GERBEN DE ZWART

Empirical Studies on Financial Markets:

private equity, corporate bonds and emerging markets

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Empirical Studies on Financial Markets: private equity, corporate bonds and emerging markets

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durfkapitaal, bedrijfsobligaties en opkomende markten

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Voorwoord (Preface)

'Dit paper overbrugt het veelvoorkomende gat tussen praktijk en wetenschap'. Met deze uitspraak startte Michael Melvin, editor van het *Journal of International Money and Finance*, de discussie over Hoofdstuk 4 tijdens de tweede emerging markets conferentie van de Cass Business School in Londen in mei 2008. Hiermee verwoordde hij precies waar ik de afgelopen vier jaar aan gewerkt heb: wetenschappelijk onderzoek met een praktische inslag. Concreet betekende dit vier dagen per week werken in de praktijk en één dag aan mijn proefschrift op de Erasmus Universiteit Rotterdam. Dit proefschrift vormt het eindresultaat waarbij de variatie van onderwerpen voortkomt uit de onderzoeken naar verschillende financiële markten waar ik in de praktijk aan gewerkt heb.

Wetenschappelijk onderzoek is net iets anders dan onderzoek in de praktijk. Grote dank ben ik dan ook verschuldigd aan de lessen en suggesties van mijn promotoren. Beste Dick, vanaf het eerste moment waarop ik je mijn promotieplannen voorlegde hebben we bijzonder prettig, maar ook efficiënt, samengewerkt. In de 30 treinminuten van Leiden naar Rotterdam en vice versa hebben we heel wat nieuwe ideeën en resultaten besproken. Beste Marno, in de begeleiding stond je iets meer op afstand, maar juist jouw frisse blik op voorlopige versies van de verschillende hoofdstukken leverde een heel andere kijk op het onderzoek. Ik heb het erg op prijs gesteld dat je mij de kans hebt gegeven om één dag per week op de Rotterdam School of Management door te brengen. Samen vormden jullie een goed team en hebben jullie een belangrijke rol gespeeld in mijn ontwikkeling op wetenschappelijk gebied. Ik hoop daarom dan ook dat we in de toekomst kunnen blijven samenwerken. Ook wil ik hier Peter Ferket danken voor het feit dat hij mij vanaf het begin af aan uitgedaagd, gestimuleerd en gesteund heeft om dit promotietraject door te zetten en af te ronden. Beste Peter, de manier waarop jij altijd uitkomt voor je eigen mening en ideeën verdient veel respect! Ik ben dan ook erg blij dat je deel uitmaakt van de grote commissie.

De leden van de kleine commissie, Angelien Kemna, Allaudeen Hameed en Frans de

Roon, wil ik bedanken voor het evalueren van dit proefschrift en hun suggesties. Ingolf Dittmann en Mathijs van Dijk wil ik ook bedanken voor het plaatsnemen in de grote commissie en hun suggesties voor hoofdstuk 3. Hiernaast wil ik mijn andere co-auteurs, Jeroen Derwall, Brian Frieser, Jaap van der Hart, Joop Huij, Thijs Markwat en Laurens Swinkels bedanken voor hun bijdragen aan dit proefschrift. Ik heb genoten van het onderzoek, onze discussies en de conferentiebezoeken. Iedere nieuwe versie voelde weer als de beste, totdat we de volgende versie hadden geschreven...

Ook wil ik mijn (voormalige) collegae bij de Erasmus Universiteit Rotterdam, Robeco en ING bedanken. Met het gevaar dat ik iemand vergeet te noemen, wil ik hier met naam noemen: David Blitz, Ronald van Dijk, Johan Duijvesteijn, Frank van Etten, Marshall Filart, Carl Ghielen, Wilma de Groot, Daniel Haesen, Paul van Homelen, Patrick Houweling, Kees Isendoorn, Willem Jellema, Maarten Jennen, Tjeert Keijzer, Erik Kole, Niels Kylstra, Marcel de Koning, Martin Martens, Ranjit Nelissen, Ad van den Ouweland, Michiel de Pooter, Martin Prins, Meenu Sahi, Carina Schlosser, Ben Tims, Tatjana Ulicevic, Eddy Verbiest, Pim van Vliet en Mikan van Zanten.

Ik wil mijn vrienden en medebestuursgenoten en leidingsleden van de Katwijkse Zeeverkenners danken voor hun begrip en de nodige afleiding in de afgelopen vier jaar. Hoogtepunten waren onder meer de vele diners met de vrienden en het KaWaKa met 150 zeeverkenners en welpen tijdens ons 75-jarig jubileum! Ik ben ook erg blij dat twee van mijn vrienden tijdens de verdediging naast mij staan, Jaap-Meinert en Klaas Jan. In de afgelopen 15 jaar hebben we al erg veel samen meegemaakt en kon ik altijd op jullie rekenen.

Het laatste dankwoord is bestemd voor mijn familie. Jullie hebben steeds belangstelling getoond in mijn bezigheden, al was het vast even schakelen om te begrijpen wat ik nu precies deed. Lieve papa en mama, jullie hebben hebben mij het doorzettingsvermogen meegegeven dat nodig was om dit proefschrift te starten en af te ronden. Dank voor jullie steun. Veruit mijn grootste dank gaat uit naar Annemiek. Lieve Annemiek, dank voor al je steun en liefde in de afgelopen jaren. Heel wat avonden en weekenden kon ik rekenen op je begrip als ik nog 'even' aan de slag ging. Nu, bijna acht jaar na onze trouwdag en 16 jaar na onze eerste ontmoeting kijken we uit naar de geboorte van onze baby in augustus. Hiermee staan we samen aan de vooravond van een totaal nieuwe uitdaging waaraan dit proefschrift niet kan tippen.

Gerben de Zwart
Rijnsburg, mei 2008

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Chapter 1

Introduction

This dissertation consists of five empirical studies on financial markets. Each study can be read independently and covers a specific financial market, either private equity, corporate bonds or emerging markets. This introductory chapter provides a brief description of each of these markets and gives an overview of the subsequent chapters.

1.1 Emerging markets

The term 'emerging market' was originally introduced by the International Finance Corporation (IFC) of the World Bank. The term 'emerging' refers to the interphase between less-developed and developed. The emerging markets include low and middle income countries with stock markets in which foreigners can buy and sell securities, like Mexico or South Africa. In addition high income economies that still have a high political risk or less developed regulations, like Israel and Korea respectively, are also classified as emerging markets. Emerging markets are extensively analysed especially since the early 1990's, because only then the relevant data, compiled by amongst others IFC, became available. Bekaert and Harvey (2002, 2003) provide a good overview of the 'big picture' in emerging markets research. Naturally the high returns and strong economic growth of emerging markets also contributed to the investor's interest.

There are two aspects that make emerging markets research interesting. First, they provide a natural 'out-of-sample' test for both established and new theories that initially are tested for developed markets. The study on stock selection strategies in emerging markets in Chapter 2 provides an example of this use of emerging markets data. Second, emerging markets have their own specific characteristics such as crises and limited regulations. Therefore they need their own (new) models. The study on analysts' earnings forecasts, in Chapter 3, clearly looks at the specific characteristics of emerging markets. Finally, the study on emerging currency markets, in Chapter 4, gives a new perspective on investment strategies for both emerging as well as developed currency markets.

Chapter 2 examines competing explanations for the profitability of stock selection strategies in emerging markets. We document that both emerging market risk and global risk factors cannot account for the significant excess returns of selection strategies based on value, momentum and earnings revisions indicators. The findings for value and momentum strategies are consistent with the evidence from developed markets supporting behavioral explanations. In addition for value stocks, the most important behavioral bias appears to be related to underestimation of long-term growth prospects, as indicated by above average analysts' forecast errors and earnings revisions for longer post-formation horizons and by quite rapidly improving earnings growth expectations. Furthermore, we find that overreaction effects play a limited role for the earnings revisions strategy setting this strategy apart from momentum strategies.

Chapter 3 presents empirical evidence that security analysts do not efficiently use publicly available macroeconomic information in their earnings forecasts for emerging market stocks. Analysts completely ignore forecasts on political stability. They do incorporate output growth forecasts, but these actually bear no relevant information for firm-level earnings growth. Inflation forecasts are taken into account correctly. In addition, the information environment appears to be crucially important in emerging markets, as we find evidence that analysts handle macroeconomic information in a better way for more transparent firms.

Chapter 4 measures the economic value of information derived from macroeconomic variables and technical trading rules for emerging markets currency investments. Using a sample of 23 emerging markets with a floating exchange rate regime over the period 1995–2007, we document that both types of information can be exploited to implement profitable trading strategies. In line with evidence from surveys of foreign exchange professionals concerning the use of fundamental and technical analysis, we find that combining the two types of information improves the risk-adjusted performance of the investment strategies.

1.2 Corporate bonds

Usually, companies use a mix of financial resources to achieve an optimal capital structure, where debt and equity are the most important sources of financing. Today, firms very often raise debt directly from the capital markets by issuing their own bonds. In its simplest form these corporate bonds are a financial obligation by the company to pay interest at specified future dates during the lifetime of the bond and the notional at maturity. For bearing the risk of bankruptcy of the issuing firm during the lifetime of the bond, investors require a higher compensation than for government bonds. Furthermore, the holder of a corporate bond has priority over the claims of stockholders in the case of a bankruptcy.

During the last 15 years the analysis of corporate bonds has expanded substantially, although the first study by Fisher (1959) dates back much longer. This growing interest is due to the enormous growth of the corporate bond market in both the US and Europe as well as from the introduction of derivatives on corporate bonds, like credit default swaps. Nevertheless, empirical research from an investor's perspective is limited due to the lack of reliable historical data on corporate bond prices and returns. To the best of our knowledge, Chapter 5 adds to the literature by being the first study that incorporates both individual corporate bonds and all US corporate bond mutual funds to address anomalous patterns in corporate bond returns. Prior studies either focus on individual corporate bonds (see Gebhardt *et al.* (2005) among others) or mutual funds (see Elton *et al.* (1995) or Huij and Derwall (2007) among others).

Chapter 5 documents that common risk factors do a good job in explaining the cross-section of returns on corporate bond portfolios with medium to long maturity, but significantly underestimate the returns on corporate bonds with a short maturity. A substantial portion of short-term corporate bond returns is independent of risk premiums associated with market risk, term and default risk, yield curve dynamics, liquidity risk and premiums associated with macro-economic variables. Comparable evidence of a short-term corporate bond anomaly also shows up in portfolios of corporate bond mutual funds, indicating that the anomaly withstands important practical issues, such as short-selling restrictions, transaction costs, and trade impact.

1.3 Private equity

Private equity covers the entire spectrum of investments in securities of companies that do not have a listing on a stock exchange. The asset class became widely known to the general public only in the 1980s, when several US private equity firms were frequently in the news because of the large takeovers they did. Nevertheless the origins of private equity date back to the 1940s in both the US and Europe. Since then the asset class has grown significantly. This growth was driven by governmental stimulations on the availability of capital for small private businesses in the 1950s, the introduction of the limited partnership as a legal structure in the 1970s and regulatory changes for pension funds and banks in the early 1980s. In the 1980s large institutional investors took over the role of leading investors in private equity from private individuals. This spurred a further growth of the private equity asset class. Of course the success of several companies that were initially funded through private equity such as Microsoft, Google, Starbucks, Apple Computers and Hewlett-Packard also contributed. The late 1990s showed a substantial increase in the number of independent private equity firms. This was partly based on the successes of the private equity segment that provided money to start-up companies during the initial phase of the 'internethype' and the subsequent successful initial public offerings (IPO) in the public market. The industry experienced a correction when the end of this hype was combined with a global macroeconomic downturn. Driven by the recovery of global macro economic growth the private equity market recovered. Fueled by low interest rates and a high level of liquidity in the financial markets, the segment focusing on buying existing companies experienced high growth during the past three years.

Today, the interest in private equity from institutional investors is still growing. For example, Cumming and Johan (2007) survey the attitude of Dutch institutional investors towards private equity and find that currently 29% of the respondents are investing in private equity, while another 6% of the respondents intends to invest in private equity over the next two to five years. Furthermore, the respondents who already invest in private equity expect an increase of their private equity portfolio allocation in the near future. Despite this enthusiasm from institutional investors there is not much formal research into private equity investment strategies for these investors with a long-term horizon. Chapter 6 fills this gap.

Chapter 6 develops a reinvestment strategy for institutional private equity investors. The strategy aims to keep the private equity portfolio weight equal to a desired strategic asset allocation, while taking into account the illiquid nature of private equity. Historical simulations (1980–2005) show that this dynamic strategy is capable of maintaining a stable investment level that is close to the target. This result does not only hold for unrestricted portfolios, but also for investments limited to buy-out or venture capital, a specific region (Europe or US), or fund manager experience. This finding is of great importance for institutional investors like pension funds or insurance companies, because private equity funds have a finite lifetime and uncertain cash flows, forcing investors to constantly maintain their private equity portfolio.

To summarize, this dissertation consist of five studies that can be read independently. Chapters 2, 3 and 4 concern different aspects of emerging markets and discuss stock selection, analysts' earnings forecasts and currencies, respectively. Chapter 5 is concerned with asset pricing in corporate bonds. Chapters 6 studies investment strategies for institutional investors in private equity.

Chapter 2

The Success of Stock Selection Strategies in Emerging Markets: Is it Risk or Behavioral Bias?[*]

2.1 Introduction

Research in emerging markets finance has been rapidly expanding over the past two decades, see Bekaert and Harvey (2002, 2003) for comprehensive surveys of the past, present and future of the area. Relatively few studies exist that investigate individual stock selection for emerging markets, see Claessens *et al.* (1998), Fama and French (1998), Patel (1998), Achour *et al.* (1998, 1999b,c,a), Rouwenhorst (1999), Barry *et al.* (2002), and Van der Hart *et al.* (2003). The general conclusion from these studies appears to be that stock selection strategies that work well in developed markets also generate significant outperformance in emerging markets. The most recent analysis by Van der Hart *et al.* (2003), based on almost 3000 securities from 32 countries and an extensive set of selection strategies, finds that in internationally diversified (but country-neutral) portfolios, value stocks outperform growth stocks, past winners (based on six-month momentum) outperform past losers, and stocks with (relatively) high analysts' earnings revisions outperform stocks with low revisions.

There is an ongoing debate concerning the underlying reasons for (or the appropriate interpretation of) the profitability of value, momentum and revisions strategies. Roughly speaking, on the one hand, the excess returns of these stock selection strategies are believed

[*]This chapter is based on the article by Van der Hart, De Zwart and Van Dijk (2005) in the *Emerging Markets Review*. We thank an anonymous referee and participants at the Inquire Europe meeting held in Prague, October 2004, for useful comments and suggestions. We also thank Willem Jellema for excellent assistance in collecting the data.

to be compensation for risk involved, whereas on the other hand they are attributed to behavioral biases, with investors either under- or overreacting to the release of new firm-specific information. To add to this discussion, in this paper we perform an 'out-of-sample' test of these competing explanations, by examining whether they can account for the profitability of stock selection strategies in emerging markets. As most research in this area has been conducted for developed markets, emerging markets provide an excellent opportunity to study the source of return premiums on a relatively independent sample.

We find that both emerging market risk and global factor risk (using a four-factor model including market, book-to-market, size and momentum factors) cannot explain the excess returns of the selection strategies in emerging markets. Relatively few factor loadings are found to be significant, while excess returns of the strategies remain of the same magnitude and significant after accounting for risk. We find more convincing evidence in favor of behavioral explanations for value and momentum anomalies put forward in the context of developed markets. In addition, we present new results supporting an underrreaction effect for the earnings revisions strategy.

For value strategies, our findings are in accordance with the underreaction or extrapolation hypothesis developed in Lakonishok *et al.* (1994), which posits that the outperformance of value stocks arises because investors systematically underestimate the earnings growth prospects of such stocks. We find that the actual earnings growth of value stocks in emerging markets equals the average earnings growth after just a few years, indicating that the difference in valuation between value and growth stocks indeed is not justified by subsequent earnings developments. At the same time, we find that the evidence for emerging markets is also in line with the results of Doukas *et al.* (2002), who document that analysts in fact are more optimistic about value than growth stocks, seemingly contradicting the behavioral interpretation of Lakonishok *et al.* (1994). We suggest a possible reconciliation for these contrasting views, based on the idea that the most important behavioral bias is related to underestimation of long term earnings growth prospects for value stocks. This hypothesis is supported by our finding that analysts' forecast errors (defined as actual earnings minus the corresponding earnings forecast) and earnings revisions for value stocks are below average only up until approximately one year after portfolio formation. After this initial period, analysts indeed become less optimistic about value than growth stocks. In addition, we observe that the expected earnings growth for value stocks improves quite rapidly and exceeds the average expected growth within two years after portfolio formation.

For the momentum strategy, we find elements of both underreaction and overreaction, in agreement with the evidence from developed markets. On the one hand, stocks with high past returns have higher earnings forecast errors and earnings revisions for about one year after portfolio formation, indicating an underreaction effect, similar to the findings of Chan *et al.* (1996) for the US. On the other hand, in line with Jegadeesh and Titman (2001) and Nagel (2002), we also find that momentum strategies have a pronounced reversal in excess returns between three and five years after portfolio formation, indicating an overreaction effect.

For the earnings revisions strategy, our results lend unequivocal support to an underreaction explanation. In line with the US evidence of Chan *et al.* (1996) and our own findings for the emerging markets momentum strategy, stocks with high past earnings revisions continue to have earnings revisions (and earnings forecast errors) above average for about one year after portfolio formation. Contrary to the momentum strategy, we find no return reversal for the earnings revisions strategy up until five years after portfolio formation, indicating a distinct difference between these strategies. To the best of our knowledge, return reversals for earnings revisions strategies have not been examined before, even for developed markets.

The plan of the paper is as follows. Section 2.2 describes the data and stock selection strategies. Section 2.3 summarizes the results concerning their profitability and the robustness thereof. Sections 2.4 and 2.5 explore the competing explanations for the excess returns of the strategies in terms of risk and behavior, respectively. Finally, Section 2.6 concludes.

2.2 Methodology

2.2.1 Data

Stock returns, earnings and book value data are drawn from the S&P/IFC Emerging Markets database. Monthly total stock returns are measured in US dollars, and account for dividends, stock splits and other capital adjustments, cf. Rouwenhorst (1999). The returns contain some extreme observations, which are at least partly due to data errors. To avoid a potentially disrupting impact from large data errors, we compare the total returns from S&P/IFC with corresponding total returns from the Factset Pricing database, as well as with price returns from both sources. In case of extreme return observations with large differences between the data sources, we use the smallest absolute value to err on the side of caution. In addition, we cap monthly returns at 300% or 150%, depending on whether or not the S&P/IFC data is confirmed by Factset Pricing.

We exclude stocks that are not included in the IFC Investable Composite index[1] and stocks that have a real investable market value less than 100 million in December 1998 US dollars, applying a 10 percent annual inflation rate. This makes the selection strategies feasible for a large international investor, while it also mitigates the problem of survivorship bias in the Emerging Markets database, due to backfilled data for some countries in the period before inclusion in the IFC Investable Composite index, see Harvey (1995) for a detailed discussion. In addition, we omit countries with less than four stocks and countries for which the data necessary for the particular selection strategy is available for less than 30 percent of the stocks. We discard these "small" countries because the selection strategies construct local return factor portfolios from the top and bottom 15 percent stocks in each country separately.

The data from S&P/IFC are supplemented with analysts' earnings forecasts from the Institutional Brokers Estimate System (IBES). These are used to compute earnings revisions, defined as the number of analysts with upward revisions minus the number of analysts with downward revisions divided by the total number of analysts providing an earnings forecast in a particular month, following Achour *et al.* (1998).

Combining the different databases, we implement the stock selection strategies described below over the period from December 1988, the inception month of the IFC Investable Composite index, until June 2004. The number of stocks that are used for testing the strategies starts at about 100 in December 1988, grows quite rapidly to about 700 in 1994 and varies between 600 and 900 stocks in the remaining years.

2.2.2 Stock Selection Strategies

We investigate stock selection strategies based on the value indicators book-to-market (B/M) and earnings-to-price (E/P), based on momentum as measured by the total return

[1]The IFC Investable Composite Index consists of stocks from the following countries, with the first month of inclusion in parenthesis. In case two months are provided, the second indicates the last month of inclusion. Latin America: Argentina (Dec 1988), Brazil (Dec 1988), Chile (Dec 1988), Colombia (Feb 1991 - Nov 2001), Mexico (Dec 1988), Peru (Jan 1994), Venezuela (Jan 1990 - Nov 2001); Asia: China (Oct 1995), India (Nov 1992), Indonesia (Sep 1990), Korea (Jan 1992), Malaysia (Dec 1988), Pakistan (Mar 1991 - Nov 2001), Philippines (Dec 1988), Sri Lanka (Jan 1994 - Nov 2001), Taiwan (Jan 1991), Thailand (Dec 1988); Europe: Czech Republic (Jan 1996), Greece (Dec 1988 - Apr 2001), Hungary (Apr 1994), Poland (Apr 1994), Portugal (Dec 1988 - Mar 1999), Russia (Nov 1997), Slovakia (Nov 1997 - Nov 2001), Turkey (Aug 1989); Africa & Middle East: Egypt (Nov 1997), Israel (Dec 1996), Jordan (Dec 1988 - Nov 2001), Morocco (Nov 1997), South Africa (Apr 1995), and Zimbabwe (Apr 1994 - Nov 2001). Malaysia was not included during the period Oct 1998 - Oct 1999.

over the previous six months (6MR), and based on analysts' earnings revisions, measured by the past three-month average earnings revisions for the current fiscal year (ER FY1). The methodology underlying the portfolio construction is described below.

All strategies are applied without a delay between the moment of ranking and the moment of portfolio formation. As the IFC and IBES databases contain data as published, all sorting characteristics would have been available to investors at the time of ranking and, hence, the selection strategies do not use any future information.[2] At the beginning of each month, we rank the stocks by country on each of the above characteristics in descending order. For each country in the sample, equally weighted 'top' and 'bottom' portfolios are formed from the 15 percent stocks ranked highest and lowest, respectively.[3] These country portfolios are then combined into internationally diversified portfolios, in which each stock receives an equal weight. Each month, new portfolios are constructed which are held for a period of six months. After formation, the portfolios are not rebalanced, except to account for stocks leaving the IFC Investables index. These stocks exit the relevant portfolio and the weights of the remaining stocks are adjusted proportionally. As we construct new portfolios every month and use a six-month holding period, at any point in time the strategies effectively hold stocks from six portfolios, each formed one month apart. To handle the problems concerned with overlapping returns, we calculate monthly returns for a particular strategy as the average of the returns on the six similar portfolios, cf. Jegadeesh and Titman (1993, 2001) and Rouwenhorst (1998).

[2]Apart from worries about the timely availability of the sorting variables, another reason to implement momentum strategies with a delay (usually of one-month) is to attenuate the effects of bid-ask bounce, see Achour *et al.* (1998) and Rouwenhorst (1999), among others. Because of the minimum capitalization requirement that we impose, the smallest, and probably least liquid, stocks are not included in our sample and, hence, bid-ask bounce is less important at the monthly frequency. Therefore, we also implement the momentum strategies without delay, such that, for example, the 6-month momentum factor that is used to rank the stocks at the beginning of month t is based on the average return from the beginning of month $t-6$ to the end of month $t-1$.

[3]Stocks are selected in each country separately to avoid any implicit country allocation. We examine the added value of country selection by ranking stocks globally and forming equally weighted portfolios consisting of the top and bottom 15 percent stocks in this alternative ranking. We find that such 'global ranking' adds considerably to the profitability of the stock selection strategies. The excess returns due to country selection are, however, much more volatile than the excess returns due to stock selection.

Table 2.1: Returns of Univariate Stock Selection Strategies

Factor	# Stocks	Top	EWI	Bottom	TMI	t(TMI)	TMB	t(TMB)
B/M	576	1.46	0.93	0.74	0.53	3.76	0.73	3.39
E/P	576	1.26	0.93	0.58	0.32	3.04	0.68	3.76
6MR	576	1.30	0.93	0.58	0.36	3.51	0.74	3.75
ER FY1	489	1.03	0.79	0.45	0.24	3.13	0.59	4.80

Note: At the beginning of each month between December 1988 and June 2004, all stocks for which the necessary information is available are ranked by country in descending order according to the value of the factor indicated in the first column. B/M is the book-to-market ratio; E/P is the earnings-to-price ratio; 6MR is the average return over the previous six months; ER FY1 is the past three-month average earnings revisions for the current fiscal year. For each country equally weighted portfolios are formed from the top and bottom 15 percent of stocks, which are combined into equally weighted internationally diversified portfolios (Top and Bottom). EWI is the equally weighted index of all stocks in the sample. Positions are held for six months and are not rebalanced. Monthly, non-overlapping returns are computed as the average return on the six similar portfolios which are held during each month. Column 2 reports the average number of stocks in the different samples. Columns 3-5 report the average returns of the Top, EWI and Bottom portfolios, expressed as percentage per month. Columns 6-7 and 8-9 report the average excess returns and the corresponding t-statistics of the Top Minus EWI (TMI) portfolio and the Top Minus Bottom (TMB) portfolio, respectively.

2.3 Profitability of Stock Selection Strategies

In this section, we evaluate the performance of the stock selection strategies based on value, momentum and earnings revisions. Table 2.1 shows the average monthly returns during the six-month holding period for the top portfolio, an equally weighted index consisting of all stocks in the relevant sample (EWI) and the bottom portfolio, as well as the excess returns of the top portfolio versus the equally weighted index (TMI) and versus the bottom portfolio (TMB).

All four selection strategies prove to be successful, in the sense that the excess returns of the top portfolio are positive and strongly statistically significant. Compared to the EWI, the average monthly excess returns of the top portfolio vary from 0.24% for the earnings revisions strategy to 0.53% for the B/M strategy. The average returns for the top versus bottom portfolio range between 0.59% and 0.74% per month, with the highest average return for the momentum strategy and the lowest again for the earnings revisions strategy. These magnitudes of the strategies' excess returns are similar to those found in Van der Hart *et al.* (2003), as well as the results reported in Rouwenhorst (1999) for B/M and momentum and in Achour *et al.* (1998) for earnings revisions.

Table 2.2: Subsample Returns of Univariate Stock Selection Strategies

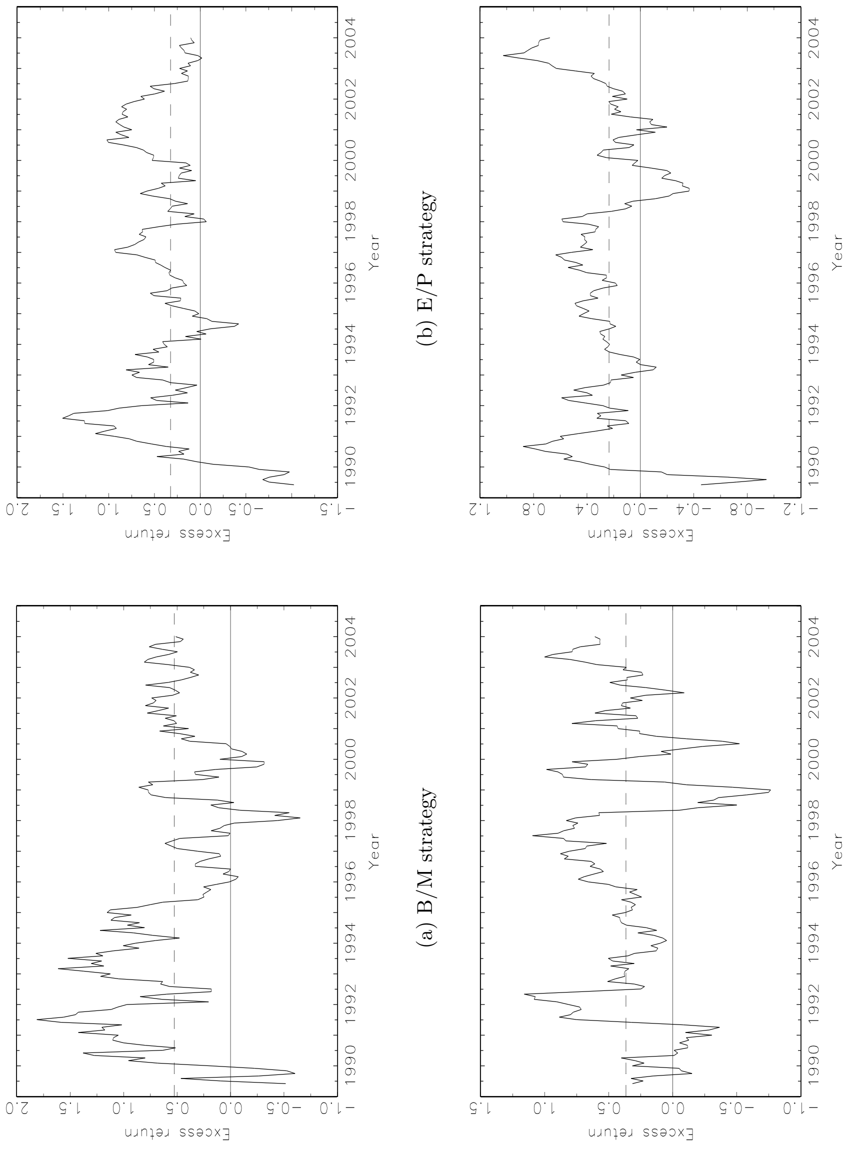
	1989.7-1994.6		1994.7-1999.6		1999.7-2004.6	
Factor	TMI	t(TMI)	TMI	t(TMI)	TMI	t(TMI)
B/M	0.84	2.66	0.36	1.71	0.43	2.59
E/P	0.44	1.81	0.33	2.10	0.44	3.82
6MR	0.26	1.43	0.38	2.28	0.43	2.16
ER FY1	0.30	2.12	0.27	2.78	0.29	2.73

Note: The table reports the average excess returns, expressed as percentage per month, and the corresponding t-statistics of the Top Minus EWI (TMI) portfolio over the indicated five-year subsample periods. See Table 2.1 for further details on the portfolio construction methodology.

It is worth noting that in case the performance of the top portfolio is measured relative to the bottom portfolio, the excess returns generated by the B/M, E/P and 6MR strategies are very close. In contrast, when the top portfolio is compared with the EWI, the B/M strategy markedly outperforms the other two strategies, by approximately 0.2% per month. Hence, for the E/P and 6MR strategies a substantial part of the profits from a zero-investment strategy based on the TMB portfolio would come from the sell side, while this is not the case for the B/M strategy. Because of short sales restrictions in emerging markets, implementing the TMB strategy as a zero-investment strategy may not be feasible in practice; see Bekaert and Urias (1996), Alexander (2000) and De Roon *et al.* (2001). The E/P and 6-month momentum strategies therefore are mostly relevant for avoiding or underweighting 'bad' stocks, see Achour *et al.* (1998).

To analyze the stability of the strategies' performance, Figure 2.1 plots 12-month moving average excess returns of the top portfolios relative to the EWI, while Table 2.2 shows the TMI excess returns for three five-year subsample periods. All strategies have positive excess returns in all three subperiods, and most excess returns are statistically significant. For the B/M strategy, the average excess return decreased considerably over time, from 0.84% over the period July 1989-June 1994 to 0.39% over the period July 1994-June 2004. In contrast, for the E/P and earnings revisions strategies the excess returns were quite stable across sub-periods, while the performance of the momentum strategy even improved notably over time. Finally, Figure 2.1 reveals that the B/M strategy was heavily affected by the Asia crisis in 1997 during which it underperformed relative to the EWI, while the momentum and earnings revisions strategies had negative excess returns following the Russia crisis in 1998. In contrast, the performance of the E/P strategy was affected to a much lesser extent during these periods.

Figure 2.1: Evolution of the monthly excess returns over time.



(a) B/M strategy

(b) E/P strategy

(c) 6MR strategy

(d) ER FY1 strategy

In the following sections we explore the different explanations for the apparent success of stock selection strategies in emerging markets as documented above, in terms of exposure to risk and in terms of behavioral biases.[4]

2.4 Risk-Based Explanations for the Profitability of Selection Strategies

If the selection strategies tended to select stocks with high sensitivity to overall movements in emerging equity markets, their excess returns would possibly only be a reward for this additional risk. To examine this possibility, we use the regression

$$R_{p,t} - R_{f,t} = \alpha + \beta_{\mathrm{EM}}(R_{\mathrm{EM},t} - R_{f,t}) + \varepsilon_t, \tag{2.1}$$

where $R_{p,t}$ is the monthly return on the equally weighted top or bottom portfolio of a particular strategy, $R_{\mathrm{M},t}$ is the corresponding benchmark return on the equally weighted index consisting of all emerging market stocks in our sample (EWI), and $R_{f,t}$ is the 1-month US T-bill rate.

The estimation results presented in Table 2.3 show that for all strategies the betas of the top and bottom portfolios are close to one. Only the B/M strategy appears to bear higher 'emerging market risk', as the betas of its top and bottom portfolios are significantly greater and less than one, respectively. We find significant deviations from one for the betas of portfolios of the other three strategies as well, but these are of the opposite sign as expected under a risk-based explanation. For the E/P and 6MR strategies, the betas of their bottom portfolios are significantly greater than one, while the beta of the top portfolio of the earnings revisions strategy is significantly less than one. The excess returns after correcting for emerging market risk, as measured by the intercept α in (2.1), remain statistically significant for all portfolios except the bottom portfolio of the B/M strategy. They in fact are very close to the raw excess returns reported in Table 2.1. In sum, the excess returns of the stock selection strategies do not appear to be compensation for excess emerging market risk.

Next, we investigate whether the return and risk properties of the selection strategies depend upon whether the emerging markets as a whole go up or down. This is motivated

[4] Figure 2.1 shows the 12-month moving average of monthly excess returns of the top portfolio relative to the equally weighted index for strategies based on book-to-market (B/M), earnings-to-price (E/P), past 6-month return (6MR), and past three-month earnings revisions for the current fiscal year (ER FY1). The dashed line indicates the mean monthly excess return.

Table 2.3: Emerging Market Risk of Top and Bottom Portfolios in Stock Selection Strategies

Strategy	Portfolio	α	$t(\alpha)$	β_{EM}	$t(\beta_{\mathrm{EM}}-1)$	$\overline{R}^2$
B/M	Top	0.53	3.64	1.07	3.05	0.92
	Bottom	−0.17	−1.52	0.96	−2.36	0.94
E/P	Top	0.34	3.04	1.00	0.12	0.95
	Bottom	−0.35	−3.22	1.07	4.02	0.95
6MR	Top	0.38	3.49	1.00	0.20	0.95
	Bottom	−0.36	−3.15	1.06	3.22	0.95
ER FY1	Top	0.25	3.16	0.98	−1.82	0.97
	Bottom	−0.34	−3.93	1.01	0.96	0.97

Note: The table presents coefficient estimates and t-statistics from the regression

$$R_{p,t} - R_{f,t} = \alpha + \beta_{\mathrm{EM}}(R_{\mathrm{EM},t} - R_{f,t}) + \varepsilon_t,$$

where $R_{p,t}$ is the monthly return of the equally weighted top or bottom portfolio, $R_{\mathrm{EM},t}$ is the EWI benchmark return, and $R_{f,t}$ is the 1-month US T-bill return. $t(\alpha)$ is the t-statistic of α, and $t(\beta_{\mathrm{EM}}-1)$ is the t-statistic of β_{EM} minus one. The regression $\overline{R}^2$ is adjusted for degrees of freedom.

by the finding of Ang *et al.* (2006) that the cross-section of US stock returns reflects a premium for downside risk; see also Estrada (2000, 2001) for a downside risk analysis in emerging markets. This is reflected in the model

$$\begin{aligned} R_{p,t} - R_{f,t} = {} & \alpha^- I_{\{R_{\mathrm{EM},t}-R_{f,t}<0\}} + \beta^-_{\mathrm{EM}}(R_{\mathrm{EM},t} - R_{f,t}) I_{\{R_{\mathrm{EM},t}-R_{f,t}<0\}} + \\ & \alpha^+ I_{\{R_{\mathrm{EM},t}-R_{f,t}\geq 0\}} + \beta^+_{\mathrm{EM}}(R_{\mathrm{EM},t} - R_{f,t}) I_{\{R_{\mathrm{EM},t}-R_{f,t}\geq 0\}} + \varepsilon_t, \end{aligned} \quad (2.2)$$

where the returns $R_{p,t}$, $R_{\mathrm{EM},t}$ and $R_{f,t}$ are defined as before, and $I_{\{A\}}$ denotes the indicator function for the event A, such that $I_{\{A\}} = 1$ if A occurs and 0 otherwise. Hence, β^+_{EM} and β^-_{EM} measure emerging market risk when the market goes up and down, respectively, while α^+ and α^- measure the corresponding excess returns. Table 2.4 presents the results from estimating (2.2) for the top and bottom portfolios of the four strategies. It is seen that the difference between upside and downside betas generally is very small, indicating that the strategies do not bear excessive downside (or upside) emerging market risk. This being said, we do find more substantial differences in excess returns in up and down markets. For example, α^- and α^+ for the top portfolio of the B/M strategy are equal to −0.05% and 0.65%, respectively, indicating that the outperformance of this strategy is attained completely in months when emerging markets as a whole go up. This contrasts quite sharply with results for the US in Lakonishok *et al.* (1994), who document that value

Table 2.4: Downside and Upside Emerging Market Risk of Top and Bottom Portfolios in Stock Selection Strategies

Strategy	Portfolio	α^-	$t(\alpha^-)$	β^-_{EM}	$t(\beta^-_{\text{EM}}-1)$	α^+	$t(\alpha^+)$	β^+_{EM}	$t(\beta^+_{\text{EM}}-1)$	$\overline{R}^2$
B/M	Top	−0.05	−0.15	0.99	−0.25	0.65	2.28	1.07	1.48	0.93
	Bottom	0.08	0.31	1.00	−0.05	−0.16	−0.73	0.95	-1.42	0.94
E/P	Top	0.18	0.68	0.98	−0.55	0.36	1.65	1.00	0.08	0.95
	Bottom	−0.60	−2.34	1.02	0.63	−0.48	−2.21	1.10	2.82	0.96
6MR	Top	0.53	2.06	1.02	0.62	0.32	1.54	1.01	0.21	0.95
	Bottom	−0.23	−0.87	1.07	1.65	−0.52	−2.34	1.08	2.24	0.95
ER FY1	Top	0.23	1.31	0.98	−0.68	0.40	2.47	0.95	-1.81	0.97
	Bottom	−0.34	−1.76	1.01	0.22	−0.47	−2.60	1.04	1.21	0.97

Note: The table presents coefficient estimates and t-statistics from the regression

$$R_{p,t} - R_{f,t} = \alpha^- I_{\{R_{\text{EM},t}-R_{f,t}<0\}} + \beta^-_{\text{EM}}(R_{\text{EM},t} - R_{f,t})I_{\{R_{\text{EM},t}-R_{f,t}<0\}} + \\ \alpha^+ I_{\{R_{\text{EM},t}-R_{f,t}\geq 0\}} + \beta^+_{\text{EM}}(R_{\text{EM},t} - R_{f,t})I_{\{R_{\text{EM},t}-R_{f,t}\geq 0\}} + \varepsilon_t,$$

where $R_{p,t}$ is the monthly return of the equally weighted top or bottom portfolio, $R_{\text{EM},t}$ is the EWI benchmark return, $R_{f,t}$ is the 1-month US T-bill return, and $I_{\{A\}}$ is the indicator function for the event A. $t(\alpha)$ is the t-statistic of α, and $t(\beta_{\text{EM}} - 1)$ is the t-statistic of β_{EM} minus one. The regression $\overline{R}^2$ is adjusted for degrees of freedom.

stocks outperform glamour stocks especially in negative market return years. For the E/P and earnings revisions strategies, we also find that excess returns of the top portfolio relative to the market are larger in positive market return months. Note, however, that for the E/P strategy the bottom portfolio also performs relatively better in upward markets, such that the outperformance of the top versus bottom portfolio is not sensitive to the direction of the overall market. The same holds for the momentum strategy, although in that case we find that $|\alpha^+| < |\alpha^-|$. In sum, the evidence in Table 2.4 indicates that the selection strategies do not expose investors to greater downside (or upside) emerging market risk.

Finally, we consider the possibility that the excess returns are rewards for exposures to global risk factors by using the four-factor regression model developed by Fama and French (1993, 1996) and Carhart (1997). This model explains portfolio returns in excess of the risk-free rate ($R_{p,t} - R_{f,t}$) by sensitivities to the excess return on the market portfolio ($R_{\text{M},t} - R_{f,t}$) and the difference between the returns on portfolios of stocks with high and low book-to-market values ($R_{\text{HML},t}$, HML=High-Minus-Low), on portfolios of stocks with small and large market capitalization ($R_{\text{SMB},t}$, SMB=Small-Minus-Big), and on portfolios of stocks with high and low momentum ($R_{\text{UMD},t}$, UMD=Up-Minus-Down). That is, the

Table 2.5: Four-Factor Regressions for Top and Bottom Portfolios in Stock Selection Strategies Using Global Factor Portfolios

Portfolio		α	$t(\alpha)$	β_{M}	$t(\beta_{\mathrm{M}}-1)$	β_{HML}	$t(\beta_{\mathrm{HML}})$	β_{SMB}	$t(\beta_{\mathrm{SMB}})$	β_{UMD}	$t(\beta_{\mathrm{UMD}})$	$\overline{R}^2$
B/M	Top	0.89	1.99	0.89	−0.97	0.19	1.22	0.49	3.83	−0.13	−1.48	0.36
	EWI	0.33	0.85	0.85	−1.50	0.13	0.99	0.42	3.82	−0.11	−1.37	0.40
	Bottom	0.11	0.29	0.86	−1.46	0.05	0.37	0.36	3.35	−0.06	−0.73	0.41
	TMI	0.54	3.53	0.03	0.77	0.06	1.06	0.06	1.51	−0.03	−0.85	−0.00
	TMB	0.78	3.39	0.02	0.34	0.14	1.82	0.13	1.96	−0.07	−1.59	0.02
E/P	Top	0.64	1.55	0.86	−1.29	0.18	1.27	0.45	3.87	−0.10	−1.22	0.38
	EWI	0.33	0.85	0.85	−1.50	0.13	0.99	0.42	3.82	−0.11	−1.37	0.40
	Bottom	0.03	0.06	0.91	−0.78	0.11	0.77	0.42	3.49	−0.14	−1.63	0.39
	TMI	0.31	2.66	0.01	0.25	0.05	1.15	0.02	0.73	0.01	0.31	−0.01
	TMB	0.68	3.58	−0.07	−1.35	0.07	1.01	0.02	0.45	0.04	1.03	0.02
6MR	Top	0.55	1.34	0.89	−1.04	0.18	1.28	0.44	3.82	0.01	0.14	0.37
	EWI	0.33	0.85	0.85	−1.50	0.13	0.99	0.42	3.82	−0.11	−1.37	0.40
	Bottom	0.14	0.34	0.88	−1.10	0.09	0.63	0.42	3.62	−0.23	−2.82	0.42
	TMI	0.22	2.13	0.04	1.47	0.05	1.30	0.02	0.64	0.11	5.58	0.13
	TMB	0.50	2.63	0.01	0.10	0.09	1.38	0.01	0.26	0.24	6.28	0.18
ER FY1	Top	0.33	0.84	0.91	−0.92	0.22	1.58	0.39	3.49	−0.08	−0.98	0.39
	EWI	0.13	0.32	0.90	−0.99	0.21	1.51	0.40	3.53	−0.09	−1.20	0.39
	Bottom	−0.19	−0.47	0.92	−0.75	0.16	1.13	0.40	3.46	−0.09	−1.16	0.40
	TMI	0.22	2.68	0.01	0.25	0.01	0.21	−0.01	−0.51	0.02	1.08	−0.01
	TMB	0.58	4.41	−0.02	−0.67	0.05	1.16	−0.01	−0.36	0.02	0.67	0.01

Note: The table presents coefficient estimates and t-statistics from the four-factor model

$$R_{p,t} - R_{f,t} = \alpha + \beta_{\mathrm{M}}(R_{\mathrm{M},t} - R_{f,t}) + \beta_{\mathrm{HML}} R_{\mathrm{HML},t} + \beta_{\mathrm{SMB}} R_{\mathrm{SMB},t} + \beta_{\mathrm{UMD}} R_{\mathrm{UMD},t} + \varepsilon_t,$$

where $R_{f,t}$ is the 1-month US T-bill return, $R_{\mathrm{M},t}$ is the US market return, and $R_{\mathrm{HML},t}$ (High-Minus-Low), $R_{\mathrm{SMB},t}$ (Small-Minus-Big), and $R_{\mathrm{UMD},t}$ Up-Minus-Down) are returns on US book-to-market, size and momentum factor portfolios. $R_{p,t}$ is the return on the top or bottom portfolio of a particular strategy, the corresponding sample of emerging market stocks (EWI), or the excess return on the top portfolio relative to the equally weighted index (TMI) or bottom portfolio (TMB). The risk-free interest rate is not included on the left-hand side in regressions involving the TMI and TMB excess returns. $t(.)$ is the t-statistic for the regression coefficients. $t(\beta_{\mathrm{M}}[-1])$ is the t-statistic of β_{M} minus one for the regressions with $R_{p,t}$ being the return on the top or bottom portfolio or the equally weighted index; $t(\beta_{\mathrm{M}}[-1])$ is the t-statistic of β_{M} for the regressions involving the TMI and TMB excess returns. The regression $\overline{R}^2$ is adjusted for degrees of freedom.

model is given by

$$R_{p,t} - R_{f,t} = \alpha + \beta_{\mathrm{M}}(R_{\mathrm{M},t} - R_{f,t}) + \beta_{\mathrm{HML}} R_{\mathrm{HML},t} + \beta_{\mathrm{SMB}} R_{\mathrm{SMB},t} + \beta_{\mathrm{UMD}} R_{\mathrm{UMD},t} + \varepsilon_t. \quad (2.3)$$

The four-factor model is estimated with $R_{p,t}$ being the returns on the top and bottom portfolios in the different strategies, the returns on the equally weighted index of the corresponding samples of emerging market stocks (EWI), and the TMI and TMB excess returns. For the TMI and TMB excess return regressions, the risk-free interest rate is not included on the left-hand side of (2.3). As proxies for the global risk factors, we use the

US returns data available on the website of Kenneth French.[5]

The estimation results in Table 2.5 show a number of interesting features. First, the estimates of β_{M} are significantly less than one for all top and bottom portfolios and indexes of emerging market stocks. This finding can probably be attributed to the fact that the emerging markets were not completely liberalized and integrated with global equity markets during our sample period, especially during the first part; see Bekaert and Harvey (2000a,b) and Edison and Warnock (2003), among others.[6]

Note that for all selection strategies the betas for the top portfolios are not significantly greater than the betas for the corresponding EWI and bottom portfolios. The resulting estimates of beta when the excess returns of the top portfolio relative to the EWI or bottom portfolio are used as dependent variable therefore are close to zero for all selection strategies considered. Second, the returns for the emerging market portfolios are positively correlated with the returns for small versus big stocks, as evidenced by the positive and statistically significant estimates of β_{SMB} for the top, index and bottom portfolios of all strategies. In contrast, the emerging market portfolios are virtually insensitive to the HML and UMD factors. The estimates of β_{HML} are never significant (at the two-sided 5% significance level) for the top, EWI and bottom portfolios, while the estimate of β_{UMD} is significant only for the bottom portfolio of the momentum strategy. Third, the sensitivities of the TMI and TMB excess returns are never significantly different from zero, except for the SMB and UMD factors in case of the B/M and momentum strategies, respectively. Fourth, and perhaps most important, the estimated intercepts α for the TMI and TMB excess returns are significantly different from zero for all strategies, and are very close to the raw excess returns reported in Table 2.1. The only exception appears to be the momentum strategy, for which a sizeable part of the excess return is accounted for by global momentum risk. Overall, however, global book-to-market, size and momentum risk factors cannot explain

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

[6] Van der Hart *et al.* (2003) investigate the effects of financial market liberalization on the performance of stock selection strategies. Estimating the four-factor model separately for returns on portfolios consisting of stocks from liberalized or non-liberalized countries only, no significant differences in factor loadings are found. Alternatively, estimating (2.3) with a five-year rolling sample indicated that liberalization did affect the risk properties of the selection strategies, in the sense that the estimates of β_{M} show a tendency to increase over time. The exposures to the other factors in the model, as well as the intercept α, also show substantial variation. However, there are no easily discernible patterns. For example, it is not the case that α gradually declines over time or becomes insignificant. A more thorough investigation of this issues, using models that allow the factor loadings to vary with conditioning variables, as in Ferson and Harvey (1999), or that allow for time-varying integration, as in Bekaert and Harvey (1995, 1997), is interesting for further research.

the outperformance of stock selection strategies in emerging markets. This corroborates the results obtained by Rouwenhorst (1999) using a two-factor model with only the HML factor included next to the market portfolio return.

