2. We find that both the two-regime model and the three-regime model perform well in modelling the excess stock return series, as the p-values of both the LR-test and the Jarque-Bera test are large. However, the two-regime model fails to capture the higher-order moments of the distribution of the real returns on short-term government bills. We therefore choose to work with the three-regime model in our further analysis.

Chapter 6

Efficient joint liability contracts and guarantor contracts in microfinance

6.1 Introduction

Since the late 1970s the poor in developing economies have increasingly gained access to small loans with the help of microfinance programs. Well-known examples are the Grameen Bank in Bangladesh, Banco Sol in Bolivia and Bank Rakyat in Indonesia. Stimulated by the success of the microfinance programs, the academic world has shown increased interest in this field. The literature focuses on explaining how and why microfinance works from a theoretical perspective. Group lending contracts based on joint liability lending, which are used in many programs, have received special attention. With joint liability lending the group of borrowers is made responsible for the repayment of the loan, i.e. all group members are jointly liable. Many models focus on the advantages of such schemes as compared to individual contracts in settings where providers of loans cannot distinguish safe from risky borrowers due to asymmetric information (see e.g., Banerjee et al. (1994), Ghatak and Guinnane (1999), Ghatak (2000), Gangopadhyay et al. (2005)).

With some notable exceptions (e.g., Ahlin and Townsend (2007)) existing joint liability lending models assume that project returns of group members are independent. In general, however, people who participate in microfinance projects live quite close to each other and are exposed to similar risks. Therefore it seems highly important to analyse joint liability lending in a setting where project returns are correlated. This is the first objective of this chapter. More specifically, we show that, whereas Ghatak (2000, p. 625) suggests that positive project correlation reduces the effectiveness of joint liability lending since the joint liability component is paid less often when projects tend to succeed or fail together, it can actually help to achieve a first-best separating equilibrium. Hence, our model suggests that even when projects are positively correlated joint liability debt contracts may be feasible. We provide the conditions under which this will be the case.

We also point at a drawback of joint liability contracts that has received little attention so far. This drawback is that, in the absence of collateral, borrowers' project returns must be relatively high to ensure feasibility of joint liability contracts. We therefore consider an alternative in the form of guarantor contracts, similar to the contracts studied by Gangopadhyay and Lensink (2005) and Bond and Rai (2008). Such contracts specify that one client receives a contract without joint liability, while the other client pledges to repay her peer's loan, should her project fail, in exchange for an interest rate discount on her own loan. We show that for this contract type the threshold for borrower's project returns is indeed lower for a wide range of model parameters.

6.2 The model

6.2.1 Agents

There is a population of potential clients, normalized to unity and consisting of two client types, safe (S) and risky (R). These types occur in proportions q and $1-q$ respectively, with $q \in (0,1)$. Clients are endowed with one unit of labour, but have no capital. At time $T = 0$ they can either borrow a unit of capital and embark on a project with random pay-off at $T = 1$ or carry out a project which requires no capital and yields certain pay-off u at $T = 1$. The random pay-off is given by $X_i R_i, i \in \{S, R\}$, where X_i is a Bernoulli random variable with parameter p_i, and $p_S > p_R$. To avoid technicalities, we will assume that $p_R > \frac{1}{2}$.[1] Project pay-offs upon success, R_S and R_R, are known constants. All clients are risk-neutral and their utility at $T = 1$ equals their project pay-off less loan repayments. At $T = 0$ they have no assets that can serve as collateral. It is assumed that all clients know each other's types.

[1] This is a common assumption that is also made in, for example, Ghatak (2000).

Loans are provided by a risk-neutral microfinance institution (MFI), which requires a repayment of $\gamma > 1$ per unit of capital to break even. The MFI acts as a benevolent social planner and has the objective of maximizing the clients' total welfare. It is fully informed about the market structure described above, except for the fact that it cannot a priori distinguish risky clients from safe clients.[2]

It is assumed that

$$p_R R_R \geq p_S R_S > \gamma + u \tag{6.1}$$

which implies that both projects are socially efficient, and would be financed by the MFI in the full information case. Furthermore the outside utility u of the safe project satisfies

$$u > p_S \left(R_S - \frac{\gamma}{\overline{p}} \right) \tag{6.2}$$

where $\overline{p} = q p_S + (1 - q) p_R$. This implies that the safe project pay-off is too low to make borrowing at the individual break-even pooling rate $\overline{p}$ profitable for safe clients. Individual lending under asymmetric information thus leads to underinvestment; while the safe types have a socially efficient project, the presence of risky types drives the individual interest rate up to a level at which it is unprofitable for safe clients to carry it out (Stiglitz and Weiss (1981)).

6.2.2 Loan types

The MFI can offer individual loans, symmetric group loans and guarantor group loans. Individual loans specify only a repayment amount r at $T = 1$. Symmetric group loans are defined as in Ghatak (2000). For each of two clients who decide to form a group together, they consist of an identical repayment amount r, which has to be repaid whenever the client's project succeeds, and of an identical joint liability amount c, which has to be paid in addition to r whenever the client's success coincides with her peer's failure. Guarantor loans take the following form: one of the two clients in a group gets a loan which specifies a repayment component r only. Her peer gets a loan which specifies a repayment component r' and, additionally, a joint liability component $c = r$. As the proceeds from her projects are the only assets available to a client at $T = 1$, her payments to the MFI upon project failure

[2] In the microfinance literature, the information asymmetry between the institution and the clients is typically attributed to the existence of local information networks (based on, e.g., social relationships) that are accessible to the clients, but not to 'outsiders'.

equal 0 for both symmetric contracts and guarantor contracts.

These contracts must satisfy three conditions. First, all repayment amounts and joint liability amounts must be positive. Second, for any contract that will be chosen with non-zero probability by client type i, the total payments should be lower than the project return R_i, as at $T = 1$ the project return is the client's only collateral. Also, symmetric group lending loans must satisfy the ex post incentive compatibility condition $c \leq r$ (Gangopadhyay et al. (2005)). Were this not the case, a client would prefer to donate r to her failing peer, so that she could feign success and repay her loan, rather than paying the higher amount c to the MFI himself. This condition is satisfied by definition for a guarantor contract.

We will denote the set of all feasible contracts by $\mathcal{F}$. Upon observing a subset of contracts $F \in \mathcal{F}$ offered by the MFI, clients form groups with the objective of maximizing their expected utility. The group formation process is assumed to be free of costs or frictions for the clients. During this process, a type i client can offer a side contract, consisting of a claim of size $b < R_i$ contingent upon the success of her project to potential partners. The proceeds from such side contracts can be claimed as collateral by the MFI at $T = 1$.

6.2.3 The first-best benchmark

In order to compare the effectiveness of symmetric contracts and guarantor contracts in different market settings, we will make use of a first-best full information benchmark. In this full information benchmark the expected contract payments of both client types equal the MFI's break-even value γ and side contracts are unnecessary. From a theoretical perspective, this benchmark is suitable for comparison with the analysis of, for example, Ghatak (2000). It is also relevant from a practical perspective, as MFI's often have to compete with local profit-maximizing moneylenders, who possess more information about client types. Whenever the first-best benchmark can be attained, both client types will prefer to borrow from the MFI rather than from fully informed moneylenders, provided that the cost of capital of the moneylenders is higher than the cost of capital of the MFI. Moreover, this benchmark rules out cross-subsidization of one client type by the other type, which is undesirable from the perspective of the social planner.

Our analysis will proceed as follows. In subsection 6.3.1 we briefly introduce the Ghatak (2000) model based on independent projects, as extended by Gangopadhyay et al. (2005). We show that the first-best benchmark cannot be attained in this setting. Subsequently we extend this model to a general project correlation pattern in subsection 6.3.2. In subsection 6.3.3 we demonstrate that, with this extension, the first-best solution follows for certain parameter combinations. In section 6.4 we analyse the properties of guarantor contracts within this general setting and compare the performance of both contract types in a setting with correlated projects.

6.3 Symmetric contracts

6.3.1 Review of the analysis for independent projects

In the context of the underinvestment problem, the challenge is to design a group lending contract which yields the first-best for the safe clients, as the risky clients can always be offered an individual lending contract at a rate $\frac{\gamma}{p_R}$. As shown in Ghatak (2000), when projects are independent any symmetric contract $C = (r, c)$ will induce *positive assortative matching*. The optimal choice of safe clients upon observing a symmetric contract will be to form a group with safe peers, even if risky clients offer them side contract payments. Consequently, if a risky client wants to take a symmetric contract, she will have to do so with a risky peer.

Let us denote the expected contract payments of a client of type i who forms a group with a client of type j and signs contract C by $P^e_{ij}(C)$. By definition, a contract C that yields the first-best must satisfy $P^e_{SS}(C) = \gamma$. A further necessary condition is $P^e_{RR}(C) \geq \gamma$. If this condition is not satisfied, a pair of risky clients will find it profitable to take contract C together. The expected payments on this contract will be less than the MFI's break-even rate, thus making contract C infeasible for the MFI.

The expected payments of a client of type i can be expressed as

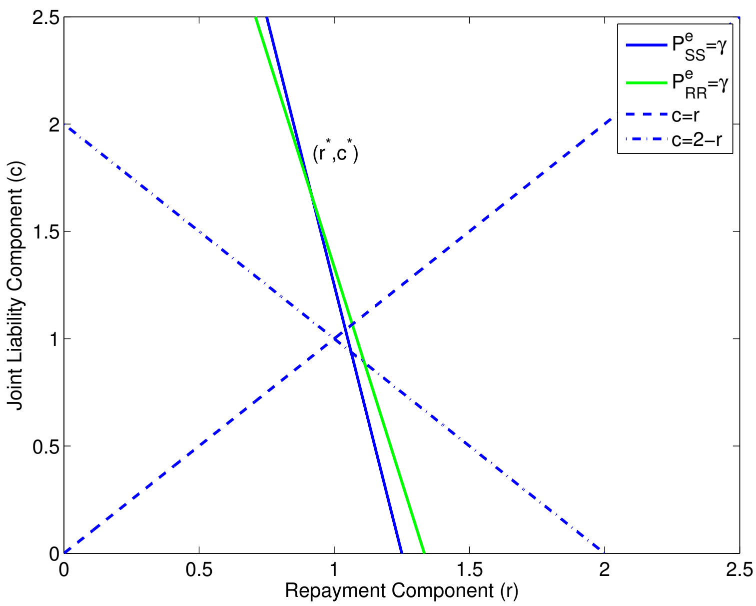
$$P^e_{ii} = p_i r + p_i(1 - p_i)c.$$

In Figure 6.1 we display the sets of contracts such that $P^e_{SS}(C) = \gamma$ and $P^e_{RR}(C) = \gamma$. The set of contracts satisfying the two necessary conditions for the first-best is given by all combinations of r and c on the line $P^e_{SS}(C) = \gamma$ with $r < \tilde{r}$ and $c > \tilde{c}$, where $(\tilde{r}, \tilde{c})$ is the intersection point of the solid lines. The coordinates of this point are given by

$$(\tilde{r}, \tilde{c}) = \gamma \left(\frac{p_S + p_R - 1}{p_S p_R}, \frac{1}{p_S p_R} \right).$$

The intuition behind this result is as follows: the probability that a safe client has to repay for a safe peer is lower than the probability that a risky client has to repay for a risky peer. Thus, a safe client who is in a group with a safe peer (which is guaranteed by the positive assortative matching result) will be more willing to accept a contract with a high joint liability component c than a risky client who is in a group with a risky peer. If we want to prevent that risky clients take the contract designed for safe clients, leading to an expected loss for the MFI, we must set a joint liability component that is high enough to discourage them from doing so.

Figure 6.1. **Contracts satisfying first-best conditions.**



This figure shows the set of contracts that satisfy the first-best conditions $P^e_{SS}(C) = \gamma$ and $P^e_{RR}(C) = \gamma$ for model parameters $p_S = \frac{4}{5}$, $p_R = \frac{2}{3}$ and $\gamma = 1$. Project correlation is assumed to equal zero.

Unfortunately, however, there are no *feasible* contracts satisfying $P^e_{SS}(C) = \gamma$ and $P^e_{RR}(C) \geq \gamma$. As pointed out by Gangopadhyay et al. (2005) the intersection point has $\tilde{r} < \tilde{c}$. Therefore, the ex post incentive compatibility condition is violated for all contracts on the line segment that could yield the first-best. This is bad news for symmetric group lending schemes.

What is the second-best alternative for the safe clients? Dropping the first-best restriction that *both* clients should have expected payments equal to γ, we turn to contracts that yield the *aggregate* welfare-maximizing solution. Any feasible symmetric contract C must satisfy $qP^e_{SS}(C) + (1-q)P^e_{RR}(C) \geq \gamma$, as both client types will be able to sign it, if they so desire. The set of contracts that satisfies this condition with equality has

$$\overline{p}r + (\overline{p} - \overline{p^2})c = \gamma \tag{6.3}$$

where we define $\overline{p^2} = qp_S^2 + (1-q)p_R^2$. In this set, the contract that yields the smallest distortion as compared to the first-best benchmark (e.g., the lowest expected payments for safe clients) has the maximum feasible value of the joint liability component.[3] This optimal contract will depend on the pay-off of the safe client's project R_S. Straightforward algebra yields that the intersection of (6.3) with boundaries of the feasible region in the positive quadrant is given by

$$(r^*, c^*) = \begin{cases} \left(\frac{\gamma}{2\overline{p}-\overline{p^2}}, \frac{\gamma}{2\overline{p}-\overline{p^2}}\right) & \text{for } R_S > \frac{2\gamma}{2\overline{p}-\overline{p^2}} \\ \left(\frac{\gamma-(\overline{p}-\overline{p^2})R_S}{\overline{p^2}}, \frac{\overline{p}R_S-\gamma}{\overline{p^2}}\right) & \text{else.} \end{cases}$$

If the return of the safe client's project is high enough, the ex post incentive compatibility condition will be binding, while the limited liability condition will bind in all other cases. The corresponding expected payments of a member of a safe client group equal

$$P^e_{SS}(r^*, c^*) = \begin{cases} \frac{2p_S-p_S^2}{2\overline{p}-\overline{p^2}}\gamma & \text{for } R_S > \frac{2\gamma}{2\overline{p}-\overline{p^2}} \\ \frac{p_S^2}{\overline{p^2}}\left(\gamma - (1-q)(p_S - p_R)\frac{p_R}{p_S}R_S\right) & \text{else.} \end{cases}$$

The group lending contract (r^*, c^*) can still result in a Pareto improvement for all clients as compared to the individual lending case, provided that $P^e_{SS}(r^*, c^*) < p_S R_S - u$. Instead of opting out, the safe clients will now participate. The risky clients will also be better off as they will be effectively cross-subsidized by their safe peers. The contract is not robust to competition, however. The MFI's outreach to safe clients can be hampered by fully informed competitors, such as moneylenders. If there is a moneylender with break-even cost of capital γ' such that $\gamma' < P^e_{SS}$, she can offer an individual contract with interest rate $r^m = (P^e_{SS} - \varepsilon)/p_S$ and capture

[3] This can be seen as follows. Note that the iso-lines corresponding to a given expected payment for safe clients, as depicted in Figure 6.1, have slope $1/(p_S - 1)$. The iso-lines for a given expected payment on a contract that can be signed by both types have slope $\overline{p}/(\overline{p^2} - \overline{p}) > 1/(p_S - 1)$. Consequently the point on the latter iso-line that minimizes safe client payments corresponds to the maximum feasible c (and the lowest feasible r).

the whole market of safe clients, causing an expected welfare loss of $r^m - \gamma$ for each client as compared to the first-best benchmark.

Remark that, for given p_S, we have $\frac{\partial P_{SS}^{e*}}{\partial p_R} < 0$ and $\frac{\partial P_{SS}^{e*}}{\partial q} < 0$. The level of cross-subsidization resulting from standard group lending contracts decreases if either the difference between the success probabilities decreases, or the proportion of safe clients increases. Moreover, for R_S below the threshold of $2\gamma/(2\overline{p} - \overline{p^2})$, we have $\frac{\partial P_{SS}^{e*}}{\partial R_S} < 0$. The intuition behind this result is as follows. If the safe project return is high, so will be the joint liability component in contract (r^*, c^*), as opposed to the repayment component. Safe client groups tend to pay the joint liability component relatively less often than risky client groups, while the converse holds for the repayment component.

We conclude that, when projects are independent, standard joint liability contracts are likely to increase outreach if clients' projects are similar in terms of success probabilities, if the proportion of safe clients is high, and if the pay-off of their projects is high as well. As we will see in section 4, guarantor contracts can be a useful complement to standard contracts if these conditions are not met.

However, projects are very unlikely to be independent in the typical context of a microfinance program. Clients embarking on similar project types will be affected by the same shocks, in terms of, for example, weather conditions or aggregate market demand. This induces positive correlation between project success between clients of the same type. One can also think of market settings where the correlation between projects of the same type is negative due to, for example, limited total demand for project output in a local market. If one of the clients manages to market her crops successfully, the probability that her peer will do so too may decrease.

In the following sections, we will show that for certain correlation patterns, the first-best benchmark can be attained using symmetric contracts. In these settings traditional symmetric microfinance contracts can be expected to perform particularly well in terms of outreach. Interestingly, strong positive correlation between safe projects turns out to facilitate this. This may seem somewhat counter-intuitive, as positive project correlation generally has a negative effect on repayment, as the joint liability component is paid less often when projects tend to succeed or fail together (Ghatak (2000, p. 625)). However, if this effect is larger for safe clients than it is for risky clients, it can help to achieve a first-best separating equilibrium. It is not the magnitude of correlations that matters for screening purposes, but the relative values of the correlations between two safe projects and two risky projects.

6.3.2 Introducing project correlation

Recall that client i's project success corresponds to the Bernoulli random variable X_i with parameter p_i taking the value 1 and failure corresponds to this random variable taking the value 0. Let us denote the probabilities of the four possible combinations of the realizations of X_i and X_j by

$$\boldsymbol{p}_{ij} = \begin{pmatrix} p_{ij}^s \\ p_{ij}^c \\ p_{ji}^c \\ p_{ij}^f \end{pmatrix} = \begin{pmatrix} P\{X_i = 1, X_j = 1\} \\ P\{X_i = 1, X_j = 0\} \\ P\{X_i = 0, X_j = 1\} \\ P\{X_i = 0, X_j = 0\} \end{pmatrix} \tag{6.4}$$

where the superscript s stands for success of both projects, the superscript f stands for failure of both projects and the superscript c stands for the situations in which joint liability needs to be paid.