We close this section by noting that whether the HML, SMB and UMD factors are indeed proxies for risk is subject to discussion and interpretation. Instead of being risk proxies, these factors could also capture certain market inefficiencies themselves. Consequently, finding an insignificant alpha in multi-factor models such as (2.3) does not necessarily imply that the sorting characteristic upon which the particular strategy is based is just proxying for risk. The alpha also goes to zero in case the inefficiencies captured by the factors are correlated with the inefficiencies captured by the strategy. In sum, it is difficult to distinguish between the risk-based and behavioural explanations using multi-factor models. Note that our results are not subject to this caveat, given that we find highly significant estimates of alpha in (2.3) for strategies considered; hence for our purposes, we can leave this discussion aside. However, we would like to remark that one could interpret the regression results more neutrally by speaking for example of developed market style returns instead of global risk factors. This would still give relevant information on whether the emerging markets strategies move in tandem with developed markets, or that they have their own dynamics.

2.5 Behavioral Explanations for the Profitability of Selection Strategies

In this section we explore whether behavioral explanations can account for the success of the stock selection strategies in emerging markets. We discuss value strategies and momentum and earnings revisions strategies separately. Although momentum and revisions strategies prove to have different features in some respect, they are treated together as the same characteristics are examined.

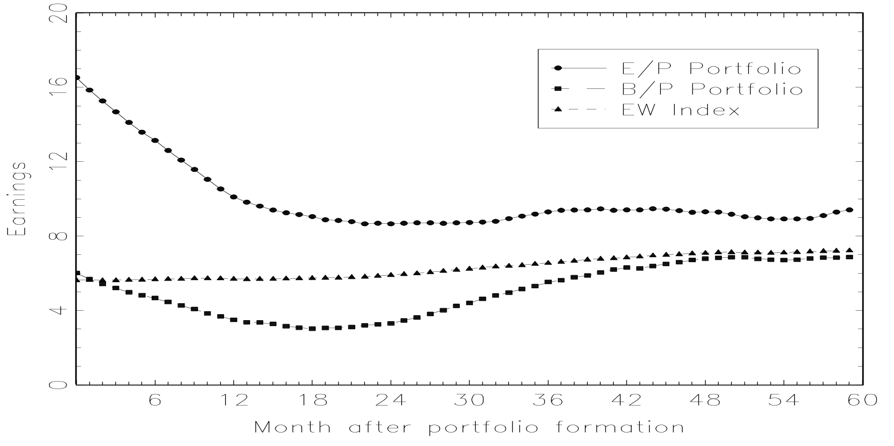
2.5.1 Value Strategies

Lakonishok *et al.* (1994) provide a behavioral explanation for the significant excess returns of value strategies. They argue that investors are excessively pessimistic (optimistic) about future earnings growth of value (growth) stocks, because they extrapolate past growth rates too far into the future. Using a sample of US stocks and various measures of growth, including earnings, Lakonishok *et al.* (1994) demonstrate that glamour stocks grow much faster than value stocks before portfolio formation. During the post-formation period, earnings growth rates continue to be lower for value stocks than for glamour stocks for the first two years, but this pattern is reversed over the following three years, resulting in approximately equal growth rates over the complete five-year period. Hence, actual post-formation earnings growth of value stocks relative to growth stocks turns out to be substantially higher than what they were during the pre-formation period or than what investors expected them to be according to multiples such as the E/P ratio. Buying and selling stocks with low and high expected earnings growth, respectively, then produces excess returns.

To examine whether this behavioral explanation may account for the excess returns of the value strategies in emerging markets, we examine how earnings of the stocks in the B/M and E/P top portfolios and in the complete sample of stocks develop after portfolio formation. Figure 2.2 shows the earnings yield, defined as the average earnings as a percentage of the initial invested capital, for the first five years after portfolio formation.

By construction, for the E/P portfolio the earnings yield is higher at formation date. Over the next 18 to 24 months, average earnings of the E/P top portfolio fall, whereas earnings of the average stock in the sample increase gradually. However, the earnings level of the value portfolio remains above that of the average stock in the sample. More importantly, after approximately 24 months earnings growth rates are about equal, such that the difference in earnings levels remains fairly constant thereafter. For the B/M strategy, we find similar results. Although the difference in initial earnings yield is much smaller, we do find negative growth during the first 18 months after portfolio formation. This is followed by above average growth in the subsequent period, such that after three and a half years the stocks in the B/M portfolio again have higher earnings levels than the average stock. The improvement in earnings growth may lead to valuation ratios for the value portfolios that are more in line with the market average. This is indeed the case. The average fall in earnings is more than compensated for by a rise in the stock price, leading to an improvement in the price-to-earnings ratio. Concluding, the differences in valuation ratios between value and growth stocks are not justified by subsequent earnings developments. After two years, the earnings growth rate of value stocks is equal to the growth rate of the average stock. Hence, our findings for value strategies in emerging markets correspond with the evidence for this behavioral explanation in Lakonishok *et al.* (1994).

Figure 2.2: Evolution of earnings after portfolio formation.



Earnings, expressed as percentage of initial investment, after portfolio formation for the top portfolio of the B/M and E/P strategies and the equally weighted index of all stocks in the sample.

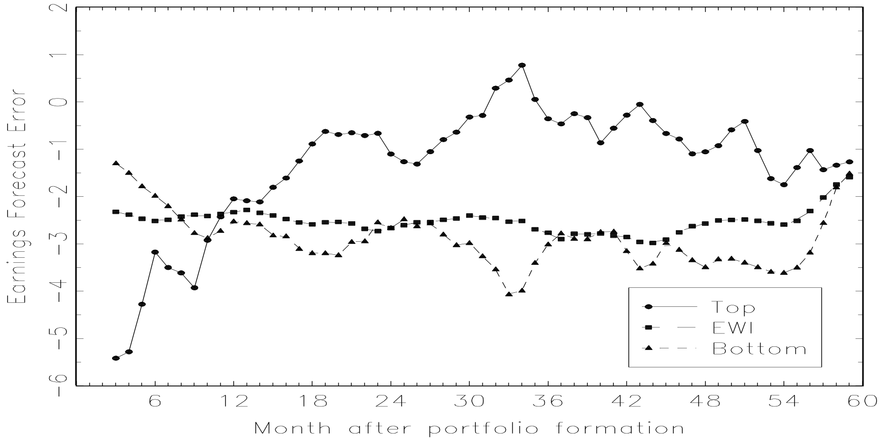
More recently, Doukas *et al.* (2002) argue that the results of Lakonishok *et al.* (1994) do not imply that investors actually underestimate the growth prospects for value stocks. To the contrary, using analysts' earnings forecasts for the next three years, they find that analysts are on average more (over)optimistic for value stocks than for growth stocks. In addition, they find that value stocks have larger negative revisions of earnings estimates than growth stocks. Based on this evidence they conclude that the superior return performance of value stocks cannot be explained by excessive pessimism about future earnings growth.

In our view, the evidence from Doukas *et al.* (2002) is not necessarily at odds with the evidence from Lakonishok *et al.* (1994). It may be argued that long-term developments are most important for equity valuation and that, hence, the three year post-portfolio formation period considered by Doukas *et al.* (2002) is too short. Analysts might overestimate the short-run earnings developments of value stocks, but at the same time underestimate the potential for earnings growth to revert to the mean at longer horizons. The improvement in the earnings growth rate and the strong recovery in P/E ratio for value stocks discussed above indicate that their long-term earnings prospects improve sharply after just a few years. We put this hypothesis to the test using analysts' earnings forecast errors, earnings revisions and earnings growth forecasts, during the five years after portfolio formation.

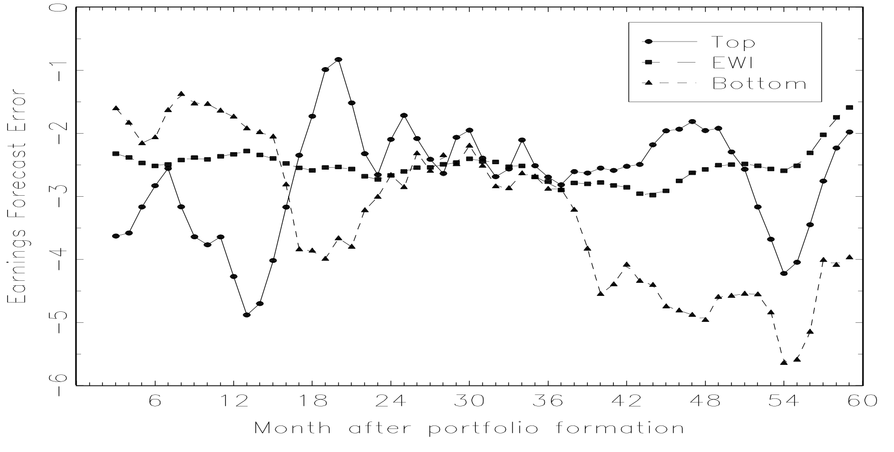
For an individual stock, the earnings forecast error in month t, denoted FE_t, is defined only once a year, namely eight months prior to fiscal year end. In that case, FE_t is equal to the difference between the actual earnings in the current fiscal year ($\mathrm{FY0}_{t+8}$) and the consensus analysts' forecast issued in month t ($\mathrm{FY1}_t$), expressed as percentage of the stock price at the time of the forecast (P_t); that is $\mathrm{FE}_t = 100 \times (\mathrm{FY0}_{t+8}–\mathrm{FY1}_t)/P_t$. We define the consensus forecast as the median forecast reported by IBES. The eight month horizon is adopted from Easterwood and Nutt (1999) and Doukas *et al.* (2002) and is chosen to ensure that the previous year's annual report was available to analysts at the time they issued their forecasts. We also follow Easterwood and Nutt (1999) in eliminating observations for which the forecast error is greater than 100 in absolute value. Figure 2.3 plots the three-month moving average mean earnings forecast errors for the top and bottom portfolios of the value strategies. Note that these graphs truly concerns the post-formation period, in the sense that the leftmost point corresponds with the error for analysts' earnings forecasts issued in the first three months following portfolio formation. For the B/M strategy, we observe that immediately following portfolio formation, earnings forecast errors for the top and bottom portfolios are substantially below and above average, respectively.[7] In fact, this continues to be the case until 18 months after portfolio formation. Hence, analysts indeed appear to be more optimistic about the earnings prospects of value than growth stocks, as reported in Doukas *et al.* (2002). In the remaining post-formation period, however, the pattern is reversed. While the earnings forecast error for growth stocks remains close to the average, it becomes substantially larger than average for value stocks, implying that analysts are relatively pessimistic about value stocks' earnings in the longer term. For the E/P strategy, we observe a similar reversal in earnings forecast errors, although in this case the error for growth stocks dips below average around 18 months after portfolio formation, while for value stocks it remains at par. The implication is however the same, namely that

[7]Notice that for the EWI, the forecast error is negative for each month in the post-formation period. This demonstrates the notion that analysts are (too) optimistic about future earnings for the average stock in the sample. In addition to systematic positive bias in analysts' earnings forecasts (see Easterwood and Nutt (1999) for recent evidence), the extent of this bias has also been found to be predictable from observable firm characteristics, see Abarbanell and Bernard (1992), among others. Analysts' forecasts are therefore usually dismissed as being irrational or inaccurate. A recent study by Lim (2001) shows that positively and predictably biased forecasts may in fact be optimal if the incentive structure of analysts is taken into account. If analysts balance forecast accuracy and improved access to management information, such biased forecasts are rational. Furthermore, Hong and Kubik (2003) document that optimistic analysts promoting stocks are more likely to experience favorable job separations. Hence, career concerns may also lead to upward biases in analysts' forecasts.

Figure 2.3: Evolution of earnings forecast errors after portfolio formation.



(a) B/M strategy



(b) E/P strategy

The figure shows the three-month moving average of earnings forecast errors after portfolio formation for top and bottom portfolios of the (a) B/M strategy and (b) E/P strategy and for the relevant equally weighted index.

analysts are relatively optimistic (pessimistic) about growth (value) stocks.

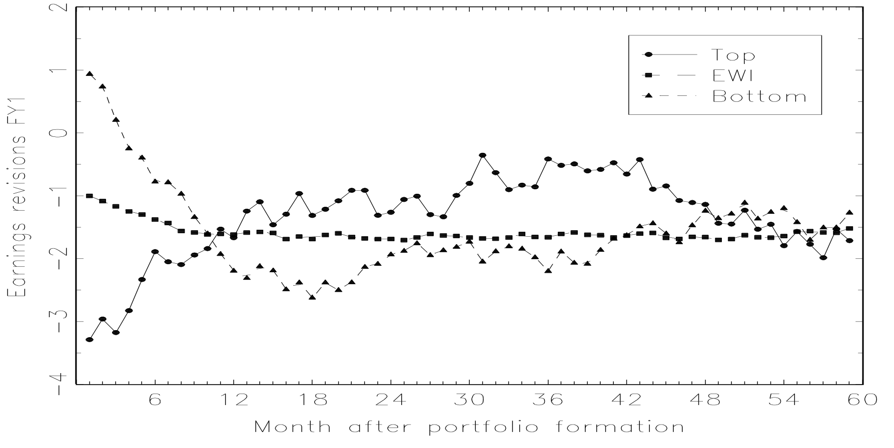
The above analysis is corroborated by the development of analysts' earnings revisions after portfolio formation, as shown in Figure 2.4. Analysts' revisions are more negative for stocks in the B/M and E/P top portfolios until 10 and 15 months after portfolio formation, respectively, again indicating that they were too optimistic about the earnings prospects for value stocks.[8] For the B/M strategy, earnings revisions for these stocks rise (substantially) above average between one and four years after portfolio formation. During roughly the same period, earnings revisions for growth stocks fall below average. For the E/P strategy, the differences are smaller, but the earnings revisions for the top portfolio do remain above the revisions for the bottom portfolio during the period between 15 and 48 months after portfolio formation.

Finally, the improvement in earnings prospects is also confirmed by looking at the developments of the earnings growth expected by analysts after portfolio formation for each of the portfolios. Figure 2.5 depicts the difference between the consensus earnings forecast for the next fiscal year (FY2) versus the most recent actual earnings (FY0). Like in the earnings figures in Figure 2.2, the expected earnings change is normalized by calculating this number as a percentage of the initially invested capital at portfolio formation. For the E/P strategy, the expected earnings change is much lower for the top portfolio, as to be expected. However, it reverts to the mean quite rapidly. The expected earnings change for the top portfolio exceeds those for the equally weighted index and for the bottom portfolio within two and three years, respectively. For the B/M strategy, the starting point differs as the expected earnings change at portfolio formation is already slightly higher for the top portfolio. What is the same, however, is that the expected earnings change increases more strongly for the top portfolio. The growth characteristics of expensive stocks based on E/P and B/M appear to be rather short-lived.

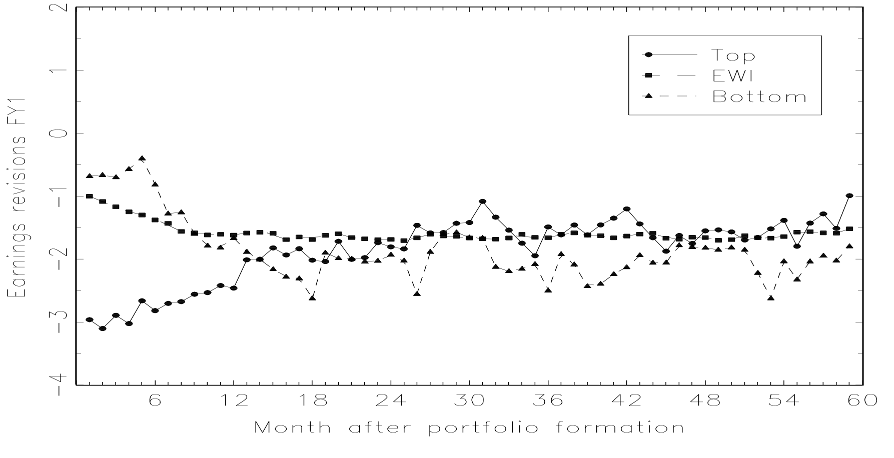
Concluding, just like Lakonishok *et al.* (1994), we find that the relative cheapness of value stocks is not justified by subsequent earnings developments. For value stocks, earnings as percentage of the initial investment remain well above the averages for the complete sample and for growth stocks, while both the actual earnings growth and its forecast revert to the mean quite rapidly. Like Doukas *et al.* (2002), we do find that analysts appear too optimistic about the earnings prospects for value stocks in the short term. We also find that this reverses in the longer term as value stocks have above average earnings forecast errors and earnings revisions after about one year after portfolio formation. This

[8]Notice that for the EWI, forecast revisions are negative for each month in the post-formation period, confirming that analysts are (too) optimistic about future earnings for the average stock in the sample.

Figure 2.4: Evolution of earnings revisions after portfolio formation.



(a) B/M strategy

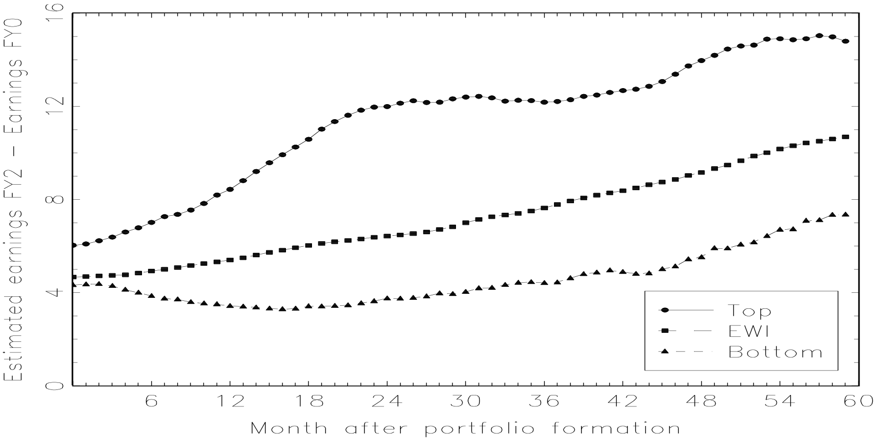


(b) E/P strategy

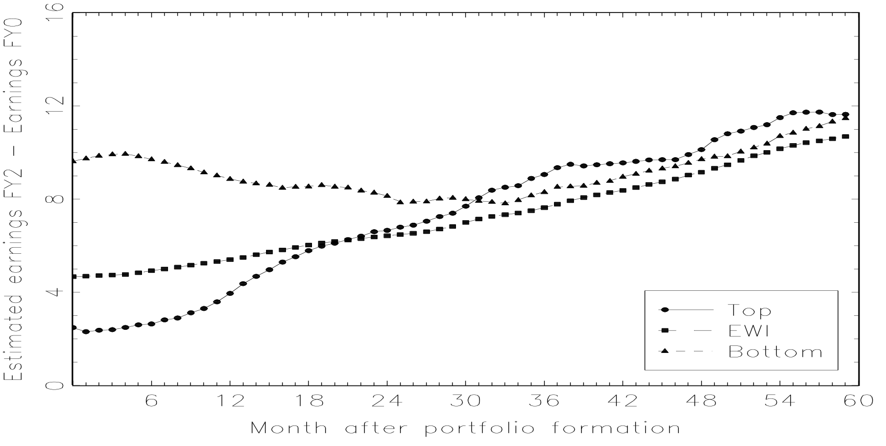
The figure shows the monthly earnings revisions after portfolio formation for top and bottom portfolios of the (a) B/M strategy and (b) E/P strategy and for the relevant equally weighted index, expressed as percentage.

indicates that analysts are too pessimistic about the long term growth perspectives

Figure 2.5: Evolution of estimated earnings minus actual earnings after portfolio formation.



(a) B/M strategy



(b) E/P strategy

The figure shows the difference between estimated earnings for the next fiscal year and the most recent actual earnings for top and bottom portfolios of the (a) B/M strategy and (b) E/P strategy and for the relevant equally weighted index, expressed as percentage of initial investment.

for value stocks.

2.5.2 Momentum and Earnings Revisions Strategies

A number of studies have tested behavioral explanations for momentum strategies in developed markets (see amongst others Chan *et al.* (1996), Jegadeesh and Titman (2001), Lee and Swaminthan (2000), Hong *et al.* (2000), Nagel (2002), and Cooper *et al.* (2004)). Underreaction and overreaction effects are part of these explanations. In this section we investigate whether these effects are present in the emerging markets momentum strategy as well, by examining three variables that might serve as indicators for under- or overreaction: analysts' earnings revisions, analysts' forecast errors and cumulative excess returns after portfolio formation.

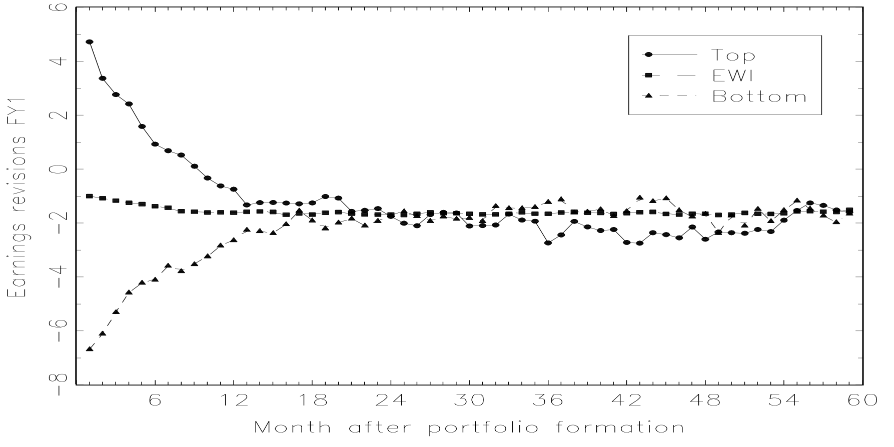
Chan *et al.* (1996) put forward a behavioral explanation for the profitability of momentum and earnings revisions strategies, based on the idea that financial markets respond only gradually to new information, to earnings-related news in particular. Using a sample of US stocks, they find empirical evidence that stocks with high price momentum or high past earnings revisions have higher returns around earnings announcements, higher earnings revisions and higher earnings surprises for some time after portfolio formation. Momentum and earnings revisions strategies thus are successful because they exploit the initial underreaction of investors to the information in past returns and past earnings revisions.

Figure 2.6 shows how earnings revisions for the top and bottom portfolios in the momentum and the earnings revisions strategies and for the complete sample of emerging market stocks develop during the five years after portfolio formation. For both strategies, earnings revisions of the top (bottom) portfolio remain higher (lower) than earnings revisions for the complete sample until 18 months after portfolio formation.[9] This agrees with the behavioral explanation of Chan *et al.* (1996) that the market does not incorporate news in earnings revisions promptly.

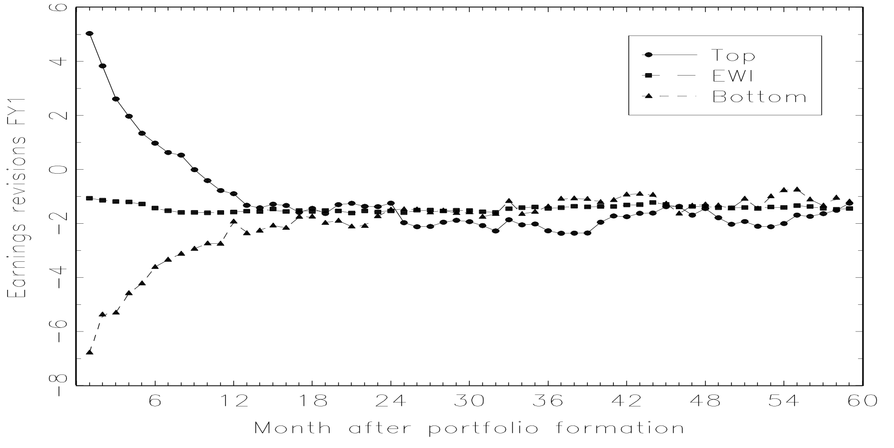
Alternative interpretations of the observed pattern in earnings revisions are possible as well. For example, one can argue that analysts are slow in adjusting their estimates and that earnings revisions therefore are not a good proxy for market surprises. We therefore examine analysts' forecast errors, defined as before, in Figure 2.7. The patterns in this variable confirm the underreaction hypothesis: despite higher past returns and earnings revisions, stocks in the top portfolios of the momentum and revisions strategies continue to show above average, and in fact positive forecast errors until more than a year after portfolio formation.

[9] The difference in earnings revisions is significant for each of the first 12 months after portfolio formation, for both the earnings revisions strategy and the momentum strategy.

Figure 2.6: Evolution of earnings revisions after portfolio formation.



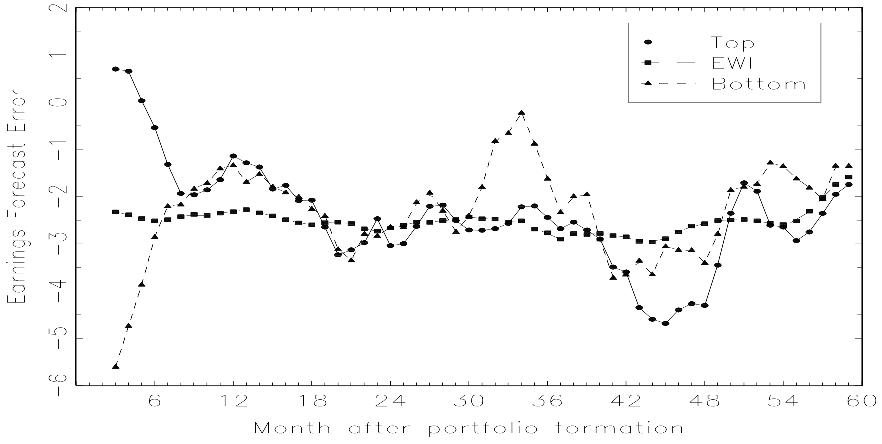
(a) 6MR strategy



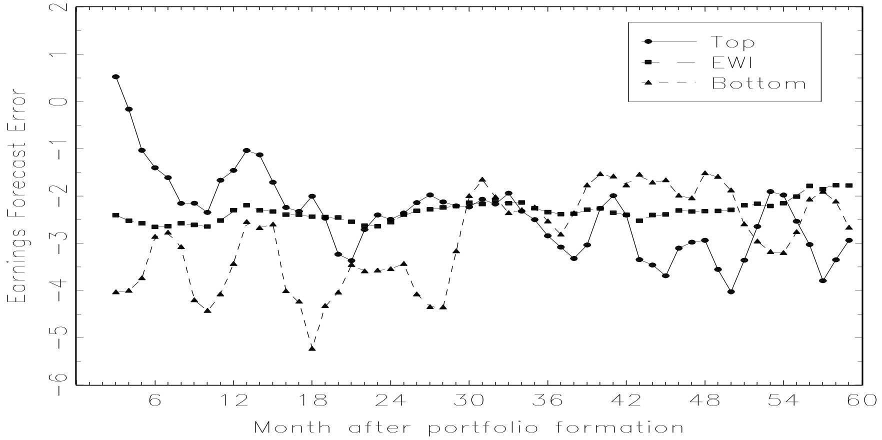
(b) ER FY1 strategy

The figure shows the monthly earnings revisions after portfolio formation for top and bottom portfolios of the (a) 6MR strategy and (b) ER FY1 strategy and for the relevant equally weighted index, expressed as percentage.

Figure 2.7: Evolution of earnings forecast errors after portfolio formation.



(a) 6MR strategy



(b) ER FY1 strategy

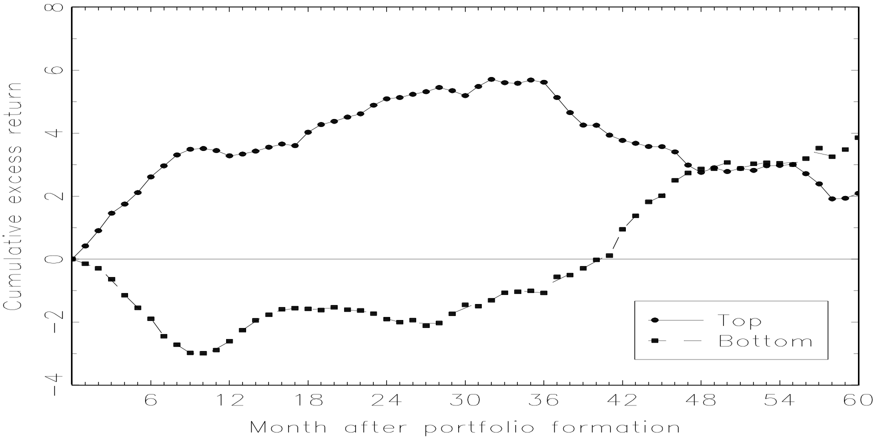
Three-month moving average of earnings forecast errors after portfolio formation for top and bottom portfolios of the (a) 6MR strategy and (b) ER FY1 strategy and for the relevant equally weighted index.

Behavioral models, such as the ones in Barberis *et al.* (1998), Daniel *et al.* (1998) and Hong and Stein (1999), imply that excess returns of momentum portfolios should become zero or negative after the initial holding period. These theoretical models do not offer any guidance, however, regarding the length of the post-holding period over which these return reversals should occur. To further support their underreaction hypothesis, Chan *et al.* (1996) show that there is no evidence of a return reversal during the first three years after portfolio formation. In contrast, Jegadeesh and Titman (2001), among others, find that a return reversal does occur when extending the post-portfolio formation period to five years. For emerging markets, Figure 2.8 shows the cumulative excess returns during the first five years after portfolio formation, both for the momentum and the earnings revisions strategies.

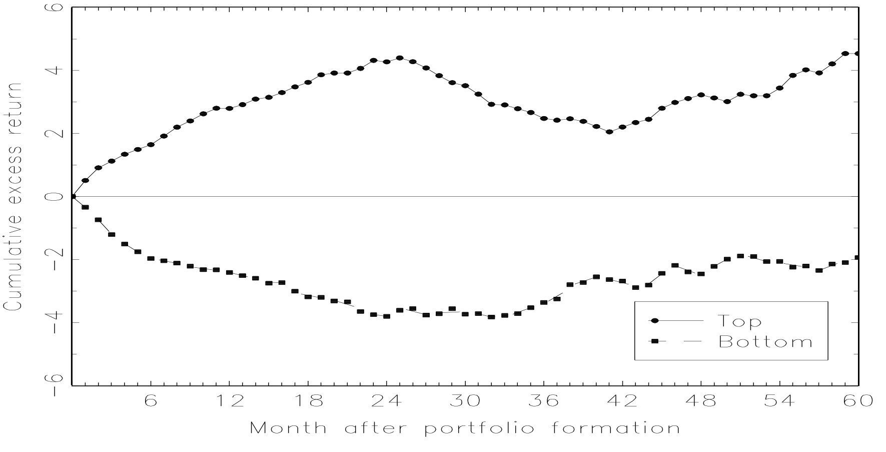
For the momentum strategy, we observe a return reversal for the top portfolio after approximately three years. Its magnitude is, however, not large enough to completely annihilate the excess returns within the five year period considered. However, the excess return on the bottom portfolio reverses after one year already, such that after three and a half years the bottom portfolio outperforms the equally weighted benchmark and after four years its cumulative performance is comparable to the top portfolio. Hence, although we do not observe a return reversal as strong as documented by Nagel (2002) for momentum strategies in the UK, we do find that four years after portfolio formation past winners and losers can no longer be distinguished. The results for the revisions strategy are rather different. High earnings revisions stocks continue to outperform the market average after the six-month holding period, and a return reversal does not occur during the first five years after portfolio formation.

Concluding, the momentum strategy seems to have elements of both overreaction and underreaction effects, as the analysts' earnings revisions and forecast errors suggest an underreaction, while the five-year post-formation returns suggest an overreaction. A possible solution may be found in Lee and Swaminthan (2000), who investigate the interaction between momentum and turnover, and find different behavior for high turnover momentum stocks versus low turnover momentum stocks in the US. Nagel (2002) finds similar results for the UK and relates them to implicit value effects. An interesting topic for further research would be to test these results for emerging markets. For the earnings revisions strategy, both the earnings revisions by analysts after portfolio formation as well as the five-year excess returns point towards an initial underreaction. This shows that the revisions strategy has different characteristics than the momentum strategy.

Figure 2.8: Evolution of cumulative excess returns after portfolio formation.



(a) 6MR strategy



(b) ER FY1 strategy

The figure shows the cumulative excess returns on top and bottom portfolios of the (a) 6MR strategy and (b) ER FY1 strategy over the relevant equally weighted index during 60 months after portfolio formation.

2.6 Conclusions

Stock selection strategies based on value, momentum and earning revisions prove to generate significant excess returns in emerging markets. In this paper, we investigate different explanations for the success of these strategies, using stocks included in the IFC Investable Composite Index over the period December 1988 - June 2004.

We find little if any evidence for risk-based explanations. The excess returns remain significant after correcting for (potentially different upside and downside) emerging market risk, as well as after correcting for global market risk, value, size and momentum factors. Only the performance of the momentum strategy can partly be attributed to a global momentum risk factor.

We do find that the emerging markets results are consistent with the evidence from developed markets concerning behavioral explanations. For value stocks, our findings are in accordance with an overreaction explanation, as the actual and expected earnings growth of these stocks reverts to the mean in a few years and the earnings as percentage of initial investment remains well above average. The overreaction explanation seems to be contradicted by the finding that value stocks have below average (and substantially negative) earnings forecast errors and earnings revisions up to a year after portfolio formation. As a possible solution we suggest that the most important behavioral bias could be related to underestimation of long-term growth rates for value stocks. This conjecture is supported by the observation that earnings forecast errors and earnings revisions for these stocks become above average for longer post-formation horizons and by the finding that estimated earnings growth becomes above average within two years after portfolio formation. For the momentum strategy, both underreaction and overreaction effects appear to be at work. High upward earnings revisions by analysts after portfolio formation suggest an initial underreaction. However, in the five-year post-formation period, we also observe a strong return reversal, indicating an overreaction effect. In contrast, the evidence does support an underreaction explanation for the earnings revisions strategy. Stocks with high past earnings revisions continue to have high upward earnings revisions for twelve months after portfolio formation, while there is no return reversal until at least five years after portfolio formation. As the earnings revisions strategy seems to have no or limited overreaction effects, this sets it apart from momentum strategies.

Still, our results do not prove that the risk-based explanation is incorrect. The analysis shows that the excess returns are not simply due to higher beta, more exposure to global factors for value, size and momentum or higher downside risk, but it still might be the case that other, yet unidentified risk measures would be able to explain the results. Also, although the data is consistent with behavioral explanations, it does not prove it. Other explanations might be feasible as well. It therefore remains difficult to reach a clear verdict on the competing explanations. However, our conclusion is that the circumstantial evidence in the current literature and in our study points towards the behavioral explanation as the most probable one. Investors in emerging markets are more likely to get a better risk/return reward by incorporating value, momentum and revisions strategies.

Such further research could involve using a broader set of risk indicators to test whether the strategies lead to portfolios bearing more risk in dimensions not measured by the value, size and momentum factors. A specific possibility would be to account for macroeconomic risk explicitly, see Chordia and Shivakumar (2002) and Griffin *et al.* (2003). However, one should be aware that it might be difficult to separate the risk-based and behavioral explanation, as proposed risk factors might also be correlated to the inefficiencies themselves instead of just being a proxy to risk. Preferably, risk factors have a direct link to the likelihood and magnitude of undesirable situations for investors. At the same time, a broader set of indicators that would correlate with investor sentiment could be tested to provide further evidence for behavioral explanations. Another source of data that could provide interesting indicators of sentiment concerns company policies. Overoptimism of investors might be interrelated with overoptimism of management, which could be tested by looking for example at investment policy of the company and subsequent return on these investments. Finally, the most direct way to test behavioral explanations is to study the actual behavior of market participants, like in Odean (1998) for example. This would give important complimentary evidence.

Chapter 3

The Inefficient Use of Macroeconomic Information in Analysts' Earnings Forecasts in Emerging Markets*

3.1 Introduction

This study provides evidence on the role of macroeconomic information in analysts' earnings forecasts in emerging markets. Specifically we investigate whether analysts incorporate forecasts of key macroeconomic variables such as output, inflation and political stability into their firm-level earnings forecasts in an efficient way. Finding that this is not the case, we examine two competing explanations: either whether analysts actually ignore valuable information for corporate earnings provided by these macroeconomic forecasts, or whether they include irrelevant information.

Security analysts are potential intermediaries in the process of information disclosure. Their role as producers of firm-specific information has been widely investigated for developed markets, see Brown (1978) and O'Brien (1988), among many others. In emerging markets, the availability of firm-specific information is hampered for a variety of reasons, such as the limited set of regulations on information disclosure or the lack of enforcement thereof, see Morck *et al.* (2000), Bae *et al.* (2006) and Bae *et al.* (in press), among others. In that light it is perhaps not surprising that Chan and Hameed (2006) find that, through their earnings forecasts for emerging market stocks, analysts actually produce market-wide

*This chapter is based on the ERIM working paper by De Zwart and van Dijk (2008). We thank Kees Isendoorn for excellent research assistance. We are grateful to Mathijs van Dijk, Ingolf Dittmann, Allaudeen Hameed, Jaap van der Hart, Angelien Kemna, Randall Morck and Marno Verbeek for helpful suggestions. We would also like to thank seminar participants at the Erasmus University.

information instead of revealing firm-specific news. This naturally leads to the question whether analysts base their earnings forecasts on firm-specific information only, or whether they also make use of macroeconomic information. The use of the latter type of information can be justified if the difficulties associated with the collection of firm-specific information also apply to security analysts. If this is the case, a natural follow-up question would be if analysts use the publicly available macroeconomic information in the best possible way.

In this paper we examine the role of macroeconomic information in analysts earnings forecasts as follows. We start with investigating whether earnings forecast errors are uncorrelated with publicly available information in forecasts for important macroeconomic variables. This should be the case if analysts incorporate such information in their earnings forecasts efficiently. While a large number of empirical studies document that analysts' earnings forecasts are biased, relatively little attention has been paid to the role of macroeconomic information in explaining this bias. Notable exception is O'Brien (1994), who finds that US macroeconomic news explains a significant part of the variation in US corporate earnings and that macroeconomic news that arrives after the earnings forecast issuance is reflected in analysts' forecast errors. More recently Basu *et al.* (2006) find that analysts do not fully include inflation survey forecasts in their earnings forecasts for US stocks. Our study is the first to comprehensively investigate the relationship between earnings forecasts and macroeconomic forecasts in emerging markets. Furthermore, in addition to inflation forecasts as in Basu *et al.* (2006), we include forecasts of real output growth and the outlook on political stability, in order to capture a more comprehensive assessment of the overall macroeconomic situation in a given emerging market. In our analysis we control for well-documented "micro"-information determinants of analysts' earnings forecasts, including market capitalization (Lang and Lundholm, 1996; Lim, 2001), analyst coverage (Lim, 2001; Chan and Hameed, 2006) and, in particular, prior-year earnings (Abarbanell and Bernard, 1992; Easterwood and Nutt, 1999).

Our analysis provides convincing evidence that analysts do not make efficient use of macroeconomic forecasts for their earnings forecasts of emerging market companies. Controlling for firm characteristics, we find that the earnings forecast error is significantly related to forecasts of output growth and political stability, which are available at the time when the earnings forecast was made. Earnings forecast errors are not related to inflation forecasts, suggesting that the information in this variable is correctly incorporated in the earnings forecasts.

The finding that analysts do not exploit macroeconomic forecasts in an optimal way can arise for two different reasons: Either analysts ignore valuable macroeconomic information or they take irrelevant information into account when producing their earnings forecasts. In the second step of our analysis, we distinguish between these competing explanations by examining how actual earnings growth and earnings forecasts are related to the macroeconomic forecasts. We find that the political stability forecasts do contain useful information for realized earnings, but this is ignored completely by the analysts. Although we find a positive association between actual corporate earnings growth and actual output growth, there is no such relation between earnings growth and output growth forecasts. Hence, the quality of these forecasts does not seem sufficient to provide a useful source of information for firm-level earnings. Analysts, however, overreact and adjust their earnings forecasts in the opposite direction.

In addition, we document the importance of the information environment in emerging markets by distinguishing between companies with high and low transparency. This is done according to two transparency measures: the availability of an ADR listing, following Lang *et al.* (2003) and Baker *et al.* (2002), and the time that it takes a company to release its annual report, where stocks releasing their annual report within three months after the end of the prior fiscal year are labeled as 'fast reporting' and all other stocks as 'slow reporting'. Our results clearly demonstrate that analysts handle macroeconomic information in a better way for more transparent firms. This confirms the finding of Lim (2001) for US stocks that analysts' earnings forecast bias is related to the information uncertainty environment, and in fact expands it by documenting this effect for macroeconomic information.