Ahlin and Townsend (2007) show that any joint distribution that preserves p_i and p_j as the unconditional probabilities of success must take the form

$$\boldsymbol{p}_{ij} = \begin{pmatrix} p_i p_j + \epsilon_{i,j} \\ p_i(1-p_j) - \epsilon_{i,j} \\ p_j(1-p_i) - \epsilon_{i,j} \\ (1-p_i)(1-p_j) + \epsilon_{i,j} \end{pmatrix}. \tag{6.5}$$

In this expression, positive values of ϵ increase the probability of symmetric outcomes (joint success or failure), while decreasing the probability of asymmetric outcomes (one group member succeeds while the other fails). This corresponds to positive correlation of project outcomes. Negative values of ϵ correspond to negative correlation, while $\epsilon = 0$ amounts to the independent outcome case.

Although this parametrization is sufficient to conduct the analysis below, it is useful, for the sake of exposition, to relate ϵ to the correlation coefficient of the random variables X_i and X_j. As shown in the Appendix, this relationship is

$$\epsilon_{i,j} = \rho_{i,j}\sqrt{p_i p_j (1-p_i)(1-p_j)}, \tag{6.6}$$

where $\rho_{i,j} \in \left(\frac{p_i - 1}{p_i}, 1\right]$ if $i = j$ and $\rho_{i,j} \in \left(\frac{-\sqrt{(1-p_S)(1-p_R)}}{\sqrt{p_S p_R}}, \frac{\sqrt{p_R(1-p_S)}}{\sqrt{p_S(1-p_R)}}\right)$ else.[4]

[4] Note that the correlation coefficient has a somewhat different interpretation in the context of binary

In our subsequent analysis, we will assume that ρ_{RR} can take any value between $\frac{p_R-1}{p_R}$ and 1. As for safe project correlations, we will assume that they are positive. Also, we normalize the correlation between safe and risky projects ρ_{SR} at 0.[5]

6.3.3 The full information benchmark with correlated projects

Introducing correlation induces two major changes as compared to the analysis of section 6.3.1. First, the set of contracts (r_S, c_S) that yield the first-best outcome for a safe client who matches with a risky peer now satisfies

$$p_S r_S + p_{SS}^c c_S = \gamma. \tag{6.7}$$

As compared to the case of independent projects, these contracts are on a line that is pivoted clockwise around the point $\left(\frac{1}{p_i}, 0\right)$. This situation is shown in Figure 6.2, where we have introduced positive correlations $\rho_{SS} = 0.8$ and $\rho_{RR} = 0.2$. The intuition is that if projects are positively correlated, clients are more likely to either succeed or fail together and the probability of having to pay the joint liability payment decreases. Therefore, clients are willing to accept a higher value of c for a given decrease in r as compared to the case of independent projects.

The intersection with the line $p_R r_R + p_{RR}^c c_R = \gamma$ now occurs in the point

$$(r^*, c^*) = \left(\frac{(p_{RR}^c - p_{SS}^c)\gamma}{p_S p_{RR}^c - p_R p_{SS}^c}, \frac{(p_S - p_R)\gamma}{p_S p_{RR}^c - p_R p_{SS}^c} \right).$$

This means that the problem with the ex post incentive compatibility condition we encountered in the independent project model is solved whenever

$$(p_S - p_R) \leq p_{RR}^c - p_{SS}^c.$$

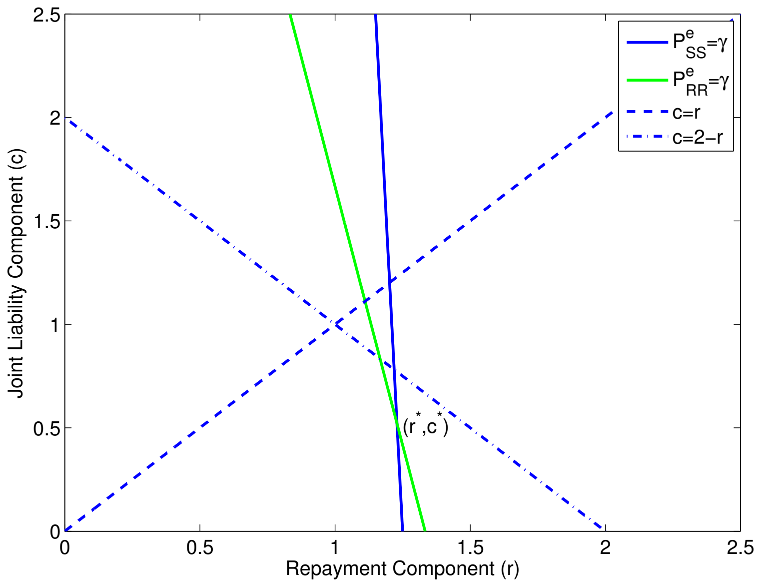
random variables, as compared to variables with an elliptical distribution. Most notably, its upper and lower bounds now depend on the parameters of the distribution. For example, the strongest possible negative association between two Bernoulli random variables with parameter p corresponds to a correlation coefficient of $(p-1)/p$ instead of -1. Apart from these differences, however, the interpretation of the correlation coefficient is similar (e.g. independence implies a zero correlation coefficient, increasing correlation coefficient applies a higher degree of positive association, for variables with identical parameter p the upper bound is unity), and hence useful for exposition.

[5] Both the assumptions of positive safe project correlation and zero correlation between safe and risky projects can be relaxed at the expense of extra notation.

In terms of correlations and success probabilities we can write this as[6]

$$\rho_{SS} \geq 1 - \frac{p_R(2-p_R)-p_S}{p_S(1-p_S)} + \frac{p_R(1-p_R)}{p_S(1-p_S)}\rho_{RR}. \tag{6.8}$$

Figure 6.2. **Set of contracts that satisfy the first-best conditions.**



This figure shows the set of contracts that satisfy the first-best conditions $P^e_{SS}(C) = \gamma$ and $P^e_{RR}(C) = \gamma$ for model parameters $p_S = \frac{4}{5}$, $p_R = \frac{3}{4}$ and $\gamma = 1$. Project correlations for safe borrowers equal $\rho_{SS} = 0.8$ and for risky borrowers $\rho_{RR} = 0.2$. Cross-correlations between safe and risky projects are zero. The dashed lines indicate the ex post incentive compatibility condition and the return feasibility condition for the case that safe project returns equal 100% of the borrowed amount.

Assuming that condition (6.8) is satisfied, the MFI can offer any symmetric contract (r, c) satisfying equation (6.7) with $c^* \leq c \leq r$. We only need to ensure that homogeneous groups will be formed if it does so. This is immediate whenever $\rho_{SS} \geq 0$ and $\rho_{RR} \geq 0$. The positive assortative matching result will hold *a fortiori* as homogeneous groups will be more attractive for both safe types and risky types as compared to the independent case. If the correlation between risky projects is negative, however, risky clients will be willing to offer a larger side contract to the safe clients than they would do if projects were independent. The positive assortative matching result does not hold for all combinations of ρ_{SS} and ρ_{RR}. This is the

[6] Note that this relationship implies $\rho_{RR} < 1 - \frac{p_S - p_R}{p_R(1-p_R)}$ as ρ_{SS} must be smaller than one.

second change induced by introducing correlations.

We therefore need to verify which correlation patterns result in the formation of homogeneous groups.[7] The expected payments of both client types, as compared to their benchmark payments of γ are given by

$$P^e_{S,SR}(C) - \gamma = p_S(p_S - p_R + \rho_{SS}(1-p_S))c \tag{6.9}$$

$$P^e_{R,SR}(C) - \gamma = \frac{p_R - p_S}{p_S}\gamma + \rho_{SS}p_R(1-p_S)c$$

The expected payments of both clients are increasing in c. The safe client is always worse off matching with a risky client as (6.9) is always positive. However, the risky client may be able to bribe the safe client into matching with her. The minimal side contract payment b^S that the safe client will demand as compensation and the maximal payment b_R the risky client will be willing to offer satisfy, respectively[8],

$$\begin{aligned} p_S p_R b^S &= p_S(p_S - p_R + \rho_{SS}(1-p_S))c \\ p_R b_R &= \frac{p_S - p_R}{p_S}\gamma - \rho_{SS}p_R(1-p_S)c. \end{aligned}$$

Straightforward algebra shows that the threshold value of c such that $b_R = b^S$ is given by

$$c^t = \frac{(p_S - p_R)\gamma}{p_S(p_S - p_R + \rho_{SS}(1+p_R)(1-p_S))}.$$

Whenever this value is below c^* homogeneous matching is guaranteed for all feasible contracts satisfying (6.7). This amounts to the correlation between safe client's projects being sufficiently positive, hence reducing the expected payments of a homogeneous safe group, so that safe clients will refuse the risky client's side contract offer. In terms of model parameters, this amounts to

$$\rho_{SS} > -\frac{1-p_R}{1-p_S}(p_S - p_R) - p_R\frac{1-p_R}{1-p_S}\rho_{RR}. \tag{6.10}$$

Given that ρ_{SS} is positive, this condition is automatically satisfied for $\rho_{RR} >$

[7] Remark that if a symmetric contract is to yield the first-best benchmark, it must induce homogeneous group formation. If two different client types take a symmetric contract, then equal expected payments on this contract imply $p_S r + p_S(1-p_R)c = p_R r + p_R(1-p_S)c$, that is $c = -r$, which is not feasible.

[8] Recall that the risky client pays the side contract whenever she succeeds; the safe client will only derive utility from this payment if she succeeds as well; otherwise the side payment is taken as (partial) collateral for her non-repaid loan by the MFI.

$1-\frac{p_S}{p_R}$. In that case, contract (r^*, c^*) solves the underinvestment problem whenever condition (6.8) holds. We require condition (6.10) for (r^*, c^*) to be optimal only for negative risky project correlations, that is, for $1-\frac{1}{p_R} < \rho_{RR} < 1-\frac{p_S}{p_R}$. If ρ_{SS} is too low to meet this condition, the first-best may still be feasible, though. A contract with $c > c^t$ needs to be set to prevent heterogeneous group formation. Recall that the highest value of c the MFI can set, due to the restriction $r > c$, equals $c^{\max} = \frac{\gamma}{p_S + p^c_{SS}}$. We find that $c^t < c^{\max}$ amounts to $\rho_{SS} > \frac{p_S - p_R}{1+p_S}$. Therefore, even if risky project correlations are negative and (6.10) does not hold, $\rho_{SS} > \frac{p_S-p_R}{1+p_S}$ together with (6.8) suffices for a first-best solution to exist. We summarize our results in a Proposition:

<u>Proposition 1</u>

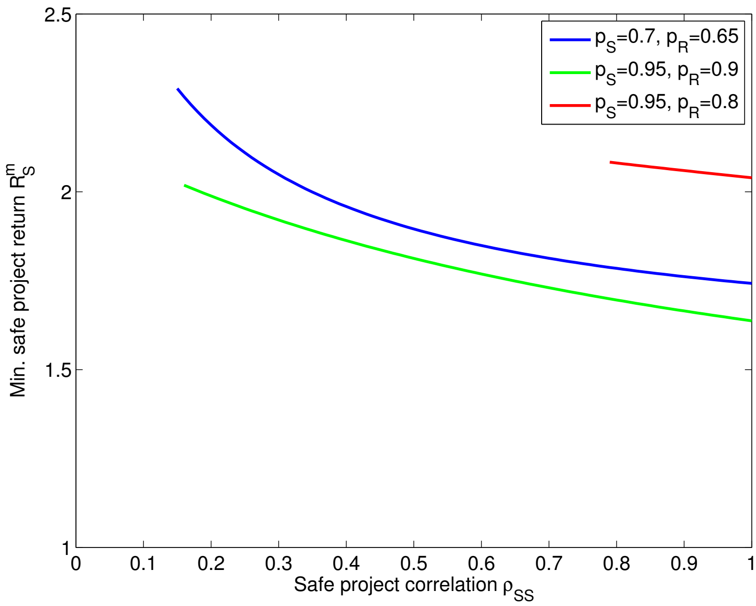
Whenever $\rho_{SS} \geq 1 - \frac{p_R(2-p_R)-p_S}{p_S(1-p_S)} + \frac{p_R(1-p_R)}{p_S(1-p_S)}\rho_{RR}$ and (i) $\rho_{RR} > 1-\frac{p_S}{p_R}$ or (ii) $\rho_{RR} < 1-\frac{p_S}{p_R}$ and $\rho_{SS} > \frac{p_S-p_R}{1+p_S}$, there exists a set of joint liability contracts resulting in the first-best welfare allocation. Moreover, if either (i) holds or $\rho_{RR} < 1-\frac{p_S}{p_R}$ along with $\rho_{SS} > -\frac{1-p_R}{1-p_S}(p_S - p_R) - p_R\frac{1-p_R}{1-p_S}\rho_{RR}$ this set includes the pooling contract (r^*, c^*), which requires the smallest safe project return in the set of feasible contracts.

We conclude that, as opposed to the case of independent projects, symmetric contracts can be expected to work well in practice across a wide range of relevant, positive correlation values. There still is an important problem, however. The contract (r^*, c^*) (and, to a larger extent, contract (r^t, c^t)) requires the return on the safe project to be of a considerable magnitude for the limited liability condition to be satisfied. In order for the contract (r^*, c^*) to satisfy the limited liability requirement, the corresponding safe project return must satisfy

$$R_S \geq \frac{((p_S - p_R) + (p^c_{RR} - p^c_{SS}))\gamma}{p_S p^c_{RR} - p_R p^c_{SS}}.$$

We have drawn these threshold values for R_S in Figure 6.3 for the range of safe project correlations under which the contract (r^*, c^*) is feasible, fixing the correlation between risky projects at 0 and normalizing γ at 1. The green line in this figure represents a market where the clients have success probabilities $p_S = 0.95$ and $p_R = 0.9$, respectively. It shows that, in this case, the safe project pay-off should exceed the MFI's cost-of capital by 95 percent if the correlation between safe projects is at the lowest feasible value (about 0.2) and by 70 percent as the correlation coefficient approaches unity. The red line depicts a scenario where the difference between success probabilities is considerably higher ($p_S = 0.95$ and $p_R = 0.8$). This is very disadvantageous for safe clients. As we saw in the independent project case, symmetric joint liability contracts are hampered by such differences. There is only a small range of correlations for which (r^*, c^*) is feasible and the required pay-off in excess of the MFI's cost of capital is over 100 percent for safe clients, even if a pay-off of a mere 6 percent could have made the project interesting, had the MFI known the client's types.[9]

Figure 6.3. **Threshold values.**



This figure displays the threshold values of safe project pay-offs required for joint liability contract feasibility, as a function of safe project correlation. Risky project correlation is assumed to equal zero. The three lines correspond to different combinations of success probabilities. Note that for certain values of the safe project correlation joint liability contracts are infeasible regardless of the safe project pay-off.

Of course these numbers are not to be interpreted literally, as in particular the assumptions that clients have no collateral at all and that their projects yield zero pay-off upon failure are obviously stylized. We will use them primarily for a relative comparison with guarantor contracts, which will be introduced in the next section. Nevertheless, a peculiar feature of the screening mechanism underlying sym-

[9] Remark that if the correlation between risky projects becomes positive, this threshold value will increase ceteris paribus, as the risky client's first-best line will pivot outward.

metric contracts is that it requires exactly those clients who have a relatively low project pay-off to produce joint liability payments.This is somewhat unsatisfactory, as in the context of the underinvestment problem it's exactly due to a relative low project pay-off that safe clients are driven out of the market. In microfinance it is of the essence to reach clients whose fledgling small-scale enterprises do not yet yield high pay-offs This is an important reason for turning to alternative group lending solutions, like guarantor contracts.

6.4 Guarantor contracts

In this section we will focus on group contracts which do *not* require safe clients to produce high joint liability payments, should their peer fail. If the MFI can design a guarantor contract which will induce risky clients to co-sign for their safe peers, it will be able to make use of the risky clients' high project returns for joint liability payments. This approach is similar to the asymmetric contracts proposed by Bond and Rai (2008). However, while Bond and Rai (2008) focus on projects with a certain rate of return and consider limited enforcement problems, we consider risky projects and concentrate on adverse selection.

Consider the guarantor contract $G = \{(r_S, 0), (r_R, r_S)\}$. This contract consists of a subcontract $(r_S, 0)$ destined for the safe client, which does not specify a joint liability component, and a subcontract destined for the risky client, which specifies a joint liability component equal to the repayment component of the safe client r_S, next to an individual repayment component r_R. The risky client acts as a guarantor for the safe client, pledging to repay her peer's debt should she fail. Alternatively, this contract can be interpreted as a group lending agreement with the risky client acting as a group leader who takes responsibility for the other client's repayment, in return for a discount on her own loan repayment.

To achieve the first-best solution for the safe clients we must set $r_S = \frac{\gamma}{p_S}$. The first-best solution for the risky clients implies $r_R = \gamma(1 + \frac{1}{p_R} - \frac{1}{p_S})$, which is a discount of $\frac{1-p_S}{p_S}\gamma$ as compared to their individual lending rate. Limited liability then implies that the risky client's return satisfies $R_R \geq (1 + \frac{1}{p_R})\gamma$.

Of course this scheme yields the first-best for all safe clients only if $q \leq \frac{1}{2}$, as each safe client should be able to find a guarantor. Note that the remaining risky clients who are not asked to form a group by a safe client can be offered an individual contract with interest rate $\frac{\gamma}{p_R}$.[10]

[10] We assume that, faced with the choice between two contracts between which they are indifferent,

For the guarantor contract to yield the first-best outcome in this setup, we only require that it is indeed optimal for both client types to form heterogeneous groups, with the risky client playing the role of a guarantor. There are three possible deviations from this outcome: it can be chosen by a risky pair, a safe pair, or by a safe-risky pair with the safe client taking the role of the guarantor.