Our findings contribute to earlier research on emerging markets in several ways. First, concerning the role of analysts in the information production process in emerging markets, our study provides a possible explanation for Chan and Hameed's (2006) finding that analysts produce market-wide information by showing that analysts incorporate both inflation and output forecasts in their earnings forecasts. Our study also shows that it is in fact rational for analysts to include such market-wide information in their forecasts as we find a direct relationship between earnings growth and macroeconomic developments in emerging markets. Second, regardless of the role of macroeconomic information, our results show that firm transparency is still key for analysts to come up with accurate earnings forecasts. This should stimulate policy-makers in emerging markets to further improve their regulations concerning information disclosure, and should also provide an incentive for companies to increase their transparency. Third, our findings provide evidence on the importance of political stability in emerging markets. Prior studies by Claessens *et al.* (in press), among others, uncover a negative relationship between political connections and output growth for one specific country. Our study demonstrates for a large cross-section of emerging markets that countries benefit from increased political stability in terms of higher earnings growth.

The remainder of the paper is organized as follows. In Section 3.2 we lay out our research methodology in detail and describe the data set. In Section 3.3 we report our main empirical findings. In Section 3.4 we provide additional results that demonstrate the robustness of our results. Finally, we conclude in Section 3.5.

3.2 Methodology and Data

We investigate the role of macroeconomic information in analysts' earnings forecasts for individual companies in emerging markets. In particular, we examine whether analysts make efficient use of forecasts concerning key macroeconomic variables when producing their earnings forecasts. In this section, we first describe and motivate our methodology to address this issue. In the remainder of this section, we discuss the variables used in our analysis.

3.2.1 Methodology

Our analysis is focused on the analysts' earnings forecast error FE_{it}, which we define as a percentage of the stock price at the time the forecast is made, following Abarbanell and Bernard (1992), Easterwood and Nutt (1999) and Lim (2001), among others, that is

$$FE_{it} = \frac{E_{it} - \widehat{E}_{it}}{P_{it}}, \tag{3.1}$$

where E_{it} is the realized earnings per share in local currency for firm i in fiscal year t, $\widehat{E}_{it}$ is the consensus analysts' earnings forecast made six months prior to the end of the year,[1] and P_{it} is the local stock price at the time the forecast is made. The consensus earnings forecast is defined as the median forecast reported for a specific company in a given month.

If analysts efficiently incorporate macroeconomic information into their earnings forecasts, the forecast error FE_{it} should be uncorrelated with any such information available to the analysts at the time their forecasts are made. This macroeconomic information may, for example, come in the form of the actual values of variables such as output growth and inflation in the previous fiscal year $t-1$. However, it is quite likely that analysts

[1]The reasons for choosing a six month forecast horizon are discussed in Section 3.2.2.

would attempt to incorporate more timely information, for example by considering forecasts of these same variables for the current fiscal year t, for which they are supposed to produce earnings forecasts. Hence, in the analysis below we specifically consider the question whether analysts efficiently handle information that is available in forecasts for macroeconomic variables for the current year.

In examining this issue, we account for the fact that various company characteristics may explain part of the systematic variation in earnings forecast errors, as documented by Abarbanell and Bernard (1992), Lang and Lundholm (1996), Easterwood and Nutt (1999), Lim (2001), and Chan and Hameed (2006), among others. As we use the consensus forecast we ignore analyst characteristics such as age and experience, which also have been shown to be correlated with earnings forecast errors, see Jacob *et al.* (1995) and Mikhail *et al.* (2003), for example. Hence, we estimate the following regression model:

$$FE_{it} = \alpha + \sum_j \beta_j \widehat{M}_{jt} + \sum_j \gamma_j S_{jt} + \varepsilon_{it}, \tag{3.2}$$

where $\widehat{M}_{jt}$ is the forecast of the j-th macroeconomic variable for fiscal year t and S_{jt} is the j-th stock specific variable. The particular variables we use for the macroeconomic forecasts and company characteristics are discussed in detail below. Here it is useful to note that we make sure that both $\widehat{M}_{jt}$ and S_{jt} are available to the analysts six months prior to the end of fiscal year t, when the earnings forecasts are made. Efficient use of the information in the macroeconomic forecasts by security analysts for their earnings forecasts is equivalent to the null hypothesis that the coefficients β_j in (3.2) are equal to zero.

It is important to note that finding a relationship between the earnings forecast errors and macroeconomic forecasts in (3.2) does not necessarily imply that analysts actually ignore valuable macroeconomic information. Systematic forecast bias may also occur because analysts incorporate irrelevant macroeconomic information into their earnings forecasts. We attempt to distinguish between these competing explanations by examining how the actual earnings growth as well as the earnings forecasts are related to the macroeconomic forecasts. Specifically, we estimate the following regressions:

$$\frac{E_{it} - E_{i,t-1}}{P_{it}} = \alpha + \sum_j \beta_j \widehat{M}_{jt} + \sum_j \gamma_j S_{jt} + \varepsilon_{it}, \tag{3.3}$$

$$\frac{\widehat{E}_{it} - E_{i,t-1}}{P_{it}} = \alpha + \sum_j \beta_j \widehat{M}_{jt} + \sum_j \gamma_j S_{jt} + \varepsilon_{it}. \tag{3.4}$$

Obviously the models in (3.3) and (3.4) are identical to (3.2), except that the actual change in earnings and the earnings growth forecast, respectively, replace the earnings forecast error as dependent variable.[2] The model in (3.3) measures whether the available macroeconomic forecasts are relevant for actual earnings growth and, hence, whether analysts should take this information into account in their earnings forecasts. The model in (3.4) assesses to what extent analysts do indeed incorporate the macroeconomic forecasts into their earnings forecasts. If the coefficients β_j are equal to zero in (3.3) but differ from zero in (3.4), the analysts ignore valuable information in the macroeconomic forecasts. In the opposite case, the analysts do take the macroeconomic forecasts into account, but this information actually is irrelevant for earnings growth. This noise should be ignored by analysts in their forecasts.

Although the models in (3.2), (3.3) and (3.4) are linear regressions, we do not use ordinary least squares (OLS) for parameter estimation. Especially due to the occurrence of emerging markets' crises, outliers in both the realized earnings change and the forecast error as well as in the macroeconomic forecasts are present. OLS estimates are unduly influenced by such aberrant observations, which are extremely large and quite pervasive in samples such as ours. At the same time, given the more erratic behavior of emerging markets, we do not want to follow the common practice of trimming or removing outliers from the sample altogether. Instead we use a robust estimation method similar to Chan and Lakonishok (1992) to estimate (3.2) and all subsequent regressions. Specifically, we use Huber (1981)'s Generalized M-estimator, which downweights observations with extremely large values of the residual, the regressor, or both. We refer to Appendix A for a detailed description of this estimation method. Throughout we compute heteroskedasticity-consistent standard errors and corresponding t-statistics to account for variation in uncertainty of the forecast (errors) across firms and over time.

3.2.2 Analysts' earnings forecasts

We obtain consensus analysts' earnings forecasts and the corresponding actual earnings from Institutional Brokers Estimate Systems (I/B/E/S) International Inc. This data source has been used in the majority of studies on analysts' earnings forecasts in developed markets. The consensus forecast is defined as the median of all individual analysts' forecasts reported by I/B/E/S six months before the end of the fiscal year.

[2]In fact, the three models are closely related in the sense that the regression in (3.2) equals (3.3) minus (3.4). The main reason for considering all three models is our use of an outlier robust estimation Method, as discussed in detail below. If least squares were used, the coefficient estimates of the coefficients in (3.2) would be exactly equal to the difference between the coefficient estimates in (3.3) and (3.4). This is not the case, however, for the robust estimation method.

Our sample consists of all listed firms included in the S&P/ International Finance Corporation (IFC) Investable Composite index during the period 1991 - 2005.[3] All stocks in the S&P/IFC Investable Composite Index are open to foreign investors. For each country in the index Standard & Poor's selects stocks in order of liquidity until a coverage of 70-80% of the total market capitalization is reached. A review of the index constituents is conducted once per year.[4]

For each company forecast to be included in our data set we require the availability of (i) a six month ahead consensus forecast of the annual earnings per share in local currency for the current fiscal year t, (ii) actual earnings per share for years $t-2$ through t, and (iii) stock prices in local currency from the end of year $t-1$ to six months prior to the end of year t. For several reasons our sample selection rules differ somewhat from those typically applied in comparable studies for the US and other developed markets. First and foremost, we adopt a six month forecast horizon in order to be reasonably certain that the security analysts have access to the previous year's earnings figures when they make their forecast for the current fiscal year. For developed markets a longer horizon of eight months is often used, see Easterwood and Nutt (1999), among others. However, we observe that four months into the current fiscal year, the previous year's earnings are reported in the I/B/E/S database for only 62 percent of the firms included in our sample. This increases to an acceptable 89 percent after six months.

Second, we do not require a minimum number of analysts providing an earnings forecast, which is customary for developed markets. Requiring analyst coverage to be at least four, as in Easterwood and Nutt (1999) and Loh and Mian (2003), among others, would reduce the number of observations in our sample with no less than 21 percent. More importantly,

[3]The S&P/IFC Investable Composite Index consists of stocks from the following countries, with the first month of inclusion in parenthesis. In case two months are provided, the second indicates the last month of inclusion. Countries can be removed from the index when S&P/IFC no longer classifies a stock market as 'emerging'. Countries can also be added to the index when they become 'emerging'. Latin America: Argentina (Dec 1988), Brazil (Dec 1988), Chile (Dec 1988), Colombia (Feb 1991 - Nov 2001), Mexico (Dec 1988), Peru (Jan 1994), Venezuela (Jan 1990 - Nov 2001); Asia: China (Oct 1995), India (Nov 1992), Indonesia (Sep 1990), Korea (Jan 1992), Malaysia (Dec 1988), Pakistan (Mar 1991 - Nov 2001), Philippines (Dec 1988), Sri Lanka (Jan 1994 - Nov 2001), Taiwan (Jan 1991), Thailand (Dec 1988); Europe: Czech Republic (Jan 1996), Greece (Dec 1988 - Apr 2001), Hungary (Apr 1994), Poland (Apr 1994), Portugal (Dec 1988 - Mar 1999), Russia (Nov 1997), Slovakia (Nov 1997 - Nov 2001), Turkey (Aug 1989); Africa & Middle East: Egypt (Nov 1997), Israel (Dec 1996), Jordan (Dec 1988 - Nov 2001), Morocco (Nov 1997), South Africa (Apr 1995), and Zimbabwe (Apr 1994 - Nov 2001). I/B/E/S data is not available for Jordan and Zimbabwe.

[4]Stocks that have a trading volume below US$ 15 million or an investable market capitalization that falls below US$ 75 million are dropped from the index.

we do not observe a clear difference in the properties of forecast errors for firms with analyst coverage above and below four.

Third, we do not impose any minimum stock price restrictions, like Lim (2001), as this would exclude complete countries due to high inflation in the past, while these low prices generally do not lead to extreme forecast errors.

Finally, on purpose we do not narrow the sample by default restrictions on the maximum forecast error, as it is likely that not all extreme forecast errors originate from data errors but also from stock market crises and bankruptcies. Our approach to deal with these observations is as follows. All absolute forecast errors larger than 100 percent are flagged as 'extremes' and checked manually with the help of additional pricing data from Factset and Worldscope and price-to-earnings data from IFC and Worldscope. Only if an extreme value can clearly be explained in terms of data errors it is adjusted, otherwise it is kept unchanged. This leads to a maximum forecast error of 320 percent and a minimum of −910 percent. In general, the extremes are observed during stock market crises when the substantial drops in stock prices 'blow up' earnings forecast errors, and during bankruptcies when, often unexpectedly, the actual losses are severe. We deal with the remaining extremes by using robust regression methods, as explained before.

Our final sample consists of 10,102 firm-year observations, for 1973 unique firms from 29 different countries. Each firm is on average (median) 5 (4) times included in the sample. A total of 78 percent of the firm-year observations have fiscal years ending in December. Observations with the end of the fiscal year in March and June cover 10 and 7 percent of the sample, respectively, and concern a small number of countries, in particular South-Africa, Pakistan, India and Malaysia.

3.2.3 Macroeconomic variables

Our choice of macroeconomic variables M_{jt} to be included in the regression models above is guided by the idea that security analysts likely attempt to obtain a comprehensive assessment of the overall macroeconomic situation in a given emerging market. Hence, we include forecasts of three key macroeconomic variables: output growth, inflation, and a measure of political stability.

Forecasts for these macroeconomic variables can be obtained in various different ways. We decide to include survey forecasts instead of, for example, forecasts obtained from time series regression models for two reasons. First, the exact publication date of survey forecasts is generally easy to retrieve, which avoids the delicate issue of uncertain publication lags of actual macroeconomic variables. Second, survey forecasts are not subject to revisions. Both these points are important for identifying exactly which macroeconomic information is public and available to analysts at the time they make their earnings forecasts. In addition, the use of survey forecasts over other forecasts methods is motivated by studies such as Ang *et al.* (2007), who find that survey forecasts of inflation are superior over alternative forecasting methods.

We use output and inflation forecasts from Consensus Economics Inc. and the political risk index from the International Country Risk Guide (ICRG) published by Political Risk Services. Both sources provide monthly updates without any publication delay and without revisions after the initial publication. Further details are provided below. Finally, we obtain corresponding actual values of output growth and inflation from the Economist Intelligence Unit and IFS databases, respectively.[5]

Output growth

Output growth is the most natural measure of the state of the economy, and seems of obvious importance for corporate earnings growth. In addition, Ackert and Hunter (1995) uncover a positive and significant relationship between future earnings forecast errors and past output growth for US stocks.

The output growth forecasts from Consensus Economics have an identical set-up as our I/B/E/S earnings forecasts. On a monthly (or bi-monthly during the first few years of our sample period) basis professional forecasters are polled for their forecast for principal macroeconomic variables for the current and following (calendar) year. We include the consensus forecast for real GDP growth for the current year as issued in June, that is six months before the end of the year, corresponding with the earnings forecast horizon. Recall that the large majority of earnings forecasts in our sample concern fiscal years which coincide with calendar years. The consensus forecast is a simple arithmetic average of all individual forecasts. Consensus Economics started collecting survey forecasts for a few developed countries in 1989, expanding its sample to include emerging markets gradually in subsequent years. For this reason our emerging markets coverage is not complete, but still satisfactory at 89 percent.

[5]We use IFS line 64F for the CPI. The Economist Intelligence Unit real GDP data is identical to GDP-at-constant-prices in IFS line 99.

Inflation

Inflation is included following the findings of O'Brien (1994), Ackert and Hunter (1995) and Basu *et al.* (2006) for the US market. Ackert and Hunter (1995) document no relationship between earnings forecast errors and inflation, which leads them to conclude that analysts rationally include inflation forecasts in their earnings forecasts. The conclusion of Basu *et al.* (2006) is opposite, as their findings indicate that analysts do not fully account for the information in inflation forecasts in their earnings forecasts. Basu *et al.* (2006) explain these differences by cross-sectional heterogeneity in earnings exposures to inflation as documented by Chordia and Shivakumar (2005). The inflation forecast is constructed in the same way as the real GDP growth forecast, that is, we include the consensus forecast for the current year as issued in June.

Political risk

The political environment is generally believed to be important in emerging markets. Fisman (2001), for example, shows that about 25 percent of the value of Indonesian firms is related to political connections. Leuz and Oberholzer-Gee (2006) also analyse the role of political connections in Indonesia and conclude that firms with political connections dislike transparency. Claessens *et al.* (in press) show that the economic costs of political connections in Brazil lower GDP with 0.2% per annum. Motivated by these studies we analyse the role of politics in the earnings forecasts. We hypothesize a positive effect of political stability on earnings growth.

Quantifying the political situation in a country is a delicate issue, because it entails many facets. The ICRG publishes monthly survey data on 12 political factors, which are aggregated into a single political risk index. The index varies between 0 and 100, where a low score indicates high political uncertainty and a high score an investor friendly and stable political environment.[6] Each factor is assigned a numerical rating within a specified range, where the allowed range reflects the weight attributed to a factor. We refer to Erb *et al.* (1996), Bilson *et al.* (2002) and Harvey (2004) for more detailed discussion of the political risk index and its relevance for emerging stock markets. The index is available for all observations in our sample. The average score is 68.3 and is quite stable over time. The Philippines's score in 1991 of 41 is the lowest, while the 1998 and 1999 scores for Portugal are the highest (91). We use the actual change in the political risk index between the end

[6]Besides political risk the ICRG also publishes economic and financial risk measures.

of the previous fiscal year $t-1$ and six months into the current fiscal year t as the political risk forecast. Hence, essentially we assume that the political situation does not change in the remaining six months of year t.

Accuracy of macroeconomic forecasts

Obviously the quality of the macroeconomic forecasts partly determines their usefulness for analysts' earnings forecasts. Accurate forecasts of GDP growth, inflation and the political situation should provide more information than poor forecasts. Figure 3.1 provides a graphical impression of the quality of the macroeconomic forecasts by showing scatterplots of the forecasts against the corresponding realizations for each country-year observation in our sample. The graphs also include the results of a standard least squares regression of the actual value of the macroeconomic indicator M in year t on its forecast made six years before the end of the year for country k:

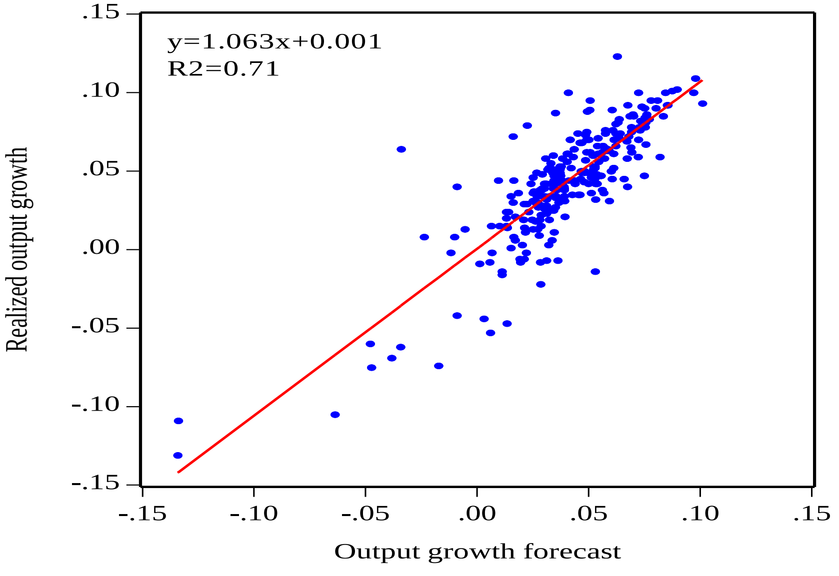
$$M_{kt} = \alpha + \beta \widehat{M}_{kt} + \eta_{kt}. \tag{3.5}$$

Figure 3.1(a) shows that analysts are too pessimistic about real GDP growth, given the slope of 1.06, but that otherwise forecasts for the GDP are of reasonably good quality given the R^2 of 0.71. For both CPI inflation (Figure 3.1b) and the change in the political situation (Figure 3.1c), analysts are too optimistic with slopes of respectively 0.90 and 0.95. Especially the forecast for inflation is good given the R^2 of 0.81, while the R^2 of the regression for the change in the political situation is 0.53. From this we conclude that the quality of the macroeconomic forecast is good enough to use in our analysis.

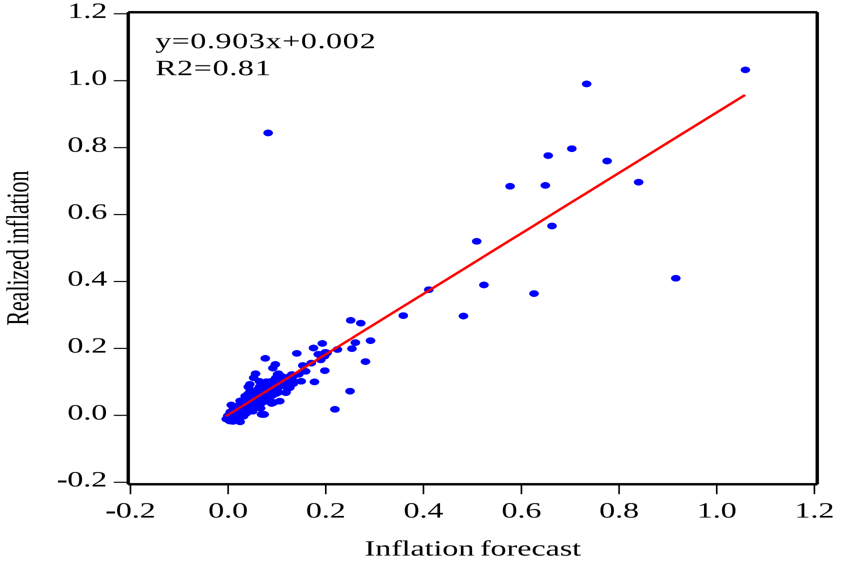
3.2.4 Company-specific variables

As discussed in the introduction, previous research has shown that the positive bias in analysts' earnings forecasts is related to firm-specific information. For that reason we include prior-year earnings growth, market capitalization, analyst coverage and price-to-book ratio as control variables S_{jt} in our regression models. We obtain the number of analysts providing earnings forecasts from I/B/E/S and collect market capitalization and the price-to-book ratio from Standard and Poor's (formerly IFC) Emerging Markets Data Base (EMBD).

Figure 3.1: Macroeconomic forecasts and realizations



(a) GDP growth



(b) CPI inflation

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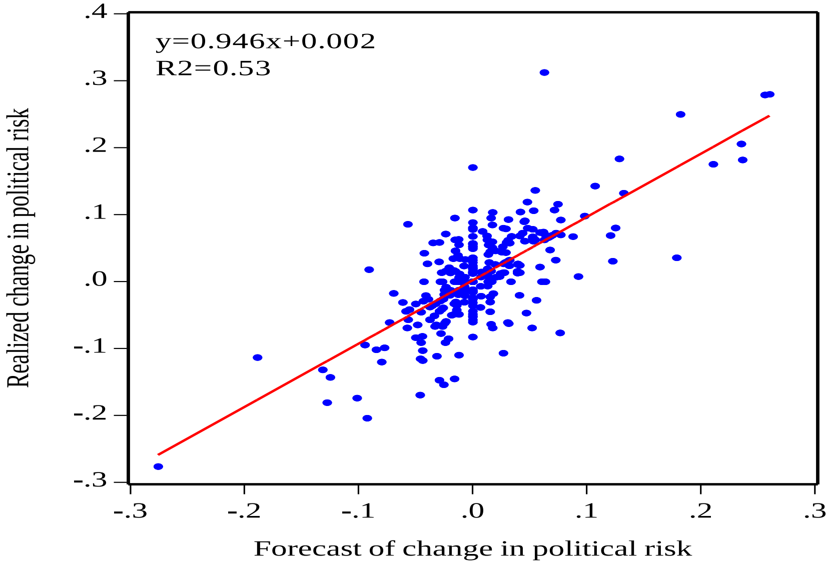

(c) Political risk

Note: The graphs in this figure show scatterplots of forecasts and realizations for GDP growth, CPI inflation and the change in political risk, as well as the fit of a regression of the macroeconomic realization on a constant and the corresponding forecast. For the CPI inflation regression the observations for Brazil in 1993 and 1994 are omitted, when realized inflation was 2477% and 916%, respectively.

Prior-year earnings growth

Several previous studies explain the bias in analysts' earnings forecasts in terms of misinterpretation of the information in prior-year earnings. De Bondt and Thaler (1990) document that predicted earnings changes are more extreme than the corresponding realized earnings changes, suggesting that analysts tend to overreact. By contrast, Abarbanell and Bernard (1992) present evidence that analysts underreact to prior-year earnings information. Easterwood and Nutt (1999) reconcile these conflicting results by showing that analysts underreact to negative earnings news, but overreact to positive news, such that analysts are systematically optimistic.

Market capitalization

The market capitalization of a stock, which we measure in US dollars, is an indication of firm's information environment. Information uncertainty is likely to be lower for larger companies. Both Lang and Lundholm (1996) and Lim (2001) show that analysts provide more accurate earnings forecast for larger firms. Therefore we expect a negative effect of the log market value on the earnings forecast error.

Analyst coverage

The number of analysts following a company and providing earnings forecasts varies widely across stocks. For example, highly volatile stocks are covered by more analysts than average, while small caps are covered by relatively fewer analysts. Based on the findings by Lim (2001) and Chan and Hameed (2006) we expect stocks with higher coverage to have smaller forecast errors as the information environment for such companies tends to be richer.

Price-to-book

Following Lim (2001) we also include the price-to-book ratio as control variable. Van der Hart *et al.* (2005) show that a portfolio of high price-to-book stocks in emerging markets has a smaller forecast error than a portfolio of low price-to-book stock during the first 11 months after portfolio formation. Hence we expect companies with a low price-to-book ratio to have a larger forecast bias.

3.3 Empirical results

3.3.1 Summary statistics

Table 3.1 presents an overview of the distribution of the firm-year observations across years and countries. The number of observations per year, which equals 673 on average, varies substantially over time. Starting relatively low at 97 in 1991, the number of firms grows rapidly to around 950 in 1997/8. Due to the effects of the Asian crisis and Russia crisis (in addition to countries such as Portugal and Greece leaving the IFC Investable index) this declines to 586 in 2003, followed by a sharp increase again during the final two years of the sample period. A similar pattern occurs for most individual countries. We also observe a positive relationship between country size and the number of observations per country,

Table 3.1: Number of observations across countries and over time

Country	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	Total
Argentina	-	-	6	21	26	26	26	28	24	20	15	10	6	2	5	215
Brazil	-	-	30	38	49	51	51	52	47	56	47	44	44	51	53	613
Chile	-	-	17	17	29	36	38	35	30	26	24	20	18	24	18	332
China	-	-	-	-	19	25	34	51	55	56	57	47	56	74	108	582
Colombia	-	-	-	-	11	12	11	12	10	6	4	-	-	-	-	66
Czech Rep.	-	-	-	-		6	5	13	13	8	7	6	6	2	5	71
Egypt	-	-	-	-	-	-	-	-	-	4	8	4	4	2	7	29
Greece	-	-	8	19	33	44	43	40	42	44	47	-	-	-	-	320
Hungary	-	-	-	-	3	11	12	12	12	13	10	8	8	5	8	102
India	-	-	1	38	70	69	75	74	81	85	72	54	48	51	70	788
Indonesia	6	27	29	35	39	43	44	38	34	29	25	19	20	22	30	440
Israel	-	-	-	-	-	-	18	24	23	22	16	18	15	16	15	167
Korea	-	19	39	66	62	60	56	43	38	29	38	79	40	138	158	865
Malaysia	39	41	55	62	73	85	89	90	78	73	66	61	59	79	81	1,031
Mexico	-	-	26	34	39	44	45	46	44	40	41	39	34	33	29	494
Morocco	-	-	-	-	-	-	-	-	-	2	2	7	-	3	1	15
Pakistan	-	-	-	14	23	22	20	18	14	9	6	-	-	-	-	126
Peru	-	-	-	-	11	12	13	17	17	15	12	8	5	4	-	114
Philippines	6	7	9	14	21	36	45	45	37	35	26	18	18	15	16	348
Poland	-	-	-	-	2	25	22	26	25	27	15	16	13	18	10	199
Portugal	-	11	14	22	23	25	27	22	21	-	-	-	-	-	-	165
Russia	-	-	-	-	-	-	-	9	7	6	9	10	10	17	16	84
Slovakia	-	-	-	-	-	-	5	5	4	3	2	-	-	-	-	19
S.Africa	-	-	-	-	55	57	66	57	56	54	57	61	63	88	99	713
Sri Lanka	-	-	-	3	15	4	4	4	3	1	-	-	-	-	-	34
Taiwan	31	54	62	77	59	60	71	90	89	59	57	58	52	63	81	963
Thailand	15	23	32	36	49	61	53	42	41	43	37	38	37	46	52	605
Turkey	-	11	26	37	41	51	55	52	56	51	54	47	30	28	26	565
Venezuela	-	-	-	-	3	4	6	7	7	6	4	-	-	-	-	37
Total	97	193	354	533	755	869	934	952	908	822	758	672	586	781	888	10,102

Note: The sample consists of 10,102 firm-year observations that have six-months ahead forecasts of annual earnings and three years of consecutive actual earnings available from I/B/E/S. Our sample includes all countries in the IFC Investable Composite index for the period 1991 - 2005.

Table 3.2: Average earnings forecast errors across countries and over time

Panel A: Median forecast error

Country	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	Total
Argentina			0.3	−0.2	−1.2	−0.8	−0.3	−0.3	−3.2	−2.2	−8.6*	−20.5*	16.6	−1.1	−1.3	−1.2
Brazil			−8.1	2.4	−1.5	−0.6	−0.6	−0.7	0.5	−0.6	−0.4	−1.0	1.5	0.8	−1.5	−0.5
Chile			0.2	0.1	0.3	−0.7	−0.4	−2.1	−1.0	−1.0	−1.0	−1.2	−0.5	−0.1	−1.4	−0.6
China					−2.4	−2.7	−1.5	−3.6	0.0	0.1	−0.5	−0.5	0.6	0.3	−0.3	−0.4
Colombia					−2.1	−1.2	−1.8	−4.2	−10.9	−15.5	−7.0					−3.1
Czech Rep.						−3.4	0.0	−1.2	−0.4	−0.7	1.2	1.5	3.0	0.1	0.2	−0.3
Egypt										−5.9	−3.5	1.8	7.2	4.8	1.1	0.3
Greece			−4.0	−1.4	−1.4	−1.0	−0.7	0.3	0.9	−0.2	−2.8					−0.7
Hungary					7.2	0.9	1.0	−1.0	−2.8	−1.9	−5.0	0.6	−2.6	1.4	0.8	−0.4
India			−0.7	0.5	0.4	−0.2	−1.7	−0.4	−0.6	0.0	−0.5	−1.1	0.2	1.1	−0.1	−0.2
Indonesia	−0.1	−0.3	−0.1	−0.4	−0.2	−0.2	−7.9	−33.9*	−2.2	−5.1	−3.1	−2.0	0.2	1.3	−0.4	−0.8
Israel							0.0	−0.3	0.5	−0.7	−3.4	−1.9	1.0	0.4	0.3	0.0
Korea		−1.3	−0.7	−0.8	−2.6	−2.6	−5.4	−31.6*	3.9	−4.8	−8.8	−0.5	−3.4	−0.5	−0.7	−1.4
Malaysia	−0.1	−0.1	0.3	0.1	0.2	0.2	−0.8	−9.6*	2.0	−0.4	−2.3	0.1	0.3	0.0	−0.7	−0.1
Mexico			−0.7	−4.4*	−1.5	0.2	−1.1	−2.8	0.0	−1.5	−2.0	−2.3	−1.4	1.8	0.3	−0.9
Morocco										−1.2	−3.7	−5.0		−0.2	−4.9	−3.1
Pakistan				−1.1	−2.7	−2.4	−1.8	−1.1	2.5	−0.3	1.3					−1.1
Peru					0.0	−1.9	−1.7	−5.3	−2.9	−4.0	−4.6	3.7	3.1	6.4		−1.9
Philippines	1.4	−1.8	−0.5	−0.1	0.0	0.2	−2.4	−7.4*	−3.5	−4.4	−1.7	−1.0	0.2	0.3	0.2	−1.1
Poland					1.8	−0.7	−1.0	−4.6	−2.7	−1.6	−6.1	−3.5	−1.3	0.2	0.7	−1.5
Portugal		−2.9	−0.9	−1.2	−0.6	0.6	0.5	0.3	−0.3							0.0
Russia								−47.5*	11.4	12.4	0.0	2.1	3.1	1.0	4.1	2.8
Slovakia							−3.7	−18.8	−52.0	11.0	−6.2					−6.7
S.Africa					0.1	−0.3	−0.7	−0.2	−0.4	−0.4	−0.3	−0.6	−1.3	−0.7	−0.2	−0.4
Sri Lanka				−3.3	−0.8	−3.6	0.4	0.0	−2.9	0.7						−1.2
Taiwan	0.2	−0.7	−0.9	0.5	−1.3	−1.1	0.0	−2.8	−0.2	−2.1	−3.4	−2.0	0.7	−0.8	−0.2	−0.7
Thailand	−1.0	0.4	−0.1	0.1	−0.5	−0.9	−31.8*	1.0	0.3	−4.7	−1.1	1.3	1.5	0.2	−0.6	−0.5
Turkey		0.0	0.0	0.0	0.0	0.0	0.0	−2.7	−4.6	−0.1	−0.8*	0.0	−0.2	0.4	1.1	0.0
Venezuela					11.5	9.0	0.4	−10.8	−4.9	−16.0	−6.3					−3.5
Total	−0.1	−0.4	−0.2	0.0	−0.3	−0.4	−1.0	−2.0	−0.4	−0.8	−1.6	−0.8	0.1	0.1	−0.2	−0.5

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Panel B: Mean forecast error

Country	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	Total
Argentina			0.1	−2.7	−3.6	−4.1	−1.7	−5.7	−8.1	−17	−9.9*	−28.1*	22.5	−1.1	−2.0	−6.1
Brazil			−28.8	1.5	−8.5	−7.3	−5.9	−6.4	−0.8	−0.4	−0.1	−8.1	2.3	1.8	−1.6	−4.1
Chile			−0.2	0.3	0.1	−1.4	−0.4	−7.4	−3.4	−2.9	−2.6	−4.6	0.5	0.5	−1.0	−2.0
China					−4.1	−4.3	−2.4	−9.1	−1.9	−1.2	−2.6	−0.7	1.2	−0.2	−0.9	−1.9
Colombia					−0.3	−0.2	−2.0	−2.9	−19.7	−22.0	−3.9					−6.2
Czech Rep.						−6.3	−1.7	−15.6	−26.2	1.6	0.4	−3.8	2.1	0.1	1.2	−8.1
Egypt										−4.7	−5.2	10.0	6.6	4.8	2.4	1.1
Greece			−5.1	−1.3	−2.1	−1.1	−1.2	0.2	1.5	−0.6	−3.1					−1.1
Hungary					4.0	0.4	1.4	−1.5	−5.5	−9.9	−5.4	−2.8	−15.6	3.0	0.4	−3.6
India			−0.7	1.0	−0.1	−0.3	−4.7	−0.8	−3.1	−2.9	−3.4	−4.5	1.8	1.6	−1.0	−1.6
Indonesia	0.1	−0.7	−0.8	−0.9	−0.8	−2.3	−12.7	−76.0*	−17.7	−43.1	−43.5	−4.2	2.3	3.3	−0.9	−14.9
Israel							0.0	−1.2	0.4	−2.4	−7.8	−2.5	0.9	−1.6	0.8	−1.5
Korea		−1.8	−3.4	−0.6	−2.5	−12.3	−24.8	−103.8*	−32.8	−66.7	−24.9	−13.7	−5.8	0.6	−2.3	−14.6
Malaysia	0.3	−0.8	0.2	0.2	0.2	−0.2	−3.3	−32.3*	−12.1	−2.1	−14.0	2.2	0.9	0.1	−1.3	−5.0
Mexico			−4.4	−12.1*	−7.0	−11.2	−31.8	−7.5	−1.5	−4.0	−4.5	−5.0	−5.5	2.9	−0.7	−7.7
Morocco										−1.2	−3.7	−4.1		−0.7	−4.9	−3.0
Pakistan				−2.1	−4.6	−2.7	−0.4	−0.9	16.4	−8.3	3.1					−0.4
Peru					0.2	−4.6	−1.0	−5.7	−5.5	−5.1	−7.5	8.7	2.6	4.0		−2.8
Philippines	0.6	−2.3	−1.3	−0.6	−0.4	−1.4	−5.7	−26.8*	−12.2	−45.5	−15.6	−15.7	−19.1	−0.6	0.0	−13.3
Poland					1.8	−0.9	−2.9	−8.5	−3.6	−4.9	−9.3	−16.0	−1.4	0.5	3.0	−4.5
Portugal		−8.4	−6.5	−1.2	−1.8	0.3	0.5	−0.1	−0.9							−1.5
Russia								−42.0*	21.1	11.1	6.0	−10.1	0.3	6.9	3.3	−0.4
Slovakia							−6.0	−38.5	−44.2	7.1	−6.2					−20.6
S.Africa					−0.4	−1.0	−1.3	−0.3	−1.8	0.2	−4.8	−1.1	−1.5	−1.0	−0.2	−1.1
Sri Lanka				−2.3	−1.5	−3.7	0.4	0.0	−2.7	0.7						−1.5
Taiwan	−0.1	−1.0	−1.3	1.2	−1.6	−2.4	−0.5	−5.0	−6.7	−3.4	−11.7	−7.3	0.0	−2.1	−1.5	−3.0
Thailand	−1.5	0.2	−1.2	−0.5	−3.6	−2.1	−59.5*	−0.3	3.5	−12.7	−6.2	−0.5	1.1	0.3	−2.1	−7.0
Turkey		3.3	0.0	0.1	−1.5	0.9	−0.6	−4.0	−14.6	−1.1	−2.3*	−0.4	0.4	1.7	−0.8	−2.1
Venezuela					20.8	8.8	−1.8	−13.4	−6.7	−12.4	−11.0					−4.7
Total	−0.1	−1.1	−3.9	−0.8	−2.1	−2.9	−8.8	−15.8	−6.6	−8.8	−8.0	−5.1	−0.7	0.5	−1.1	−5.2

Note: The forecast error is defined as $(E_{it} - \widehat{E}_{it})/P_{it}$, where E_{it} is the realized earnings per share for firm i in fiscal year t, $\widehat{E}_{it}$ is the median analysts' earnings forecast made six months prior to the end of the book year and P_{it} is the stock price at the time the forecast is made. Emerging markets crises are indicated with an asterisk: 1994 Peso crisis in Mexico; 1997-1998 Asia crisis in Thailand (start), Korea, Indonesia, Malaysia and Philippines; 1998 Russia's default; 2001 Turkey crisis and 2001-2002 Argentina default and currency crisis.

as expected. In terms of data coverage, on average our sample includes 65 percent of the constituents of the IFC Investable index, except for the first three years of the sample period during which coverage is lower at around 43 percent.

Table 3.2 displays the mean and median earnings forecast errors across countries and across years. Consistent with previous research for developed markets, we find that the overall average forecast errors are negative, suggesting that on average analysts are too optimistic about future earnings. The magnitudes of the mean and median errors of −5.2 and −0.5 percent, respectively, also are comparable to values typically found for developed markets. For example, Easterwood and Nutt (1999) report mean and median errors of −1.93 and −0.32 percent for the US over the period 1982–1995. It is worthwhile to consider the forecast errors during the emerging markets crises that occurred during our sample period. For most crises we observe substantially larger negative median forecast errors: −4.4 percent in Mexico during the 1994 (December) peso-crisis, −32 percent in Thailand during the 1997 (July) Asia crisis, −48 percent in Russia during the 1998 (August) Russia crisis and −8.6 percent (−21 percent) during the Argentina crisis in 2001 (November) and 2002 (January). Recall that most earnings forecasts in our sample were produced in June, prior to the crises' occurrence. Hence, the excessive optimism during these years suggests that analysts did not foresee these periods of turmoil. For the Turkey crisis in February 2001 we do not observe a clear deviation from the historical pattern, suggesting that analysts did incorporate negative earnings related news in their forecasts during this period of larger economic uncertainty.

3.3.2 Firm-level earnings growth and actual macroeconomic developments

Before examining the role of information in macroeconomic forecasts in analysts' earnings forecasts, we first consider the relationship between actual earnings growth and realizations of our three macroeconomic variables to determine whether and how firm-level performance is related to macroeconomic performance in the first place. Specifically we estimate the following regression:

$$\frac{E_{it} - E_{i,t-1}}{P_{it}} = \alpha + \sum_j \beta_j M_{jt} + \sum_j \gamma_j S_{jt} + \varepsilon_{it}, \tag{3.6}$$

where M_{jt} are the realizations of our macroeconomic factors in year t. Panel A of Table 3.3 presents robust estimation results for (3.6), as well as for regressions including only one of the three macroeconomic variables.

Table 3.3: The importance of macroeconomic forecasts

Panel A: Realized earnings growth and realized macroeconomic factors

	α	β_1	β_2	β_3	γ_1	γ_2	γ_3	γ_4	R^2
Univariate									
GDP	−0.04	0.14			−0.11	0.01	−3.37	14.34	0.119
	(−15.27)	(9.22)			(−14.67)	(14.29)	(−5.11)	(15.03)	
CPI	−0.04		0.02		−0.13	0.01	−3.45	14.86	0.083
	(−15.31)		(6.89)		(−15.74)	(14.29)	(−5.20)	(10.40)	
POL	−0.03			0.06	−0.11	0.01	−2.87	15.08	0.113
	(−13.63)			(8.26)	(−15.22)	(14.25)	(−4.91)	(11.44)	
Multivariate									
	−0.05	0.13	0.03	0.06	−0.14	0.01	−3.56	11.08	0.075
	(−16.87)	(8.27)	(8.68)	(6.78)	(−16.61)	(16.20)	(−5.23)	(7.63)	

Panel B: Earnings forecast errors and macroeconomic forecasts

	α	β_1	β_2	β_3	γ_1	γ_2	γ_3	γ_4	R^2
Univariate									
GDP	−0.06	0.07			0.09	0.01	−2.40	19.91	0.017
	(−24.22)	(4.18)			(16.51)	(18.23)	(−4.27)	(15.03)	
CPI	−0.05		−0.01		0.09	0.01	−2.00	22.11	0.016
	(−24.02)		(−3.26)		(16.01)	(17.53)	(−3.57)	(16.35)	
POL	−0.05			0.02	0.09	0.01	−1.80	19.37	0.018
	(−25.95)			(2.79)	(15.96)	(18.37)	(−3.64)	(17.02)	
Multivariate									
	−0.06	0.07	−0.00	0.02	0.09	0.01	−2.20	20.33	0.019
	(−22.98)	(4.07)	(−1.39)	(2.16)	(15.76)	(17.94)	(−3.86)	(15.45)	

(continued on next page)

Panel C: Earnings realizations and macroeconomic forecasts

	α	β_1	β_2	β_3	γ_1	γ_2	γ_3	γ_4	R^2
Univariate									
GDP	−0.03	−0.02			−0.11	0.01	−3.14	16.61	0.113
	(−11.62)	(−1.28)			(−12.65)	(13.90)	(−4.73)	(11.18)	
CPI	−0.04		0.03		−0.13	0.01	−3.29	15.01	0.079
	(−15.62)		(8.89)		(−15.70)	(15.74)	(−4.93)	(10.44)	
POL	−0.03			0.01	−0.11	0.01	−3.11	15.58	0.111
	(−13.35)			(1.60)	(−14.16)	(14.20)	(−5.32)	(11.81)	
Multivariate									
	−0.04	0.01	0.03	0.02	−0.13	0.01	−3.32	14.19	0.077
	(−13.95)	(0.58)	(9.37)	(2.16)	(−16.16)	(15.69)	(−4.88)	(9.80)	

Panel D: Earnings forecasts and macroeconomic forecasts

	α	β_1	β_2	β_3	γ_1	γ_2	γ_3	γ_4	R^2
Univariate									
GDP	0.03	−0.09			−0.20	−0.00	−0.78	−5.32	0.168
	(20.01)	(−9.08)			(−32.63)	(−4.86)	(−2.24)	(−7.49)	
CPI	0.02		0.03		−0.22	−0.00	−1.32	−8.39	0.136
	(12.06)		(17.69)		(−34.12)	(−0.35)	(−3.82)	(−11.15)	
POL	0.02			−0.01	−0.20	−0.00	−1.24	−5.74	0.169
	(19.38)			(−3.16)	(−33.70)	(−4.23)	(−4.02)	(−9.01)	
Multivariate									
	0.02	−0.07	0.03	−0.00	−0.23	−0.00	−1.10	−7.30	0.143
	(13.26)	(−6.01)	(15.60)	(−0.79)	(−35.25)	(−1.21)	(−3.09)	(−9.77)	

Note: This table presents estimation results for the regressions involving macroeconomic forecasts and firm characteristics

$$Y_{it} = \alpha + \beta_1 \widehat{GDP}_t + \beta_2 \widehat{CPI}_t + \beta_3 \widehat{POL}_t + \gamma_1 \left(\frac{E_{i,t-1} - E_{i,t-2}}{P_{i,t-1}} \right) + \gamma_2 MCAP_{it} + \gamma_3 COV_{it} + \gamma_4 PB_{it} + \varepsilon_{it},$$

where $\widehat{GDP}_t$ is the forecast of real GDP growth in year t, $\widehat{CPI}_t$ is the forecast of consumer price inflation in year t, and $\widehat{POL}_t$ is the forecast of the change the political risk in year t. All macroeconomic forecasts are made six months prior to the end of year t. E_{it} is the realized earnings per share in local currency for firm i in fiscal year t, and $P_{i,t-1}$ is the local stock price six months into year $t-1$ such that $(E_{i,t-1} - E_{i,t-2})/P_{i,t-1}$ is the actual earnings change in fiscal year $t-1$. $MCAP_{it}$, COV_{it} and PB_{it} are the log market capitalization in US dollar, the number of analysts covering the stock and the price-to-book ratio, respectively, all measured six months before the end of year t. The dependent variable Y_{it} is either the earnings forecast error $FE_{it} = (E_{it} - \widehat{E}_{it})/P_{it}$, where $\widehat{E}_{it}$ is the consensus analysts' earnings forecast made six months prior to the end of the year (Panel B), the actual earnings change $(E_{it} - E_{i,t-1})/P_{it}$ (Panel C), and the earnings forecast $(\widehat{E}_{it} - E_{i,t-1})/P_{it}$ (Panel D). In Panel A, the dependent variable is the the actual earnings change $(E_{it} - E_{i,t-1})/P_{it}$, while the macroeconomic forecasts are replaced by the corresponding realizations. Regressions under the heading 'Univariate' include only one of the three macroeconomic variables. The coefficient estimates for COV_{it} and PB_{it} are multiplied with 10,000. Coefficients significantly different from zero at the 10%, 5% and 1% significance levels are marked with one, two and three asterisks, respectively. All samples comprise 10,102 firm-year observations from 29 different emerging market countries.