If two risky clients sign up for a guarantor contract, the client who takes the subcontract $(r_S, 0)$ will clearly be better off as compared to the case when she co-signs a safe client, her expected payments being equal to $\frac{p_R}{p_S}\gamma$. Consequently she is willing to offer a side contract with a maximum payment of $b^H = \frac{(p_S - p_R)}{p_S p_R}\gamma$ at $T = 1$ to motivate another risky client to co-sign for her. The expected payments of her risky peer then amount to

$$\begin{aligned} P^e_{R\mathbf{R}}(G) &= p_R r_R + p^c_{RR} r_S - p^s_{RR} b \\ &= \left(1 + p_R - \frac{p_R - p^c_{RR}}{p_S}\right)\gamma - (p_R - p^c_{RR})b. \end{aligned}$$

The minimum value of the side contract required to induce the safe client to match is therefore equal to

$$b_S = \left(\frac{p_R}{p_R - p^c_{RR}} - \frac{1}{p_S}\right)\gamma.$$

The incentive compatibility constraint $b_S > b^H$ can now be written as

$$\frac{p_R}{p_R - p^c_{RR}} > \frac{1}{p_R}.$$

Let us first consider the optimal decision of two risky clients who observe that the MFI offers a guarantor contract. If both of them take the guarantor part of contract G together with a safe peer, by construction they will have expected contract payments equal to the first-best value γ. If instead they take the guarantor contract together, the client who gets the 'safe' part will clearly be better off, expecting to pay only $\frac{p_R}{p_S}\gamma$. If the correlation between risky projects is high enough, the client who plays the guarantor role will actually also be better off, as her expected joint liability pay-offs will be low. Straightforward calculations show that this happens whenever $\rho_{RR} > \frac{p_S - p_R}{1 - p_R}$. Even if this is not the case, two risky clients may still come to an agreement using side contracts. The risky client who gets the safe subcontract

risky clients will choose the socially optimal one, that is, they will rather act as a guarantor for a safe peer than take an individual contract if their expected pay-offs from both contracts are equal.

is willing to promise a maximal amount of

$$b_R = \frac{(p_S - p_R)\gamma}{p_S p_R}$$

at $T = 1$. The expected payments of her risky peer amount to

$$\begin{aligned} P^e_{RR}(G) &= p_R r_R + p^c_{RR} r_S - p^s_{RR} b \\ &= \left(\frac{p_S p_R + p_S - p_R}{p_S} + \frac{p^c_{RR}}{p_S} \right) \gamma - (p_R - p^c_{RR}) b. \end{aligned}$$

The value of b for which a risky client is just indifferent between taking the guarantor role with a risky peer or a safe peer follows from solving $P^e_{RR}(G) = \gamma$. By comparing this value to b_R it can be verified that the condition $\rho_{RR} \leq 0$ is required to prevent the formation of homogeneous risky groups, which would imply that safe clients are forced out of the market once again. Thus, in a single-period model, guarantor contracts will only work in markets where circumstances like competition induce negative correlation between risky clients' project success.[11]

It can also be profitable for a pair of safe clients to take the guarantor contract. The participant who ends up with the subcontract designed for the safe client will just have expected payments equal to γ. The other client may be even better off, provided that $r_R < r_S$ and her probability of having to pay joint liability for the safe peer is low. This situation is precluded if the probability of success of the safe client is high enough; this means that the guarantor's interest discount will be low, as she faces little risk of her peer's failure, and consequently r_R will exceed r_S. In terms of model parameters this implies

$$p_S > \frac{2p_R}{1 + p_R}. \tag{6.11}$$

For lower values of p_S we must distinguish two cases. First, if the safe project return is too low to pay the joint liability component ($R_S < 1 + \frac{1}{p_R}$) the safe client will be able to pay only R_S instead of $1 + \frac{1}{p_R}$ if her peer fails.Her expected utility

[11] The requirement that risky projects are negatively correlated is induced by the normalization $\rho_{RS} = 0$ we imposed in section 3.2. If we allow risky projects to be correlated with safe projects, this requirement can be relaxed to allow for positive correlations between risky projects such that $\rho_{RR} < \rho_{RS}$. A natural interpretation for this correlation pattern would be that the outputs of risky clients are each other's substitutes and compete in the marketplace, while the outputs of safe clients are complements for the outputs of risky clients.

from the guarantor contract equals

$$
\begin{aligned}
P_{SS}^{e}(G) &= p_{SS}^{s}(R_S - r_R) \\
&= (p_S - p_{SS}^{c})(R_S - r_R)
\end{aligned}
$$

as she only gets a positive pay-off in the event that both she and her peer succeed. Comparing this to the pay-off $p_S R_S - \gamma$ in the first-best case, we find that a safe client will prefer to take the guarantor contract whenever $(p_S - p_{SS}^{c})r_R + p_{SS}^{c} R_S \leq \gamma$. This implies that, if the difference in success probabilities between safe and risky clients is not large enough to satisfy equation (6.11) , the safe project return must exceed a threshold value for first-best guarantor contracts to exist. This value is given by the expression

$$
R_S^t = \left(\frac{1 - p_{SS}^{s}}{p_{SS}^{c}} - \frac{(p_S - p_R)p_{SS}^{s}}{p_S p_R p_{SS}^{c}} \right) \gamma.
$$

If the pay-off of the safe client does exceed $(1 + \frac{1}{p_R})\gamma$ and p_S is low enough for r_R to be lower than r_S, we just require $p_S r_R + p_{SS}^{c} c_R \geq \gamma$. In terms of correlations, this means

$$
\rho_{SS} < \frac{p_S - p_R}{p_R(1 - p_S)}.
$$

So if safe clients' project pay-off is high, a relatively low correlation between safe project is sufficient to prevent them from taking the guarantor contract together.

Let us finally consider the situation in which the risky client and the safe client swap positions. Suppose first that the safe client's project return is low, so that she will not be able to pay the joint liability component of this contract, should this necessity arise. Recall that the risky client is willing to offer a side contract with a payment up to $b_R = \frac{(p_S - p_R)\gamma}{p_S p_R}$ to be allowed to take the 'safe' part of a guarantor contract. Given this side contract payment, the expected pay-offs of a safe client who takes the guarantor contract will equal

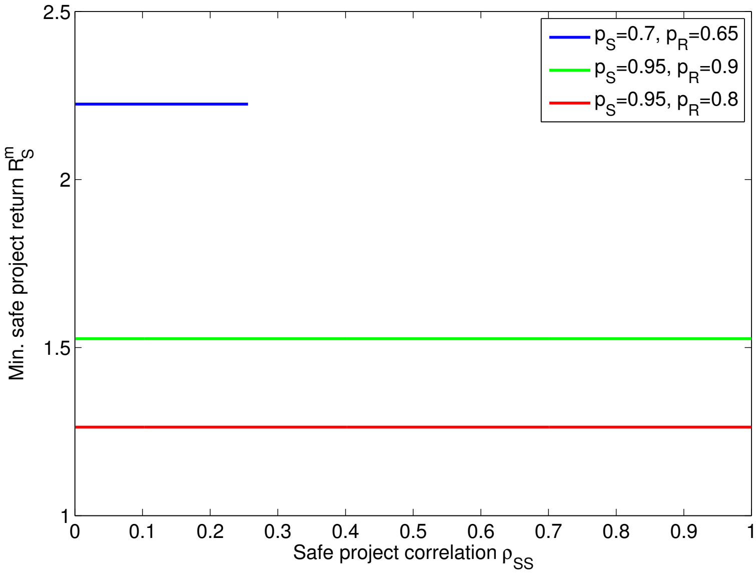
$$
\begin{aligned}
P_{SR}^{e}(G) &= p_S p_R (R_S - r_R + b_R) \\
&= p_S p_R (R_S - \gamma)
\end{aligned}
$$

Comparing to the first-best pay-off $p_S R_S - \gamma$ we find the condition

$$
R_S > \frac{1 - p_S p_R}{p_S - p_S p_R}. \tag{6.12}
$$

Likewise, if the safe client's project pay-off is high enough, it can be verified in a similar way that this matching pattern is never optimal for the safe client.

Figure 6.4. **Threshold values of safe project payoffs.**



This figure displays the threshold values of safe project pay-offs required for guarantor contract feasibility, as a function of safe project correlation. Risky project correlation is assumed to equal zero. The three lines correspond to different combinations of success probabilities.

Figure 6.4 displays the minimal values of safe project pay-offs that make guarantor contracts feasible, for the same combinations of success probabilities as in the previous section. Note that condition (6.11) holds for these probabilities, so guarantor contracts are feasible for all possible safe project correlations. We need only consider the threshold value on safe project pay-offs given in (6.12). The required excess returns amount to 53 percent for the case $p_S = 0.95$, $p_R = 0.9$ and to only 26 percent for the case $p_S = 0.95$, $p_R = 0.8$. The large difference in success probabilities actually turns into an advantage if we use guarantor contracts, as it makes the 'swapping ' strategy less attractive for the safe client.

6.5 Conclusion

We conclude that the performance of symmetric joint liability contracts and guarantor contracts depends crucially on the structure of the market in which they are employed. Symmetric joint liability contracts can be expected to perform well in markets where the differences in project riskiness are limited, the correlation between safe projects is high as compared to the correlation of risky projects, and the pay-offs of safe clients are high. Especially this last requirement may pose a problem if the objective of the MFI is to reach out to starting small-scale entrepreneurs. In this case, guarantor contracts may provide a solution, however. Such contracts can turn risky clients from effectively causing a welfare loss by driving their safe counterparts out of the individual lending market, to actually ensuring that these very same clients obtain access to credit.

Our results suggest that there is no unique matching pattern or contract type which performs well across a wide range of markets. In recent theoretical work, a similar finding was obtained by Roy Chowdhury (2007) in a framework employing social capital. An advantage of the approach we employ in this chapter is that the model parameters can be estimated from data on group lending projects. Ahlin and Townsend (2007) provide guidance about obtaining proxies of success probabilities and project correlations from survey data. Empirical scrutiny of the main predictions of this chapter will therefore be our next objective.