We find significantly positive slope coefficients for all three macroeconomic variables, confirming prior expectations. The positive slope estimate for realized output growth of 0.13 ($t = 8.3$) implies an earnings increase equal to 13 percent of economic growth on average. The coefficient estimate of realized inflation, although positive, is small at 0.02 ($t = 8.7$), suggesting a rather weak relationship between inflation and nominal earnings in emerging markets. Finally, an increase in political stability leads to a significantly positive effect on earnings growth, given the coefficient estimate of 0.06 ($t = 6.8$).

For the firm-specific information we observe a negative coefficient of the prior-year earnings growth, equal to -0.13 ($t = -16.6$). This indicates a mean reversion effect that is also documented by Easterwood and Nutt (1999) for earnings growth in the US. The positive slope of 0.01 ($t = 16.2$) for the log market capitalization suggests that the relationship between size and nominal earnings is rather weak. The same applies to analyst coverage and the price-to-book ratio with coefficient estimates of -0.00036 ($t = -5.2$) and 0.0011 ($t = 7.6$), respectively.

The fairly modest R^2 at 7.53% indicates that the relationship between earnings growth and macroeconomic developments in emerging markets is not particularly strong. Nevertheless, these results indicate that analysts may benefit from incorporating macroeconomic information into their earnings forecasts. The question is whether they indeed do this and if so, whether this is done in the best possible way.

3.3.3 Analysts' efficiency

If analysts make optimal use of macroeconomic information for their earnings forecasts, the forecast errors should be uncorrelated with any information that is available at the time the forecasts are made. We examine this issue by estimating the forecast error model in (3.2). We stress that we include the macroeconomic forecasts as they were made in June of each year, coinciding with the six-month horizon used for defining the earning forecast error such that this information is available at the time analysts issue their earnings forecasts.

The results reported in Panel B of Table 3.3 show a number of interesting features. First and foremost, we obtain significant slope coefficients for two of our three macroeconomic variables. The positive coefficient estimates for the forecasts of output growth and political risk of 0.07 ($t = 4.1$) and 0.02 ($t = 2.2$), respectively, indicating that analysts underestimate the effects of output growth and the change in political risk on earnings growth. Analysts do incorporate inflation forecasts efficiently in their earnings forecasts, given that its coefficient (-0.004, $t = -1.4$) is not significantly different from zero.

Second, we find a significantly negative intercept equal to -5.7 percent ($t = -23.0$), confirming that analysts are optimistic on average.

Third, we find that the bias in analysts' earnings forecasts also varies systematically with the included firm characteristics. The positive coefficient estimate of 0.09 ($t = 15.8$) for the prior-year earnings growth indicates that analysts do not efficiently take into account the information from last year's earnings growth. We note that this estimate resembles Easterwood and Nutt (1999)'s slope estimate of 0.13 ($t = 15.29$) and also is in line with Abarbanell and Bernard (1992)'s finding of β_1 of 0.08 ($t = 3.30$) for both US companies. Furthermore, we find a larger bias for smaller companies, in line with the result for US stocks documented by Lang and Lundholm (1996) and Lim (2001), and for an international sample of stocks by Ang and Ciccone (2002). The larger bias for companies with a low price-to-book ratio is also present in our dataset. Contrary to our expectations, we find a smaller bias for stocks with low analyst coverage. This effect is statistically significant but economically very small.

The above observations summarize our main results. Most importantly, we find significant coefficient estimates for two of the three macroeconomic variables. Analysts do not use information that is available in forecasts of output growth and the political situation in emerging markets for their earnings forecasts in the best possible way. The information in inflation forecasts seems to be accounted for correctly.

3.3.4 Interaction between macroeconomic forecasts and earnings forecasts

At first sight, our finding that earnings forecast errors are related to the output growth and political risk forecasts seems to imply that analysts ignore valuable macroeconomic information when producing their earnings forecasts for individual companies. This is not necessarily true, however. An alternative explanation is that these macroeconomic forecasts are incorporated into the earnings forecasts, but this information actually is irrelevant for earnings growth. As discussed in Section 3.2 we may shed light on the question which of these competing mechanisms is the relevant explanation by regressing the realized earnings growth and the earnings forecasts on the macroeconomic forecasts and firm characteristics, as given in (3.3) and (3.4), respectively.

The estimation results shown in Panels C and D of Table 3.3 indeed provide useful insights on this issue. First, for the inflation forecasts we find significantly positive coefficients in both regressions of the actual earnings growth and the forecasts (0.03, $t = 15.6$

and 0.03, $t = 9.4$, respectively), which furthermore are of comparable magnitude. Hence, the inflation forecasts do contain useful information for actual earnings growth for emerging markets firms, and analysts incorporate this information correctly in their forecasts.

The insignificant coefficient $\beta_3 = -0.0047$ ($t = -0.8$) of the political risk forecast in panel D suggests that analysts ignore changes in the emerging market's political situation in their earnings forecasts. Panel C, however, shows that the political risk forecast is related to actual earnings, with a significantly positive coefficient equal to 0.02 ($t = 2.2$). This implies that analysts would be able to improve their earnings forecasts by taking this information into account, as also indicated by the significant coefficient for the political risk forecast in panel B for the forecast error regression.

Finally, the most striking results are obtained for the output growth forecasts. We find a significantly negative coefficient of -0.07 ($t = -6.0$) in the regression for the earnings forecast, indicating that higher forecasts of output growth are accompanied by lower earnings forecasts. This contradicts the positive relationship found between realized earnings and output growth in panel A, so that analysts seem to respond to this information in the wrong way. At the same time, the results in panel D point out that there is no significant relationship between the output growth forecast and realized earnings with a coefficient of 0.01 ($t = 0.6$). Hence, analysts better ignore this information altogether for their earnings forecasts. This outcome confirms O'Brien (1994)'s finding that macroeconomic news that arrives after the earnings forecast issuance is reflected in the forecast error.

In sum, our findings indicate that analysts do not efficiently use the available macroeconomic information represented by forecasts for output growth and the change in the political situation in their earnings forecasts for emerging markets' stocks. Analysts do incorporate the information represented by inflation forecasts correctly. The political risk forecasts contain useful information for realized earnings, but analysts ignore this completely. Output growth forecasts do not seem useful sources of information for realized earnings. Analysts, however, 'overreact' and adjust their earnings forecast in the opposite way.

3.3.5 Transparency

As discussed in the introduction, earnings forecasting is closely related to the information environment. We return to this issue in this section and examine whether the role of macroeconomic information in analysts' earnings forecast differs systematically according to the ease with which analysts may gain access to firm-specific information. This builds upon the point made by Bae *et al.* (2006) that a firm's transparency may be an important factor determining analyst behaviour. Intuitively, if its financial statements are limited and a firm provides little or no information about its business operation's outlook, analysts need to rely more upon macroeconomic information for producing an earnings forecasts. Macroeconomic information may have little added value for a company that is more willing to disclose firm-specific information and management expectations.

We investigate the role of the information environment by distinguishing between companies with high and low transparency, according to two measures. First, we split our sample into stocks with and without ADR's, following the suggestion of Lang *et al.* (2003) and Baker *et al.* (2002). Our second measure of transparency is the time that it takes a company to release its annual report: Stocks releasing their annual report within three months after the end of the prior fiscal year are labelled as 'fast reporting', and all other stocks as 'slow reporting'. To the best of our knowledge, this second transparency measure has not been examined before. Both measures are defined such that analysts know in advance if the stock is transparent given either its ADR listing or its prompt release of the prior-year annual report.

The ADR identifier comes from the Factset Pricing database. This database contains firm-level information about the start and end dates of an ADR cross-listing. Our sample includes 2161 firm-year observations that have an ADR listing when the earnings forecasts are issued. We obtain the fiscal year-end date as well as the publication data of the annual report from the I/B/E/S database. In total we have 3522 fast-reporting firm-year observations.[7] For both measures it holds that the distribution of transparent companies in our sample is fairly uniform across countries, sectors as well as calendar years. This is important as it implies that the following analysis truly measures transparency at the firm level instead of, for example, transparency at the country level.

Table 3.4 shows the results for the regressions allowing for different coefficients for transparent and non-transparent firms. The results for the forecast error regression in panel B provide convincing evidence that analysts' handle macroeconomic information more efficiently for transparent companies, irrespective of which transparency measure is used. For fast-reporting firms, only the political risk forecast is significantly related to the forecast error, while all three macroeconomic forecasts are significant for slow-reporting

[7]While fast reporting generally is a good sign, the quality of financial statements may be doubted when companies publish their annual report very fast. Our sample contains 27 firm-year observations that report within one month, 662 within two months and 2829 within three months after the end of the book year. Excluding the companies that report within one month or within two months does not affect our results.

Table 3.4: Transparency and the importance of macroeconomic forecasts versus earnings forecast errors

Panel A: Realized earnings growth and realized macroeconomic factors

	α	β_1	β_2	β_3	γ_1	γ_2	γ_3	γ_4	R^2
ADR									
Non-ADR	−0.05	0.13	0.03	0.07	−0.14	0.01	−2.62	12.77	0.072
	(−13.74)	(6.48)	(9.55)	(6.64)	(−15.46)	(12.16)	(−3.10)	(8.41)	
ADR	−0.08	0.26	−0.01	0.16	−0.29	0.02	−5.95	18.78	
	(−3.59)	(2.12)	(−1.42)	(2.23)	(−3.25)	(3.87)	(−1.83)	(1.64)	
Fast reporting									
SLOW	−0.05	0.15	0.03	0.07	−0.14	0.02	−5.23	11.99	0.067
	(−13.71)	(6.27)	(10.81)	(5.71)	(−13.86)	(12.70)	(−5.24)	(6.01)	
FAST	−0.16	0.66	0.01	0.32	−0.52	0.05	−7.67	15.53	
	(−2.65)	(1.68)	(2.73)	(2.52)	(−3.92)	(3.20)	(−1.94)	(1.88)	

Panel B: Earnings forecast errors and macroeconomic forecasts

	α	β_1	β_2	β_3	γ_1	γ_2	γ_3	γ_4	R^2
ADR									
Non-ADR	−0.06	0.05	−0.00	0.02	0.08	0.01	−1.60	20.01	0.020
	(−19.84)	(2.33)	(−0.11)	(2.01)	(13.94)	(14.91)	(−2.24)	(14.16)	
ADR	−0.16	0.17	−0.05	0.09	0.02	0.04	−0.67	24.78	
	(−5.55)	(1.16)	(−1.04)	(1.50)	(0.27)	(5.66)	(−0.28)	(2.99)	
Fast reporting									
SLOW	−0.07	0.07	0.01	0.05	0.10	0.02	−2.43	22.75	0.021
	(−18.82)	(2.71)	(2.05)	(3.56)	(14.69)	(14.28)	(−2.78)	(11.59)	
FAST	−0.29	0.41	−0.00	−0.19	−0.00	0.08	−9.65	9.63	
	(−6.07)	(1.32)	(−0.74)	(−2.40)	(−0.03)	(6.20)	(−2.60)	(1.83)	

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Panel C: Earnings realizations and macroeconomic forecasts

	α	β_1	β_2	β_3	γ_1	γ_2	γ_3	γ_4	R^2
ADR									
Non ADR	−0.04	−0.02	0.03	0.02	−0.14	0.01	−2.42	15.15	
	(−11.33)	(−0.75)	(9.46)	(1.65)	(−15.02)	(12.23)	(−2.89)	(10.06)	0.075
ADR	−0.07	−0.05	−0.00	0.18	−0.28	0.02	−5.50	21.27	
	(−2.93)	(−0.34)	(−0.28)	(2.53)	(−3.14)	(3.85)	(−1.63)	(1.80)	
Fast reporting									
SLOW	−0.04	−0.01	0.04	0.04	−0.14	0.02	−4.30	14.83	
	(−11.27)	(−0.33)	(10.06)	(2.74)	(−13.63)	(12.34)	(−4.39)	(7.56)	0.065
FAST	−0.17	0.40	0.02	−0.12	−0.52	0.05	−12.43	13.03	
	(−2.40)	(0.85)	(2.69)	(−1.09)	(−3.88)	(2.99)	(−2.50)	(1.75)	

Panel D: Earnings forecasts and macroeconomic forecasts

	α	β_1	β_2	β_3	γ_1	γ_2	γ_3	γ_4	R^2
ADR									
Non ADR	0.02	−0.07	0.03	−0.01	−0.24	−0.00	−0.93	−6.75	
	(12.33)	(−5.30)	(14.44)	(−1.52)	(−32.05)	(−2.39)	(−2.13)	(−8.44)	0.142
ADR	0.09	−0.22	0.05	0.09	−0.29	−0.02	−4.85	−3.43	
	(4.42)	(−2.29)	(1.23)	(1.68)	(−7.83)	(−3.12)	(−1.83)	(−0.45)	
Fast reporting									
SLOW	0.02	−0.09	0.04	−0.01	−0.27	−0.00	−1.99	−8.87	
	(10.67)	(−5.57)	(13.00)	(−1.71)	(−34.18)	(−0.53)	(−3.69)	(−7.93)	0.136
FAST	0.12	−0.00	0.02	0.07	−0.52	−0.03	−2.79	3.40	
	(2.14)	(−0.01)	(3.28)	(1.62)	(−5.28)	(−2.31)	(−0.86)	(1.09)	

Note: This table presents estimation results for transparent and non-transparent stocks. Rows labelled 'ADR' ('Non-ADR') indicate the sub-sample of stocks with (without) an ADR cross-listing in the US. Rows labelled 'Fast' ('Slow') indicate the subsample of stocks that publish their annual report before (after) three months after the fiscal year end. See table 3.3 for further details.

firms. The positive coefficients for the latter group of companies furthermore suggest that analysts underreact to the information in the forecasts for inflation, output growth and political risk. For ADR stocks, we even find that none of the macroeconomic forecasts is statistically significant, while for non-ADR stocks the output growth and political risk forecasts are, and again with positive coefficients. The results in panel C demonstrate that the output growth forecast is not relevant for earnings growth, neither for transparent nor for non-transparent firms. For the inflation and political risk forecasts, the results partly depend on the transparency measure that is used to classify firms. For ADR stocks we find that the political risk forecast bears useful information for earnings growth and the inflation forecast does not, while the opposite is found for fast-reporting firms. For both non-ADR stocks and slow-reporting firms we find significantly positive coefficients for both these macroeconomic forecasts.

Overall we conclude that analysts handle macroeconomic information in a better way for more transparent companies. This confirms the finding of Lim (2001) for US stocks that analysts' earnings forecast bias is related to the information uncertainty environment, and in fact expands it by documenting this effect for macroeconomic forecasts.

3.4 Robustness

In this section we report results from a number of additional analyses, intended to check the robustness of our main finding that analysts do not optimally account for macroeconomic information in their corporate earnings forecasts.

3.4.1 Crises

Our robust estimation technique ascertains handling of outliers. Although this approach has several desirable features and has been used by others like Chan and Lakonishok (1992) or Krishnaswami and Subramaniam (1999), a potential concern is that crises still might influence our results. To address this issue explicitly we distinguish between firm-years in normal and in crises periods and consider the role of macroeconomic information for these sub-samples separately. In total we identify 391 firm-year observations in crisis periods: the Mexican peso crisis in 1994, the Asian crisis in 1997/1998, the Russian debt crisis in August 1998, Argentina's default at the end of 2001 and Turkey's currency crisis in 2001.

Estimating the four regression models in (3.2), (3.3), (3.4) and (3.6) allowing for different coefficients during crises and 'normal' periods renders estimates as reported in

Table 3.5: Crises and the importance of macroeconomic forecasts versus earnings forecast errors

Panel A: Realized earnings growth and realized macroeconomic factors

	α	β_1	β_2	β_3	γ_1	γ_2	γ_3	γ_4	R^2
Normal	−0.04	0.07	0.02	0.03	−0.14	0.01	−1.91	8.14	
	(−13.37)	(4.18)	(7.53)	(2.72)	(−17.06)	(14.22)	(−2.73)	(5.81)	0.114
Crisis	−0.88	0.64	0.01	0.58	−0.80	0.25	−17.59	321.77	
	(−4.86)	(0.95)	(2.32)	(1.19)	(−5.58)	(4.13)	(−0.53)	(6.32)	

Panel B: Earnings forecast errors and macroeconomic forecasts

	α	β_1	β_2	β_3	γ_1	γ_2	γ_3	γ_4	R^2
Normal	−0.05	0.06	−0.01	0.02	0.08	0.01	−1.13	16.36	
	(−21.01)	(3.37)	(−3.03)	(2.03)	(13.81)	(16.76)	(−1.94)	(12.99)	0.091
Crisis	−1.05	−0.90	−0.00	0.98	−0.10	0.31	0.19	225.93	
	(−6.62)	(−1.26)	(−0.29)	(1.59)	(−0.96)	(6.05)	(0.01)	(4.52)	

Panel C: Earnings realizations and macroeconomic forecasts

	α	β_1	β_2	β_3	γ_1	γ_2	γ_3	γ_4	R^2
Normal	−0.03	−0.03	0.02	0.02	−0.14	0.01	−1.65	9.97	
	(−10.76)	(−1.44)	(6.87)	(1.67)	(−16.71)	(13.72)	(−2.36)	(6.97)	0.111
Crisis	−0.97	0.08	0.02	0.35	−0.79	0.28	−23.37	328.04	
	(−5.09)	(0.08)	(2.42)	(0.45)	(−5.46)	(4.40)	(−0.71)	(6.22)	

Panel D: Earnings forecasts and macroeconomic forecasts

	α	β_1	β_2	β_3	γ_1	γ_2	γ_3	γ_4	R^2
Normal	0.02	−0.09	0.03	−0.01	−0.22	−0.00	−0.54	−7.39	
	(14.55)	(−7.73)	(13.97)	(−1.09)	(−34.18)	(−2.47)	(−1.40)	(−9.60)	0.136
Crisis	0.08	0.98	0.02	−0.63	−0.69	−0.04	−23.57	102.11	
	(0.74)	(1.55)	(2.29)	(−1.24)	(−4.89)	(−1.00)	(−1.12)	(3.75)	

Note: This table presents estimation results for normal market periods and crisis periods. Rows labelled 'Normal' and 'Crisis' indicate the sub-sample of stocks during normal market periods and crises (1994 Peso crisis in Mexico; 1997-1998 Asia crisis in Thailand (start), Korea, Indonesia, Malaysia and Philippines; 1998 Russia's default; 2001 Turkey crisis and 2001-2002 Argentina default and currency crisis), respectively. See table 3.3 for further details.

Table 3.5. Reassuringly, the results of the earnings forecast error in normal markets are largely comparable with the results for the complete data set. In particular, analysts underestimate the effects of output growth and changes in political stability during normal periods, with significantly positive coefficients in panel B that are very close to those found for the complete sample. The estimates of the corresponding coefficients in panels C and D also confirm the earlier finding that output growth forecasts do not carry relevant information for earnings growth while political risk forecasts do. Analysts treat these forecasts wrongly, in the sense that they do incorporate output forecasts in their earnings forecasts but ignore the political risk forecasts. Interestingly, the coefficient of the inflation forecast in normal markets in the forecast error regression is more than double the coefficient for the complete sample at -0.0085 compared to -0.0039, and is significantly different from zero with a t-statistic of -3.0. This indicates that analysts overestimate the effect of inflation on earnings growth when constructing their earnings forecasts. This is also borne out by the estimates in panels C and D, showing that the inflation forecast coefficient is considerably larger in the regression of the earnings forecast than of the realized earnings growth.

The results for the crisis periods also are noteworthy. From panel B we observe that the earnings forecast errors are not significantly related to our three macroeconomic forecasts during such periods. Panels C and D indicate that analysts correctly account for the inflation forecast, which bears useful information for earnings growth, and rightfully ignore the non-informative output growth and political risk forecasts.

We conclude that our primary results are confirmed after controlling for the crisis periods: analysts do not efficiently incorporate macroeconomic information into their earnings forecasts during normal market circumstances.

3.4.2 Country, sector and year effects

Next, we verify the appropriateness of our country-specific approach, rather than a global or sector-specific set-up. This is done by limiting the regressors in (3.2) to the stock-specific characteristics and including different types of dummy variables instead of the macroeconomic forecasts. First, we consider the relative importance of year, country and sector effects by including a set of corresponding dummies. For constructing the sector dummies we use the MSCI sector classification. The year dummies can tentatively be interpreted as representing a global macroeconomic factor, such as US output growth or inflation, impacting all emerging markets earnings equally. The other two types of

Table 3.6: Multivariate regressions of the forecast error on firm characteristics with country, sector and year dummies

	α	γ_1	γ_2	γ_3	γ_4	R^2
Constant	−0.05(−25.77)	0.09(15.84)	0.01(18.32)	−1.96(−3.99)	19.97(16.88)	0.017
Country	−0.05(−25.09)	0.08(15.20)	0.02(18.60)	−4.52(−7.10)	19.04(14.50)	0.020
Sector	−0.05(−25.21)	0.09(23.44)	0.01(18.19)	−2.08(−4.16)	20.55(16.45)	0.019
Year	−0.05(−23.55)	0.09(16.28)	0.01(15.17)	−0.74(−1.48)	20.64(17.08)	0.023
Country & Year	−0.05(−23.45)	0.08(15.51)	0.01(15.33)	−1.55(−2.29)	18.66(14.42)	0.030
Country × Year	−0.05(−24.05)	0.08(14.59)	0.01(14.86)	−1.86(−2.34)	15.62(11.68)	0.061
Sector & Year	−0.05(−22.83)	0.08(15.19)	0.01(14.75)	−0.82(−1.62)	21.91(17.19)	0.026
Sector × Year	−0.05(−22.63)	0.08(14.68)	0.01(14.45)	−0.66(−1.26)	22.56(16.39)	0.030

Note: This table presents coefficient estimates with heteroskedasticity-consistent t-statistics in parentheses from the regression of the earnings forecast error on firm characteristics with sector, year, and country specific dummies D_{jt}:

$$FE_{it} = \alpha + \gamma_1 \left(\frac{E_{i,t-1} - E_{i,t-2}}{P_{i,t-1}} \right) + \gamma_2 MCAP_{it} + \gamma_3 COV_{it} + \gamma_4 PB_{it} + \sum_j \delta_j D_{jt} + \varepsilon_{it}.$$

The rows labelled 'Country & Year' and 'Sector & Year' refer to the inclusion of country or sector dummies and year dummies simultaneously. The rows labelled 'Country × Year' and 'Sector × Year' refer to the inclusion of country-year and sector-year dummies, respectively. See Table 3.3 for variable definitions.

dummies cover structural differences across countries and sectors. Second, we jointly include year and country dummies or year and sector dummies. Third and of most interest, we include country-year or sector-year dummies. These dummies should shed most light on the question whether macroeconomic effects are important for explaining analysts' forecast bias. The year-country dummies have a clear economic interpretation as they can be considered as proxies for time-varying country-specific macroeconomic information. In fact, year-country dummies provide the most perfect macroeconomic factor, such that the R^2 of this regression provides an upper bound on the explanatory power than we can attain with specific macroeconomic variables. The year-sector dummies can be interpreted as sector-specific factors that change over time, such as the oil price for the energy sector or the price of semiconductors for the IT sector. A comparison of the adjusted-R^2 of the regressions with these two types of dummies should demonstrate whether the country-based approach taken in our paper is justified, or whether a sector-based approach would have been more appropriate.[8]

Table 3.6 reports the R^2's for the different dummy regressions, obtained with the robust estimation method. It can be seen that the individual time, country and sector effects are approximately equally important with R^2 values of 2.31, 2.04 and 1.89 percent, respectively. The R^2 of 6.05 percent for the year-country dummies more than doubles the R^2 of 2.95 percent obtained for the specification with year-sector dummies, clearly suggesting that the country-based macroeconomic approach taken here is indeed appropriate.

3.4.3 Macroeconomic exposures per year and per country

As a further robustness check, we explore how the information content of macroeconomic forecasts varies over time and across countries. Ciccone (2005) reports a steady decrease in analysts' earnings forecast errors for US stocks over the period 1990-2001. This motivates us to explore if and how the information content of macroeconomic forecasts varies over time for our sample of emerging market firms. We examine this issue by estimating the forecast error model (3.2) for individual calendar years. If analysts indeed have become more efficient over time the relationship between macroeconomic forecasts and earnings forecast errors should weaken for more recent years.

[8] A more technical point is that in order to avoid multicollinearity we impose that the dummy coefficients sum to 0, such that they measure the deviation from the overall intercept, see also Heston and Rouwenhorst (1995), for example.

Table 3.7: The importance of macroeconomic forecasts per calendar year

	α	β_1	β_2	β_3	γ_1	γ_2	γ_3	γ_4	R^2
1991	−0.05*	0.63*	0.04	0.21***	0.01	0.01	−7.79*	−0.73	0.12
1992	−0.08***	0.45**	0.05	0.19***	0.09***	0.01***	5.39**	15.61***	0.02
1993	−0.03***	0.09	−0.02**	0.14**	0.05	0.01*	1.17	15.65***	0.11
1994	−0.02**	−0.15	−0.00*	−0.14	−0.05	0.01***	−6.43**	10.71**	0.00
1995	−0.04***	−0.06	0.00	0.04*	0.14***	0.01***	1.97*	15.55***	0.04
1996	−0.02***	−0.14***	0.02***	−0.03	0.04*	0.00**	6.41***	17.60***	0.01
1997	−0.05***	−0.47***	0.05***	−0.00	0.04	0.01***	−3.67	43.77***	0.04
1998	−0.09***	0.10	−0.05***	0.09	0.37***	0.01***	0.62	65.67***	0.01
1999	−0.07***	0.20**	−0.11***	0.06	0.09***	0.02***	−5.21*	32.83***	0.04
2000	−0.06***	0.02	−0.04**	0.15***	0.09***	0.01***	0.42	21.96***	0.02
2001	−0.13***	0.39***	0.09***	0.11***	0.05**	0.02***	8.37***	44.94***	0.07
2002	−0.06***	0.47***	0.01	−0.02	0.09***	0.01**	−4.64	41.97***	0.00
2003	−0.02	0.16	0.01	−0.01	0.09***	0.01	−0.25	−10.11*	0.02
2004	−0.03***	0.02	0.13**	0.06	0.11***	0.01***	−2.53	−16.30***	0.01
2005	−0.07***	0.14**	0.02	−0.03	0.02	0.02***	−1.85	14.52***	0.06

Note: This table presents estimation results for the regression of the earnings forecast error on the macroeconomic forecasts and firm characteristics

$$FE_{it} = \alpha + \beta_1 \widehat{GDP}_t + \beta_2 \widehat{CPI}_t + \beta_3 \widehat{POL}_t + \gamma_1 \left(\frac{E_{i,t-1} - E_{i,t-2}}{P_{i,t-1}} \right) + \gamma_2 MCAP_{it} + \gamma_3 COV_{it} + \gamma_4 PB_{it} + \varepsilon_{it},$$

for each individual calendar year. Coefficients significantly different from zero at the 10%, 5% and 1% significance levels are marked with one, two and three asterisks, respectively. See Table 3.3 for variable definitions.

Table 3.7 displays the regression results for the forecast error model for each individual calendar year. These suggest that analysts' earnings forecasts consistently are inefficient and have not improved in recent years. Especially information in prior-year earnings growth is not taken into account correctly, as its coefficient is significantly positive for 10 out of 15 years, with no indications that this effect weakens over time. It seems that analysts assess the information concerning the political situation better over time, as the earnings forecast errors are uncorrelated with the change in political risk during the last four years of our sample period, in contrast to the significantly positive coefficient for earlier years. This is not the case for inflation and output growth, for which we still find a significantly positive relationship with the forecast error in the (prior) last year of our sample period. Also note that analysts' reaction to the inflation and output growth forecasts varies substantially over time. For some years (1996, 1997) we find evidence for underreaction (as the coefficient is negative), while for other years we find evidence for overreaction (given the positive coefficient). In contrast to the US results reported in Ciccone (2005) we conclude that analysts' inefficiency of earnings forecasts for emerging markets does not weaken during more recent years.

In addition, we examine if the value of macroeconomic information varies across countries. Table 3.8 explores the cross-country heterogeneity in the properties of earnings forecast errors. For 23 countries the individual R^2 of the regression in (3.2) is higher than the R^2 obtained with the complete sample, in particular for the Czech Republic, Russia and Egypt. The estimation results reveal a considerable amount of heterogeneity for the macroeconomic variables, as the coefficients of both output and political risk forecasts are significantly positive and negative for about the same number of countries (five and six, respectively). This also applies to the inflation forecast, as its coefficient is positive and significantly different from zero for 7 countries and significantly negative for 10 countries. Apparently these effects cancel out when the forecast errors are pooled across countries, given that we do not find a significant effect of the inflation forecast when the model is estimated for the complete sample.

Overall, we conclude that our results are robust over time but show considerable heterogeneity across countries. It would be interesting to examine whether the cross-country differences in the effects of the macroeconomic forecasts can be related to, for example, differences in the transparency and disclosure regulations and practices of the financial markets in the different emerging markets, see Bae *et al.* (in press). This would show whether transparency at the country level also affects the role of macroeconomic information for analysts' earnings forecasts, in addition to transparency at the firm level documented in Section 3.3.5. This, however, is beyond the scope of the current paper and is left for future research.

3.4.4 Stale forecasts

Another potential explanation why earnings forecast errors are correlated with output growth and political stability is related to the earnings forecasts used in this study. The I/B/E/S database contains earnings forecasts that are stale, as older forecasts that are not revised (or reaffirmed) by the analysts in a given month are retained. Given that the consensus earnings forecast is defined as the median of all individual analysts' forecasts, even a single individual stale forecast may cause the consensus to be stale as well. Such stale forecasts are likely to be biased and inefficient.

Table 3.8: The importance of macroeconomic forecasts per country

	α	β_1	β_2	β_3	γ_1	γ_2	γ_3	γ_4	R^2
Argentina	−0.05***	0.30***	0.06	−0.05	−0.06	0.00	13.34***	37.17	0.01
Brazil	−0.05***	−0.43**	0.01	0.01	0.03*	0.02***	−3.59	56.66***	0.02
Chile	−0.04***	−0.03	0.13***	0.02	0.02	0.01***	−13.03***	25.09***	0.09
China	−0.03**	0.03	−0.15***	0.16***	0.11***	0.01***	−7.23***	11.79	0.11
Colombia	−0.16*	1.19	0.46	−0.07	0.05	−0.01	34.59	75.61	0.21
Czech Rep.	−0.05	−0.45	−0.27*	−0.13	0.29***	0.02	2.02	44.77	0.70
Egypt	−0.15***	−3.64***	4.75***	0.22	−0.01	0.03	85.41**	−87.54***	0.50
Greece	0.11***	−2.83***	−0.77***	0.05	0.21***	−0.00	−0.69	28.84***	0.14
Hungary	−0.08***	−0.83**	0.18***	−0.05	0.20**	0.03***	−5.48	−15.76	0.22
India	−0.06***	0.04	−0.11**	−0.05*	0.15***	0.02***	−9.05***	8.05***	0.14
Indonesia	−0.04**	−0.15	−0.05	0.21***	0.05***	0.02***	−5.63	15.49***	0.19
Israel	−0.04*	0.34	0.11	−0.09	0.10***	0.01	−15.96	19.59	0.05
Korea	−0.12***	0.51***	0.00	−0.20*	0.02	0.02***	11.83***	43.55***	0.07
Malaysia	−0.02***	0.04	−0.14*	−0.01	0.05***	0.01**	0.85	5.63***	0.20
Mexico	−0.09***	0.13	0.11***	0.25***	0.03	0.02***	−11.74***	87.54***	0.05
Pakistan	0.01	−0.48	−0.47*	0.29***	0.03	0.00	59.57*	52.49**	0.10
Peru	−0.02	0.93***	−0.56***	−0.44**	0.13**	0.01	−31.46***	38.43	0.12
Philippines	−0.11***	−0.59**	−0.16	0.05	0.30***	0.05***	−25.03***	43.17***	0.17
Poland	−0.16***	−0.32	0.40***	−0.56***	0.14***	0.04***	−21.33**	72.66***	0.19
Portugal	0.02	−0.17	−0.56***	−0.01	−0.02	0.01	−13.34***	16.43*	0.04
Russia	−0.72***	5.77***	1.59***	0.33***	−0.03	0.07***	−33.10	−132.49*	0.50
Slovakia	−0.71	8.70***	5.04	−16.71**	0.55***	−0.05	−67.56	1009.56	0.36
S. Africa	−0.02**	0.05	−0.11**	−0.01	0.10***	0.01***	−13.98***	9.17**	0.01
Taiwan	−0.06***	0.05	0.16	−0.04	0.01	0.01***	−6.51**	30.61***	0.08
Thailand	−0.07***	−0.08	−0.32**	−0.22***	0.06***	0.03***	−15.97***	13.30**	0.00
Turkey	−0.03**	0.09	−0.02	0.02	0.16***	0.01***	−17.62***	10.67***	0.07
Venezuela	−0.09	0.38	0.30***	0.80*	0.18**	−0.02	39.93	−298.10***	0.34

Note: This table presents estimation results for the regression of the earnings forecast error on the macroeconomic forecasts and firm characteristics

$$FE_{it} = \alpha + \beta_1 \widehat{GDP}_t + \beta_2 \widehat{CPI}_t + \beta_3 \widehat{POL}_t + \gamma_1 \left(\frac{E_{i,t-1} - E_{i,t-2}}{P_{i,t-1}} \right) + \gamma_2 MCAP_{it} + \gamma_3 COV_{it} + \gamma_4 PB_{it} + \varepsilon_{it},$$

for each individual country. Coefficients significantly different from zero at the 10%, 5% and 1% significance levels are marked with one, two and three asterisks, respectively. See Table 3.3 for variable definitions.

To investigate the relevance of this potential data problem we identify consensus earnings forecasts that did not change in the past two months. In our sample about 16% of our earnings forecasts is labeled 'stale' according to this definition.[9] The average forecast error is slightly larger (−6.3%) for the stale sample than for the non-stale sample (−5.0%). We estimate the forecast error model model (3.2) allowing for different coefficients for non-stale and stale forecasts.[10] Stale forecasts do not seem to affect our conclusions, as all coefficient estimates for the non-stale forecasts are very close to those for the full sample reported in Table 3.3. The coefficients for the stale forecasts do differ and sometimes substantially, but at least have the same sign as the non-stale forecasts. Partly this can be explained by the negative correlation between our stale-dummy with analyst coverage (−22%) and market value (−15%). These negative correlations indicate that these company-specific variables partly control for the stale forecasts in our sample. In sum, our results are unlikely to be caused by the presence of stale earnings forecasts in our sample.

3.5 Conclusion

We present empirical evidence that analysts do not make efficient use of publicly available macroeconomic information when producing earnings forecasts for emerging market firms. We show that analysts do incorporate macroeconomic forecasts in their earnings forecasts, but in a sub-optimal way. Analysts show strong signs of underreaction to political stability forecasts and overreaction to output growth forecasts. The forecasts on political stability are completely ignored by analysts, while these provide valuable information for firm-level earnings growth. Analysts do incorporate output growth forecasts, but these actually bear no relevant information for firm-level earnings growth. Hence, analysts better ignore this information altogether for their earnings forecasts. Inflation forecasts are taken into account appropriately. These results are robust to controlling for firm characteristics, including prior-year earnings growth, market value, analyst coverage and the price-to-book ratio.

In addition, we show that firm transparency determines analyst behaviour as we document analysts' earnings forecasts to be more efficient for transparent stocks. We distinguish between transparent and non-transparent stocks based on either the availability of an ADR listing, or the publication of the annual report within three months after the fiscal year

[9] If we look back over 1 month (3 months) our sample contains 35% (10%) stale forecasts.
[10] Detailed results are available upon request.

end. For both measures of transparency we find that analysts correctly take into account (all) macro economic forecasts as well as the prior-year earnings growth. This result confirms Bae *et al.* (2006) and Lim (2001)'s conclusion that analysts' earnings forecast bias is related to the information uncertainty environment.

Overall our findings suggest the usefulness of macroeconomic forecast information in earnings forecasts for emerging market companies. Note that our results offer analysts, as well as investors, immediate possibilities for improving their earnings forecasts. Companies, on the other hand, can facilitate analysts in their earnings forecasts by increasing their transparency, for example by publishing their annual reports promptly after the fiscal year end. Finally, our findings provide evidence on the importance of political stability in emerging markets. Countries benefit from increased political stability in terms of higher earnings growth.

Future research could consider the role of macroeconomic information in individual analysts' earnings forecasts. More specifically we suggest to look at the difference between local analysts and foreign analysts. Bae *et al.* (in press), for example, find that local analysts have an economically and statistically significant advantage over foreign analysts. It would be interesting to examine whether the use of macroeconomic information also differs between domestic and foreign analysts. Furthermore, we have implicitly assumed a specific (quadratic) loss function for analysts and a constant relation between macroeconomic information and earnings forecasts over time and across countries and individual stocks. Following Basu and Markov (2004) and Rodriguez (2005) a closer look at the effect of these assumptions may provide more empirical evidence for analysts' inefficiency in emerging markets earnings forecasts.

Appendix: Huber's Generalized M-estimator

Robust estimation techniques are a convenient method to guard against the influence of aberrant observations. In this appendix we briefly describe the Generalized M-estimator (GM) employed in this paper in the context of a linear regression model

$$y_i = x_i\beta + \varepsilon_i, \qquad i = 1, \ldots, n, \tag{3.7}$$

where β is an unknown parameter and ε_i are independently distributed errors. A GM estimator of the linear regression coefficient β can be defined as the solution to a weighted least squares equation defined by the first order condition

$$\sum_{i=1}^{n}(y_i - x_i\beta)x_i w_r(r_i) = 0, \tag{3.8}$$

where r_i denotes the standardized residual, $r_i \equiv (y_i - x_i\beta)/(\sigma_\varepsilon w_x(x_i))$ with σ_ε a measure of scale of the residuals and w_x a weight function that is bounded between 0 and 1. The weight functions $w_r(\cdot)$ and $w_x(\cdot)$ are chosen in such a way that i-th observation receives a relatively small weight if either the regressor x_i or the standardized residual $(y_i - x_i\beta)/\sigma_\varepsilon$ becomes large, such that the outlier does not influence the estimates of β and σ_ε.

The weight function $w_r(r_i)$ is specified in terms of the Huber (1981) ψ function as $w_r(r_i) = \psi(w_r)/r_i$ for $r_i \neq 0$ and $w_r(0) = 1$. The Huber ψ function is given by

$$\psi(r_t) = \begin{cases} -c & \text{if } r_t \leq -c, \\ r_t & \text{if } -c < r_t \leq c, \\ c & \text{if } r_t > c, \end{cases} \tag{3.9}$$

The tuning constant c determines the robustness and efficiency of the estimator. We use the commonly used value of 1.345 for c as the resulting estimator has an efficiency of 95% compared to the OLS estimator in case the errors ε_i are normally distributed. We use the same function to define the regressor weights $w_x(x_i)$.

The use of the weighted least squares estimator implies that the coefficient of determination for the original data, R^2_{WLS} has different characteristics than usual. Most importantly, the R^2_{WLS} can become negative. For this reason we follow the suggestion of Verbeek (2002) and define the R^2 as the squared correlation between the actual values y_i and the fitted values $\hat{y}_i = x_i\hat{\beta}_{\mathrm{GM}}$, where $\hat{\beta}_{\mathrm{GM}}$ denotes the GM estimate of β.

Chapter 4

The Economic Value of Fundamental and Technical Information in Emerging Currency Markets*

4.1 Introduction

The literature on exchange rate forecasting has extensively analyzed the predictive content of two types of information: news on macroeconomic fundamentals as used in structural exchange rate models, and information from historical prices as used in technical trading rules. Meese and Rogoff's (1983) finding that structural models cannot outperform a naive random walk forecast at short horizons still stands after 25 years of intense research, see Cheung *et al.* (2005) for a recent assessment. There is somewhat more supportive evidence for the usefulness of macroeconomic information for forecasting exchange rates at longer horizons, see Mark (1995), Kilian (2001) and Berkowitz and Giorgianni (2001), among others. In general, the performance of technical trading rules at short horizons has been found to be considerably better, see Sweeney (1986), Levich and Thomas (1993) and Neely and Weller (1999), with Menkhoff and Taylor (2007) providing a recent comprehensive survey. Nevertheless, Olson (2004), Pukthuanthong-Le *et al.* (2007) and Neely *et al.* (in press) report that the profitability of technical trading rules has weakened substantially in

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recent years, at least for developed currencies.

The predictive ability of structural exchange rate models and technical trading rules has generally been considered in isolation. This is quite remarkable, in the sense that surveys among foreign exchange market participants invariably indicate that they regard both types of information to be important factors for determining future exchange rate movements, see Taylor and Allen (1992), Menkhoff (1997), Lui and Mole (1998), Cheung and Chinn (2001), and Gehrig and Menkhoff (2004). Not surprisingly then, most foreign exchange professionals use some combination of fundamental analysis and technical analysis for their own decision making, with the relative weight given to technical analysis becoming smaller as the forecasting (or investment) horizon becomes longer.

The weights assigned to fundamental and technical information for a given horizon may also vary over time. For example, Frankel and Froot (1990) provide empirical evidence for the switch of many professional forecasters from being "fundamentalists" (using structural models and macro data) to acting as "chartists" (using technical trading rules) during the second half of the 1980s. They motivate this changing behavior by the fact that fundamentalists experienced large negative returns in the mid-1980s, when currency prices deviated from their fundamental values. This idea of switching behavior has more recently been formalized in so-called heterogeneous agents models. Brock and Hommes (1997, 1998) develop equilibrium models in which agents update their beliefs about the future profitability of investment strategies based on their past performance. These models show that rational investors can switch between simple (costless) strategies and sophisticated (costly) strategies. When all investors follow the simple strategy prices may diverge from their fundamental value, making it worthwhile for investors to engage in sophisticated strategies, because expected profits increase. Prices are then pushed back to their fundamental value and the expected net profits for sophisticated investors are turn negative. This, which leads them to switch back to simple and costless strategies that might again result in prices moving away from their fundamental value. These heterogeneous agents models have recently been applied to currency markets, explicitly allowing for the presence of both chartists and fundamentalists, see Chiarella *et al.* (2006), and De Grauwe and Grimaldi (2005, 2006). The relative importance of these two types of traders (and, hence, the two types of information) varies over time as investors are assumed to switch between strategies according to their relative past performance. De Grauwe and Markiewicz (2006) offer an alternative interpretation of these models, in which market participants combine technical analysis and fundamental information in order to forecast future foreign exchange rates, with weights varying over time as a function of past profitability.

Most research on exchange rate forecasting has focused on developed markets. Scarcely any attention has been paid to emerging market currencies, possibly due to the fact that many emerging countries maintained a fixed or pegged exchange rate regime until fairly recently.[1] Since the mid-1990s, approximately, more and more countries have switched to a floating exchange rate regime, such that by now the time series length as well as the cross-sectional breadth are sufficient to warrant a meaningful investigation of exchange rate predictability in emerging markets. To the best of our knowledge we are the first to conduct such an analysis. Previous empirical research on heterogeneous agents models has also been limited to developed currency markets, such as Vigfusson (1997) and De Jong *et al.* (2006). These studies report only limited evidence supporting the switching behavior between fundamentalist and chartist strategies based on past performance that is assumed in the theoretical models.

In this paper we conduct a comprehensive analysis of the economic value of technical and fundamental information in emerging currency markets. Specifically, we assess the performance of currency trading strategies based on monthly fundamental information derived from the real interest rate differential, GDP growth, and the ratio of money supply to foreign exchange reserves, as well as a set of daily moving average technical trading rules. We implement these strategies for all freely floating emerging market currencies relative to the US dollar over the period 1995-2007. We also consider combined strategies in which both chartist and fundamentalist information are used, in line with the actual behavior of market participants, as discussed above. In particular, we examine a dynamic combination scheme with time-varying weights according to the relative profitability of the fundamental and technical strategies. As a benchmark we employ a naive strategy that assigns constant and equal weights to the two types of information. Throughout the empirical analysis, we also consider nine developed currencies as a control sample.

Our results can be summarized as follows. First, both fundamentalist and chartist strategies generate economically and statistically significant Sharpe ratios for emerging currency markets. This finding is consistent with McNown and Wallace (1989), who document that fundamentalist trading strategies perform well in four emerging markets over the period 1972-1986. Our positive results for technical trading rules provide out-of-sample

[1]One aspect of exchange rate forecasting in emerging markets that did receive ample attention in the past is prediction of currency crises, in particular by means of so-called early warning systems, see Kaminsky (2006) for a detailed overview.

evidence for the profits described by Martin (2001) and Lee *et al.* (2001a) for the early 1990s.

Second, we document that naively combining chartist and fundamentalist strategies generates positive risk-adjusted returns that are both economically and statistically significant. Moreover, the performance of the combined strategy is much more consistent and stable across currencies than the individual fundamentalist and chartist strategies. This provides convincing evidence for the complementary value of technical and fundamental information as suggested by questionnaires among currency traders. The dynamic combined strategies, where the weights assigned to fundamentalist and chartist strategies vary according to their past performance, do not increase the profitability of the trading strategy relative to the naive combination. Thus, we find only limited empirical support for the enhanced profitability of the investment strategies based on the heterogeneous agents models of Chiarella *et al.* (2006) and De Grauwe and Grimaldi (2005, 2006).

Third, for developed currency markets we find that fundamental trading strategies render statistically and economically significant Sharpe ratios, but this is not the case for the chartist strategies. This result is in line with Abhyankar *et al.* (2005), who conclude that investors may benefit from fundamental exchange rate models trading the US dollar against the Canadian dollar, Japanese Yen, and British Pound over the period 1977-2000. It also corroborates the findings of Olson (2004), Pukthuanthong-Le *et al.* (2007) and Neely *et al.* (in press), who document that returns to technical trading strategies in developed markets have declined over time.

The remainder of this paper is organized as follows. In Section 4.2 we describe the data. We examine the performance of the fundamentalist and chartist strategies individually in Sections 4.3 and 4.4, respectively. In Section 4.5 we integrate the chartist and fundamentalist information into combined strategies. Finally, we conclude in Section 4.6.

4.2 Data description

Our analysis is most relevant for exchange rates under a free float, as currency prices in this system are determined in principle by demand and supply, although intervention activities of central banks cannot be ruled out completely.[2] Data before 1995 is thus not considered, as most of the countries in our sample adopted a floating exchange rate regime around

[2] We refer to the conference notes of the IMF 'High-Level seminar on exchange rate regimes: Hard peg or free floating?' for an overview of central bank intervention activity in the emerging currency markets, see `http://www.imf.org/external/pubs/ft/seminar/2001/err/eng/`.

that time or later.[3] In total we examine the currencies of 23 emerging markets which currently have a (managed) floating exchange rate system: the Argentine peso, Brazilian real, Chilean peso, Colombian peso, Mexican peso and Peruvian sol from Latin-America; the Indian rupee, Indonesian rupiah, Kazakhstan tenge, Korean won, Malaysian ringitt, Phillipine peso, Sri Lanka rupee, Taiwanese dollar and Thai bath from Asia; and the Czech koruna, Hungarian forint, Israeli shekel, Polish zloty, Romanian leu, Slovak koruna, South African rand, and Turkish lira from Europe, Middle-East, and Africa (EMEA). All of these currencies became floating at some point between January 1995 and June 2007. Figure 4.1 shows the historical development of the number of emerging market countries with a floating exchange rate regime in our sample. The exact dates of the the currencies' floats are given in Table 4.1.

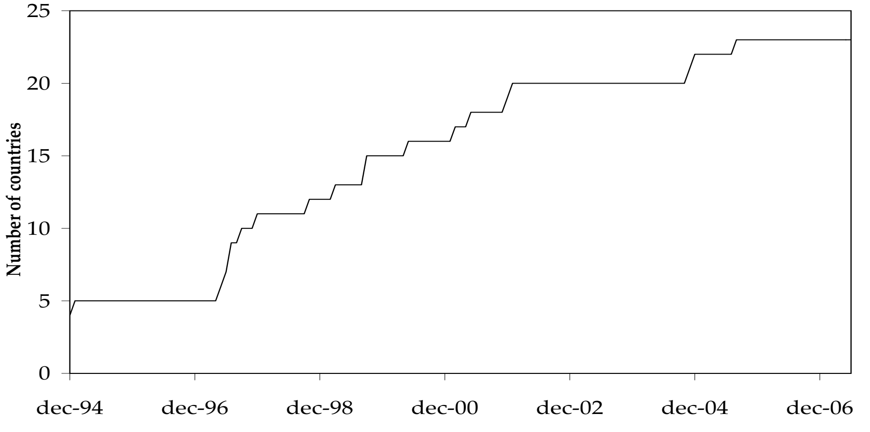
We employ daily and monthly exchange rates for the technical trading rules and the fundamental models, respectively. The exchange rates correspond to Reuters 07:00 GMT middle rate fixings against the US dollar.[4] All exchange rates are expressed in the standard way, that is, as the price of one US dollar in the emerging market currency. The sample period runs from January 1, 1995 to June 30, 2007 (3260 daily and 150 monthly observations), where it is to be understood that each currency is included in the analysis only six months after the start of its floating exchange rate regime. In practice, most investors will hold off investing in a currency for some time to avoid the often dramatic exchange rate movements immediately following the float of a currency. The market has sufficiently 'cooled down' after about half a year for most currencies.

A common instrument that can be used for *sec* investments in the currency market is the currency forward contract. These instruments enable us to invest in a currency without owning any underlying assets, for example bonds or stocks, in the country. With the help of the forward contract we lock in a specific foreign exchange rate in the future.

[3]In the late 1980s many emerging market countries pegged their currency to the US dollar or a basket of developed currencies to achieve price stability after a period of (hyper-)inflation. Some countries used a crawling peg, where the currency was allowed to depreciate at a steady rate such that the local inflation rate could be higher than the pegged rate. A side effect of the emerging markets currency crises during the 1990s has been that most emerging markets changed their exchange rate system from a pegged to a floating regime. Currently, only a small number of emerging market countries still maintain a (crawling) peg regime: China (pegged to the US dollar), Russia (pegged to a basket of the US dollar and euro), Vietnam (US dollar) and Pakistan (US dollar).

[4]Results for the Eastern European currencies (CZK, SKK, PLN, HUF and RON) relative to the EUR are similar and available upon request.

Figure 4.1: Number of emerging market countries with a floating currency.



The figure shows the number of emerging market countries with a floating exchange rate regime over the period December 1994 – June 2007.

The investment return on a currency is then defined as the difference between this forward rate and the future spot rate:

$$r_t = s_t - f_{t-1,t} \tag{4.1}$$

where s_t is the log spot rate at time t and $f_{t-1,t}$ is the log forward rate at time $t-1$ maturing at time t. In the absence of arbitrage opportunities, the forward rate is given by:

$$F_{t-1,t} = S_{t-1}\exp(i_{t-1}^{EM} - i_{t-1}^{US}) \tag{4.2}$$

where i_{t-1}^{EM} and i_{t-1}^{US} are the cash interest rates in the emerging country and the US, respectively. The cash rate is generally the offshore deposit rate for money deposited in the currency and maturity that matches the maturity of the forward contract, for example the London Interbank Offered Rate (LIBOR) for US dollars.[5] Substitution of (4.2) in (4.1) leads to the return on a foreign exchange investment:

$$r_t = s_t - s_{t-1} + i_{t-1}^{US} - i_{t-1}^{EM} \tag{4.3}$$

[5]The cash rates are quoted on an annualized basis. For our return calculations the cash rates are scaled to the a daily or monthly basis by dividing the rate by 360 days and multiplying by the number of days that a position will be held.

Many studies on trading strategies for developed exchange rate markets disregard the interest rate differential as the influence on profitability is found to be negligible, see Sweeney (1986) and LeBaron (1999), among others. For emerging markets the interest rate differentials can be substantial, as shown below, and therefore should be taken into account for a fair judgement of the investment returns. We obtain interest rates from two different sources: Bloomberg and the IMF International Financial Statistics (IFS) database. The monthly IFS data has the advantage that it is available for a longer time period, while the Bloomberg data is updated on a daily basis. As daily data entails more information, Bloomberg interbank interest rates are used from the moment they are available; otherwise IFS deposit rates are used.[6]

Summary statistics for the monthly returns of the emerging markets currencies are reported in Table 4.1.[7] The Turkish lira has the best performance with an annualized mean return of 25.6 percent per year, relative to the US dollar. Note that the Turkish lira hardly moved during its floating period (February 2001 - June 2007), but an investor was more than compensated by the interest rate differential of 25.4 percent per year. The Taiwanese dollar has the worst performance with an average return of –2.45 percent per year. The annualized standard deviations of the monthly returns range between a low of 3.4 percent for the Malaysian ringitt (July 2005 - June 2007) and a high of 26.5 percent for the Indonesian Rupiah (August 1997 - June 2007). For 12 of the 23 currencies the kurtosis is (much) higher than three, indicating a high peak and fat tails in the empirical distribution of the returns relative to a normal distribution. The tail behavior of emerging market currencies is studied in detail by Candelon and Straetmans (2006). The unreported Jarque-Bera test shows that almost none of the currency returns are Gaussian, due to the high kurtosis and the nonzero skewness. The example of the Turkish lira mentioned above already suggests that we should not disregard the interest rate differential when computing the investment return on the emerging market currencies. This is confirmed by the last two columns of Table 4.1, showing that the average interest rate differential is even larger than the spot rate return for 11 out of 23 currencies.

[6]Interest rates are available for different maturities. We use the three-month rates because our final trading strategy (see Section 4.5) holds its positions for three months on average. All interest rates are reported on an annualized basis. For daily performance evaluation we use the 'actual/365' day count convention for all countries.

[7]The (unreported) descriptive statistics for the daily returns show similar patterns, although the kurtosis is higher. This corresponds quite well with the stylized fact of asset returns that non-normality (in particular peakedness and fat tails) becomes more pronounced at higher frequencies

Table 4.1: Summary statistics currency returns

Currency	Float	Mean	Stdev	Skew.	Kurt.	FX	IRD
Emerging							
Taiwanese dollar (TWD)	Dec-94	2.45	5.52	0.06	5.43	1.9	0.6
Peruvian sol (PEN)	Dec-94	−3.17	4.00	−0.12	4.12	2.7	−5.8
Indian rupee (INR)	Dec-94	0.04	5.05	0.74	5.13	2.0	−1.9
Mexican peso (MXN)	Dec-94	−8.23	9.06	0.53	1.68	4.4	−12.7
S. African rand (ZAR)	Jan-95	−2.07	15.37	0.20	1.21	5.5	−7.6
Czech koruna (CZK)	May-97	−5.45	11.57	−0.27	−0.20	−4.5	−1.0
Israeli shekel (ILS)	Jun-97	−1.82	7.41	1.45	5.46	1.9	−3.8
Thai bath (THB)	Jul-97	−3.55	11.97	−2.43	18.33	−3.3	−0.3
Phillipine peso (PHP)	Jul-97	−4.70	8.43	−0.05	4.43	1.4	−6.1
Indonesian rupiah (IDR)	Aug-97	−11.97	26.49	−0.64	8.83	0.4	−12.3
Korean won (KRW)	Dec-97	−5.47	9.60	−0.14	4.58	−4.6	−0.8
Slovak koruna (SKK)	Oct-98	−8.92	10.26	−0.24	−0.29	−6.2	−2.7
Brazilian real (BRL)	Feb-99	−13.31	17.61	1.10	5.24	0.9	−14.2
Chilean peso (CLP)	Sep-99	0.19	9.27	−0.14	−0.34	0.7	−0.5
Colombian peso (COP)	Sep-99	−5.05	9.14	−0.12	3.30	0.1	−5.1
Polish zloty (PLN)	Apr-00	−11.80	11.01	0.08	−0.30	−7.1	−4.7
Turkish lira (TRY)	Feb-01	−25.64	16.68	0.34	1.93	−0.2	−25.4
Hungarian forint (HUF)	May-01	−13.45	12.02	0.59	1.16	−7.7	−5.7
Sri Lanka rupee (LKR)	Dec-01	−4.59	3.92	−1.39	9.41	2.9	−7.5
Argentine peso (ARS)	Jan-02	−13.77	9.28	−1.38	2.40	−4.1	−9.6
Romanian leu (RON)	Oct-04	−9.85	8.93	0.17	−0.90	−8.0	−1.9
Kazakhstan tenge (KZT)	Dec-04	−5.09	6.40	1.21	3.65	−4.1	−1.0
Malaysian ringitt (MYR)	Jul-05	−4.41	3.44	0.43	0.19	−6.0	1.6
Developed							
Australian dollar (AUD)	Dec-94	−2.59	9.88	0.21	−0.04	−1.3	−1.2
Canadian dollar (CAD)	Dec-94	−1.84	6.33	−0.09	0.01	−2.1	0.3
UK sterling (GBP)	Dec-94	−3.04	7.26	0.03	−0.14	−1.9	−1.1
Japanese yen (JPY)	Dec-94	7.13	11.02	−0.88	4.72	3.1	4.0
Euro (EUR/DEM)	Dec-94	1.31	9.37	−0.25	0.06	0.2	1.1
Swiss franc (CHF)	Dec-94	3.14	9.87	−0.28	−0.39	0.5	2.7
Norwegian krone (NOK)	Dec-94	−0.99	9.99	−0.12	0.58	−0.5	−0.5
Swedish krona (SEK)	Dec-94	−0.14	10.13	−0.31	−0.01	−0.5	0.4
N. Zealand dollar (NZD)	Dec-94	−3.70	10.58	0.28	0.43	−1.3	−2.4

Note: The table shows annualized statistics (mean, standard deviation, skewness and kurtosis) of monthly returns on 23 emerging markets and 9 developed market foreign exchange rates (based on a long US dollar position and a short position in the emerging market) for the period January 1995 - June 2007. The returns include the spot rate change as well as the interest rate differential between the US and the specific country. Columns 7-8 report the average, annualized return on the foreign exchange rate (FX) and the average, annualized interest rate differential (IRD), respectively.

Table 4.1 also includes summary statistics of our developed markets control sample. This sample holds the G10 currencies: Australian dollar, Canadian dollar, UK pound, Japanese yen, Euro, Swiss franc, Norwegian krone, Swedish krona, and the New Zealand dollar, all relative to the US dollar. We use the German Deutschmark for the history of the euro prior to 1999. The New Zealand dollar performs best with an annualized return of 3.7 percent. The Japanese yen shows the worst performance with an average return of -7.1 percent per year. The average volatility is 9.4 percent, with much less variation across currencies than for the emerging markets.

Finally, we compute the cross-correlations of the monthly returns. The average correlation between all possible pairs of emerging markets exchange rates is 0.18. Most correlations are in fact close to zero, although some currencies within the same region have a correlation of up to 0.50 for Asia and 0.75 for Europe. These small correlations are advantageous for our empirical analysis, as it means that the trading strategies can benefit from diversification if we combine the currencies in a portfolio. The cross-correlations among emerging market currencies are considerably smaller than those for the developed exchange rates, which generally exceed 0.75. For example, the correlation between the euro and Swiss Franc is equal to 0.94. The main exception is the correlation of the Japanese yen with the other developed currencies, which is substantially lower and equals 0.32 on average.

4.3 Fundamentalist trading strategies

Fundamentalists believe that the exchange rate is intimately linked to macroeconomic variables such as output, inflation, and the trade balance, among others. Hence, news in these economic "fundamentals" is responsible for exchange rate movements. A wide variety of structural exchange rate models is available that might be used for forecasting the future exchange rate. Cheung *et al.* (2005) conclude that "old-fashioned", basic structural models, such as the real interest rate differential (see Frankel (1979), for example) perform at least as good as more recent, elaborate models. This motivates us to use relatively simple structural models in our empirical analysis. In particular, we assume that fundamentalists derive their exchange rate forecasts from information on the real interest rate differential, the growth rate of GDP, and the growth rate of the ratio of the money supply (M2) to foreign exchange reserves.[8] Furthermore, we do not explicitly estimate regression models

[8]Data on inflation, GDP, M2 and Reserves are taken from the IFS database. The Taiwan data comes from the website of the Taiwanese Central Bank.

that include these variables like Garrat and Lee (2007). Instead we simply use them to generate buy and sell signals for the different currencies based on a prediction of the sign of the exchange rate return in the next month, as explained in detail below. On the one hand, this is motivated by the fact that the time period during which the emerging market currencies are floating generally is already rather short. Using part of the available sample for model estimation would leave only a very limited number of observations for out-of-sample forecasting. On the other hand, as pointed out by Leitch and Tanner (1991), among others, correctly forecasting the *sign* of asset returns is perhaps more crucial than forecasting their magnitude when it comes to economic forecast evaluation measures such as the performance of trading strategies.

The three macroeconomic variables are used to generate buy and sell signals as follows. First, we consider the real interest rate differential (RID) as an example. Given the high inflation in emerging markets we do not consider the nominal differential but the real interest differential, see Isaac and de Mel (2001) for discussion of the real interest rates differential literature. The RID forecasting rule can be thought of in terms of the variable RID_t, defined as

$$RID_t = \begin{cases} 1 & \text{if } i_{t-1}^{EM} - \pi_{t-1}^{EM} < i_{t-1}^{US} - \pi_{t-1}^{US}, \\ -1 & \text{otherwise,} \end{cases} \tag{4.4}$$

where i_{t-1}^{X} is the short-term interest in country X and π_{t-1}^{X} is the corresponding inflation rate. The values 1 and -1 for RID_t correspond to a long position in the US dollar and in the emerging market currency, respectively. In other words, in month t we take a long (short) position in the emerging market currency if its real interest rate in month $t-1$ is above (below) the US one.

The levels of GDP in the countries under consideration differ substantially, therefore we consider the relative GDP growth rates as more appropriate for forecasting the direction of the future exchange rate movement. As higher GDP growth leads to higher income, we expect an increased demand for money and therefore a stronger currency. Hence, we take a long position in the emerging market currency if its GDP growth over the past 12 months was higher than the US GDP growth, and a short position when GDP growth was lower. The GDP buy-sell indicator may thus be defined as

$$GDP_t = \begin{cases} 1 & \text{if } \Delta GDP_{t-1}^{EM} < \Delta GDP_{t-1}^{US}, \\ -1 & \text{otherwise,} \end{cases} \tag{4.5}$$

where ΔGDP_{t-1}^{X} is the GDP growth rate in country X.

Our third and final fundamental variable, the growth rate of the ratio of M2 money supply ($M2$) to foreign exchange reserves (RES), influences exchange rates through the rules of demand and supply. A loss of international reserves or a large rise in the domestic money supply can lead to less confidence in a currency and therefore less demand and more supply. Let $\Delta\left(\frac{M2^X_{t-1}}{RES^X_{t-1}}\right)$ denote the 12-month growth rate of the money-reserves ratio in country X in period $t-1$. The investment decision is based on the buy-sell indicator

$$M2R_t = \begin{cases} 1 & \text{if } \Delta\left(\frac{M2^{EM}_{t-1}}{RES^{EM}_{t-1}}\right) > \Delta\left(\frac{M2^{US}_{t-1}}{RES^{US}_{t-1}}\right) \\ -1 & \text{otherwise,} \end{cases} \tag{4.6}$$

that is, we take a long position in the currency with the lowest growth of the money-reserves ratio.

Although in the following we also consider the strategies based on the RID, GDP and $M2R$ signals individually, we mainly focus on an investor who combines the different fundamental signals for making her ultimate decision. Of course, there are infinitely many ways to combine the three pieces of information. Here we take the simple average of the three signals, that is

$$F_t = \frac{RID_t + GDP_t + M2R_t}{3}. \tag{4.7}$$

Note that the combined fundamentalist signal will be +1 (+1/3) if all three (two) strategies are negative on the non-US currency, and vice versa.

The fundamental buy-sell indicators RID_t, GDP_t, $M2R_t$, and F_t are used to implement trading strategies with monthly rebalancing. The return of the fundamental strategy based on signal Y_t for currency i, $r^Y_{i,t}$, is computed as $r^Y_{i,t} = Y_t \cdot r_{t,i}$, where $r_{i,t}$ is the return on a short position in the non-US currency (and thus a long position in the US dollar) for month t. This is a long-short investment strategy, because we will be long in one currency and short in the other currency. The risk free rate is therefore an appropriate benchmark. For this reason we use the Sharpe Ratio as the main criterion to judge the performance of the strategies, because our returns are self financed (excess) returns.

The strategies are implemented for all the emerging and developed currencies individually. In addition, we consider the performance of equally-weighted (EW) and volatility-weighted (VW) portfolios. The weights in the latter portfolio are set proportional to the inverse of the ex post volatility of the spot rates, as measured by the standard deviation over the whole sample period. This is based on the idea that in that case each currency contributes an approximately equal amount to the total portfolio risk. The return of the equal-weighted and volatility weighted portfolios are computed as

$$r_t^{Y,EW} = \frac{1}{n_t} \sum_{i \epsilon \Omega_t} r_{i,t}^Y \qquad \text{and} \qquad r_t^{Y,VW} = \frac{1}{\sum_{i \epsilon \Omega_t} \frac{1}{\sigma_i}} \sum_{i \epsilon \Omega_t} \frac{1}{\sigma_i} r_{i,t}^Y \tag{4.8}$$

where Ω_t is the set of available currencies at time t, n_t the number of currencies in Ω_t at t, and σ_i is the volatility of the spot rate for country i. We acknowledge that the use of the full-sample standard deviation to weight the currencies entails some form of data-snooping and also avoids the fact that, especially for the emerging markets, the volatilities vary over time. More advanced weighting schemes using an ex ante volatility measure would, however, put serious limitations on the sample period available for forecast evaluation. Hence, these are left for future research.

The results for the fundamental strategies based on the individual *RID*, *GDP* and $M2R$ signals are summarized in Table 4.2. Several interesting conclusions emerge. First, the performance of the strategies for individual currencies based on *RID* or *GDP* is on average positive, while the performance of the $M2R$ strategy is mostly negative. Especially for the *GDP* strategy the average return is also significantly different from zero (in terms of t-values at a 5 percent significance level) for quite a large number of currencies, while no significantly negative average returns occur. The $M2R$ strategy renders a significantly negative average return for two individual countries, compared to only one significantly positive return. Thus, the *RID* and *GDP* strategies seem to provide considerably more accurate forecasts of future exchange rate movements than the $M2R$ strategy. Within the strategies the results vary dramatically across countries. For example, the average returns on the *RID* strategy range between 14.3 and –5.1 percent for Turkey and Kazakhstan, respectively. For the other strategies the variation is even more pronounced. This also shows up in the volatilities of the individual strategies, see India and Slovakia, for example.

For the developed currencies, we also find that the $M2R$ strategy performs relatively worse for most countries. A difference with the emerging markets is, however, that the real interest rate differential seems to be more informative for the exchange rate movements than the relative GDP growth rates. Except for the Swedish krona, the RID strategy results in positive average returns for all developed currencies, which furthermore are statistically significant for four of the eight countries.

Table 4.2: Performance of fundamental trading strategies

	Average return			Standard deviation		
	RID	*GDP*	*M2R*	*RID*	*GDP*	*M2R*
Emerging						
TWD	−0.21	−0.87	−1.37	5.6	5.6	5.5
PEN	3.20*	2.38*	−1.02	4.0	4.0	4.1
INR	2.66**	−0.04	0.75	5.0	5.0	5.0
MXN	4.01	9.59*	−1.33	9.3	8.9	9.4
ZAR	1.02	2.11	−7.70**	15.4	15.4	15.2
CZK	0.20	7.48*	1.45	11.7	11.5	11.7
ILS	1.82	0.97	−1.98	7.4	7.4	7.4
THB	1.57	−1.15	−3.35	12.0	12.0	12.2
PHP	2.66	4.70**	−3.06	8.5	8.4	8.5
IDR	−4.72	11.64	−4.68	26.7	26.5	26.7
KRW	3.15	−2.33	5.14	9.7	9.7	9.6
SKK	1.31	8.64*	6.02**	10.6	10.3	10.4
BRL	13.31*	11.48**	2.67	17.6	17.7	18.0
CLP	5.39	−0.19	−4.65	9.1	9.3	9.2
COP	1.20	6.33**	0.88	9.3	9.1	9.3
PLN	8.73*	4.90	5.04	11.2	11.4	11.4
TRY	14.30*	25.64*	−19.64*	17.8	16.7	17.4
HUF	7.09	14.20*	−8.96**	12.5	11.9	12.4
LKR	0.41	4.59*	2.14	4.1	3.9	4.1
ARS	−0.69	13.77*	−11.83*	10.1	9.3	9.5
RON	−0.81	9.85	14.07**	9.4	8.9	8.4
KZT	−5.09	5.09	−2.86	6.4	6.4	6.5
MYR	−4.41	4.41	−1.58	3.4	3.4	3.6
Developed						
AUD	5.61*	5.95*	−0.10	9.8	9.8	9.9
CAD	0.93	−2.63	−2.91	6.3	6.3	6.3
GBP	1.58	3.23	−0.25	7.3	7.3	7.3
JPY	5.85**	7.13*	−7.84*	11.1	11.0	11.0
EUR	5.42*	1.39	0.16	9.3	9.4	9.4
CHF	7.26*	3.03	0.20	9.7	9.9	9.9
NOK	3.79	−4.45	−2.10	9.9	9.9	10.0
SEK	−0.76	−2.26	5.86*	10.1	10.1	10.0
NZD	1.00	11.57*	0.02	10.6	10.1	10.6
Portfolios						
EM-EW	2.21**	4.32*	−1.63	4.1	4.2	4.2
EM-VW	1.49*	2.49*	−0.64	1.9	1.9	1.6
DEV-EW	3.41*	2.55*	−0.77	5.3	3.9	4.3
DEV-VW	3.23*	2.18*	−0.79	5.1	3.8	4.0

Note: The table shows average return, in annualized percentage points, and standard deviations for the fundamental strategies based on the real interest differential (*RID*), relative GDP growth (*GDP*) and relative growth in the M2 to reserves ratio (*M2R*) applied to all exchange rates over their floating currency regime periods (see Table 4.1). * and ** indicate that the average return is significantly different from zero at the 5% and 10% level, respectively.

The results in Table 4.2 do not take into account transaction costs. To investigate the influence of such costs, we record the number of transactions in each strategy and compute break-even transaction costs. The average number of transactions per year is equal to approximately 1, 0.5 and 1.5 for the *RID*, *GDP* and $M2R$ strategies, respectively. Compared to trend strategies these numbers are rather low (as shown in the next section), which results in relatively high levels of break-even transaction costs. For most countries and strategies having a positive performance, break-even transaction costs exceed 2 percent, which for most currencies is clearly above the level of transactions costs encountered in practice by a large institutional investor. More detailed results on the *RID*, *GDP* and $M2R$ strategies are not shown here to save space, but are available upon request.

Combining the individual currencies in a portfolio results in significantly positive returns for the *RID*- and *GDP*-based strategies, except for the equally-weighted emerging market portfolio based on the real interest rate differential. The benefits of diversification across currencies become clear by noting the low volatilities of the portfolio returns. For the emerging markets, we also observe a substantial difference in returns for the equally-weighted and volatility-weighted portfolios, especially for the *GDP* strategy. This is due to the fact that the countries generating the highest average returns for this strategy, including Turkey, Argentina, Indonesia and Brazil, also have the highest exchange rate volatility (see Table 4.1) and thus receive a relatively small weight in the volatility-weighted portfolio. The reduction in average return from 4.32 to 2.49 percent when going from equal weighting to volatility weighting is, however, more than compensated by the reduction in volatility, from 4.2 to 1.9, such that the Sharpe ratio in fact increases. For the $M2R$ strategy the portfolio performances are negative, albeit insignificant, as expected from the poor performance of this strategy for the individual currencies.

Our next step is to combine the individual fundamental signals, as in (4.7). Table 4.3 reports results of this combined strategy. The most pronounced effect of combining the three fundamental signals is a substantial reduction in volatility. For almost all currencies, the volatility of the combined strategy is about 50% lower compared to the individual strategies. The same applies to the volatility at the portfolio level. At the same time, the average portfolio returns for the combined strategy are also lower than those for the individual *RID* and *GDP* strategies, due to the inclusion of the poorly performing $M2R$ strategy. The reduction in returns is relatively small though compared to the emerging market *RID* strategy, such that the resulting Sharpe ratio is considerably higher. For the volatility-weighted portfolio, for example, the Sharpe ratio reaches 0.96, compared to 0.80

Table 4.3: Performance of combined fundamentalist trading strategy

	Mean	Stdev	Sharpe	t-value	#TR	BETC
Emerging						
TWD	−0.81	3.6	−0.23	−0.79	1.02	−0.4
PEN	1.52	2.2	0.70	2.42	1.13	0.7
INR	1.12	2.7	0.42	1.45	0.52	1.1
MXN	4.09	5.6	0.73	2.53	0.88	2.3
ZAR	−1.52	10.1	−0.15	−0.52	0.58	−1.3
CZK	3.04	7.0	0.43	1.35	1.31	1.2
ILS	0.27	3.9	0.07	0.21	0.87	0.2
THB	−0.97	5.0	−0.19	−0.58	1.39	−0.4
PHP	1.43	5.2	0.28	0.85	0.88	0.8
IDR	0.75	11.4	0.07	0.20	0.86	0.4
KRW	1.99	5.4	0.37	1.11	1.03	1.0
SKK	5.32	5.7	0.94	2.69	0.89	3.0
BRL	9.16	10.0	0.92	2.59	0.80	5.7
CLP	0.18	5.4	0.03	0.09	1.45	0.1
COP	2.80	4.5	0.62	1.68	0.50	2.8
PLN	6.22	7.2	0.86	2.23	1.09	2.9
TRY	6.77	10.5	0.64	1.56	0.62	5.5
HUF	4.11	7.1	0.58	1.39	0.88	2.3
LKR	2.38	2.4	1.00	2.23	0.67	1.8
ARS	0.42	3.4	0.12	0.27	0.67	0.3
RON	9.30	4.0	2.32	2.76	1.71	2.7
KZT	−0.95	2.2	−0.44	−0.63	0.32	−1.5
MYR	−0.53	1.2	−0.43	−0.53	0.44	−0.6
Developed						
AUD	3.82	7.0	0.55	1.90	1.19	1.6
CAD	−1.54	2.8	−0.56	−1.94	1.24	−0.6
GBP	1.52	3.6	0.43	1.48	0.99	0.8
JPY	1.71	6.8	0.25	0.88	0.39	2.2
EUR	2.32	4.9	0.48	1.66	0.47	2.5
CHF	3.50	5.2	0.67	2.32	0.74	2.3
NOK	−0.92	5.8	−0.16	−0.55	1.32	−0.3
SEK	0.95	4.7	0.20	0.70	1.93	0.2
NZD	4.20	6.2	0.67	2.35	0.86	2.5
Portfolios						
EM-EW	1.65	2.41	0.68	2.37	1.28	0.6
EM-VW	1.11	1.15	0.96	3.35	0.90	0.6
DEV-EW	1.73	2.52	0.69	2.39	1.46	0.6
DEV-VW	1.51	2.32	0.65	2.27	1.03	0.7

Note: The table shows mean return (in annualized percentage points), standard deviation, the Sharpe ratio and its t-value, the average number of transactions per year (#TR) and the breakeven transaction costs (BETC) for the fundamental strategy combining signals from the real interest differential (*RID*), relative GDP growth (*GDP*) and relative growth in the M2 to reserves ratio (*M2R*), applied to all exchange rates over their floating currency regime periods (see Table 4.1). Transactions are reported as the single counted average number of transactions per year; therefore turnover is twice the number of transactions. The four bottom lines report the same statistics for equally-weighted (EW) and volatility-weighted (VW) portfolios for emerging (EM) and developed (DEV) markets.

for the corresponding portfolio in the *RID* strategy. Due to the larger return difference, the combined strategy performs worse than the *GDP*-based strategy, which achieves a Sharpe of 1.30. The decline in average returns is also much larger for the developed portfolios, such that both the individual *RID* and *GDP* strategies outperform the combined strategy.

Returning to the results for individual emerging market currencies, we observe that the performance differences across countries of the combined strategy are much less extreme than for the individual strategies in Table 4.2. We find positive average returns for 18 of the 23 currencies, while none of the five negative average returns are significant. In sum, combining the fundamental signals results in an attractive and fairly robust fundamentalist trading strategy.

4.4 Chartist trading strategies

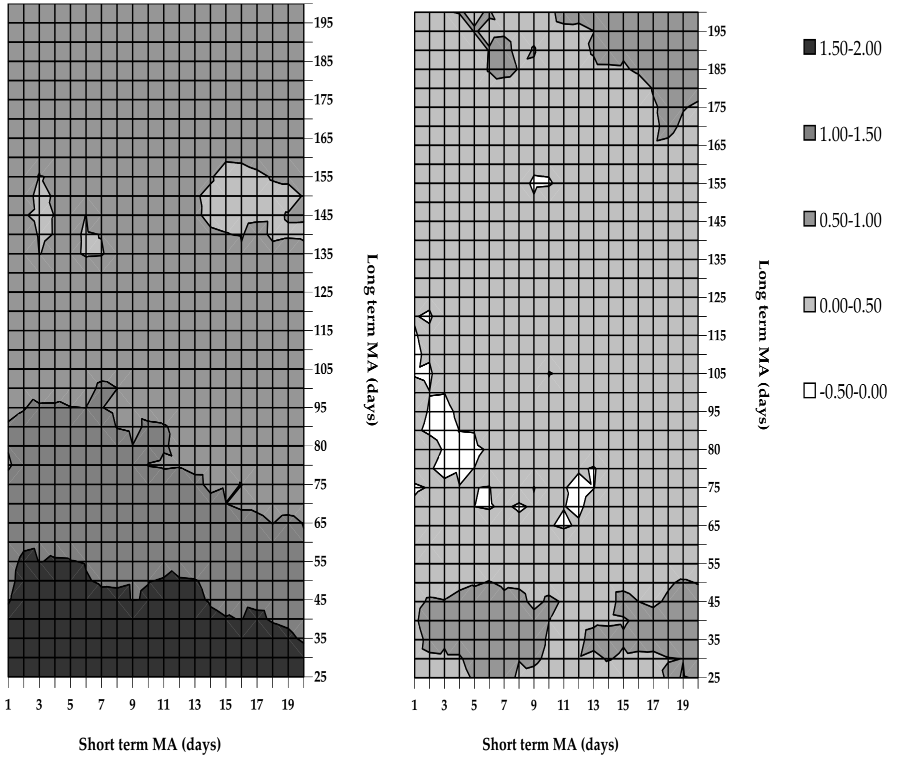
Among the different types of technical trading rules employed by chartists moving average rules are by far the most popular. The general idea of these rules is to give a buy signal when a fast moving average of the spot rate over the previous K days is above a slow moving average taken over the previous L days, that is

$$MA_t(K,L) = \begin{cases} 1 & \text{if } \frac{1}{K}\sum_{k=1}^{K} S_{t-k} \geq \frac{1}{L}\sum_{l=1}^{L} S_{t-l}, \\ -1 & \text{otherwise,} \end{cases} \tag{4.9}$$

where $K < L$. Moving average rules are sometimes referred to as trend-following rules, as they generate long (short) signals when the exchange rate has recently been rising (falling). We compute the returns of the moving average strategy as before, with the difference that the signal in (4.9) is updated daily.

The results of moving average rules are known to be sensitive to the choice of K and L. To prevent that our conclusions are based on one specific parameter setting, we decide to combine a range of moving average rules instead of testing one particular rule. To determine a reasonable range for the lengths of the fast and slow moving averages, we vary K between $1 - 20$ days in steps of one day and L between $25 - 200$ days in steps of 5 days. Figure 4.2 shows the empirical results for the individual moving average strategies based on (4.9) for each of the resulting 720 different combinations of K and L. Panels (a) and (b) of Figure 4.2 show the average t-values for the 23 emerging markets currencies and for the nine developed currencies, respectively. For the emerging markets we observe that the average t-value of these strategies is positive for all settings. The average t-values are high

Figure 4.2: Moving average strategy heat-maps.



(a) Emerging Markets (b) Developed Markets

The figure shows the heat-map of the average t-values for moving average strategies with the short term moving average ranging between $1 - 20$ days and the long term moving average between $25 - 200$ days. The average t-value of the emerging markets in panel a) is based the average of 23 emerging market currencies. The developed market average in panel b) is based on nine developed market currencies. See Section 4.2 for details for the models with a relatively short slow moving average ($L < 100$), independent of the length of the fast moving average.

The results for the developed markets are disappointing. For all settings the t-value is between –0.5 and 1. Closer inspection of these results reveals that they actually are poor for each of the individual developed currencies. This finding is in line with Olson (2004), Pukthuanthong-Le *et al.* (2007) and Neely *et al.* (in press), who report that profit opportunities for the moving average rules in the developed currency markets disappeared by the mid-1990s.

Based on these results we decide to select all rules with a fast moving average between 5 and 20 days and a slow moving average between 25 and 65 days, resulting in 144 combinations of K and L. The simple average of the resulting buy-sell signals $MA_t(K, L)$ obtained from (4.9) is defined as the buy-sell indicator C_t, which is employed in the chartist trading strategy.

Table 4.4 reports the performance statistics of the chartist strategy. The trend strategy renders a positive return for 21 of the 23 currencies, where 10 are significant at a 5% level. One of the best risk-adjusted results is obtained for Taiwan, with a Sharpe ratio of 1.23 and t-statistic of 4.26. This is in line with Lee *et al.* (2001b), who find that moving average technical trading rules work well for Taiwan over the period 1988-1995. The high Sharpe ratios for Colombia, Romania and Kazakhstan are also worth mentioning (1.23, 1.22 and 2.02 respectively), although their floating regime history is shorter than for Taiwan. Negative returns, albeit not significant, are found for the Mexican peso and the Sri Lanka rupee. Our findings for Mexico are in contrast with the positive results reported by Lee *et al.* (2001a) for the period 1992-99. Apart from the different sample period, this discrepancy can be explained by the fact that Lee *et al.* (2001a) do not take into account the interest rate differential in the calculation of the exchange rate returns. As seen in Table 4.1, with an average of 12.7 percent per year the interest rate differential is far from negligible for the Mexican peso.

Combining the individual currencies again achieves a large reduction in risk. The equal-weighted portfolio based on the moving average trading rules has a highly economically and statistically significant Sharpe ratio of 1.24. The Sharpe ratio further increases to 1.52 for the volatility-weighted portfolio, as the moving average strategy performs well for the relatively less volatile currencies (Taiwan, Peru, India, Israel and Philippines), while it performs worse for some of the more volatile currencies (Mexico and Czech Republic).

Table 4.4: Performance of combined chartist trading strategy

	Mean	Stdev	Sharpe	t-value	#TR	BETC
Emerging						
TWD	5.00	4.1	1.23	4.26	5.86	0.43
PEN	2.14	3.5	0.62	2.15	6.21	0.17
INR	4.84	4.4	1.09	3.79	5.55	0.44
MXN	−2.94	9.8	−0.30	−1.04	8.25	−0.18
ZAR	5.96	13.1	0.46	1.58	6.84	0.44
CZK	1.13	11.0	0.10	0.32	7.80	0.07
ILS	4.88	5.9	0.83	2.56	6.48	0.38
THB	6.22	7.8	0.80	2.46	6.45	0.48
PHP	4.63	6.3	0.73	2.26	5.91	0.39
IDR	14.53	21.4	0.68	2.08	6.87	1.06
KRW	4.53	7.8	0.58	1.75	7.29	0.31
SKK	3.52	8.7	0.41	1.16	7.22	0.24
BRL	10.92	16.4	0.67	1.88	6.39	0.85
CLP	6.14	8.3	0.74	2.01	6.41	0.48
COP	9.98	8.1	1.23	3.33	5.72	0.87
PLN	3.47	9.4	0.37	0.96	7.25	0.24
TRY	8.56	13.0	0.66	1.60	7.14	0.60
HUF	1.19	9.3	0.13	0.30	8.43	0.07
LKR	−0.97	3.2	−0.30	−0.67	5.01	−0.10
ARS	3.72	7.8	0.48	1.07	7.07	0.26
RON	10.05	7.8	1.30	1.94	6.07	0.83
KZT	7.81	3.9	2.02	2.91	4.43	0.88
MYR	1.84	3.4	0.54	0.66	6.39	0.14
Developed						
AUD	0.13	9.1	0.01	0.05	8.08	0.01
CAD	0.44	5.7	0.08	0.27	7.96	0.03
GBP	−1.26	6.1	−0.21	−0.72	8.43	−0.07
JPY	2.94	9.1	0.32	1.12	7.71	0.19
EUR	3.43	7.8	0.44	1.53	7.50	0.23
CHF	1.10	7.8	0.14	0.49	7.92	0.07
NOK	0.04	7.8	0.00	0.02	8.24	0.00
SEK	2.25	8.5	0.26	0.91	7.67	0.15
NZD	2.10	10.1	0.21	0.72	7.98	0.13
Portfolios						
EM-EW	4.52	3.63	1.24	4.32	6.65	0.34
EM-VW	2.58	1.70	1.52	5.25	6.42	0.20
DEV-EW	1.24	4.77	0.26	0.90	7.94	0.08
DEV-VW	1.07	4.60	0.23	0.80	7.96	0.07

Note: The table shows performance statistics for the technical trading strategy combining signals from moving average rules with different lengths of the fast and slow moving averages applied to all exchange rates over their floating currency regime periods (see Table 4.1). See Table 4.3 for further details.

Trend models with daily rebalancing as considered here may lead to high turnover. For that reason we again consider the effects of transactions costs. Columns 6 and 7 in Table 4.4 show the number of transactions and the break-even transaction costs, respectively. Averaged across individual currencies, the number of transactions equals approximately 6.7 per year, which means that the chartist investor trades about once every two months in each currency. Compared to the fundamental strategies these numbers are rather high. For most countries and strategies having a positive performance, break-even transaction costs exceed 0.4 percent, which for most currencies is still above the level of transactions costs encountered in practice by a large institutional investor.

Thus, based on our empirical analysis, we conclude that chartists may benefit from applying a moving average trading rule in emerging markets currencies. Note that this is not the case for the developed markets in our control sample. Although the average return is positive for eight of the nine currencies, none of these are significantly different from zero. Even combining the currencies into a portfolio does not render significantly positive risk-adjusted returns, possibly as a result of the limited diversification potential due to the high cross-correlations among these currencies.

4.5 Combining fundamentalist and chartist trading strategies

In the previous two sections we analyzed the profitability of fundamentalist and chartist investment strategies for emerging currency markets. Our empirical results indicate that both types of strategies generate significantly positive risk-adjusted returns over the period 1995-2007. In this section, we investigate whether the performance can be further improved by combining fundamental and chartist information. We start by examining a naive equally-weighted combination of both types of information. Subsequently, this is extended to a combined strategy where the relative weight given to fundamental and chartist signals is based on their past performance.