6.A Derivation of equation 6.6

By filling in the first and second moments of a Bernoulli random variable into the definition of the correlation coefficient we obtain:

$$\rho_{ij} = \frac{E(X_i X_j) - p_i p_j}{\sqrt{p_i(1-p_i)}\sqrt{p_j(1-p_j)}}. \tag{6.A.1}$$

Note that, by definition, we must have $p^s_{ij} + p^c_{ij} = p_i$ and $p^s_{ij} + p^c_{ji} = p_j$ in (6.4). Also, $E(X_i X_j)$ in (6.A.1) equals p^s_{ij}. Using these relationships we find that, for identical projects $(i = j)$, the probabilities corresponding to the minimal and the maximal correlation, $\rho_{l,ij}$ and $\rho_{h,ij}$ are given by[12]

$$\boldsymbol{p}_{l,ij} = \begin{pmatrix} 2p_i - 1 \\ 1 - p_i \\ 1 - p_i, \\ 0 \end{pmatrix}, \boldsymbol{p}_{h,ij} = \begin{pmatrix} p_i \\ 0 \\ 0 \\ 1 - p_i \end{pmatrix}.$$

By plugging these probabilities in equation (6.A.1) we find that the minimal correlation between identical projects equals $\rho_l = \frac{p_i - 1}{p_i}$ while the maximal correlation equals $\rho_h = 1$. Likewise, for different project types $(i \neq j)$, the probabilities for minimal and maximal correlation correspond to

$$\boldsymbol{p}_{l,ij} = \begin{pmatrix} p_S + p_R - 1 \\ 1 - p_R \\ 1 - p_S \\ 0 \end{pmatrix}, \boldsymbol{p}_{h,ij} = \begin{pmatrix} p_R \\ p_S - p_R \\ 0 \\ 1 - p_S \end{pmatrix},$$

with minimal and maximal correlations

$$\rho_{l,ij} = \frac{-\sqrt{(1-p_S)(1-p_R)}}{\sqrt{p_S p_R}}, \rho_{h,ij} = \frac{\sqrt{p_R(1-p_S)}}{\sqrt{p_S(1-p_R)}},$$

[12] Maximizing/minimizing the correlation amounts to maximizing/minimizing p^s_{ij}. By definition the maximal value of p^s_{ij} equals p_i. Using the restrictions $p^s_{ij} + 2p^c_{ij} + p^f_{ij} = 1$ and $p^s_{ij} + p^c_{ij} = p_i$, we obtain the minimal value of p^s_{ij} by setting $p^f_{ij} = 0$.

respectively. For any correlation $\rho_{ij} \in [\rho_{l,ij}, \rho_{h,ij}]$, we can use equation (6.A.1) to find the corresponding probability p_{ij}^s and the remaining probabilities follow immediately:

$$\boldsymbol{p}_{ij} = \begin{pmatrix} p_{ij}^s \\ p_{ij}^c \\ p_{ji}^c \\ p_{ij}^f \end{pmatrix} = \begin{pmatrix} p_i p_j + \rho_{ij}\sqrt{p_i p_j (1-p_i)(1-p_j)} \\ p_i(1-p_j) - \rho_{ij}\sqrt{p_i p_j (1-p_i)(1-p_j)} \\ p_j(1-p_i) - \rho_{ij}\sqrt{p_i p_j (1-p_i)(1-p_j)} \\ (1-p_i)(1-p_j) + \rho_{ij}\sqrt{p_i p_j (1-p_i)(1-p_j)} \end{pmatrix}.$$

Chapter 7

Conclusion

This thesis focused on quantifying asset allocation decisions and diversification benefits. In Chapter 2 we examined the relationship between stock returns and inflation and its implications for asset allocation. We proposed an approach that differs from previous studies in two ways. Where previous studies analysed the inflation hedging potential of stocks, we have focused on their inflation exposure. Furthermore, we have proposed an economic, rather than a statistical, measure for quantifying this inflation exposure.

To quantify the impact of inflation exposure on stock holdings we compared the allocation to stocks and inflation-indexed bonds for two investor types. The first type disregards inflation risk and adopts the Fisherian view that inflation expectations are priced into stock return expectations. The second agnostic type takes the view that inflation expectations may affect stock returns, event hough there is substantial uncertainty about the exact relationship.

Applying this method to U.S. data in the Great Moderation era, we found the cost of ignoring the relationship between stock return and inflation expectations to be substantial, even in an environment with stable inflation. Over the period 2003-2011, the agnostic strategy implied an average 0.7 percent annual certainty equivalent gain for an investor with a ten-year horizon and a typical risk aversion level. We also noted, however, that this result might be driven by the recent financial crisis. The relationship between both expected and unexpected inflation and expected stock returns is negative for the 1985-2008 period, but the signs switch at the onset of the crisis, which is characterized by negative stock returns and low inflation. Excluding the crisis from our sample period, the average annual gains decrease to 0.3 percent annually, still amounting to over 10 percent of expected portfolio returns.

The remainder of the chapters focused on emerging markets finance. Due to the introduction of funded pension plans and due to growing interest in contractual savings products, assets under management by institutional investors in emerging markets have grown spectacularly over the last two decades. After an initial period characterized by strict regulation of investments, both institutional investors and individual pension plan participants are increasingly free to decide about their preferred asset allocation. However, the risk-return characteristics of emerging market assets at longer investment horizons have thus far received but little attention in the literature.

Taking the perspective of a domestic investor, we have empirically investigated three topics that play an important role in the debate on asset allocation in emerging markets: 1) the privileged position of domestic government bonds 2) foreign investment restrictions 3) the impact of changes in economic regime and crises on asset allocation decisions. In view of the substantial differences between emerging markets, we have adopted a case study approach for each topic.

In Chapter 3 we examined the market for government securities in India. For the purpose of debt financing, the Government of India relies to a large extent on the statutory liquidity ratio (SLR). This ratio requires financial institutions to maintain liquid instrument reserves of 23% (as of July 2012) of their total assets. However, the Government of India recognizes the potential of harnessing domestic savings and actively deploys initiatives to raise awareness about government securities amongst small investors. We have studied the portfolio problem of an Indian investor who allocates his wealth to domestic stocks and bonds. India's New Pension System (NPS) actually allows individual participants to decide annually upon their preferred allocation.

We have used a two-factor model to relate the fluctuations of bond prices in the secondary market to changes in the unobserved real interest rate and to changes in inflation expectations. Both processes were found to be persistent, but expected inflation much more so than the real interest rate. We established that, as a consequence, the inflation risk associated with long-term bonds outweighs their interest rate hedging potential. This makes long-term bonds unattractive for conservative investors, who prefer to invest in short-term debt instruments. The optimal portfolios of moderately risk-averse investors do contain a substantial long-term bond component, though, in spite of the associated inflation risk. This can partly be explained from the term premium associated with these bonds, and partly by the fact that domestic stocks, the other premium-bearing investment, are very volatile. Thus, even in a setting with relatively high and persistent inflation, bonds are in high demand with moderately risk-averse investors.

These findings have two policy implications. First, in order to entice risk-averse investors to participate in the market for long-term government securities, the Government of India should commit to a credible monetary policy aimed at anchoring inflation expectations. Alternatively, it could consider introducing inflation-indexed bonds, which have contributed positively to several Latin American pension reforms. This is of particular importance for the popularity of the New Pension System, where government bonds are the safest investment option. As this system is voluntary, risk-averse investors are currently likely to opt out of participating and invest in a short-term savings account, or choose a traditional form of saving for retirement.

Second, as our results suggest that for moderately risk averse investors the demand for bonds is closely related to the riskiness of the Indian stock market, policymakers should take into account that if the volatility of this market decreases, bond demand is likely to fall. This will also be the case when other investment opportunities, like for example foreign assets, become available to investors.

In Chapter 4 we quantified the financial benefits from investing abroad for investors in India, Malaysia, Pakistan and Thailand. In these four Asian markets, investment in international assets is curtailed. We extended previous studies on diversification benefits from an emerging market context, by adopting a dynamic, rather than a static portfolio selection approach. This allowed us to address the question whether the magnitude of diversification benefits and the optimal allocation to foreign assets depend on the investment horizon. Our analysis revealed that the dynamic properties of asset returns have but a small impact on asset allocation decisions. From the perspective of emerging market investors, there is little evidence of predictability or mean reversion in domestic and foreign equity returns. Foreign bond holdings become riskier in the long run however, primarily due to exchange rate effects.

In the debate on pension fund regulation, one of the arguments in favour of easing quantitative portfolio restrictions is that this allows fund managers to adapt to regime changes in financial markets. Chapter 5 analysed the effects of such changes on investors' asset allocation decisions. Using data from the Philippines, we estimated a bivariate Markov-switching vector autoregressive model to capture regime changes in both the government debt market and the stock market. This model allowed us to identify and date inflationary periods in the debt market and crisis episodes in the stock market. We consequently studied the optimal allocation to stocks for a buy-and-hold investor with power utility at a typical risk aversion level.

We found considerable differences between his asset allocation profiles in the two turmoil states as compared to regular market conditions. Under regular conditions, investors' allocation to stocks is decreasing as the probability of going through a stock market crisis episode increases with the holding horizon. For a typical level of risk aversion the decrease in stock holdings is substantial, from 33% of the portfolio at a three-month horizon to 25% at a one-year horizon and 16% at a five-year horizon. Surprisingly the allocation to stocks is lower in the inflationary regime than under regular circumstances. According to our model, this can be explained by the fact that inflationary periods are followed by stock market crashes with a probability of about 40%. The strategy in this crash regime is to strongly reduce stock holdings, even at holding horizons well in excess of five years.

These results are surprising in the sense that we would expect the upper bound on stock investment to be detrimental for investors during inflationary episodes, when returns on government instruments are low. Our model suggests, however, that even in such episodes, stock holdings should be decreased, as high inflation tends to precede periods of stock market turmoil. While the presence of regimes does suggest the need for portfolio adjustment by long-term investors, it does not provide an argument for loosening investment limits on domestic equity. Moreover it suggests that under normal market circumstances long-term investors should be more cautious than short-term investors in their allocation to stocks.