Table 4.5 shows the performance statistics of the strategy that is based on an equally-weighted combination of the fundamental signal F_t and the chartist signal C_t. This strategy mimics the behavior of a currency trader who puts equal value on fundamentalist and chartist information. The benefits of combining both sources of information is clearly borne out by the results for the individual emerging markets. The 'naive' combination yields positive risk-adjusted returns for all 23 currencies, with no less than 12 being significant

Table 4.5: Performance of equally-weighted fundamentalist-chartist trading strategy

	Mean	Stdev	Sharpe	t-value	#TR	BETC
Emerging						
TWD	2.09	2.63	0.80	2.77	3.44	0.30
PEN	1.83	2.12	0.87	3.01	3.67	0.25
INR	2.98	2.83	1.06	3.67	3.04	0.49
MXN	0.57	5.35	0.11	0.37	4.57	0.06
ZAR	2.22	7.75	0.29	0.99	3.71	0.30
CZK	2.09	7.07	0.30	0.92	4.55	0.23
ILS	2.57	3.13	0.82	2.54	3.67	0.35
THB	2.72	4.38	0.62	1.87	3.92	0.35
PHP	3.03	3.34	0.91	2.79	3.39	0.45
IDR	7.70	11.11	0.69	2.12	3.86	1.00
KRW	3.26	5.29	0.62	1.86	4.16	0.39
SKK	4.42	5.46	0.81	2.33	4.06	0.54
BRL	10.04	9.10	1.10	3.10	3.59	1.40
CLP	3.16	5.05	0.63	1.69	3.93	0.40
COP	6.39	4.67	1.37	3.70	3.11	1.03
PLN	4.85	6.83	0.71	1.84	4.17	0.58
TRY	7.67	8.47	0.91	2.20	3.88	0.99
HUF	2.65	6.65	0.40	0.95	4.66	0.28
LKR	0.70	1.99	0.35	0.79	2.84	0.12
ARS	2.07	3.08	0.67	1.51	3.87	0.27
RON	10.48	5.83	1.80	2.14	3.89	1.35
KZT	3.43	2.36	1.45	2.10	2.38	0.72
MYR	0.66	1.65	0.40	0.48	3.41	0.10
Developed						
AUD	1.98	6.20	0.32	1.11	4.63	0.21
CAD	−0.55	2.80	−0.20	−0.68	4.60	−0.06
GBP	0.13	4.06	0.03	0.11	4.71	0.01
JPY	2.33	5.32	0.44	1.52	4.05	0.29
EUR	2.88	5.14	0.56	1.95	3.98	0.36
CHF	2.30	5.10	0.45	1.57	4.33	0.27
NOK	−0.44	5.00	−0.09	−0.31	4.78	−0.05
SEK	1.60	5.04	0.32	1.10	4.80	0.17
NZD	3.15	6.48	0.49	1.69	4.42	0.36
Portfolios						
EM-EW	3.08	2.22	1.39	4.81	3.97	0.39
EM-VW	1.83	1.12	1.63	5.65	3.66	0.25
DEV-EW	1.48	2.98	0.50	1.72	4.70	0.16
DEV-VW	1.30	2.83	0.46	1.60	4.50	0.15

Note: The table shows performance statistics for the equally-weighted fundamentalist-chartist strategy applied to all exchange rates over their floating currency regime periods (see Table 4.1). See Table 4.3 for further details.

at the 5 percent level. We also note that turnover is reduced compared to the chartist strategy in Table 4.4, such that for most currencies the break-even transaction costs are considerably higher than transaction cost levels encountered in practice.

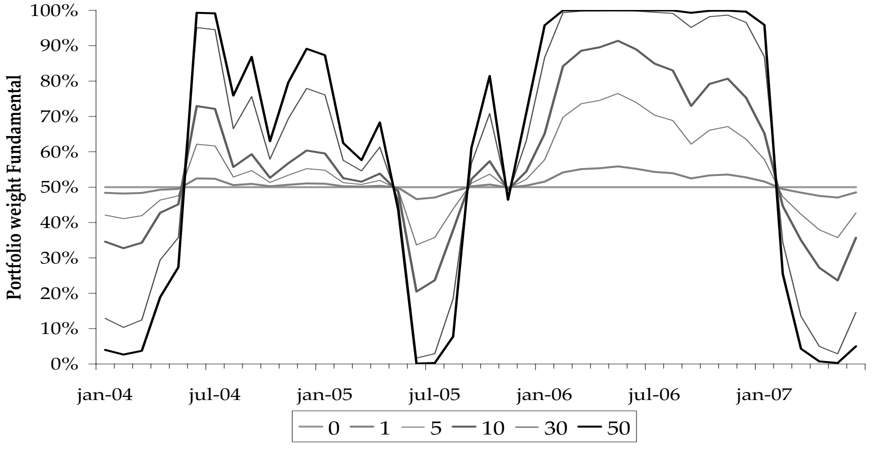
At the portfolio level, the highly significant Sharpe ratios equal 1.39 and 1.63 for the equally-weighted and volatility-weighted portfolios, respectively, which also are higher than the Sharpe ratios for the fundamental and chartist strategies individually. The Sharpe ratio of the combined strategy is significantly higher than the fundamental strategy according to the Jobson and Korkie (1981) test (and Memmel's (2003) adjustment). Although the Sharpe ratio of the chartist strategy is not significantly different from the combined strategy at the 5% level, the Jobson-Korkie t-values of 1.80 and 1.44 for the equal and volatility weighted portfolios, respectively, are pointing in this direction.[9] This indicates that over the past 12 years an emerging markets currency trader would have earned higher risk-adjusted returns from combining fundamentalist and chartist trading rules, even with a naive equally-weighted combination.

This result for emerging markets is in line with the questionnaire results obtained by Taylor and Allen (1992), Lui and Mole (1998), Cheung and Chinn (2001), and Gehrig and Menkhoff (2004), which indicate that foreign exchange dealers, based in the major foreign exchange trading centers, view technical and fundamental analysis as complementary sources of information. In contrast, a naive combination does not seem to add sufficient value for an investor in the developed markets. We observe that none of the individual developed currencies has a risk-adjusted return that is statistically significant at the 5% level. Sharpe ratios are even negative (albeit insignificant) for Canada and Norway. The equally-weighted and volatility-weighted portfolios of developed currencies yield t-values of 1.72 and 1.60, respectively, indicating that the risk-adjusted returns (0.50 and 0.46) are not significantly different from zero.

In the heterogeneous agents models developed in Chiarella *et al.* (2006), De Grauwe and Grimaldi (2005, 2006) and De Grauwe and Markiewicz (2006), agents determine the weights assigned to the different available investment strategies based on their relative past performance. In order to test whether this type of strategy delivers superior returns we consider a combined investment strategy with monthly rebalancing and dynamic weights

[9] Details are not reported here to save space, but are available upon request.

Figure 4.3: The relationship between γ and dynamic weights illustrated.



The figure shows the sensitivity of the dynamic weights in the combined fundamental-technical trading strategy to the choice of γ in (4.10) for the Indonesian rupee.

placed on fundamental and chartist signals as follows:

$$W_t^F = \frac{\exp\left(\gamma \sum_{j=1}^{J} r_{t-j}^F\right)}{\exp\left(\gamma \sum_{j=1}^{J} r_{t-j}^F\right) + \exp\left(\gamma \sum_{j=1}^{J} r_{t-j}^C\right)}, \tag{4.10}$$

$$W_t^C = \frac{\exp\left(\gamma \sum_{j=1}^{J} r_{t-j}^C\right)}{\exp\left(\gamma \sum_{j=1}^{J} r_{t-j}^F\right) + \exp\left(\gamma \sum_{j=1}^{J} r_{t-j}^C\right)} = 1 - W_t^F, \tag{4.11}$$

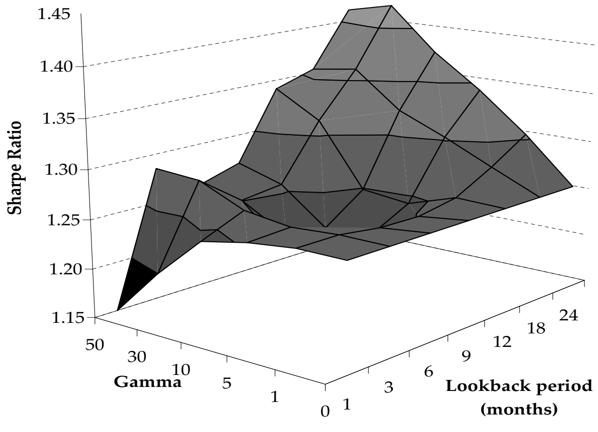
where W_t^F and W_t^C are the weights on the fundamentalist and chartist signals, respectively, r_t^F and r_t^C are the returns on the fundamentalist and chartist trading strategies in month t, and J is the length of the look-back period of the investor. The parameter $\gamma \geq 0$ determines the strength of the deviation from the equally weighted average and thus measures the 'aggressiveness' of the dynamic weighting scheme. Note that the limiting case $\gamma = 0$ implies equal weighting, as this reduces W_t^F and W_t^C to 0.5. Figure 4.3 shows an example of the sensitivity of the dynamic weights, with $J = 12$ months, for the choice of γ for Indonesia over the period 2004-2007.

Table 4.6: Performance of dynamic combined fundamentalist-chartist trading strategy

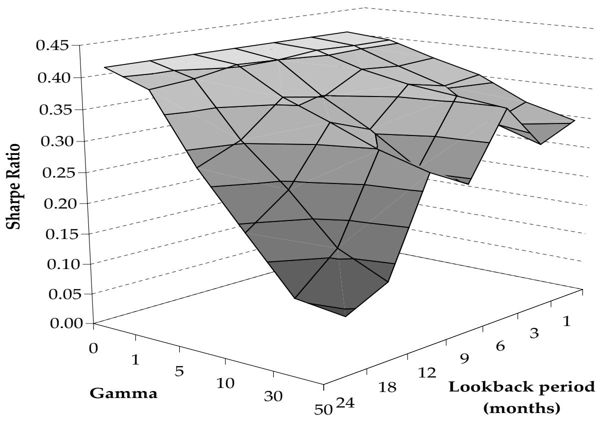
	Dynamic weights				Equally-weighted			
	Mean	Stdev	Sharpe	t-value	Mean	Stdev	Sharpe	t-value
Emerging								
TWD	4.49	3.78	1.19	3.78	2.37	2.69	0.88	2.80
PEN	2.51	2.68	0.94	2.98	2.38	2.22	1.07	3.41
INR	3.78	3.17	1.19	3.79	3.12	2.60	1.20	3.81
MXN	0.05	8.19	0.01	0.02	−0.41	5.35	−0.08	−0.24
ZAR	5.29	13.81	0.38	1.21	2.18	8.40	0.26	0.82
CZK	1.83	7.00	0.26	0.72	3.12	6.72	0.46	1.29
ILS	1.99	3.91	0.51	1.40	2.62	3.16	0.83	2.29
THB	4.97	4.79	1.04	2.76	3.38	3.18	1.06	2.83
PHP	4.37	5.17	0.85	2.32	2.80	2.48	1.13	3.09
IDR	6.72	9.32	0.72	1.96	4.39	6.74	0.65	1.77
KRW	1.91	4.80	0.40	1.06	3.12	4.37	0.71	1.90
SKK	6.28	6.60	0.95	2.38	4.98	5.65	0.88	2.20
BRL	13.58	16.72	0.81	1.98	11.35	9.87	1.15	2.80
CLP	3.91	7.05	0.55	1.28	2.79	5.24	0.53	1.23
COP	7.62	6.51	1.17	2.70	6.98	5.18	1.35	3.11
PLN	1.58	6.77	0.23	0.51	4.42	6.82	0.65	1.41
TRY	4.88	10.93	0.45	0.88	7.37	7.13	1.03	2.05
HUF	1.13	5.28	0.21	0.41	1.00	5.75	0.17	0.33
LKR	−0.80	1.32	−0.60	−1.05	−0.60	1.59	−0.38	−0.65
ARS	0.27	1.43	0.19	0.33	0.53	1.48	0.35	0.61
RON	22.60	5.74	3.94	1.97	23.24	5.78	4.02	2.01
KZT	NA	NA	NA	NA	NA	NA	NA	NA
MYR	NA	NA	NA	NA	NA	NA	NA	NA
Developed								
AUD	3.21	7.98	0.40	1.28	2.44	6.67	0.37	1.16
CAD	−0.72	4.47	−0.16	−0.51	−0.48	2.92	−0.17	−0.52
GBP	0.02	3.85	0.00	0.01	0.11	3.87	0.03	0.09
JPY	0.56	5.86	0.10	0.30	0.96	4.79	0.20	0.64
EUR	2.20	5.56	0.39	1.25	2.98	5.22	0.57	1.81
Portfolios								
EM-EW	3.83	2.91	1.31	4.17	2.78	2.21	1.26	3.99
EM-VW	1.93	1.21	1.59	5.06	1.61	1.05	1.53	4.86
DEV-EW	1.06	3.54	0.30	0.95	1.28	3.12	0.41	1.30
DEV-VW	0.92	3.39	0.27	0.86	1.14	2.97	0.38	1.21

Note: The table shows performance statistics for the combined fundamentalist-chartist strategy with weights determined by the relative performance during the past 12 months, applied to all exchange rates over their floating currency regime periods in the period 1997-2007 (see Table 4.1). See Table 4.3 for further details.

Figure 4.4: Dynamic strategy performance for varying lookback periods and γ levels.



(a) Emerging Markets



(b) Developed Markets

The figure shows dynamic weighting between fundamentalist and chartist rules. The figure shows the Sharpe ratio of the equally weighted portfolio for different lookback periods J ranging from 1 to 24 months and for different 'aggressiveness' of the dynamic strategy as measured by γ. Here $\gamma = 0$ corresponds to the naive equally-weighted strategy, while $\gamma = 50$ corresponds to the most aggressive strategy, with weights changes the fastest.

In Table 4.6 we display the results from the dynamic weighting scheme in (4.10) and (4.11) with $J = 12$ months and $\gamma = 30$, as well as the results of our equally-weighted strategy for the period 1997-2007.[10] The results from this dynamic approach are mixed for the individual countries, as about 2/3 of the Sharpe ratios (and their t-values) decrease relative to the equally-weighted strategy. Nevertheless, we observe a small increase in the level of risk-adjusted returns for both emerging market portfolios from 1.26 and 1.53 to 1.31 and 1.59 for the equally-weighted and volatility-weighted portfolios, respectively. This result does not depend on the particular configuration of the parameters J and γ, as can be seen in Figure 4.4. This figure shows the Sharpe ratios of the portfolio based on the combined strategy with dynamic weights for different look-back periods J ranging from 1 to 24 months and for different levels of 'aggressiveness' as measured by γ. Panel (a) of Figure 4.4 contains the results for the emerging markets portfolio. The Sharpe ratios are comparable for all parameter settings, although we do observe a modest increase in the Sharpe ratio when the look-back period gets longer and the strategy becomes more aggressive. The difference in Sharpe ratios between the best performing dynamic strategy (with $J = 24$ and $\gamma = 50$) and the equally-weighted strategy is not significant, however.[11] In panel (b) of Figure 4.4, where we rotate the graph by 90 degrees, it can be seen that for developed currency markets the naive equally-weighted combination seems to be best within the range of parameters considered. The Sharpe ratio declines along both dimensions with J or γ. This leads us to the conclusion that a dynamic weighting scheme between chartists and fundamentalists does not yield additional returns relative to a naive combination.

4.6 Conclusions

Empirical research on exchange rate forecasting has tended to focus on the usefulness of either technical analysis or of structural exchange rate models. Both questionnaires among foreign exchange market participants as well as recently developed heterogeneous agents models indicate that both types of information are relevant for assessing future exchange rate movements. In addition, the heterogeneous agents models suggest that the relative importance of chartism and fundamentalism varies over time according to the past performance of the corresponding trading strategies.

In this paper we analyze the economic value of combining chartist and fundamentalist

[10] We reduce the sample period to 1997-2007 such that the performance evaluation covers the same period for all values of the look-back period J, which we vary between 1 and 24 months.

[11] More detailed results are available upon request.

information for 23 emerging currency markets with a floating exchange rate regime over the period 1995-2007. We document that an equally-weighted combined chartist/fundamentalist investment strategy renders economically and statistically significant positive risk-adjusted returns. Although both fundamentalist and chartist trading rules individually also generate positive risk-adjusted returns on average, the performance of the combined strategy is far superior and, in particular, much more stable across countries. Notably, the dynamic strategy, in which the weights assigned to chartist and fundamental information are adjusted dynamically based on relative past performance, does not outperform a naive equally-weighted combination.

Further research can be done on the inclusion of other types of information in the emerging currency market. In particular, it may be of interest to expand our information set with information on (proprietary) customer order flows of investment banks, which have been studied, as far as our knowledge, only for developed markets, see Evans and Lyons (1999), among others. Gehrig and Menkhoff (2004), for example, document that many foreign exchange market participants consider flow analysis as an independent third type of information, next to technical analysis and fundamental information. The inclusion of this additional source of information may further increase the economic value of emerging markets currency investments. Another potential avenue for further research would be to investigate other statistical techniques to combine fundamental and chartist information dynamically, although it is likely that these methods require a larger number of observations than currently available for emerging markets. Bayesian Model Averaging, for example applied by Wright (2003) and Garrat and Lee (2007) for the developed currency markets, can be one of these methods.

Chapter 5

The Short-Term Corporate Bond Return Anomaly*

5.1 Introduction

Despite the massive size of the corporate bond market, surprisingly little is known about to which extent dynamics of corporate bond returns are properly explained by common risk factors. Our concern is that exceptional combinations of return and risk are achieved through investments in specific segments of the maturity spectrum, which have received limited attention in earlier studies about the pricing of corporate bonds. Sharpe ratios of US Treasury bills and short term bonds are reported by Pilotte and Sterbenz (2006) to be atypically high, while Sharpe ratios for bonds with a medium and longer maturity are reported to be similar to the Sharpe ratios of common stocks. For corporate bonds, Alexander (1980) applies the market model to examine return on long-term bonds, and Gebhardt *et al.* (2005) find that term and default risks are able to describe the returns on investment-grade corporate bonds with a remaining maturity of at least three years.

The few studies that concentrate on the cross-sectional determinants of corporate bond returns have identified several proxies for non-diversifiable risk as important. Consistent with the asset pricing theories of Merton (1973) and Ross (1976), several of these studies suggest that bond returns are explained by loadings on factors that represent term and default risks in the economy (Fama and French (1993), Gebhardt *et al.* (2005)), and by

*This chapter is based on the working paper by Derwall *et al.* (2008). We are grateful to Dick van Dijk, Ronald Kahn, Jianming Kou, Michiel de Pooter, Richard Sloan and Marno Verbeek for helpful suggestions. We would also like to thank participants of the Interest Rate Term Structure Modelling Workshop at the Erasmus University Rotterdam and seminar participants at Barclays Global Investors and Maastricht University.

premiums associated with inflation and economic development (Elton *et al.* (1995)). Others have put forward factor models based on the dynamics of the term structure of Treasury securities (e.g., Litterman and Scheinkman (1991)), one-index market models (Alexander (1980)), and liquidity (De Jong and Driessen (2006)).

In this paper, we report that common risk factors do a good job of explaining the cross-section of returns on corporate bond portfolios with medium to long maturity, but significantly underestimate the returns on corporate bonds with a short maturity (but still larger than one year). Portfolios composed of corporate bonds with lowest exposure to a term risk factor earn anomalously positive returns. A substantial portion of short-term corporate bond returns is independent of risk premiums associated with term risk, default risk, yield curve dynamics, liquidity, and premiums associated with macro-economic variables. In addition, time variation in the bonds' factor loadings does not account for the abnormal returns on short-term corporate bond portfolios.

We obtain bond return data from both the Lehman Investment Grade Bond Database and the CRSP Mutual Fund Database. This study is the first to incorporate both individual corporate bonds and U.S. corporate bond mutual funds to address anomalous patterns in corporate bond returns. Studying the cross-section of returns on bond mutual funds enriches our results, because it is usually an open question whether anomalies that emerge from analyses based on hypothetical portfolios of individual bonds withstand important practical issues, such as short-selling restrictions, transaction costs, and illiquidity. Earlier studies have tended to avoid such problems by excluding bonds that are prone to pricing errors and illiquidity, such as those with particularly maturities, but this sacrifices information about the return and risk dynamics of these particular types of bonds. The powerful advantage of bond mutual funds is that they represent real portfolios that have been traded at real prices, so that the usual caveats with corporate bond data are not a concern. Our evidence of the short-term corporate bond anomaly not only shows up in hypothetical portfolios of individual corporate bonds, but also in portfolios of corporate bond funds.

The contribution to the literature can be summarized as follows. Our evidence contributes to earlier research on the determinants of corporate bond returns by among others Litterman and Scheinkman (1991), Elton *et al.* (1995), Gebhardt *et al.* (2005). Prior studies of individual corporate bonds (Alexander (1980) and Gebhardt *et al.* (2005)) have been confined to bonds with medium to long-term maturity whereas this study, inspired by the results of Pilotte and Sterbenz (2006), examines a wider range of maturity spectrums.

In doing so, our study finds that the dynamics of short-term corporate bond returns are inconsistent with existing risk-based explanations of the return generating process. In addition, our study also adds to more general discussions in the asset pricing literature, which primarily emerged from a large body of research on equity returns.[1] An extension of these discussions to a non-equity context could provide valuable insights into, for example, the necessity of using multiple risk factors to describe the cross-section of asset returns. Moreover, our documentation of abnormal returns on short-term corporate bonds might facilitate a better understanding of the mechanisms that drive asset returns as such, including behavioral explanations of investor behavior that have originally been suggested in equity research. For example, our finding that short-term corporate bonds earn returns that are too high given their beta displays strong parallels with the low-beta stock anomaly reported by Fama and MacBeth (1973) and Karceski (2002).

Furthermore, the results have implications for various practical applications. Many important fixed-income applications, such as performance evaluation, require estimates of securities' expected return based on an asset pricing model. Most applications critically assume that the chosen model is correctly specified and consistent with the theoretical conditions embedded in the risk-return paradigm. Conventional approaches to performance attribution test whether the returns of an actively managed portfolio can be fully mimicked by investment exposures to a set of passive indexes or risk factors. Unexplained returns of the portfolio are attributed to managerial skill under the assumption that the factor model is correctly specified. The presence of return anomalies, however, implies that common factors insufficiently describe the cross-sectional variation in the returns of passive bond portfolios. These shortcomings are consequential to the interpretation of abnormal returns produced by actively managed fixed-income vehicles, which might reflect omitted-variables bias instead of skilled portfolio management.

The remainder of the paper is organized as follows. Section 5.2 describes our data. Section 5.3 discusses the methodology. Our empirical results are described in Section 5.4. Finally, section 5.5 concludes.

[1] Classical examples of studies that examine cross-sectional variation in equity returns are Fama and French (1992, 1993, 1996), Carhart (1997), and Pastor and Stambaugh (2003).

5.2 Data

This study is the first to provide evidence on the adequacy of expected return models for corporate bonds by using two comprehensive databases. We posit that these databases jointly provide the best setting to test how well existing specifications fare in explaining bond returns. The sample central to our analyses covers the period January 1990 to December 2003.[2]

5.2.1 Lehman Brothers Fixed Income Database

Following Hong *et al.* (2000) and Gebhardt *et al.* (2005), our first tests draw on a unique database that covers individual U.S. investment grade corporate bonds. This database is unique in the sense that it continues the extensively researched Lehman Brothers Fixed Income database, which became proprietary in the nineties. For this reason, our study is able to expand the analysis of expected corporate bond returns to more recent periods.

The main advantage of using individual bond data for explaining the cross-section of expected returns is that deficiencies of expected return models can be traced quite accurately to specific bond features, since cross-sectional differences in returns across bond portfolios are obtained mechanically with pre-specified discriminating criteria. Our sample of individual bonds includes all US investment-grade corporate bonds that are included in the Lehman US Credit Index.[3] To be included in the database, corporate bonds need to meet liquidity, maturity and quality requirements. Each bond must be rated investment grade by at least two rating agencies (Moody's, S&P or Fitch), publicly issued, dollar-denominated, coupon-bearing, non-convertible, and must have a minimum remaining maturity of one year. We note that our sample expands the sample used in Gebhardt *et al.* (2005) in the sense that we include bonds with a remaining maturity between one and three years.

Monthly return data on corporate bonds are not as easily available as those on government debt or stocks. To the best of our knowledge, the data from the 2003 Lehman Brothers Fixed Income Database (henceforth, LBFI) are superior to those from other databases in terms of both coverage and reliability. Moreover, the Lehman Bond indexes, which comprise bonds from LBFI, are used by the majority of bond market participants for port-

[2]Our sample follows from choices with respect to the minimum number of bonds/bond funds available in the cross-section and length of the portfolio formation period. These issues are described in more detail in Section 5.3.1. The minimum number of bonds/bond funds available in the cross-section is 50, and we set the length of the portfolio formation period to 36 months.

[3]The Lehman US Credit Index was formerly known as the US Corporate Investment Grade Index.

folio benchmarking. Hong *et al.* (2000) and Gebhardt *et al.* (2005) provide a more detailed discussion of these data.

LBFI includes 12,777 different bonds from 2,022 different issuers over the period October 1988 to December 2003. Our sample omits bonds that lack return history (i.e., 36 or more consecutive return observations), which is needed to estimate bonds' risk factor sensitivities. We focus on the period January 1993 to December 2003 to cover the same period as the mutual fund data set. This reduces our sample to 6,341 bonds from 1,301 different firms for the sample central to our analyses. Panel A in Table 5.1 presents a year-by-year overview of the summary statistics of our sample. It describes the return characteristics and reveals that the average and median monthly returns are very similar, respectively 0.68 percent and 0.65 percent. The extreme negative -98.6 percent return traces back to Enron Corporation bonds that lost almost all their value in November 2001, not long before Enron's Chapter 11 bankruptcy filing. Because only bonds with a three-year return history are eligible for inclusion, our sample covers about half of all available securities. Be that as it may, differences between the return characteristics of the total LBFI sample and those of our final sample are negligible. The sample contains, on average, 1,359 bonds per month. This number is quite constant across the sample, although lower during the credit bear market in 1993 and 1994. On average, our sample has a Moody's credit rating of A3 and an S&P rating of A-. The median dollar amount outstanding is 200 million with a maturity of 6.62 years and duration of 4.77 years. All characteristics are fairly constant through time, with the exception of amount outstanding and maturity.

5.2.2 CRSP Survivorship Bias Free Mutual Fund Database

The hunt for risk factors in current empirical asset pricing studies has mainly revolved around tests of cross-sectional variation in the returns on portfolios that are rather hypothetical.[4] Mutual funds provide an excellent laboratory for testing cross-sectional variation in returns of investable portfolios, which incorporate transaction costs and trading restrictions. At the same time, the competitive nature of the mutual fund industry ensures that fund data are sufficiently heterogeneous in terms of the risk exposures offered by these investment vehicles, which is needed to uncover which factors determine bond returns.

The 2003 CRSP universe we study includes data on all mutual funds in the United

[4]Numerous studies document that well-known anomalies in the equity literature are concentrated in small caps and illiquid stocks, see e.g., Stoll and Whaley (1983), Keim and Madhaven (1997), Loughran (1997), Hong *et al.* (2000), Ali *et al.* (2003), Lesmond *et al.* (2004).

Table 5.1: Summary statistics bond (fund) returns.

Panel A. Summary statistics Lehman Brothers corporate bonds database

	Average	Median	Max	Min	observations
1993	0.85	0.66	9.01	-10.95	975
1994	-0.12	0.02	15.54	-10.01	714
1995	1.51	1.29	27.46	-20.89	1,025
1996	0.41	0.26	8.77	-16.08	1,381
1997	0.87	0.88	10.28	-18.07	1,632
1998	0.67	0.52	40.02	-21.99	1,659
1999	-0.11	0.17	21.05	-19.85	1,518
2000	0.73	0.84	23.20	-32.66	1,383
2001	0.86	0.83	32.27	-98.56	1,549
2002	0.97	1.14	47.07	-75.76	1,670
2003	0.72	0.55	20.04	-28.69	1,592
Total	0.68	0.65	47.07	-98.56	1372

Panel B. Summary statistics CRSP corporate bond funds

	Average	Median	Max	Min	observations
1993	0.86	0.65	4.62	-2.85	127
1994	-0.21	-0.13	5.02	-7.21	139
1995	1.16	0.99	8.89	-16.22	216
1996	0.32	0.24	11.35	-6.95	319
1997	0.73	0.83	7.54	-64.24	413
1998	0.51	0.44	6.18	-16.67	489
1999	-0.12	-0.01	4.37	-4.86	526
2000	0.87	0.88	8.26	-8.73	586
2001	0.51	0.56	5.29	-5.76	566
2002	0.55	0.61	7.69	-6.96	586
2003	0.42	0.43	6.49	-9.86	608
Total	0.50	0.51	11.35	-64.24	416

Note: Panel A reports the return statistics, expressed as percentage per month, and the average number of observations per month of the investment grade corporate bond of the 2003 Lehman Brothers Fixed Income Database. To be included in our sample, corporate bonds need to meet the liquidity, maturity and quality requirements set by Lehman. Furthermore, each bond must be rated investment grade by at least two rating agencies (Moody's, S&P or Fitch), publicly issued, dollar-denominated, coupon-bearing, non-convertible, and have a minimum remaining maturity of one year. Lastly, our sample omits bonds that lack a return history (i.e., 36 or more consecutive return observations), which is needed to estimate bonds' risk factor sensitivities.

Panel B reports the return statistics, expressed as percentage per month, and the average number of observation per month of the investment grade bond mutual funds of the 2003 survivorship-free CRSP U.S. mutual fund database. We select all bond funds that are classified as corporate, at the final quarter of each year and omit government, high-yield, mortgage-backed, money market, and municipality bond funds. In order to avoid that expenses affect our asset pricing test statistics, we have added back funds' expenses to the reported returns.

States for any given date since 1962, including dead funds. The database covers monthly total returns of more than 21,400 open-ended mutual funds. Of these funds, approximately 7,000 are dead. The database also includes important supplementary data, such as fund classifications by Wiesenberger, Micropal/ Investment Company Data Inc., and Strategic Insight, and the expenses history of each bond fund. We select all bond funds that are classified as corporate, at the final quarter of each calender year.[5] We omit government, high-yield, mortgage-backed, money market, and municipality bond funds. Furthermore, we require a minimum of 50 funds in the cross-section at each point in time. Our resulting sample covers 1,765 funds the period January 1990 to December 2003. Next, we drop funds with fewer than 36 consecutive return observation over the entire sample period, and add back the management fee. Adding back the management fee and other 'non-transaction cost' fund expenses, which can run up to more than one percent per year, is crucial for our analysis, as we would otherwise observe a negative premium on all funds. Our remaining sample covers 1,090 funds.

Panel B in 5.1 presents the return statistics of our fund sample. Average and median return are very similar. Moreover, the returns are in line with those of our individual bond sample in panel A. The large negative return of 64.24 percent in 1997 traces back to the last reported return of the Sterling Partners Short Term Fixed Income fund before it stopped reporting in 1997. Differences in return characteristics between our sample (where we require funds to have a return history of at least 36 months) and the total CRSP bond fund sample are negligible.

5.3 Methodology

Our exploration into the cross-section of corporate returns follows the common approach in the empirical literature (see, e.g., Fama and French (1993, 1995, 1996) and Daniel *et al.* (1997)). The essence of the methodology involves two stages, where the first stage involves ex ante formation of portfolios based on cross-sectional predictors of bond returns, and the second stage concerns ex post factor regressions of the portfolio returns on common risk factors. The key question is whether all of the cross-sectional variation in the portfolios' returns is captured by risk factors.

[5]Our sample consists of bond funds with the following classifications: Wiesenberger (OBJ): CBD; Micropal/Investment Company Data, Inc. (ICDI OBJ): BQ; Strategic Insight (SI OBJ): CGN Or CHQ Or CIM Or CMQ Or CSM

5.3.1 Construction of Portfolio Quintiles

To study cross-sectional variation in corporate bond returns we adopt a portfolio construction approach in the tradition of Fama and French (1993, 1996) and Gebhardt *et al.* (2005). These studies allocate securities to mutually exclusive portfolios based on two a priori specified selection criteria that have been found to predict expected returns. We then test whether the cross-section of portfolio returns are captured by common factors, which is detailed in the next section of this paper. The decision to examine the cross-section of returns on portfolios rather than securities deserves some explanation. One alternative would be to perform a cross-sectional analysis of individual security returns. We rejected this alternative because individual security returns tend to be very noisy, unlike returns of well-diversified portfolios.

In line with Gebhardt *et al.* (2005), the corporate bond portfolios we construct for our asset pricing tests are formed after a two-dimensional sort of all individual bonds in the Lehman database on their sensitivity to the two factors in the following model:

$$r_{it}^{*} = \alpha_i^{2F} + \beta_{1i}^{2F}\mathrm{TERM}_t + \beta_{2i}^{2F}\mathrm{DEFAULT}_t + \varepsilon_{it}^{2F}, \tag{5.1}$$

where r_{it}^{*} denotes the excess return of bond i in period t, β_{1i}^{2F} denotes the sensitivity of bond i to the term factor, β_{2i}^{2F} denotes the sensitivity of bond i to the default factor and ε_{it}^{2F} denotes the residual return. The term risk factor (TERM) is defined as the monthly difference between the return on the Lehman U.S. Treasury Index and the Ibbotson one-month Treasury-Bill rate. The default risk factor (DEFAULT) is defined as the monthly difference between the return on the Lehman U.S. Credit Index and the return on the Lehman U.S. Treasury Index. The U.S. Treasury Index includes all public obligations of the U.S. Treasury with a remaining maturity of one year. These risk factors can be seen as proxies for underlying term and default risks in the economy that are of hedging concern to investors: unexpected changes in the term structure of bond yields and changes in default risk due to changes in economic conditions.

Using Equation (5.1), we can construct double-sorted quintile portfolios with different TERM and DEFAULT risk attributes. We first allocate all available bonds to quintiles using their TERM premium sensitivity as the discriminating criterion, and then independently allocate the bonds within each quintile to five quintiles based on their sensitivity to DEFAULT. Using rolling 36-month regressions, we update the factor sensitivities and rebalance all portfolios on a monthly basis. When applied on the sample of individual bonds, this sorting approach ultimately produces monthly post-formation returns on the

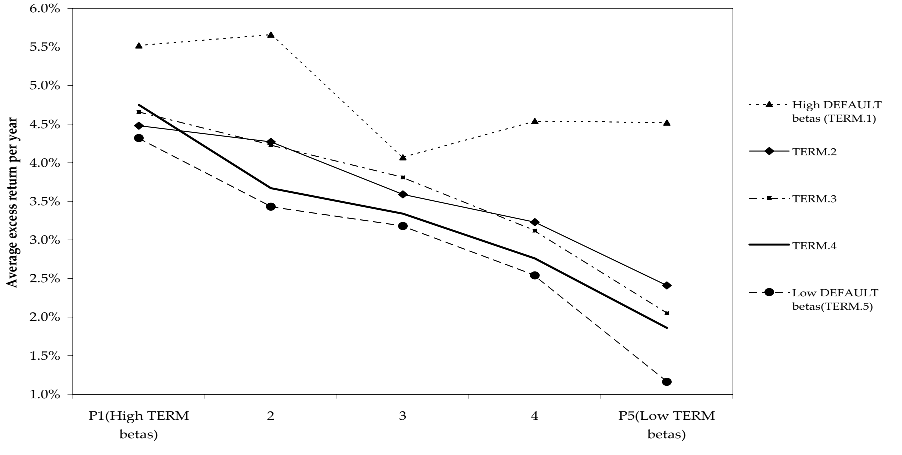
5 by 5 quintile portfolios over the period October 1991 to December 2003 (the first 36 months are used to initialize the procedure).

We obtain portfolios composed of corporate bond mutual funds in a similar manner. We estimate TERM and DEFAULT sensitivities for all corporate bond funds in the CRSP mutual fund database on a rolling-window basis and form double-sorted quintile portfolios using the aforementioned portfolio allocation rule. The post-formation returns on the 5 by 5 equal-weighted quintile portfolios cover the period January 1993 to December 2003.

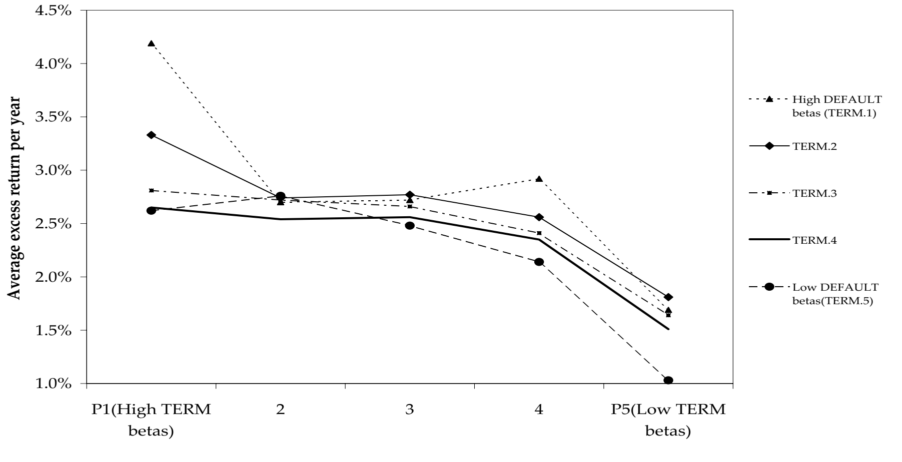
Hence, the portfolios altogether are constructed in a way such that they experience significant cross-sectional variation in the sensitivity to term risk and default risk. The idea to use betas with respect to these risk factors as criteria for portfolio allocation follows from Gebhardt *et al.* (2005), who report that TERM and DEFAULT betas are more important for explaining expected returns of corporate bond portfolios than corporate bond characteristics (duration and credit rating). Figure 5.1, which displays simple average portfolio excess returns, confirm the well-established view that realized returns compensate fixed-income investors for bearing term and default risks inherent in corporate bonds. First, if we look along the TERM dimension, we observe that average portfolio return decreases with TERM exposure. This is in line with the notion that returns on long-term bonds tend to be higher than those on short-term bonds. Second, if we look vertically along the default dimension, we observe that average return increases with DEFAULT sensitivity, also when holding TERM exposure constant. The two distinct return patterns can be identified from the portfolios composed of individual bonds (Panel A) as well as those of mutual funds (Panel B), but the return differences across mutual fund portfolios are economically smaller than those observed across individual-bond portfolios. For example, the return difference between the high default/high term-risk portfolio and the low default/low term-risk counterpart is more than 4.3 percent per year for the individual bond sample whereas this difference amounts to 2.5 percent for the bond fund sample.

An interesting observation emerges from the Sharpe ratios reported in Figure 5.2, Panels A and B. Consistent with Pilotte and Sterbenz (2006)' conclusion from a study of US Treasury securities, we observe that Sharpe ratios vary inversely with maturity: Sharpe ratios for the low TERM-beta portfolios are almost twice the Sharpe ratios of high TERM-beta portfolios. These high Sharpe ratios for short-term corporate bonds imply that investors who primarily focus on volatility as relevant risk measure would prefer leveraging short-term corporate bonds instead of buying long-term corporate bonds to obtain exceptional return/risk combinations. Whether these atypically high Sharpe ratios imply a challenge

Figure 5.1: Average excess returns TERM and DEFAULT portfolios.



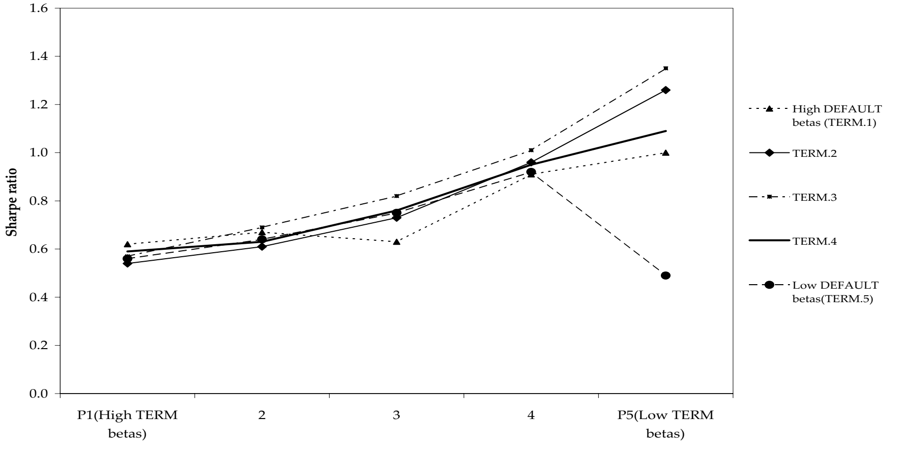
(a) Average returns individual corporate bond portfolios



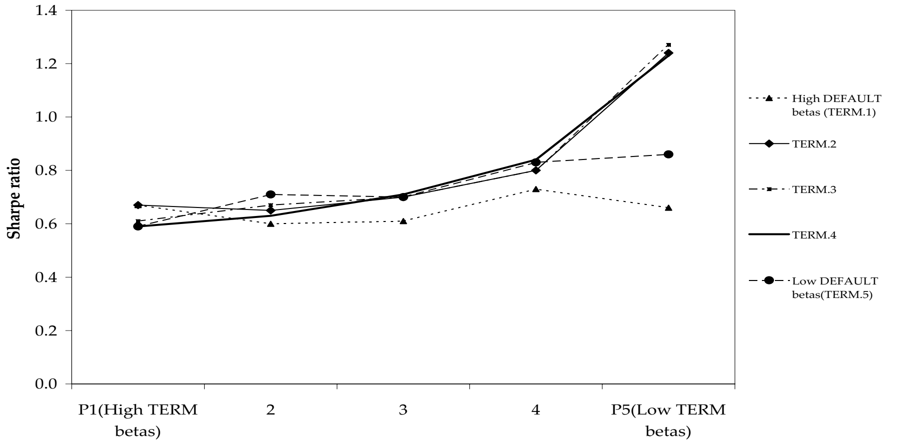
(b) Average returns mutual corporate bond fund portfolios

Average excess returns (annualized) for individual bond portfolios (a) and mutual fund portfolios (b). The portfolios are formed on two-dimensional sorts of individual bonds and bond mutual funds into 5x5 portfolios on their sensitivities to the two factors in the following model: $r_{it} = \alpha_i + \beta_{1i}\text{TERM}_t + \beta_{2i}\text{DEFAULT}_t + \varepsilon_{it}$, where TERM and DEFAULT are proxies for term and default risk. The model is estimated using 36-month rolling regressions, and the portfolios are updated on a monthly frequency.

Figure 5.2: Sharpe ratios TERM and DEFAULT portfolios.



(a) Sharpe ratios individual corporate bond portfolios



(b) Sharpe ratios corporate bond fund portfolios

Sharpe ratios for individual bond portfolios (a) and mutual fund portfolios (b). The portfolios are formed on two-dimensional sorts of individual bonds and bond mutual funds into 5x5 portfolios on their sensitivities to the two factors in the following model: $r_{it} = \alpha_i + \beta_{1i}\mathrm{TERM}_t + \beta_{2i}\mathrm{DEFAULT}_t + \varepsilon_{it}$, where TERM and DEFAULT are proxies for term and default risk. The model is estimated using 36-month rolling regressions, and the portfolios are updated on a monthly frequency.

to common risk factors when it comes to pricing short-term corporate bonds is explored throughout the remainder of this paper.

5.3.2 Factor Model Specifications

The key issue in empirical studies on asset pricing concerns the ability of common factors to capture the cross-section of asset returns. In our attempt to explain the post-formation returns on the 25 portfolios formed on TERM and DEFAULT betas, we rely on a set of factors that originate from earlier related studies on expected bond returns. Our universe of factor models includes: (i)a single-factor model for bonds inspired by Sharpe (1964) and Lintner (1965), which was tested on corporate bond returns by Friend *et al.* (1977) and Alexander (1980), (ii) a two-factor specification advanced by Fama and French (1993) and Gebhardt *et al.* (2005), (iii) a three-factor model composed of factors extracted from factor-analytical approaches (see, e.g., Litterman and Scheinkman (1991)), and (iv) the Elton *et al.* (1995) model which augments multiple benchmark indexes with risk premiums associated with fundamental economic variables.

Single-factor model

The single-factor model for bonds is in spirit similar to a model for stocks with one aggregate market index as explanatory variable. The market model we test incorporates the returns on a broad market index from Lehman Brothers:

$$r_{it} = \alpha_i^{1F} + \beta_i^{1F}\mathrm{MARKET}_t + \varepsilon_i^{1F}, \tag{5.2}$$

where r_{it} denotes the post-formation excess returns of term-default-beta portfolio i in period t, β_{1i}^{1F} denotes the sensitivity of portfolio i to the market factor and ε_{it}^{1F} denotes the residual return.

To compute the first factor affecting bond returns (MARKET), we take the return on the Lehman U.S. Government/Credit Index in excess of the Ibbotson Treasury-Bill rate from Kenneth French's website. Here, the Lehman U.S. Government/Credit index serves as a proxy for the aggregate return on the government and investment-grade corporate bond market. This widely recognized index was created in 1979 and is market value weighted. It includes Treasuries, Agencies, debt guaranteed by the US Government, and all bonds in US Credit Index.

Next, we consider three multifactor model specifications that appear repeatedly in studies involved with the pricing of bonds or bond portfolios. These multifactor models could be theoretically motivated by Merton (1973)'s intertemporal asset pricing theory, or by the Arbitrage Pricing Theory of Ross (1976).

Two-factor model

The second factor model we examine is a two-factor model specification similar to Gebhardt *et al.* (2005). The model contains two returns spreads that are intended to capture securities' exposure to term and default risks and which account for most of the variation in bond returns according to Fama and French (1993). The two-factor model takes the form:

$$r_{it} = \alpha_i^{2F} + \beta_{1i}^{2F}\mathrm{TERM}_t + \beta_{2i}^{2F}\mathrm{DEFAULT}_t + \varepsilon_{it}^{2F}, \tag{5.3}$$

where β_{1i}^{2F} denotes the sensitivity of portfolio i to the term factor, β_{2i}^{2F} denotes the sensitivity of portfolio i to the default factor and ε_{it}^{2F} denotes the residual return. The term risk factor (TERM) is defined as the monthly difference between the return on the Lehman U.S. Treasury Index and the Ibbotson one-month Treasury-Bill rate. The default risk factor (DEFAULT) is defined as the monthly difference between the return on the Lehman U.S. Credit Index and the return on the Lehman U.S. Treasury Index. We point out that this model is employed for both ex ante quintile portfolio formation and ex post evaluation.

Three-factor principal components model

The third model is a three-factor model that augments the single-factor model with two principal components, where the two principal components (PC1 and PC2) are orthogonal to the Lehman US Government/Credit index and extracted from the residual returns on passive Lehman Treasury bond indexes with different maturities:

$$r_{it} = \alpha_i^{3F} + \beta_{i1}^{3F}\mathrm{MARKET}_t + \beta_{i2}^{3F}\mathrm{PC1}_t + \beta_{i3}^{3F}\mathrm{PC2}_t + \varepsilon_i^{3F}, \tag{5.4}$$

To capture the effect of changes in the term structure in treasury yields that are not fully picked up by duration, we rely on the principal components analysis (PCA) by Huij and Derwall (2007). In their PCA setup, excess returns on Treasury indexes with varying maturities are individually regressed on a constant and a proxy for the overall bond market conform Equation (5.2).[6] PCA is then performed on the time series of the residuals from

[6]We include indexes with maturities of 1 to 3 years, 3 to 5 years, 5 to 7 years, 7 to 10 years, 10 to 20 years and more than 20 years.

each regression (plus the intercept). We find that 94.9 percent of the variation of the residuals is explained by two largest eigenvalues. We then construct the principal components' risk factors by taking the first two normalized components as portfolios weights for the Treasury indexes' return series. Models that incorporate principal components follow the intuition and empirical findings of Litterman and Scheinkman (1991), Knez *et al.* (1994), Duffee (1996) and others, who advocate three unique factors to describe bond returns: level, slope and convexity.

Four-factor model

The fourth factor model we focus on is a four-factor model that comprises a mixture of factor-mimicking portfolios and two fundamental variables related to unexpected changes in inflation (INF) and economic growth (GDP). The choice of fundamental variables follows from Elton *et al.* (1995), who find evidence that adding fundamental economic variables to bond pricing models leads to an improvement in the explanation of expected bond returns. Consistent with an APT setup, we arrive at a model of the form:

$$\begin{aligned} r_{it} = \alpha_i^{4F} + \beta_{i1}^{4F}\mathrm{TERM}_t + \beta_{i2}^{4F}\mathrm{DEFAULT}_t + \\ \beta_{i3}^{4F}(\mathrm{INF}_{t-1} + \lambda_{\mathrm{INF}}) + \beta_{i4}^{4F}(\mathrm{GDP}_{t-1} + \lambda_{\mathrm{GDP}}) + \varepsilon_i^{4F}, \end{aligned} \tag{5.5}$$

where INF_{t-1} is the one-month lagged unexpected change in inflation, GDP_{t-1} is the one-month lagged unexpected change in economic growth, and λ_{INF} and λ_{GDP} are the risk premiums for sensitivities to changes in inflation and economic growth, respectively.

As in Elton *et al.* (1995), we obtain the risk premiums by simultaneously estimating the following regression for a set of passive benchmark indexes using nonlinear least squares:

$$r_{it} = \delta_i + \beta_{i1}^{4F}\mathrm{TERM}_t + \beta_{i2}^{4F}\mathrm{DEFAULT}_t + \beta_{i3}^{4F}\mathrm{INF}_{t-1} + \beta_{i4}^{4F}\mathrm{GDP}_{t-1} + \varepsilon_i^{4F}, \tag{5.6}$$

subject to the restriction:

$$\delta_i = \beta_{4,i}^{4F}\lambda_{\mathrm{INF}} + \beta_{5,i}^{4F}\lambda_{\mathrm{GDP}}. \tag{5.7}$$

We use this restriction to derive proxies for the unobservable "true" risk premiums associated with two economic variables: inflation and economic development. Similar to Elton *et al.* (1995), we derive unexpected changes in inflation and economic growth using the US real GDP and inflation forecasts from Consensus Economics Inc. This company polls professional forecasters on a monthly basis for their forecast for principal macroeconomic variables for the current (calendar) year and for the following year.[7] In our study, we calculate the 12-month forward forecast as the weighted average of the current year and the following year, where the weight of the current year is defined as the fraction of the remaining number of months in the current year and the total number of months in a calendar year.

To calibrate the parameters in the APT model for determining the risk premiums, we use the same indexes as Elton *et al.* (1995).[8] When we jointly estimate the regressions for the nine passive indexes over the period January 1993 to December 2003, we obtain $\hat{\lambda}_{INF} = -0.51$ and $\hat{\lambda}_{GDP} = -0.08$. These estimates closely correspond to those reported by Elton *et al.* (1995).

5.3.3 Tests for the Adequacy of Expected Return Models

The models for expected bond portfolio returns that are described in the previous section follow a linear factor structure:

$$r_{it} = \alpha_i + \beta_{1i}x_{1t} + \beta_{2i}x_{2t} + \ldots + \beta_{ki}x_{kt} + \varepsilon_{it}, \tag{5.8}$$

where r_{it} denotes the excess return of bond portfolio i in period t, β_{ji} denotes the sensitivity of portfolio i ($i = 1, ..., N$) to factor j ($j = 1, ..., k$), and ε_{it} denotes the residual return. The intercept term α_i measures the empirical deviations from the prediction of the factor model or the pricing error.

To test the empirical fit of models describing bond returns, we use the aforementioned quintile portfolios and consider the portion of the portfolios' cross-sectional variation that is not explained by the employed factor models, i.e., the portfolios' alphas. More specifically, we conduct Gibbons *et al.* (1989) tests (henceforth, GRS) and examine whether the returns of bond portfolios can be fully described by a linear function of their sensitivity to factors in the model. GRS is underpinned by the simple condition that an accurately specified model leaves no cross-sectional variation in expected returns unexplained. Using GRS, we formally test the hypothesis that the alphas for the bond portfolios are jointly indistinguishable from zero:

[7] Consensus Economics started collecting survey forecasts in 1989.

[8] The following Lehman bond indexes are used as the dependent variables: 1 to 3 years U.S. Government bonds, U.S. Treasury Intermediate, U.S. Treasury Long, Investment Grade Industrial, Investment Grade Financial Institutions, U.S. Intermediate Credit Aaa, U.S. Long Credit Aaa, U.S. Intermediate Credit Baa and U.S. Long Credit Baa.

$$GRS \equiv \left(\frac{T-N-k}{N}\right)\left(1+\hat{\mu}'\hat{\Omega}^{-1}\hat{\mu}\right)^{-1}\hat{\alpha}'\hat{\Sigma}^{-1}\hat{\alpha} \sim F(N, T-N-k), \tag{5.9}$$

where $\hat{\mu}$ is a k by 1 vector of sample means of the factors' excess returns, $\hat{\Omega}$ is an k by k matrix that holds the unbiased estimate of the factor returns' covariance matrix, $\hat{\alpha}$ is a N by 1 vector of estimated alphas and $\hat{\Sigma}$ is an N by N matrix that holds the unbiased estimate of the residual variance-covariance matrix. Assuming that the errors are independently and normally distributed, independent of the returns on the factor portfolios, the GRS statistic follows an F-distribution with N degrees of freedom in the numerator and $T-N-k$ degrees in the denominator under the null of zero alphas.

5.4 Empirical Results

We apply conventional asset pricing tests to evaluate the portfolios' post-formation returns and estimate the spread between the portfolios' risk-adjusted returns after controlling for exposures to the risk factors discussed in Section 5.3.2.

5.4.1 Portfolio evaluations with common factor models

We run regressions of each portfolio's excess return on the excess return of the (multi-) factors and an intercept term. We pay attention to the estimates of the abnormal returns across the beta-sorted portfolios, their post-formation betas with respect to the common risk factors, and we examine the time-series regressions' R^2 values. The variation in post-formation alpha and beta across the portfolios helps to understand whether common factors capture the cross-sectional dynamics of corporate bond returns, and to what extent corporate bond returns are anomalous. If a set of factors accurately captures priced bond risk then portfolios, that differ in average return, should have different sensitivities to the common factors and be unable to earn a return beyond that suggested by factor betas.

When we look at our single-factor market model, we confirm our earlier suspicion that abnormal returns on corporate bonds trace back to the lower-maturity range. Although Panels A and B of Table 5.2 confirm that variation in the portfolio returns are in part explained by cross-sectional variation in beta, column 3 of these panels shows that abnormal portfolio returns tend to increase and reach values that are statistically significant as maturity decreases. The majority of corporate bond portfolios that earn an economically and statistically significant abnormal return, after controlling for beta, are concentrated

Table 5.2: Single-factor model regressions using portfolios sorted on term and default.

	A. Individual bonds						B. Bond mutual funds					
	Return	Sharpe	Alpha	Alpha-t	MARKET	Adj.-R^2	Return	Sharpe	Alpha	Alpha-t	MARKET	Adj.-R^2
P1.1	5.52%	0.63	1.11%	0.69	1.59	0.67	4.19%	0.68	0.82%	0.93	1.22	0.80
P1.2	4.48%	0.55	-0.17%	-0.16	1.68	0.85	3.33%	0.68	0.40%	1.20	1.06	0.96
P1.3	4.66%	0.58	-0.02%	-0.02	1.69	0.89	2.81%	0.62	0.07%	0.29	0.99	0.97
P1.4	4.75%	0.60	0.18%	0.22	1.65	0.90	2.65%	0.60	-0.04%	-0.18	0.97	0.98
P1.5	4.32%	0.57	-0.12%	-0.19	1.61	0.92	2.62%	0.60	-0.03%	-0.12	0.96	0.97
P2.1	5.66%	0.68	1.52%	0.96	1.50	0.66	2.70%	0.61	0.22%	0.36	0.90	0.83
P2.2	4.27%	0.62	0.38%	0.44	1.40	0.85	2.74%	0.66	0.27%	0.91	0.89	0.95
P2.3	4.23%	0.70	0.71%	1.09	1.27	0.89	2.72%	0.68	0.31%	1.59	0.87	0.98
P2.4	3.67%	0.64	0.29%	0.60	1.22	0.93	2.54%	0.64	0.14%	0.76	0.87	0.98
P2.5	3.43%	0.65	0.29%	0.69	1.14	0.94	2.76%	0.72	0.43%	2.36	0.84	0.98
P3.1	4.07%	0.64	0.91%	0.74	1.14	0.65	2.72%	0.62	0.38%	0.55	0.85	0.76
P3.2	3.59%	0.74	0.73%	1.72	1.03	0.93	2.77%	0.71	0.46%	1.28	0.84	0.92
P3.3	3.81%	0.83	1.10%	2.73	0.98	0.93	2.66%	0.71	0.40%	1.77	0.82	0.97
P3.4	3.34%	0.77	0.77%	2.21	0.93	0.94	2.56%	0.72	0.40%	2.14	0.78	0.97
P3.5	3.18%	0.76	0.76%	1.71	0.87	0.89	2.48%	0.71	0.38%	1.65	0.76	0.96
P4.1	4.54%	0.92	2.14%	2.16	0.87	0.62	2.92%	0.74	0.96%	1.29	0.71	0.66
P4.2	3.23%	0.97	1.30%	3.75	0.70	0.90	2.56%	0.81	0.68%	2.57	0.68	0.93
P4.3	3.12%	1.02	1.33%	4.38	0.65	0.91	2.41%	0.81	0.63%	2.92	0.65	0.95
P4.4	2.76%	0.96	1.11%	3.32	0.60	0.87	2.35%	0.85	0.70%	3.29	0.60	0.94
P4.5	2.54%	0.93	1.02%	2.83	0.55	0.83	2.14%	0.84	0.64%	2.75	0.54	0.92
P5.1	4.52%	1.01	2.76%	2.46	0.64	0.41	1.69%	0.67	0.72%	1.13	0.35	0.40
P5.2	2.41%	1.27	1.45%	4.12	0.35	0.67	1.81%	1.25	1.02%	4.81	0.29	0.80
P5.3	2.05%	1.36	1.30%	4.49	0.27	0.65	1.64%	1.28	0.95%	4.87	0.25	0.78
P5.4	1.86%	1.10	1.10%	2.95	0.28	0.54	1.51%	1.24	0.83%	4.92	0.25	0.82
P5.5	1.16%	0.50	0.43%	0.67	0.26	0.26	1.03%	0.87	0.38%	2.17	0.23	0.79
	GRS (p-value): 2.41 (0.00)						GRS (p-value): 3.13 (0.00)					

(continued on next page)

Table 5.2 continued

Each month, we perform two-dimensional sorts of individual bonds and bond mutual funds into 5x5 portfolios on their sensitivities to the two factors in the following model: $r_{it} = \alpha_i + \beta_{1i}\text{TERM}_t + \beta_{2i}\text{DEFAULT}_t + \varepsilon_{it}$, where TERM and DEFAULT are proxies for term and default risk. The model is estimated using 36-month rolling regressions, and the portfolios are updated on a monthly frequency. We then run single-factor regressions on the post-ranking returns of the resulting portfolios. The table lists the portfolios' post-ranking returns, Sharpe ratios, parameter estimates, and R^2 values. Panel A reports the results for the LBFI database, and Panel B for the CRSP Mutual Fund database. The samples cover 6,341 individual bonds and 1,090 bond mutual funds over the period January 1993 to December 2003. All values are annualized.

in the lower end of the maturity spectrum. Panel B demonstrates that the anomalously positive returns on corporate bonds with relatively low-TERM exposure are material from a practical perspective: although abnormal returns on low-TERM corporate bond funds are economically smaller than those of individual bond portfolios, most of them in range P3.1–P5.5 continue to be statistically and economically significant. The GRS test articulates the pricing errors associated with a substantial number of short-term corporate bond portfolios and mutual funds. GRS statistics in Panels A and B reject the null of jointly zero intercepts at the convectional significance levels.

Table 5.3, columns 1 and 2, shows that the short-term corporate bond anomaly continues to be left unexplained when we employ two-factor regressions with TERM and DEFAULT factors as explanatory variables. Compared to the single-factor model, the abnormal returns on low-TERM corporate bond portfolios are economically smaller, but nonetheless statistically and economically significant. The GRS tests rejects the null hypothesis that abnormal returns on the quintile portfolios' are jointly indistinguishable from zero. Note that the two-factor model has been tested on the Lehman Fixed Income Database over the period 1973–1996 by Gebhardt *et al.* (2005). Apart from our focus on a more recent period, our study also differs from theirs by including all bonds with a remaining maturity between 1 and 3 years. These two differences could explain the discrepancy between the Gebhardt *et al.* (2005) study and the results reported here.[9]

Table 5.4 reports the results of factor regressions involving the market factor and two term-structure components, PC1 and PC2. These components appear to help marginally in the explanation of returns on low-TERM-beta portfolios. But while the abnormal returns on low-TERM corporate bond portfolios and mutual funds that we observe under the three-

[9]In fact, unreported tests suggest that the two-factor model explains the cross-section of returns on corporate bonds that have a remaining maturity of three years and higher. These results are available upon request.

factor model are smaller than those obtained from earlier factor regressions, a substantial portion of the returns is not explained by market, steepness and curvature factors. As with earlier factor models, GRS rejects the null hypothesis that the intercept terms from the factor regressions are jointly zero.[10]

The four-factor regressions that we report on in Table 5.5 produce mixed results concerning the explanation of short-term corporate bond returns. Regressions involving TERM and DEFAULT factors in conjunction with premiums associated with inflation (INF) and economic development (GDP) yield fewer portfolios with statistically significant abnormal returns, but produce abnormal returns that are in magnitude larger than those observed previously. Especially the unexplained returns on portfolios P5.1–5.5, those with the lowest maturity, earn abnormal returns that can amount up to 7.24 percent per year. Not surprisingly, the GRS test rejects this four-factor specification as an appropriate model for expected returns of individual corporate bond portfolios. However, this rejection is less pronounced when it comes to explaining returns on corporate bond mutual funds. Two of the ten mutual funds (P4.1–P5.5) that hold low-TERM corporate bonds earn statistically significant abnormal returns, namely P4.3 and P5.2, and one portfolio (P4.4) earns a marginally significant abnormal return. GRS does not reject the model for describing the cross-section of returns on corporate bond mutual funds.

At first glance, the results hint that macro-economic variables could be useful in capturing much of the abnormal returns on investable low-TERM corporate bond portfolios. But two caveats warrant a careful interpretation of these results. First, we hasten to argue that the risk premiums associated with GDP and inflation, are prone to "ex post over-fitting" critiques. The risk premiums are fitted on nine different passive indexes with different maturities and credit quality, based on returns realized over a period that matches the period we use to evaluate the quintile portfolios. The average correlation between these indexes and our 25 portfolios is 0.81 for individual bond portfolios, and 0.87 for bond fund portfolios. These high correlations explain why it is likely that we mechanically eliminate abnormal returns through estimation of macroeconomic risk premiums. Second, the intuition behind the loadings on the INF and GDP factors, reported in Table 5.5, is not

[10]It appears that portfolios with higher default risk are more sensitive to the curvature factor than are the lower default portfolios. As we observe the sensitivity to the PC1, steepness risk factor, to be stable over maturities, but almost monotonically decreasing over default. Portfolios with higher default risk seem to be more exposed to the steepness of the yield curve as the sensitivities are almost equal per default portfolio. Secondly, the sensitivity to the PC2, curvature risk factor, increases almost monotonically within each maturity block and is not stable over default as well.

Table 5.3: Two-factor regressions using portfolios sorted on term and default.

	A. Individual bonds					B. Bond mutual funds				
	Alpha	Alpha-t	TERM	DEF	Adj.-R^2	Alpha	Alpha-t	TERM	DEF	Adj.-R^2
P1.1	0.37%	0.41	1.43	2.29	0.90	0.47%	0.88	1.12	1.35	0.93
P1.2	-0.49%	-0.70	1.57	1.54	0.93	0.34%	1.54	1.00	0.72	0.98
P1.3	-0.23%	-0.35	1.59	1.33	0.94	0.08%	0.39	0.94	0.55	0.98
P1.4	0.06%	0.09	1.57	1.13	0.93	0.01%	0.06	0.93	0.46	0.97
P1.5	-0.14%	-0.23	1.53	0.91	0.94	0.11%	0.40	0.92	0.30	0.96
P2.1	0.80%	0.88	1.35	2.18	0.89	-0.02%	-0.07	0.83	0.96	0.94
P2.2	0.07%	0.12	1.30	1.37	0.94	0.22%	1.02	0.84	0.60	0.97
P2.3	0.53%	1.18	1.19	1.05	0.95	0.34%	1.80	0.83	0.45	0.98
P2.4	0.24%	0.61	1.16	0.78	0.96	0.20%	1.02	0.83	0.39	0.98
P2.5	0.34%	0.87	1.09	0.54	0.95	0.56%	2.89	0.81	0.25	0.98
P3.1	0.36%	0.50	1.03	1.65	0.88	0.10%	0.24	0.78	1.00	0.91
P3.2	0.66%	1.99	0.97	0.72	0.95	0.38%	1.41	0.78	0.63	0.95
P3.3	1.10%	2.93	0.93	0.56	0.94	0.42%	1.92	0.77	0.44	0.97
P3.4	0.85%	2.42	0.89	0.39	0.94	0.46%	2.26	0.74	0.35	0.97
P3.5	0.89%	2.02	0.84	0.25	0.89	0.50%	2.06	0.73	0.23	0.95
P4.1	1.74%	2.61	0.78	1.25	0.83	0.63%	1.42	0.64	1.00	0.88
P4.2	1.29%	3.91	0.66	0.43	0.91	0.66%	2.78	0.64	0.42	0.95
P4.3	1.37%	4.46	0.62	0.30	0.90	0.69%	3.03	0.62	0.26	0.94
P4.4	1.18%	3.48	0.57	0.22	0.87	0.77%	3.43	0.57	0.22	0.94
P4.5	1.08%	2.99	0.53	0.20	0.83	0.75%	3.22	0.52	0.12	0.92
P5.1	2.37%	2.64	0.56	1.08	0.61	0.55%	0.98	0.32	0.50	0.52
P5.2	1.37%	4.48	0.32	0.36	0.75	1.04%	4.81	0.27	0.13	0.79
P5.3	1.29%	4.50	0.25	0.18	0.65	0.99%	4.93	0.24	0.08	0.77
P5.4	1.15%	3.09	0.27	0.06	0.54	0.88%	5.11	0.24	0.06	0.81
P5.5	0.42%	0.65	0.25	0.16	0.26	0.39%	2.18	0.22	0.13	0.78
	GRS (p-value): 2.72 (0.00)					GRS (p-value): 3.12 (0.00)				

Note: This table presents estimation results of the two-factor Gebhardt *et al.* (2005) model on the post-ranking returns of the term and default risk sorted portfolios. See Table 5.2 for further details.

Table 5.4: Three-factor regressions using portfolios sorted on term and default.

	A. Individual bonds						B. Bond mutual funds					
	Alpha	Alpha-t	MARKET	PC1	PC2	Adj.-R^2	Alpha	Alpha-t	MARKET	PC1	PC2	Adj.-R^2
P1.1	0.08%	0.13	1.60	0.31	-1.80	0.95	0.15%	0.30	1.22	0.23	-0.84	0.93
P1.2	-0.30%	-0.59	1.68	-0.05	-1.12	0.97	0.13%	0.57	1.06	0.10	-0.27	0.98
P1.3	-0.03%	-0.05	1.69	-0.08	-0.85	0.95	-0.13%	-0.62	0.99	0.09	-0.12	0.98
P1.4	0.31%	0.49	1.65	-0.13	-0.64	0.94	-0.21%	-0.99	0.97	0.08	-0.05	0.98
P1.5	0.03%	0.06	1.60	-0.12	-0.38	0.94	-0.06%	-0.23	0.96	0.02	0.09	0.97
P2.1	0.52%	0.66	1.50	0.31	-1.66	0.92	-0.40%	-1.07	0.90	0.25	-0.49	0.93
P2.2	-0.00%	-0.00	1.41	0.09	-0.89	0.95	-0.03%	-0.15	0.90	0.13	-0.18	0.97
P2.3	0.38%	0.77	1.28	0.11	-0.52	0.94	0.11%	0.66	0.87	0.09	-0.05	0.98
P2.4	0.03%	0.06	1.22	0.11	-0.20	0.94	-0.03%	-0.20	0.87	0.08	-0.01	0.98
P2.5	0.16%	0.39	1.14	0.06	-0.01	0.94	0.40%	2.40	0.84	0.02	0.09	0.98
P3.1	0.00%	0.01	1.15	0.32	-1.16	0.88	-0.29%	-0.66	0.85	0.27	-0.56	0.90
P3.2	0.28%	0.78	1.04	0.21	-0.14	0.95	0.01%	0.04	0.84	0.20	-0.19	0.96
P3.3	0.65%	1.92	0.98	0.22	0.04	0.95	0.10%	0.60	0.82	0.14	-0.04	0.98
P3.4	0.47%	1.65	0.93	0.16	0.16	0.96	0.22%	1.29	0.78	0.09	-0.01	0.98
P3.5	0.49%	1.39	0.88	0.16	0.28	0.93	0.21%	1.22	0.76	0.10	0.15	0.98
P4.1	1.22%	1.84	0.87	0.36	-0.80	0.83	0.20%	0.41	0.72	0.31	-0.58	0.86
P4.2	0.83%	3.27	0.70	0.23	0.05	0.95	0.30%	1.58	0.68	0.18	-0.04	0.97
P4.3	0.95%	4.56	0.65	0.20	0.13	0.96	0.35%	2.43	0.65	0.14	0.09	0.98
P4.4	0.79%	3.26	0.60	0.17	0.19	0.93	0.45%	3.12	0.60	0.13	0.11	0.97
P4.5	0.72%	2.36	0.55	0.16	0.14	0.88	0.45%	3.05	0.54	0.11	0.18	0.97
P5.1	1.85%	2.12	0.64	0.36	-0.77	0.65	0.06%	0.10	0.36	0.30	-0.17	0.56
P5.2	0.99%	3.67	0.35	0.21	-0.09	0.81	0.76%	4.70	0.29	0.13	0.06	0.88
P5.3	1.02%	3.93	0.27	0.13	-0.00	0.72	0.73%	5.19	0.25	0.12	0.09	0.89
P5.4	0.95%	2.58	0.28	0.08	0.07	0.56	0.66%	5.66	0.25	0.09	0.10	0.92
P5.5	0.31%	0.47	0.27	0.05	-0.09	0.26	0.18%	1.27	0.23	0.11	0.05	0.87
	GRS (p-value): 2.90 (0.00)						GRS (p-value): 3.16 (0.00)					

Note: This table presents estimation results of the three-factor principal components model on the post-ranking returns of the term and default risk sorted portfolios. See Table 5.2 for further details.

Table 5.5: Four-factor regressions using portfolios sorted on term and default.

	A. Individual bonds							B. Bond mutual funds						
	Alpha	Alpha-t	TERM	DEF	INF	GDP	R^2	Alpha	Alpha-t	TERM	DEF	INF	GDP	R^2
P1.1	3.28%	1.44	1.43	2.33	0.37	0.62	0.90	1.64%	1.23	1.12	1.36	0.34	-0.75	0.93
P1.2	0.40%	0.22	1.57	1.55	0.17	-0.09	0.93	0.35%	0.63	1.00	0.72	0.03	-0.13	0.98
P1.3	-0.35%	-0.21	1.60	1.32	0.07	-0.47	0.93	-0.02%	-0.04	0.94	0.55	0.01	-0.14	0.98
P1.4	-0.26%	-0.15	1.57	1.12	0.00	-0.29	0.93	0.40%	0.69	0.93	0.46	0.13	-0.31	0.97
P1.5	1.77%	1.18	1.53	0.94	0.20	0.65	0.94	0.33%	0.48	0.92	0.30	0.01	0.14	0.96
P2.1	2.73%	1.20	1.35	2.21	0.27	0.29	0.89	1.06%	1.27	0.83	0.96	0.31	-0.63	0.95
P2.2	0.77%	0.58	1.31	1.37	0.17	-0.27	0.94	0.63%	1.15	0.85	0.60	0.16	-0.45	0.97
P2.3	1.32%	1.17	1.20	1.05	0.24	-0.56	0.95	0.70%	1.48	0.83	0.45	0.11	-0.27	0.98
P2.4	-0.42%	-0.43	1.16	0.78	-0.13	0.10	0.96	0.70%	1.40	0.83	0.39	0.11	-0.16	0.98
P2.5	0.74%	0.75	1.09	0.54	0.07	-0.01	0.95	0.94%	1.96	0.81	0.25	0.12	-0.29	0.98
P3.1	2.76%	1.51	1.02	1.69	0.25	0.78	0.88	1.37%	1.33	0.78	1.00	0.36	-0.77	0.92
P3.2	0.56%	0.66	0.97	0.72	0.04	-0.31	0.95	0.85%	1.26	0.79	0.63	0.17	-0.45	0.95
P3.3	1.37%	1.44	0.93	0.56	0.08	-0.17	0.93	0.74%	1.37	0.78	0.44	0.13	-0.39	0.97
P3.4	0.65%	0.73	0.89	0.38	-0.04	0.01	0.94	1.06%	2.08	0.74	0.35	0.13	-0.17	0.97
P3.5	0.99%	0.88	0.84	0.26	-0.03	0.24	0.89	0.25%	0.41	0.73	0.22	-0.03	-0.08	0.95
P4.1	3.67%	2.19	0.78	1.27	0.26	0.33	0.83	1.88%	1.73	0.65	1.01	0.39	-0.94	0.88
P4.2	0.85%	1.02	0.66	0.42	-0.07	0.01	0.91	0.91%	1.51	0.64	0.43	0.04	0.02	0.95
P4.3	1.68%	2.15	0.61	0.31	0.03	0.10	0.90	1.16%	2.01	0.62	0.27	0.07	0.04	0.94
P4.4	1.79%	2.09	0.57	0.22	0.07	0.16	0.87	0.97%	1.70	0.57	0.22	0.04	-0.05	0.94
P4.5	1.37%	1.49	0.53	0.20	0.05	0.02	0.83	0.72%	1.23	0.52	0.12	-0.04	0.18	0.92
P5.1	5.98%	2.65	0.56	1.12	0.46	0.76	0.62	1.28%	0.89	0.32	0.51	0.10	0.11	0.51
P5.2	0.87%	1.13	0.32	0.36	-0.01	-0.38	0.75	1.43%	2.63	0.27	0.14	0.07	-0.01	0.79
P5.3	2.69%	3.76	0.25	0.19	0.24	-0.01	0.66	0.59%	1.16	0.24	0.08	-0.06	-0.06	0.76
P5.4	4.44%	5.00	0.27	0.10	0.50	0.31	0.59	0.68%	1.55	0.24	0.05	-0.01	-0.11	0.81
P5.5	7.34%	4.96	0.25	0.24	1.14	0.14	0.39	0.31%	0.69	0.22	0.12	0.03	-0.20	0.78
	GRS (p-value): 2.12 (0.00)							GRS (p-value): 1.03 (0.44)						

Note: This table presents estimation results of the four-factor Elton *et al.* (1995) model on the post-ranking returns of the term and default risk sorted portfolios. See Table 5.2 for further details.

entirely clear. Factor loadings are to some degree random across the quintile portfolios, and there are a number of fundamental differences in sensitivity to INF and GDP between corporate bond portfolios in Panel A and corporate bond mutual funds in Panel B. These counterintuitive results cast doubts on a plausible economic explanation of abnormal short-term corporate bond returns using macro-economic risk premiums.

Our last indication that common risk factors face problems explaining short-term corporate bond returns is provided by the regression R-squares of the aforementioned factor models. Independent of the employed factor specification, the time-series variation in return on the ten portfolios with lowest TERM sensitivity is less well explained by common factors than is variation in the returns of all other portfolios.

The bottom line of the empirical evidence up to this point is that the returns of corporate bonds with medium- or long-term remaining maturity are well explained by a number of factors that earlier studies have brought forward for explaining bond returns. But short-term corporate bonds have delivered anomalously positive returns, given their sensitivities to these common factors.

5.4.2 Robustness: alternative specifications

The evidence of abnormal returns on low-TERM portfolios that we observed in previous sections of this study creates an appetite for alternative risk-based interpretations of the anomaly. There are several avenues to pursue in order to arrive at such explanations. Recent research has concentrated on liquidity risk in the corporate bond market, which might be priced via factors other than those we used in conventional models of the bond return generating process (see for example Chacko (2006) and De Jong and Driessen (2006) for studies on bond liquidity). Other studies argue that asset returns are best described using conditional factor models that allow for time variation in portfolios' factor loadings (see for example Ferson *et al.* (2006)). In this section, we first examine whether the low-TERM bond anomaly can be explained by the Pastor and Stambaugh (2003) liquidity risk factor. Subsequently, we examine whether corporate bond returns are better captured by conditioning factor exposures on economic information.[11]

[11] We also examined the cross-section of corporate bond returns using the size, SMB, and value, HML, factors of the Fama and French (1993) model. Our results show that this model is clearly rejected according to the GRS test statistics. Detailed results are available upon request.

Bond single-factor model extended with a liquidity factor

This section examines whether liquidity can explain the short-term bond anomaly. Liquidity might be an issue for low-TERM portfolios as it is a well-known fact that short term bonds are less liquid. Most short term bonds have been in the markets for some time. Generally, the older a bond gets, the larger part of the issue that will be held by buy-and-hold investors, which reduces trading and increases illiquidity (Sarig and Warga (1989)). Partly for this reason, Lehman excludes bonds with a remaining maturity of one year and less from their indices (and dataset). Nevertheless, existing academic studies have yet to reach consensus on the threshold remaining matirity for exclusion, because it ranges from 3 months (Ericsson and Renault (2001)), one year (Elton *et al.* (2002), Houweling *et al.* (2005)), two years (Alexander *et al.* (2000)) to three years (Gebhardt *et al.* (2005)).

Our model follows Pastor and Stambaugh (2003), who estimate a liquidity factor for capturing equity returns. We extend the bond single-factor model (5.2) with their liquidity risk factor, LIQUIDITY, which results in the following model:

$$r_{i,t} = \alpha_i^{1FC} + \sum_j^N \beta_{j,i}^{NF} F_j, t + \beta_{j+1,i} LIQUIDITY_t + \varepsilon_{i,t}, \tag{5.10}$$

here LIQUIDITY is the updated value-weighted liquidity risk factor of excess returns for the equity market from Pastor and Stambaugh (2003) and F_j is factor j of the N-factor model. The LIQUIDITY portfolio is constructed after a sort of all stocks on the "strength of volume-related return reversals". For further details on the construction of the liquidity portfolios, see Pastor and Stambaugh (2003).

Table 5.6 shows that this model yields marginally higher R^2 values compared to all factor models. The liquidity factor model offers little improvement upon the single-factor model in terms of both time-series and cross-sectional explanatory power, and the model is clearly rejected according to the GRS test statistics in Panels A and B. An additional indication that the short-term bond anomaly cannot be explained by liquidity is documented by De Jong and Driessen (2006), who report that both equity and bond liquidity explains a significant part of credit returns. Nevertheless they conclude that their model underestimates expected returns for short maturity bonds.

Table 5.6: Liquidity factor regressions using portfolios sorted on term and default.

	A. Individual bonds					B. Bond mutual funds				
	Alpha	Alpha-t	MARKET	LIQUIDITY	R^2	Alpha	Alpha-t	MARKET	LIQUIDITY	R^2
P1.1	1.06%	0.71	1.59	0.01	0.68	1.00%	1.21	1.23	0.01	0.81
P1.2	-0.31%	-0.32	1.66	0.01	0.85	0.69%	2.06	1.07	0.00	0.95
P1.3	-0.30%	-0.36	1.66	0.01	0.88	0.17%	0.69	1.00	-0.00	0.97
P1.4	-0.02%	-0.03	1.62	0.00	0.89	0.12%	0.53	0.98	0.00	0.97
P1.5	-0.18%	-0.29	1.59	0.01	0.92	0.11%	0.45	0.97	0.00	0.97
P2.1	1.31%	0.90	1.46	0.02	0.66	0.41%	0.73	0.91	0.01	0.84
P2.2	0.12%	0.14	1.36	0.01	0.84	0.41%	1.44	0.90	0.00	0.95
P2.3	0.49%	0.77	1.23	0.00	0.88	0.38%	1.99	0.87	0.00	0.98
P2.4	0.12%	0.25	1.18	-0.00	0.92	0.28%	1.50	0.88	-0.00	0.98
P2.5	0.13%	0.31	1.10	0.01	0.93	0.54%	3.06	0.85	0.00	0.98
P3.1	0.75%	0.67	1.11	0.02	0.66	0.55%	0.87	0.86	0.01	0.78
P3.2	0.64%	1.46	0.99	0.00	0.91	0.46%	1.34	0.84	0.00	0.92
P3.3	0.96%	2.37	0.95	0.00	0.91	0.43%	1.96	0.82	-0.00	0.96
P3.4	0.64%	1.80	0.90	0.00	0.92	0.43%	2.39	0.78	0.00	0.97
P3.5	0.71%	1.64	0.85	0.00	0.88	0.41%	1.94	0.76	-0.00	0.96
P4.1	1.85%	2.03	0.84	0.02	0.62	1.04%	1.53	0.71	0.01	0.68
P4.2	1.18%	3.52	0.68	0.00	0.89	0.86%	3.25	0.70	0.00	0.93
P4.3	1.26%	4.25	0.63	0.00	0.90	0.73%	3.57	0.65	-0.00	0.95
P4.4	1.09%	3.41	0.58	0.01	0.86	0.78%	3.63	0.61	-0.00	0.94
P4.5	0.96%	2.75	0.53	0.00	0.82	0.67%	2.97	0.55	-0.00	0.92
P5.1	2.62%	2.52	0.61	0.00	0.39	0.97%	1.65	0.36	-0.00	0.41
P5.2	1.48%	4.44	0.34	0.00	0.66	1.23%	5.69	0.30	-0.00	0.78
P5.3	1.33%	4.93	0.26	0.01	0.65	1.05%	5.55	0.26	-0.00	0.78
P5.4	1.13%	3.28	0.27	0.01	0.55	0.85%	5.31	0.25	0.00	0.82
P5.5	0.44%	0.75	0.26	0.02	0.28	0.37%	2.22	0.23	0.00	0.79
	GRS (p-value): 2.25 (0.00)					GRS (p-value): 3.50 (0.00)				

Note: This table presents estimation results of the extended bond single-factor model with an equity liquidity risk factor:$r_{i,t} = \alpha_i^{1FC} + \beta_{1,i}^{1F} MARKET_t + \beta_{2,i} LIQUIDITY_t + \varepsilon_{i,t}$ (where LIQUIDITY is the update value-weighted liquidity risk factor from Pastor and Stambaugh (2003)) on the post-ranking returns of the term and default risk sorted portfolios. See Table 5.2 for further details.

Conditional time-varying risk exposures

So far, we assumed expected returns and risks to be constant over time. Here, we investigate time-varying exposures to common risk factors. We use a variant of the Ferson and Schadt (1996) model to arrive at a conditional version of the single-factor model for bonds. Time variation in factor sensitivity is captured by variables describing the interaction between benchmark factor returns and a set of lagged instrumental variables:

$$r_{i,t} = \alpha_i^{1FC} + \beta_{1,i}^{1F} MARKET_t + B_i'[z_{t-1} MARKET_t] + \varepsilon_{i,t}, \qquad (5.11)$$

where z_{t-1} is a vector that consists of lagged values of three pre-determined information variables. We use the variables that Ferson *et al.* (2006) identify as relevant in predicting variation in exposures to common risk factors for fixed-income securities: the lagged level of the one-month Treasury bill rate, the lagged default spread in the investment-grade bond market, and a measure of industrial production and capacity utilization.[12] The resulting model includes four scaled factors and an intercept.

The results in Table 5.7 point out that the conditional market model is only marginally better in explaining time-series variation in bond returns compared to its unconditional counterpart. Moreover, conditioning risk on economic information does not help to subsume the abnormal return on bonds with relatively short maturities. GRS strongly rejects the notion that cross-sectional variation in the returns of individual bond portfolios (Panel A) and those of bond funds (Panel B) are captured by the conditional bond single-factor model.

5.5 Conclusion

This study on the cross-section of U.S. corporate bond returns shows that common risk factors underestimate the returns of bond with short-term maturities. The returns of short-term bonds, realized over the period 1993 to 2003, are underestimated by well-known risk factors including market risk (Alexander (1980)), term and default risk (Gebhardt *et al.* (2005)), steepness and curvature (Litterman and Scheinkman (1991), Knez *et al.* (1994)), premiums associated with inflation and economic development (Elton *et al.* (1995)) and liquidity risk (Pastor and Stambaugh (2003), De Jong and Driessen (2006)). We confirm

[12]We define the default spread as Moody's BAA-rated corporate bond yield minus the AAA-rated corporate bond yield. We obtain our data on industrial production and capacity utilization from the Federal Reserve Board website.

Table 5.7: Ferson & Schadt regressions using portfolios sorted on term and default.

	A. Individual bonds				B. Bond mutual funds			
	Alpha	Alpha-t	MARKET	R^2	Alpha	Alpha-t	MARKET	R^2
P1.1	1.24%	0.76	1.83	0.67	1.02%	1.21	1.73	0.82
P1.2	-0.02%	-0.01	1.41	0.85	0.52%	1.70	1.06	0.96
P1.3	0.12%	0.14	1.49	0.89	0.08%	0.35	1.06	0.98
P1.4	0.33%	0.41	1.51	0.90	-0.00%	-0.02	1.30	0.98
P1.5	-0.09%	-0.14	0.99	0.93	-0.07%	-0.25	0.98	0.97
P2.1	1.60%	1.01	1.10	0.65	0.29%	0.52	1.06	0.85
P2.2	0.42%	0.48	0.90	0.85	0.28%	1.05	0.92	0.96
P2.3	0.78%	1.20	1.05	0.89	0.28%	1.65	0.80	0.98
P2.4	0.35%	0.76	0.83	0.94	0.13%	0.77	0.96	0.98
P2.5	0.33%	0.86	0.71	0.95	0.35%	2.03	0.76	0.98
P3.1	0.97%	0.80	1.33	0.65	0.43%	0.65	0.88	0.78
P3.2	0.71%	1.69	0.62	0.93	0.48%	1.42	0.78	0.93
P3.3	1.14%	2.83	0.70	0.93	0.36%	1.72	0.66	0.97
P3.4	0.83%	2.45	0.66	0.94	0.38%	2.03	0.79	0.97
P3.5	0.77%	1.79	0.41	0.90	0.38%	1.63	0.78	0.96
P4.1	1.97%	1.98	0.15	0.62	0.96%	1.37	0.56	0.70
P4.2	1.25%	3.69	0.39	0.90	0.69%	2.73	0.67	0.94
P4.3	1.31%	4.30	0.34	0.91	0.63%	2.91	0.54	0.95
P4.4	1.13%	3.43	0.40	0.88	0.71%	3.30	0.60	0.94
P4.5	0.97%	2.95	0.26	0.86	0.64%	2.80	0.50	0.92
P5.1	2.50%	2.22	0.03	0.40	0.74%	1.15	0.46	0.40
P5.2	1.42%	4.23	0.18	0.70	1.02%	4.73	0.33	0.79
P5.3	1.22%	4.27	0.24	0.66	0.90%	4.63	0.15	0.78
P5.4	1.05%	2.88	0.47	0.57	0.80%	4.70	0.21	0.82
P5.5	0.45%	0.73	1.37	0.34	0.41%	2.69	0.24	0.84
	GRS (p-value): 2.25 (0.00)				GRS (p-value): 3.21 (0.00)			

Note: This table presents estimation results of the Ferson and Schadt (1996) model on the post-ranking returns of the term and default risk sorted portfolios. See Table 5.2 for further details.

that the anomaly is not specific to hypothetical portfolios derived from our unique sample of individual corporate bonds. Our finding that short-term corporate bond portfolios in the form of U.S. mutual funds earn an abnormal return, suggests that the anomaly withstands pricing errors, illiquidity problems, typical investment restrictions and transaction costs.

The results add new insights to the importance of the maturity dimension for pricing corporate bonds. Prior studies of individual corporate bonds (Alexander (1980) and Gebhardt *et al.* (2005)) have concentrated on bonds with medium to long-term maturity. This study, inspired by Pilotte and Sterbenz (2006), uncovers anomalous returns using a wider range of maturities. In doing so, we find support for the conclusion that short-term corporate bond returns are inconsistent with existing risk-based factor models.

Consequently, this study lays the foundations for further research on the determinants of short-term corporate bond returns. Because the anomaly displays parallels with the low-beta stock anomaly documented earlier (e.g., in Fama and MacBeth (1973)), our results might be relevant to behavioral explanations of the return-generating process that have been brought forward in the equity pricing literature. Karceski (2002), for example, hypothesizes that large aggregate demand for high-beta stocks relative to low-beta stocks in specific market states forces up (down) the price of high-beta (low-beta) stocks so that common equity factors are not priced to the degree predicted. One potential avenue for further research would be to investigate whether time-variation in aggregate demand for long-term bonds relative to demand for short-term bonds accounts for the short-term bond anomaly.

Chapter 6

A Recommitment Strategy for Long Term Private Equity Fund Investors*

6.1 Introduction

Nowadays many institutional investors, such as pension funds, insurance companies and endowments, have included private equity in their strategic asset allocation. The vast majority of these investments takes place indirectly through 'funds', because entering, managing, and exiting direct private equity investments requires a high level of expertise and experience. In private equity funds, investors bring in capital, while the fund's management brings in her expertise (Cumming *et al.*, 2005), experience (Sørensen, 2006), specialization (Gompers *et al.*, in press), and network (Hochberg *et al.*, 2007). Most institutional investors aim for a specific private equity exposure as part of their strategic asset allocation. To the best of our knowledge, prior studies on optimal strategic asset allocation, like Chen *et al.* (2002), ignore the illiquid nature of private equity. The illiquidity is due to the lack of a well-developed secondary market and to restrictions on the sale of private equity fund investments, see Sahlman (1990) and Lerner and Schoar (2004) for a discussion.[1]

*This chapter is based on the ERIM Working paper De Zwart *et al.* (2007). We are grateful to Tjeert Keijzer, Erik Kole, Ludovic Phalippou, Per Strömberg and Marno Verbeek for helpful suggestions. We would also like to thank participants of the Inquire Europe meeting held in Stockholm, October 2007 and seminar participants at Robeco.