Next to these three papers on asset allocation in emerging markets, this thesis contains the results of our investigations into two different topics. The first of these two topics, treated in Chapter 6, is related to microfinance. While the increasing popularity of contractual savings plays a key role on the supply side of capital markets in emerging economies, the success of microfinance is instrumental in catering to individuals' demand for capital. We investigated the practice of group lending, which is often used by microfinance institutions in order to reduce the costs of loans and to mitigate problems stemming from information asymmetries. In a typical group lending contract, if one of the members of a group fails to repay his loan, his successful peers are obliged to make an additional joint liability payment to compensate for the lender's loss. An uninformed lender can separate safe from risky borrowers by offering two contracts, one with a low interest rate and high liability and another with high interest and low liability.

Previous literature suggested that correlation between borrowers' project returns limits the effectiveness of this approach, as joint liability payments are made less often when borrowers succeed or fail together. In our contribution, we have shown that this is not necessarily the case. We have derived that, if the correlation between safe project outcomes is sufficiently larger than the correlation between risky project outcomes, the joint liability payment required to achieve the separation result decreases. This leads to a better welfare result than in the independent project case, where separation is only possible when joint liability is in excess of the repayment of principal and interest, and therefore not incentive compatible.

Although our model is stylized, the insight that outcome correlation need not be detrimental, given some differentiation between projects, is not unimportant. It may contribute to explaining why group lending contracts have been successful exactly in environments where correlation between project outcomes was likely to be high. The results also have implications for the design of new microfinance programmes. In particular, they suggest that if a group lending approach is considered, it is important to investigate both the project types that can be expected in a given region and the outcome correlation within and between these types.

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Samenvatting

Reeds in de Oudheid bestond het inzicht dat het voordelig is om financiële middelen over meerdere beleggingen te spreiden. Zo schrijft de Babylonische Talmoed voor om het vermogen evenredig te verdelen over land, koopwaar en contanten. In de academische beleggingsleer is de spreidingsgedachte in de jaren '50 van de vorige eeuw geformaliseerd door Harry Markowitz (1952, 1959). De vertaling van Markowitz' diversificatiemodellen naar verantwoorde beleggingsbeslissingen geeft echter tot op de dag van vandaag aanleiding tot methodologisch en empirisch onderzoek.

De uitdagingen in dit veld zijn globaal onder te verdelen in drie categorieën. De eerste uitdaging is methodologisch en heeft betrekking op het verkrijgen van bruikbare schattingen van met name de verwachte rendementen van financiële instrumenten. Conventionele statistische methodes leveren vaak onrealistische of sterk fluctuerende beleggingsvoorschriften op. Ondanks een veelvoud aan methodologische innovaties wordt in een recent overzichtsartikel van DeMiguel et al. (2009) aangetoond, dat het nog altijd niet eenvoudig is om een simpele beleggingsregel, waarin alle beschikbare instrumenten gelijk gewogen worden, te overtreffen.

De tweede uitdaging bestaat uit het kwantificeren van verschillen tussen beleggingsvoorschriften voor de korte en de lange termijn. Deze kunnen substantieel verschillen door zowel theoretische als empirische eigenschappen van financiële instrumenten. Zo zal een langetermijnbelegger op de obligatiemarkt niet alleen kijken naar de verhouding tussen risico en rendement, maar ook naar het feit dat obligaties juist renderen wanneer de rente daalt (*interest rate hedging*). Of dit impliceert dat een groter deel van het vermogen in obligaties dient te worden belegd, hangt echter af van het bijbehorende inflatierisico. De relatieve kracht van deze twee factoren en het resulterende beleggingsvoorschrift dient empirisch te worden getoetst.

De derde uitdaging bestaat ten slotte uit het identificeren van de diversificatievoordelen die kunnen worden behaald door het toevoegen van nieuwe soorten beleggingen aan de portefeuille. Vooral buitenlandse beleggingen hebben traditioneel veel aandacht gekregen in de empirische literatuur. Recenter is de aandacht verschoven naar 'alternatieve' beleggingen zoals vastgoed, grondstoffen, of hedgefondsen.

Dit proefschrift bestaat uit een verzameling essays die op verschillende manieren bijdragen aan het onderzoek dat in deze drie velden wordt verricht. Gekozen is voor een brede verkenning van thema's die middels het methodologische instrumentarium van de beleggingsleer kunnen worden onderzocht. De nadruk ligt hierbij op het bestuderen van de statistische eigenschappen van rendementen in opkomende economieën en de implicaties daarvan voor de beleggingsbeslissingen van lokale beleggers (hoofdstukken 3-5). Het belang hiervan is in de afgelopen jaren sterk toegenomen door zowel de opkomst van gefinancierde pensioenstelsels als de groei van lokale kapitaalmarkten in deze economieën.

Het tweede en het zesde hoofdstuk wijken af van dit hoofdthema. In hoofdstuk 2 wordt onderzocht in hoe verre aandelenrendementen blootgesteld zijn aan inflatieschommelingen en welke gevolgen dat heeft voor de optimale omvang van de aandelenportefeuille. Dit hoofdstuk is methodologisch nauw verwant aan hoofdstukken 3-5. Ofschoon het onderwerp voor opkomende economieën relevant is, hebben we in dit hoofdstuk echter gekozen voor een analyse van de Verenigde Staten, op grond van de beschikbaarheid van gegevens over inflatieverwachtingen. Hoofdstuk 6 richt zich op microfinanciering, een financieel fenomeen dat bij uitstek betrekking heeft op ontwikkelingslanden. Dit hoofdstuk onderscheidt zich echter door het gebruik van diversificatietheorieën die meer verwant zijn aan de speltheorie dan aan de beleggingsleer.

Hoofdstuk 2: een nieuw perspectief op inflatierisico in aandelenportefeuilles

Institutionele beleggers, zoals pensioenfondsen, stellen zich ten doel om deelnemers een kasstroom uit te keren die meegroeit met het algemene prijspeil. Zodoende zijn zij geïnteresseerd in financiële instrumenten waarvan de rendementen niet lijden onder een stijging van de inflatie.

Reeds sinds de oliecrisis van 1973 en de daaropvolgende prijsstijging is in de academische literatuur onderzoek gedaan naar de vraag welke instrumenten deze eigenschap bezitten. Aanvankelijk werden aandelen, die immers uiteindelijk een claim vormen op fysieke goederen, als een belegging beschouwd die geschikt is om het inflatierisico te beperken. De theorieën van o.a. Modigliani en Cohn (1979) en Barnes et al. (1999) postuleren echter een negatief verband tussen aandelenrendementen en inflatie. Empirisch onderzoek heeft vooralsnog gemengde resultaten opgeleverd over dit verband. Dit komt met name doordat de hoge volatiliteit van aandelenrendementen ten opzichte van inflatieveranderingen het achterhalen van de relevante coëfficiënten bemoeilijkt.

In hoofdstuk 2 wordt een nieuwe benadering van dit vraagstuk voorgesteld. Er wordt verondersteld dat de belegger, in plaats van te pogen om het exacte verband tussen aandelenrendementen en inflatie te achterhalen, de onzekerheid over dit verband juist meeneemt in zijn beslissingsprobleem. De optimale keuze van deze belegger wordt vervolgens vergeleken met die van een belegger die uitgaat van de veronderstelling dat inflatieverwachtingen volledig ingecalculeerd zijn in aandelenrendementen. Dit maakt het mogelijk om de economische impact van inflatierisico bloot te leggen.

Toepassing van deze methode op data uit de Verenigde Staten in de periode 1985-2010 toont aan dat een belegger met een horizon van 10 jaar op jaarbasis gemiddeld 0.7 procent beter af is door inflatierisico mee te nemen in de beleggingsbeslissing. Op deze manier wordt aangetoond dat dit risico een rol van belang speelt bij de keuze van een optimale aandelen-allocatie. Dit effect kan deels toegeschreven worden aan de recente financiële crisis. Als de gegevens uit de crisisperiode worden weggelaten, resteert echter nog steeds een voordeel van 0.3 procent op jaarbasis, hetgeen circa 10 procent uitmaakt van het verwachte jaarlijkse rendement in deze periode.

Hoofdstukken 3-5: Case studies over asset allocatie in opkomende markten

Hoofdstukken 3-5 hebben betrekking op vraagstukken rondom het opzetten van pensioenplannen in opkomende markten. Doorgaans wordt ervoor gekozen om de beleggingsbeslissingen binnen deze pensioenplannen aanvankelijk sterk te reguleren. We vestigen de aandacht op een drietal verschijnselen die in de beginfase van deze plannen zijn waargenomen. In de eerste plaats wordt vaak disproportioneel veel belegd in lokale staatsobligaties ten koste van, bijvoorbeeld, de lokale aandelenmarkt. In de tweede plaats worden de mogelijkheden om in het buitenland te beleggen ingeperkt. In de derde plaats wordt gebruik gemaakt van centraal vastgestelde limieten op verschillende types beleggingen. Dit beperkt de mogelijkheden die portefeuillebeheerders hebben om in te spelen op economische ontwikkelingen.

Hoewel deze keuzes in de beginfase van een pensioenstelsel en zeker in afwezigheid van een voldoende ontwikkelde lokale aandelen- en kapitaalmarkt verdedigbaar zijn, spreekt het voor zich dat ze op de langere termijn nadelig zijn voor het opbouwen van gediversifieerde beleggingsportefeuilles. Zodoende is het belangrijk om te onderzoeken wat de huidige impact van deze beperkingen is en welke voordelen het geleidelijk afbouwen ervan spaarders en beleggers in ontwikkelingslanden zou opleveren.

Hoofdstuk 3: De lokale vraag naar staatsobligaties in India

Vanuit dit perspectief wordt in hoofdstuk 3 het recent gelanceerde nationale pensioenfonds van India bekeken. In dit moderne stelsel hebben deelnemers de mogelijkheid om jaarlijks hun gewenste beleggingsmix samen te stellen, bestaande uit aandelen, bedrijfsobligaties en staatsobligaties. De belangrijkste restrictie betreft een plafond van 50% op de aandelencomponent van de portefeuille.

Onze bijdrage richt zich op de rol van langlopende staatsobligaties in deze portefeuille. De vraag naar Indiase staatsobligaties wordt hierbij opgesplitst in drie componenten. De eerste component is toe te schrijven aan de risicopremie die deze obligaties bieden bovenop de kortetermijnrente en aan de mate waarin ze correleren met andere beleggingen, zoals aandelen. De tweede component houdt verband met het feit dat de rendementen op staatsobligaties tegengesteld zijn aan fluctuaties van de reële rente. Door het bezit van deze obligaties kan een belegger zich indekken tegen periodes met lage reële rentes, waardoor hij zijn consumptie ook in dergelijke periodes constant kan houden (hedging-effect). De derde, negatieve, vraagcomponent is verbonden met het inflatierisico dat nominale obligaties met zich meebrengen.

Onze resultaten laten zien, dat de optimale keuze sterk afhangt van de mate van risico-aversie van de belegger. Voor sterk risicomijdende beleggers is vooral het samenspel tussen het hedging-effect en het inflatierisico van belang. Het laatstgenoemde effect domineert in het geval van India, waardoor staatsobligaties voor deze beleggers niet aantrekkelijk zijn. Dit lijkt in lijn te liggen met de argumenten die o.a. door Viceira (2010) zijn aangevoerd tegen een grote rol van lokale staatsobligaties in pensioenbeleggingen; dit zou een uitnodiging zijn voor inflatoire financiering van de staatsschuld.

Voor beleggers met een lagere mate van risico-aversie zijn de conclusies echter anders. Bij deze beleggers, die meer geïnteresseerd zijn in de relatieve verhouding tussen risico en rendement op korte termijn, bestaat, ondanks het inflatierisico, wel degelijk vraag naar staatsobligaties. Dit komt voort uit de historische rendementen van deze obligaties en uit hun relatief lage volatiliteit ten opzichte van lokale aandelen, die ze vooral voor beleggers met een gemiddeld risicoprofiel aantrekkelijk maakt. Al met al levert dit, althans voor het geval van India, een meer genuanceerd beeld op van de rol van staatsobligaties dan vooralsnog in de literatuur is geschetst, aangezien er ondanks het inflatierisico bij bepaalde beleggers wel degelijk vraag naar lokale staatsobligaties bestaat. Hierbij moet uiteraard de kanttekening worden geplaatst, dat in de analyse alleen lokale financiële instrumenten meegenomen zijn, overeenkomstig de heersende restricties op beleggingen in het buitenland. Indien beleggers toegang zouden krijgen tot minder volatiele buitenlandse markten, dan zou deze vraag deels kunnen wegvallen.

Tegelijkertijd toont onze analyse echter aan, dat er voor risico-averse beleggers geen geschikte langlopende instrumenten bestaan, waardoor hun optimale strategie noodgedwongen bestaat uit kortlopende instrumenten. Het uitbrengen van geïndexeerde obligaties, naar het voorbeeld van Chili, zou een mogelijke oplossing kunnen zijn om deze beleggers voor de obligatiemarkt te mobiliseren.

Hoofdstuk 4: De meerwaarde van beleggen in het buitenland

Het vierde hoofdstuk is gewijd aan de diversificatievoordelen die voor beleggers in ontwikkelingslanden te behalen zijn wanneer beleggen in het buitenland wordt toegestaan. Dit onderwerp heeft recent veel aandacht gekregen in de literatuur, o.a. in het werk van Driessen en Laeven (2007), Chiou (2008) en Kumara en Pfau (2011). Allen vonden significante voordelen.

Onze bijdrage aan deze literatuur bestaat eruit, dat we het perspectief nemen van een langetermijnbelegger, die de tijdreeksdynamiek van rendementen op zowel lokale als buitenlandse instrumenten meeneemt. Tijdreekseffecten kunnen een belangrijk effect hebben op het risicoprofiel van beleggingen op de langere termijn. In de afgelopen decennia is bijvoorbeeld een uitgebreide discussie ontstaan over het zogenaamde 'mean reversion'-effect, waardoor aandelen op de lange termijn minder risicovol zouden zijn dan op korte termijn. Dit zou impliceren dat langetermijnbeleggers relatief meer aandelen zouden moeten aanhouden dan kortetermijnbeleggers. Indien een dergelijk effect in opkomende markten niet zou bestaan, zou het buitenlandse aandelen relatief aantrekkelijker maken voor langetermijnbeleggers en vice versa indien dit effect in opkomende markten juist sterker zou zijn.

Aangezien er vooralsnog weinig onderzoek gedaan is naar dergelijke effecten in opkomende markten en naar hun samenspel met de tijdreekseigenschappen van ontwikkelde markten, wordt in hoofdstuk 4 een aanpak voorgesteld die het mogelijk maakt om een hoge mate van onzekerheid over het door de belegger te hanteren model mee te nemen. Aan de hand van deze aanpak worden de beleggingshorizoneffecten in kaart gebracht voor beleggers in vier opkomende economien: India, Maleisië, Pakistan en Thailand. De belangrijkste conclusie is dat eventuele horizoneffecten teniet worden gedaan door de model-onzekerheid waar beleggers in opkomende economieën mee te maken hebben.

Hoofdstuk 5: De impact van beurscrashes en inflatie op beleggingsbeslissingen voor de lange termijn

In het vijfde hoofdstuk bestuderen we, aan de hand van een case-study gebaseerd op data uit de Filipijnen, de gevolgen van wisselende economische omstandigheden ('regimes') op beleggingsbeslissingen in ontwikkelingslanden. Door te kijken hoe de optimale allocatie naar aandelen en obligaties afhangt van de economische omstandigheden kunnen we beoordelen in hoeverre vooraf vastgestelde beleggingslimieten een negatieve invloed zouden kunnen hebben op het beleggingsbeleid. We bestuderen bovendien wisselende regimes ook gevolgen hebben voor de beslissingen van beleggers met een lange horizon.

Het model legt, op basis van waarnemingen van rendementen op Filipijnse aandelen en de rente op kortlopende spaartegoeden, drie regimes bloot. Een stabiel regime wordt onderbroken door aandelenmarktcrises en inflationaire periodes. De twee laatstgenoemde situaties wisselen elkaar doorgaans af. Deze dynamiek ontneemt beleggers de mogelijkheid om in periodes van negatieve rendementen op een van deze markten hun vermogen naar de andere markt over te hevelen. Zij lopen een grote kans in de daaropvolgende periode alsnog getroffen te worden.

Een andere belangrijke bevinding is, dat de impact van economische regimes ook voor langetermijnbeleggers merkbaar is. Een stereotype belegger met een horizon van vijf jaar reduceert zijn optimale allocatie naar aandelen met 6% in het inflationaire regime en met 15% in het crisisregime. Dit illustreert het belang van handelingsvrijheid voor institutionele beleggers bij het bepalen van de optimale allocatie. In het geval van de Filipijnen zouden de bestaande beperkingen (een maximum op de aandelenbelegging) overigens geen effect hebben gehad, aangezien in de twee speciale regimes de optimale aandelenproportie juist daalt.

Hoofdstuk 6: Groepsleningen en diversificatie binnen microfinancieringsinstellingen

Tot slot wordt in hoofdstuk 6 aandacht besteed aan een ander financieel fenomeen dat in de afgelopen twee decennia een steeds grotere rol is gaan spelen in opkomende markten, namelijk microfinanciering. Bij het verstrekken van krediet in deze markten speelt diversificatie van de kredietportefeuille een belangrijke rol. Groepsleningen behoren tot de middelen die een microfinancieringsinstelling (MFI) kan aanwenden om dit te bereiken. Door alle leden van een groep aansprakelijk te stellen voor het terugbetalen van de lening van elke individuele deelnemer kan de MFI de portefeuille diversifiëren.

Onze bijdrage bestaat uit twee onderdelen. Allereerst gaan we in op een belangrijk kritiekpunt dat in de literatuur over groepsleningen aan de orde is gebracht. Dit heeft betrekking op het feit dat de diversificatiemogelijkheden in de praktijk beperkt zouden zijn ten gevolge van een hoge correlatie tussen de uitkomsten van de projecten van de leden van een groep. Wij laten zien dat dit niet noodzakelijkerwijs ten koste hoeft te gaan van de effectiviteit van de contracten. In sommige gevallen kan zelfs een resultaat worden behaald dat een hoger maatschappelijk nut oplevert dan indien de uitkomsten geen correlatie zouden vertonen.

Het tweede onderdeel van de bijdrage heeft betrekking op asymmetrische groepsleningen, waarbij de aansprakelijkheid voor het terugbetalen niet reciprook is. De ene deelnemer zegt toe voor de ander in te staan, in ruil voor een korting op de rente die hij zelf dient te betalen. Er wordt aangetoond, dat dergelijke contracten, in vergelijking met symmetrische groepsleningen, vooral potentie hebben wanneer de rendementen op de projecten van de deelnemers relatief laag zijn.