[1]Lerner and Schoar (2004) show that restrictions on the transfer of fund-ownership are used by young funds and funds with an investment focus in industries with longer investment cycles to attract deep-pockets' investors, that is investors who have a low probability of facing a liquidity shock. This will make fundraising for a follow-on fund easier as these investors have an increased probability to re-participate, which will be a good signal to new potential investors. Although this set-up of the private equity market structure looks more complex than public equity, Axelson *et al.* (2007) show that the financial structure of private equity funds is optimal for three characteristics of the industry: (1) pooling of investments, (2)

This makes it difficult to achieve and maintain the desired strategic exposure to private equity. First, the target allocation to private equity cannot be bought instantaneously, like for bonds or public equity. Second, cash pay-outs of the private equity investments can not be reinvested immediately either, while these pay-outs are significant, because private equity funds have a finite lifetime (normally between 10 and 14 years).

Private equity fund investments start with an initial commitment, where the investor commits herself for a certain amount of capital to the fund. These commitments are only gradually invested ('called') by the fund, often taking a couple of years. In addition, often, not even all committed capital is eventually invested. Finally, pay-outs ('distributions') from liquidated investments typically start to occur when a fund is only just a few years old, often already before all committed capital has been invested. This again lowers the effective private equity allocation. In sum, attaining a certain target investment exposure to private equity and maintaining it at that level is not straightforward.

The central question that arises from the above is: How much and when should new private equity fund commitments be made to achieve and to maintain the desired strategic allocation for a prolonged period, given that the cash in- and outflows are (highly) uncertain? The aim of this paper is to answer this question by designing an appropriate (re)commitment strategy. At the outset we stress that our focus is on getting passive exposure to private equity and not on designing a strategy that outperforms the market.[2] Furthermore, we do not examine the motivation to include private equity in the strategic asset allocation decision, but we will assume that the decision to pursue a certain private equity exposure has already been made.[3]

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nonlinear profit sharing with the fund manager to limit governance problems and (3) a financial structure that combines ex-post fundraising and specific deal financing.

[2]Lerner *et al.* (2007) report that some institutional investors have been more successful than others at investing in private equity. It would be interesting to examine which factors determine the performance of a private equity investment strategy, but this is not the aim of our paper.

[3]A possible motivation to include private equity in an investment portfolio is provided by its risk and return characteristics. These have been studied extensively (i) at the firm level (Gompers and Lerner, 1998; Cochrane, 2005), (ii) at the fund level (Ljungqvist and Richardson, 2003a; Kaplan and Schoar, 2005; Phalippou and Gottschalg, 2007) and (iii) at the index level (Moskowitz and Vissing-Jorgensen, 2002; Chen *et al.*, 2002; Woodward and Hall, 2003). An important issue here concerns the private equity risk premium, in particular its comparison with the public equity premium. The consensus view seems to be that private equity investments should offer a higher return than public equity, for example due to their illiquidity. However, conclusions from empirical research are mixed. Rather poor returns are reported by Moskowitz and Vissing-Jorgensen (2002) and Phalippou and Gottschalg (2007). Kaplan and Schoar (2005) report comparable average returns for private equity and the S&P 500 index, while Ljungqvist and Richardson (2003a) claim that private equity investments outperform the aggregate public equity market by 6-8% per annum, see also Cochrane (2005). More recent studies focus on (explanations for) cross-sectional return

Our recommitment strategy makes new commitments to private equity funds every quarter. In addition, the strategy is dynamic in nature by taking into account the characteristics of the current portfolio. The level of the new commitments is determined by the past quarter's distributions in cash, the uninvested capital from earlier commitments as well as the exposure of the current portfolio relative to its target, indicated as 'investment degree' in the remainder of this paper. Committing the paid out cash distributions is intuitive, as these liquidated investments should as soon as possible be reinvested in private equity to keep the allocation at the desired level. Commitments which are not invested within a certain period of time are recommitted in order to prevent leakage of private equity exposure. Finally, the current investment degree of the existing portfolio is used to either reduce or increase the new commitment to bring the exposure to the desired level.

Our results, based on historical simulations using the Thomson Venture Economics database, can be summarized as follows. Our main finding is that our recommitment strategy is capable of maintaining a stable investment degree that is close to the target allocation, while keeping the probability of being over-exposed within reasonable bounds. This conclusion holds for portfolios diversified across venture capital and buy-out capital and across the US and Europe. In addition, sensitivity analysis shows that our strategy remains equally successful when the portfolio is restricted to a certain type of private equity capital (buy-out or venture capital), to a specific region (US or Europe), or to varying fund manager experience (first-time or follow-on funds). More generally, the principle of our private equity recommitment strategy can easily be expanded to other illiquid asset classes that involve illiquidity and commitments, like direct real estate or infrastructure funds.

In addition, we find that achieving the target exposure is possible only when commitments for the initial portfolio, that is during the first year, are higher than the desired strategic allocation. This so-called 'overcommitment', though, creates the possibility of liquidity problems in the event that the amount of capital that is called for investment exceeds the available capital. It may also result in a breach of investment policy guidelines if these do not allow a larger private equity allocation than the target exposure. Nevertheless our analysis indicates that a 30% overcommitment during the build-up period (in our case one year) is required to achieve the desired exposure to private equity when starting a new portfolio. Furthermore, we show, with perfect foresight, that the quality of the strategy further improves if an investor uses the 3-year future investment degree of

differences between private equity funds (Cumming and Walz, 2004; Kaplan and Schoar, 2005) and the drivers of returns (Phalippou and Gottschalg, 2007).

the current portfolio to scale up or down new commitments (instead of the current investment degree). Alternatively, an investor that can permit herself a higher allocation could consider overcommitment also when reallocating uncalled capital and distributions. We find that this brings the average portfolio exposure closer to the target, but at the cost of a higher risk of being overexposed. Finally, we compare our novel commitment strategy with the few alternatives that have been put forward previously. Cardie *et al.* (2000) present a commitment rule stating that investors should commit their complete private equity allocation target every other year, or half of the allocation each year. A possible drawback of this strategy is that it neglects past portfolio developments when making new commitments. Nevins *et al.* (2004) derive a link between the target for committed capital and the target for invested capital. The resulting commitment strategy rests on the crucial assumption that the rate of investments and the rate of distributions are the same for all private equity funds and constant over time, which is unlikely to hold in practice. In our analysis, we find that indeed both these commitment strategies are not capable of keeping the investment degree stable for a prolonged period of time. In particular, the investment degree remains permanently above its target.

The paper proceeds as follows. Section 6.2 describes the Thomson Venture Economics data. Section 6.3 discusses the cash flow dynamics for an investor in private equity funds. Section 6.4 develops the novel recommitment strategies. Section 6.5 presents the empirical results, while Section 6.6 concludes.

6.2 Data

We use private equity fund data obtained from Thomson Venture Economics (TVE).[4] Our data set is comparable with Jones and Rhodes-Kropf (2003), Kaplan and Schoar (2005) and Phalippou and Gottschalg (2007), to which we refer for more information about the way TVE collects the data and potential biases in the database.

The TVE database contains information on 2,786 individual private equity funds over the period 1980Q1-2005Q4, and includes quarterly contributions, distributions and the fund's net asset value (NAV). Reported cash flows are in US dollars and are net of management fees, performance fees ('carried interest') as well as other costs. We make several

[4]Obtained in the period until Q2 2006. We are aware that the Thomson Venture Economics database is backfilled. This backfilling will not distort our results, because we use the only cash flow data and not the returns.

Table 6.1: Distribution of private equity funds across investment types and regions

	Region			
Investment type	US	Europe	Global	Total
Venture capital	1090	591	–	1681
Buy-out capital	535	401	1	937
Total	1625	992	1	2618

Note: The table reports the number of funds for each region (US, Europe, and world) and type (Buy-out or Venture capital) combination.

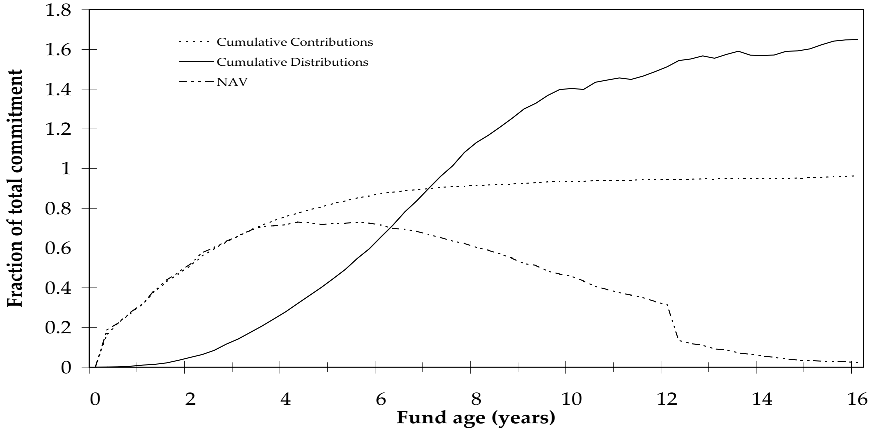
corrections and adjustments to the data, detailed in the data appendix, after which there are 2,618 funds left for analysis. Several fund characteristics also are available, including the regional focus (US or Europe (EU)), the type of investment (venture capital (VC) or buy-out capital (BO)), the fund managers experience (‘first-time’ or ‘follow-on’), and the year of the fund’s formation (‘vintage year’). The distribution of funds over the different investment types and regions is shown in Table 6.1. Close to two-thirds of all funds are venture capital funds, while about 60 percent are US-oriented funds.

6.3 Descriptive statistics

6.3.1 Private equity cash flows

Private equity investments start with the investor committing a certain amount of capital to the fund. No capital is exchanged when this decision is made, but from that moment onwards the investor is obligated to provide capital whenever the fund manager asks for it. During a fund’s lifetime commitments are irrevocable and the fund manager independently decides on the fund’s investments and disinvestments. Investors only control the initial size of their commitments, they do not know in advance when and into which companies their money will be invested. As investment opportunities arise, part of the committed capital will be called by the fund manager. These contributions include the capital that actually is invested but also fees. Private equity funds typically unwind their investments by distributing the proceeds of sold participations to the investors (‘limited partners’). Figure 6.1 shows the average cumulative cash flows (contributions and distributions) over the lifetime of the funds in our data set. We scale these cash flows by the total commitment to the fund to make the individual fund statistics comparable and independent of the fund

Figure 6.1: Average contributions, distributions and Net Asset Values.



The figure present the average cumulative contributions, average cumulative distributions and average NAVs of individual private equity funds over the period 1980Q1–2005Q4.

size.[5]

From this figure we observe that it takes several years before the committed capital is invested. Investments are largest in the first year of the fund's lifetime when, on average, 32% of the commitments are invested. After that the pace at which capital is invested gradually decelerates. In the second year after the start of a fund on average 19% of the commitments is called, followed by 15, 10, 7 and 5% capital calls in the next four years. After approximately six years cumulative contributions level off. Note that on average only about 90% of total commitments is eventually called by the private equity fund. The average cumulative distributions show a typical S-shape. Starting after two years, distributions are made at an accelerating pace up to seven or eight years, followed by a steady decline until eventually cumulative distributions level off at around 1.5 times the total commitments after 12 years.

Figure 6.1 also shows the average value of investments over the fund's lifetime, again expressed as a fraction of total commitments. The 'net asset value' (NAV) of a private equity fund is defined as the sum of the NAVs of the individual investee companies. These NAVs are based on the fund manager's subjective valuation, as private equity investments

[5]The size of a private equity fund is defined as the sum of all the investors' commitments to the fund.

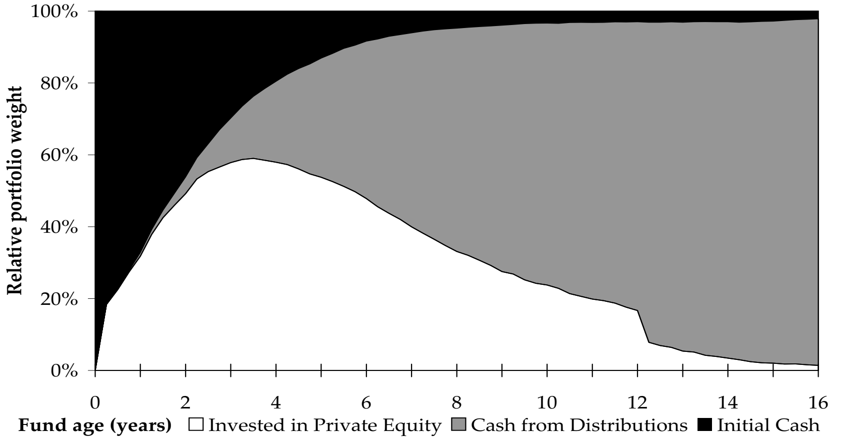
are not evaluated by the market and the fund manager is not subject to standardized reporting guidelines.[6] Generally, a manager keeps the NAV at investment cost during the first years of an investment. After a while valuations are updated with additional information from, for example, comparable listed companies or from a new financing round. Due to the pattern of contributions and distributions, NAV builds up quickly during the first few years of the fund's lifetime, reaches its maximum between four and six years, and then gradually drops off again over the remaining years. It appears that the average NAV does not decrease completely to zero even after 15 years. This occurs because some funds keep a residual value, although not showing any signs of activity (as mentioned before, the lifetime of a typical private equity fund ranges between 10-14 years). Phalippou and Gottschalg (2007) show that writing off these 'living-dead' investments lowers the average private equity returns. Following Ljungqvist and Richardson (2003b), who suggest that these residual values are unreliable, we set the NAV equal to zero after 12 years if there are no signs of activity at that point or after the last activity if any cash flows take place in year 13 or later. The effect of this write-off rule is observable in the NAV at the end of year 12 in Figure 6.1.[7]

The average fund's cash flow characteristics suggest that attaining a desired level of investment exposure to private equity and maintaining it for a prolonged period is not straightforward. Commitments are only gradually called to be invested and distributions already occur before all committed capital has been invested, while in practice of course the timing of these cash flows is typically unknown ex ante. The impact of these dynamics on private equity investment exposure are shown in Figure 6.2. This graph shows the portfolio weights of the cash from the initial commitment, the cash from the distributions, and NAV of the actual private equity investments over a fund's lifetime as percentage of the total capital involved. From Figure 6.2 it is very clear that committed capital does not equal the actual invested capital. The percentage of capital actually invested in private equity reaches its maximum in the fourth year of the fund's lifetime, where it equals not more than 60%. Hence, at that point still only 60% of total capital is actually invested, while 40% is left in cash. At all other times private equity exposure is less than 60%. Obviously this is undesirable for institutional investors.

[6]Valuing companies in accordance with certain guidelines is increasing though, for example using the International Private Equity and Venture Capital Guidelines developed by the European (EVCA), French (AFIC) and British (BVCA) venture capital associations.

[7]As we focus on cash-flows and not on returns this adjustment has little impact on our analysis. Results including the residual NAV values, which are available upon request, are qualitatively similar.

Figure 6.2: Cash versus actual private equity fund investment.



The figure shows the average relative portfolio weight of the available cash at start (100), cash from the distributions and the value of the actual private equity investment (NAV), 1980Q1-2005Q4.

6.3.2 Cash flows over time

As the vast majority of private equity funds has a finite lifetime most managers introduce a new fund every three to four years. All funds that start in a specific year belong to the same 'vintage year'. The summary statistics discussed before mask a great deal of variation in the cash flows and NAV across vintage years. This is borne out by Table 6.2, which presents the maximum investment degree and its timing (in quarters), as well as the number of funds, for each vintage year in our sample period (1980–2005). The results for vintage years 2001–2005 have to be treated with caution, because the average investment degree of these funds is still increasing. As a result both the magnitude and timing of its maximum cannot be determined with certainty yet.

First of all, the number of funds per vintage year illustrates the growth in private equity: from 22 funds that started in 1980 to 301 in 2000. The peaks in the number of funds occurring at the end of the 1980s and 1990s in Table 6.2 give an indication of the cyclical pattern in supply and demand for private equity capital. Note in particular the steep decline in the number of new funds after the collapse of the dot-com bubble in 2001, to just 21 in 2005. Second, we observe that the magnitude of the maximum investment

Table 6.2: Timing and magnitude of maximum investment degree across vintage years

Vintage year	# funds in vintage year	Maximum investment degree Mean	Timing	$CC_{t=4y}$	$CD_{t=4y}$
1980	22	0.72	Q10	0.83	0.32
1981	24	0.85	Q14	0.90	0.09
1982	29	0.85	Q13	0.88	0.07
1983	63	0.83	Q13	0.92	0.23
1984	82	0.77	Q16	0.87	0.13
1985	76	0.75	Q9	0.92	0.26
1986	70	0.71	Q15	0.83	0.16
1987	116	0.68	Q18	0.78	0.14
1988	95	0.67	Q18	0.74	0.11
1989	114	0.66	Q17	0.74	0.11
1990	67	0.67	Q18	0.78	0.18
1991	61	0.55	Q17	0.63	0.15
1992	58	0.69	Q13	0.82	0.35
1993	94	0.57	Q12	0.75	0.43
1994	105	0.62	Q14	0.77	0.29
1995	111	0.61	Q17	0.77	0.38
1996	104	0.62	Q14	0.81	1.07
1997	180	0.64	Q12	0.81	0.73
1998	213	0.65	Q9	0.81	0.40
1999	248	0.57	Q12	0.75	0.12
2000	301	0.55	Q23	0.65	0.11
2001*	172	0.54	Q20	0.59	0.13
2002*	86	0.39	Q16	0.49	0.11
2003*	60	0.61	Q12	-	
2004*	46	0.36	Q8	-	
2005*	21	0.15	Q4	-	
Av. 80s	69	0.75	Q14	0.84	0.16
Av. 90s	124	0.62	Q14	0.77	0.41

Note: For each vintage year from 1980 to 2005, the table reports the number of funds, the magnitude and timing (in quarters) of the maximum investment degree and the cumulative contributions and distributions after 4 years. The average maximum investment degrees and timing for vintage years 2001-2005 are unreliable as the maximum and its timing cannot be determined with certainty yet. Vintage year statistics are based on the average distributions, contributions and NAV for all funds that were started during that year.

degree varies over time and exhibits a downward trend. At the beginning of the 1980s it amounted to about 80%, while funds at the end of the 1990s only achieved a maximum investment degree of around 60%. Furthermore, the time it takes to reach the maximum investment degree varies substantially, between 11 and 23 quarters. It seems that it takes more time to reach to maximum invested degree for funds that started during economic downturns as in 1990–1991 and 2000–2001.

The considerable variation in the timing and height of the maximum investment degree across different vintage years reflects the fluctuations in private equity investment opportunities, documented by Gompers and Lerner (1998), which are due to fluctuations in supply and demand for private equity. The supply of private equity capital has been reported to vary over time due to changes in regulatory factors, in particular capital gains tax rates (Poterba, 1989; Gompers and Lerner, 1998),[8] state policies such as ERISA (Gompers and Lerner, 1998), and harmonization like the International Financial Reporting Standards (Cumming and Johan, 2007) or to labor market rigidities (Jeng and Wells, 2000).

The cyclical nature of the cash flows is further illustrated in the last two columns of Table 6.2. These columns show the cumulative contributions and distributions after 16 quarters. The sharp contrast between the maximum investment ratios in the 1980s and 1990s is less pronounced in the contributions. During the 1980s on average 84% of the commitments is called after four years while this is 77% for the 1990s. The differences in distributions across vintage years are much larger, ranging from a low of 7% for funds that started in 1982 to a high of 107% for funds dating from 1996. Averaging per decade, we find that the total distributions in the 1980s are almost three times lower (16%) than in the 1990s (41%). Hence, we conclude that the lower maximum investment degrees during the 1990s do not arise because less commitments are actually invested, but are due to the fact that distributions take place earlier.

The considerable variation in the size and timing of the cash flows motivates us to design a dynamic recommitment strategy that takes into account the composition of the current portfolio when making new commitments to achieve and maintain the desired exposure to private equity.

[8]Although Gompers and Lerner (1998) also document that the effect of changes in capital gains tax rates mostly appears to occur through the demand for capital.

6.4 Commitment strategies

Our hypothetical investor aims to achieve and maintain a certain target allocation to private equity. Although in practice this may be part of a larger investment portfolio, here we simplify the problem by focusing on the private equity part only. Thus the investor constructs a 100% private equity portfolio. The main objective is to keep the investment degree as close as possible to one, where the investment degree (ID_t) is defined as

$$ID_t = \frac{NAV_t}{NAV_t + \text{cash}_t}, \tag{6.1}$$

where NAV_t is the sum of the NAVs of the private equity investments held at the end of quarter t, and cash_t is the amount of cash or uninvested capital, computed as cash_{t-1} minus the sum of all contributions made in quarter t plus the sum of all distributions received during quarter t. Hence, the objective of keeping the investment degree as close as possible to one can be rephrased as keeping the amount of cash as close as possible to zero. An important consideration is that at the same time liquidity shortfall should be avoided as much as possible. Liquidity shortfall occurs at the moment required investments exceed the amount of available capital such that cash becomes negative and the investment degree larger than one. Recall that all capital calls have to be paid as the commitments made at the start of the fund are irrevocable. This could lead to liquidity problems if the investor does not have enough cash or credit lines available to fulfill the capital call or lead to a breach of the investment guidelines if a higher private equity allocation is not allowed in a more diversified portfolio setting.

The investment problem as described above is difficult, if not impossible to solve analytically. Hence, our investor considers three heuristic recommitment strategies. First, however, we consider the issue of constructing an initial private equity portfolio to which the recommitment strategies can be applied.

6.4.1 Setting up the initial portfolio

Implementing a recommitment strategy to maintain a constant exposure to private equity requires an already existing portfolio. In practice, the composition of this portfolio and accompanying characteristics may be given, but this need not necessarily be the case. As discussed in the introduction, a mature private equity portfolio can, in general, not be bought instantaneously, due to the lack of a well-developed secondary market. Hence, the start-up of a private equity portfolio is an interesting problem in its own right. Here we construct the initial portfolio over a one year period by making equal commitments to 16 randomly selected private equity funds with the same vintage year (4 new commitments per quarter).[9] This is in line with Weidig and Mathonet (2004), who report that a diversified private equity portfolio contains approximately 20 funds. As discussed in Section 6.2, the average maximum investment degree of private equity funds (60%, in year four) is well below one. This suggests that achieving a certain level of private equity investments requires an overcommitment strategy, where commitments exceed the target exposure. For example, for the average fund in our sample a commitment of 167% (that is, 67% overcommitment) would be required to obtain a private equity exposure of 100% in year four.

From Section 6.3.2 we know that cash-flow characteristics of private equity funds evolve over time. In particular, the maximum investment degree has declined due to more rapid distributions, while the timing of this maximum also varies. Based on the findings in Section 6.3.2, a 30% overcommitment is applied to set-up the initial portfolio and achieve an investment degree close to one. We choose this overcommitment percentage to limit liquidity risk and to make sure that we are not overinvested in the 1980s, although a larger overcommitment of about 60% would be preferred for the portfolios that start in the 1990s.

6.4.2 Recommitment strategies

Our investor considers three heuristic recommitment strategies to maintain her exposure to private equity at the desired level. Strategy I simply states that distributions received during quarter t are (re)committed to new private equity funds at the same time. The advantage of this strategy is that the possibility of liquidity shortfall is avoided altogether. However, given that committed capital will be called only gradually over a number of years after the initial commitment, the effective investment degree may be expected to fall below one. In addition, this strategy implicitly assumes that all committed capital will eventually be called. However, as seen in Section 6.2, this is not the case as on average

[9]Normally an investor would spread her initial commitments over 2 – 3 years to benefit from vintage year diversification, while a limited number of investors tries to buy an existing portfolio in the secondary market. The secondary market is no open market and not very deep because many funds put restrictions on the transfer of fund-ownership (Lerner and Schoar, 2004). In order to examine the relevance of this issue, we also conduct the empirical analysis discussed in the next section with initial portfolios built up in two or three years. Doing so, the investment degrees differ during the first few years as the portfolio gets invested more slowly. After about five years, all portfolios converge, showing that the construction of the initial portfolio does not seem to affect the quality of the recommitment strategies after the portfolio matures. Detailed results are available upon request.

private equity funds call only 90% of committed capital. This results in 'leakage', that is uncalled commitments remaining within the portfolio as cash and accumulating over time. For this reason, strategy II extends strategy I by setting commitments at the end of quarter t equal to the sum of the current distributions and uncalled capital from the commitments made P quarters ago, at $t - P$.

Although recommitting uncalled previous commitments as in strategy II should help to improve the average investment degree, it cannot possibly achieve the target exposure completely. The data analysis in Section 6.2 reveals that the investment degree for individual funds on average only reaches up to 60% of committed capital as shown in Figure 6.2. Obviously this applies not only to the commitments made for the initial portfolio in the first year, but also to the capital involved in the recommitment of distributions and uncalled previous commitments. Hence, in order to counter the effects of this underinvesting and maintain the target exposure, overcommitment also seems necessary at the recommitment stage.

An important but difficult choice to be made is the overcommitment percentage to be applied. As shown in Table 6.2, the average (maximum) investment degree varies substantially across vintage years, suggesting that a constant overcommitment percentage is not appropriate. On the other hand, implementing a strategy with a dynamic overcommitment percentage is not straightforward. Ideally, the overcommitment percentage for new commitments in a given quarter would be based on the actual investment degree that will be attained by funds from the current vintage year, but in practice this is of course unknown. We argue that the current investment degree of the existing private equity portfolio also provides valuable information regarding the appropriate overcommitment percentage for new commitments. Intuitively, the further this investment degree falls below one, the more aggressive we should recommit capital to new private equity funds in order to bring the exposure back to the target level. Hence, strategy III sets the new commitments at the end of quarter t equal to the distributions received during that quarter and uncalled commitments made P quarters before as in strategy II, but now multiplied with the reciprocal of the investment degree of the current private equity portfolio. Hence, in strategy III the new commitments at the end of quarter t are determined by:

$$C_t = \frac{1}{ID_t} \left(D_t + UC_{t-P} \right), \tag{6.2}$$

where C_t is the amount of new commitments made at the end of quarter t, ID_t is the investment degree of the current private equity portfolio, D_t are the distributions received during quarter t, and UC_{t-P} is the amount of uncalled capital of commitments made P quarters ago.

An important choice to be made in strategies II and III obviously is the 'lag-time' P. In the empirical analysis below we set $P = 24$ quarters, based on the observation that for the average private equity fund, the cumulative contributions level off after approximately six years as shown in Figure 6.1, also see Ljungqvist and Richardson (2003b).

6.4.3 Implementation

We evaluate the performance of the three recommitment strategies by means of historical simulation using the TVE database. Hence, we form initial portfolios for vintage years from 1980 up to and including 2000, and apply the recommitment strategies for the remainder of the sample period. Several implementation issues are worth mentioning. First, we impose no restrictions on the portfolio of private equity funds concerning the type of funds (venture capital or buy-out capital), the investment region (US or Europe), the maximum number of funds invested in or the maximum portfolio weights. The only restriction is that the commitments must be sufficiently diversified. Reinvestment strategies when limited to a certain type of funds or to a specific region are analysed in Section 6.5.2 below.

Second, after the portfolio construction period in the first year, the different recommitment strategies are applied for the remainder of the sample period as described before. For assigning the new commitments to be made in a particular quarter, four funds with the relevant vintage year are drawn randomly from the TVE data set, again independent of the region (EU or US) or investment type (venture capital or buy-out). The new commitment will be equally assigned to each of the four random funds from the concerning vintage year.

Finally, throughout we assume no return on cash because our portfolio would be part of a larger portfolio. In order to avoid dependence of the results on the particular initial portfolio that is constructed and on the funds selected for the recommitments, we simulate 1,000 portfolios and average the results for evaluation.

6.5 Results

We evaluate the quality of the recommitment strategies by considering various properties of the investment degree, in particular its mean, standard deviation and probability of liquidity shortfall (that is, the probability that the investment degree exceeds one and money needs to be borrowed to fulfill capital calls). When computing these statistics, we discard the first three years of the portfolio's life, in order to avoid any influence of the initial portfolio formation period.

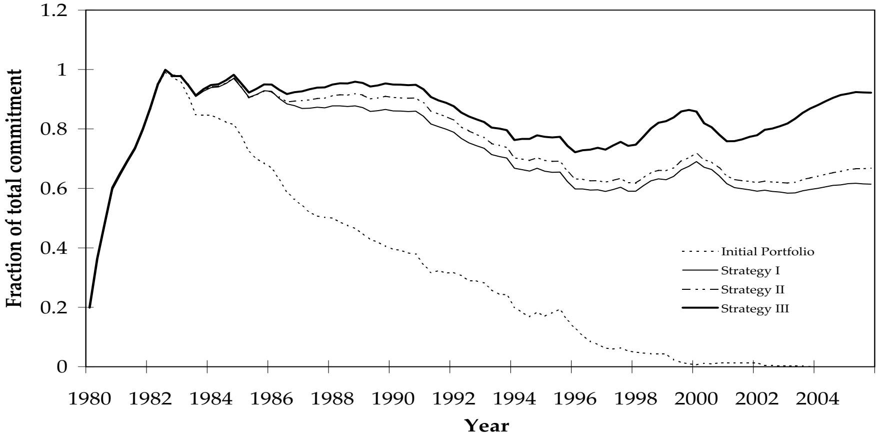
6.5.1 Main results

Panel (a) in Figure 6.3 shows how the average investment degree evolves over time when applying strategies I–III for the 1,000 private equity portfolios with vintage year 1980. Summary statistics for all vintage years are given in Table 6.3. When applying strategy I, which sets current commitments equal to current distributions, the investment degree remains well below the target level of one. This does not come as a surprise as committed capital is not called instantaneously, such that the portfolio always contains a certain amount of cash. In fact, the average investment degree comes very close to the target level of one between two and three years after formation due to the overcommitment in the initial portfolio. This, however, is followed by a decline to a considerably lower level, such that the average investment degree varies between 0.65 and 0.81 for the years 1996 and 1999, respectively, with an average across all vintage years of 0.73. Also note that, although it would seem that an investment degree in excess of one cannot occur for this strategy by construction, we do observe a positive probability of liquidity shortfall for most vintage years. This is due to the overcommitment applied during the formation of the initial portfolio.

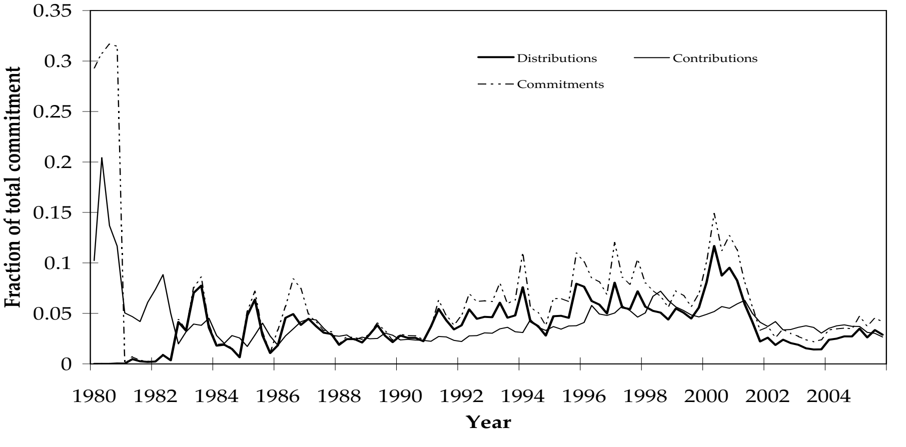
The first recommitment strategy suffers from two problems that result in an average investment degree below the target level of one. First, not all committed capital is called instantaneously but with a delay that can extend to several years. Second, part of the committed capital is never called at all. The results from the second recommitment strategy suggest that the first problem is the most important one. Strategy II aims to remedy the second problem by increasing the commitments at time t with uncalled capital from the commitments made at $t - P$, where we set $P = 24$ for reasons discussed before. The results show that this increases the average investment degree, but only by a small amount, from 0.73 to 0.75. From panel (a) in Figure 6.3 it is clear that the improvement starts approximately six years after the initial portfolio formation, as expected.

As discussed in the previous section, it seems necessary to apply overcommitment at the recommitment stage as well to achieve an investment degree that is closer to the target value of one. Using the investment degree of the existing portfolio for setting the overcommitment percentage for the current recommitments as in strategy III appears to be quite effective, because it increases the investment degree and lowers the variation of

Figure 6.3: Evolution of cash flows and investment degree over time for vintage year 1980



(a) Initial portfolio and strategy I–III for 1980



(b) Average (re)commitments and cash flows using strategy III for 1980

The figure shows the average investment degree of private equity fund portfolios maintained with recommitment strategies I–III for vintage year 1980 (panel (a)) and (re) commitments and cash flows of strategy III for vintage year 1980 (panel (b)).

Table 6.3: Summary statistics of the investment degree in recommitment strategies I – III across vintage years

Vintage	Strategy I			Strategy II			Strategy III		
year	Mean	StdDev	$P_{(ID>1)}$	Mean	StdDev	$P_{(ID>1)}$	Mean	StdDev	$P_{(ID>1)}$
1980	0.74	0.05	2%	0.77	0.05	3%	0.86	0.05	5%
1981	0.73	0.05	9%	0.77	0.05	9%	0.87	0.06	10%
1982	0.75	0.07	10%	0.81	0.06	12%	0.88	0.07	13%
1983	0.77	0.07	13%	0.80	0.07	13%	0.88	0.07	14%
1984	0.79	0.07	16%	0.80	0.07	16%	0.88	0.07	19%
1985	0.78	0.09	16%	0.80	0.09	16%	0.88	0.09	17%
1986	0.73	0.05	1%	0.76	0.05	1%	0.85	0.06	3%
1987	0.72	0.06	3%	0.75	0.06	4%	0.85	0.07	7%
1988	0.73	0.06	6%	0.75	0.06	6%	0.85	0.07	9%
1989	0.71	0.07	1%	0.73	0.07	1%	0.83	0.07	3%
1990	0.74	0.09	8%	0.75	0.09	7%	0.85	0.09	10%
1991	0.66	0.06	0%	0.71	0.07	0%	0.83	0.07	5%
1992	0.70	0.06	0%	0.71	0.06	0%	0.82	0.07	2%
1993	0.69	0.08	0%	0.72	0.09	0%	0.84	0.10	6%
1994	0.72	0.06	0%	0.75	0.07	0%	0.84	0.07	4%
1995	0.69	0.10	1%	0.70	0.10	0%	0.84	0.12	8%
1996	0.65	0.08	0%	0.66	0.08	0%	0.86	0.16	15%
1997	0.74	0.09	1%	0.76	0.09	1%	0.85	0.08	6%
1998	0.77	0.12	2%	0.77	0.12	3%	0.87	0.10	9%
1999	0.81	0.11	5%	0.82	0.11	5%	0.86	0.09	8%
2000	0.78	0.18	9%	0.77	0.18	8%	0.82	0.19	12%
Average	0.73	0.08	5%	0.75	0.08	5%	0.85	0.09	9%

Note: The table shows properties of the investment degree for private equity portfolios maintained using recommitment strategies I, II and III. Strategy I sets current commitments equal to current distributions, Strategy II sets current commitments equal to current distributions plus uncalled commitments and Strategy III sets current commitments equal to current distributions plus uncalled commitments divided by the investment degree. Reported are the mean, standard deviation (StdDev) and the fraction of observations with an investment degree higher than 1 ($P_{(ID>1)}$). Vintage year statistics are based on 1,000 simulated portfolios. In each simulation, the initial portfolio is composed of 16 randomly selected funds from the relevant vintage year. Quarterly recommitments in subsequent years are equally distributed among four randomly selected new funds from that year. The first three years of the portfolios' life are not included in the investment degree statistics. The results for vintage years 2001-2005 are not reported as these portfolios are too immature to illustrate the effectiveness of the strategies.

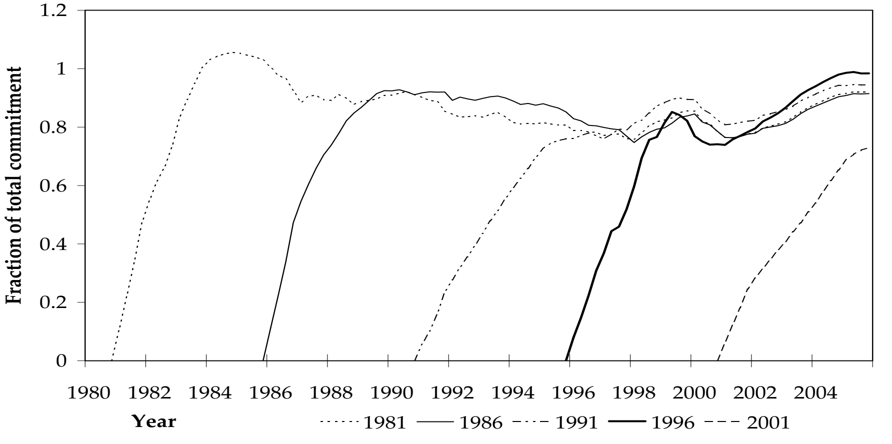
the average investment degrees of the different vintage years. Table 6.3 shows that the average investment degree rises to 0.85, well above the level attained with strategies I and II. Not surprisingly, this comes at the cost of a higher risk of being overinvested, although the increase in the probability of liquidity shortfall is quite modest from 5% to 9%. We also note that the range of the average investment degree across the different vintage years is much smaller, between 0.82 and 0.88. This is confirmed by Figure 6.4, showing the investment degree for selected vintage years (1981, 1986, 1991, 1996, 2001). We observe that the average investment degree behaves similarly once the portfolios mature. For example, for all vintage years the investment degree declines in the year 2000, driven by the large distributions made during the dot-com bubble in that year. Due to the overcommitment effect, however, the investment degree quickly increases again in subsequent years.

From Gompers and Lerner (1998, 2000), Kaplan and Schoar (2005) and Gompers *et al.* (in press) we learn that both capital flows and returns in the private equity market are cyclical. For example, the venture capital market experienced a boom in 1981–1983 and in 1998–2000 when investments grew dramatically in personal computer hardware manufacturers, and in internet and telecommunication companies, respectively. The question rises to what extent our recommitment strategy is cyclical in nature. This may be the case for several reasons. First, we might invest aggressively when the market becomes overvalued, because we will receive more distributions than normal that will be invested again. Second, it might be that we make larger commitments at times when investments are difficult to find due to our dynamic overcommitment, while simultaneously the uncalled commitments might be relatively large, resulting in additional recommitments after 6 years. This can lead to an undesirable accumulation of new commitments.

The detailed picture of the cash flows involved in strategy III, provided by panel (b) of Figure 6.3 for the 1980 portfolios, leads us to the answer to this question. First, on average the distributions amount to 5% of the total portfolio value per quarter, while the actual investments (contributions) are slightly lower but much more constant than the distributions. These orders of magnitude are fairly stable across vintage years.[10] The new commitments do show some cyclicality in, for example, the year 2000. Nevertheless, the stability of the actual contributions illustrates that the cyclicality of our strategy is limited. Second we observe a rise in the commitments in year 7 due to the recommitments of the uncalled capital of the initial portfolio. We do not see this effect occurring again at a later stage, showing that by then the portfolios mature and do not become cyclical in nature.

[10]Detailed results for other vintage years are available upon request.

Figure 6.4: Evolution of the investment degree for different vintage years.



The figure shows the average investment degree of private equity fund portfolios maintained with recommitment strategy III for vintage years 1981, 1986, 1991, 1996, 2001.

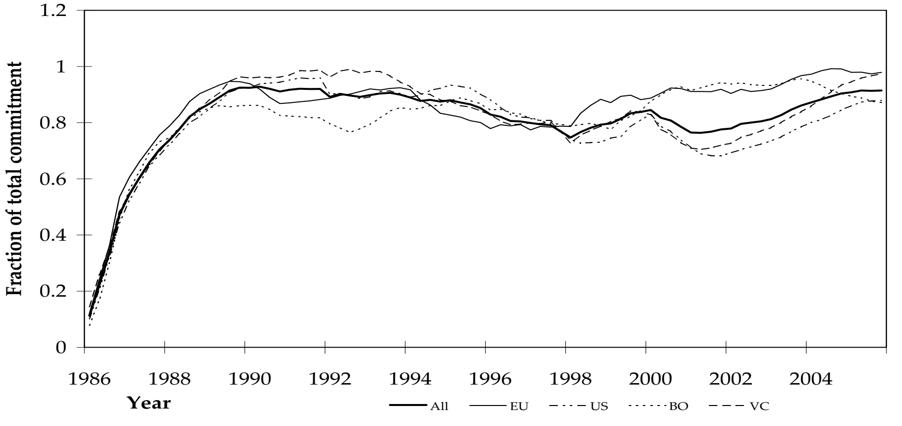
The bottom line of our results so far is that strategy III is very well able to bring the investment degree close to the target level with an acceptable risk of being overinvested. The potential cyclical behavior of our portfolio is small and not a major issue because our aim is to get a passive exposure to the private equity market that includes investments in over- and undervalued periods.

6.5.2 Portfolio restrictions

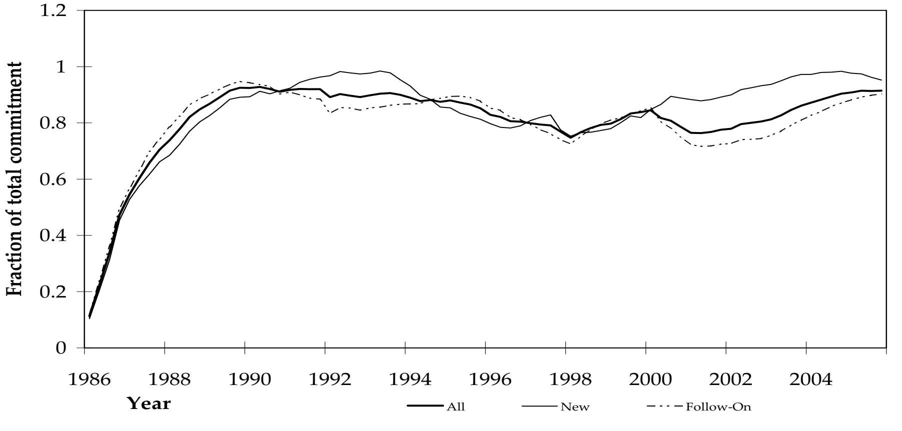
Investment focus

So far we considered unrestricted portfolios, not imposing any limitations on the investment focus or accessibility. Here we examine the performance of our strategy when restrictions are imposed on the type of funds (VC or BO) or the investment region (US or Europe). Panel (a) in Figure 6.5 shows the average investment degree for the unrestricted portfolios as well as the portfolios consisting of VC, BO, US or European funds only for vintage year 1986. Before 1986 the number of European funds as well as the number of buyout capital funds were very limited. Table 6.4 shows the corresponding summary statistics for all vintage years.

Figure 6.5: Evolution of the investment degree for restricted portfolios.



(a) Investment focus restriction



(b) Fund access restriction

The figure shows the average investment degree of private equity fund portfolios maintained with recommitment strategy III for vintage year 1986 using all or only European (EU), US, buy-out (BO), or venture capital (VC) funds (panel (a)), or only new (first time) and follow-on funds (panel (b)).

Table 6.4: Summary statistics of the investment degree in recommitment strategies for restricted portfolios

Vintage	Investment focus				Fund access	
year	EU	US	BO	VC	FO	FT
1980	NA	0.84	NA	0.86	NA	NA
1981	NA	0.86	NA	0.86	NA	NA
1982	NA	0.88	NA	0.89	NA	NA
1983	NA	0.86	NA	0.88	0.84	0.95
1984	NA	0.85	NA	0.87	0.85	0.94
1985	1.04	0.84	NA	0.89	0.88	0.91
1986	0.89	0.84	0.86	0.86	0.83	0.89
1987	0.90	0.83	0.89	0.85	0.83	0.89
1988	0.92	0.82	0.89	0.84	0.82	0.91
1989	0.88	0.81	0.88	0.82	0.82	0.87
1990	0.93	0.80	0.91	0.82	0.80	0.92
1991	0.91	0.82	0.87	0.83	0.82	0.90
1992	0.85	0.80	0.85	0.82	0.80	0.86
1993	0.93	0.79	0.89	0.82	0.81	0.90
1994	0.89	0.82	0.86	0.85	0.82	0.91
1995	0.97	0.79	0.87	0.84	0.81	0.95
1996	0.99	0.81	0.92	0.88	0.83	1.04
1997	0.92	0.80	0.89	0.85	0.81	0.95
1998	0.94	0.82	0.85	0.89	0.85	0.94
1999	0.89	0.84	0.84	0.87	0.88	0.84
2000	0.92	0.74	0.73	0.86	0.76	0.92
Average	0.92	0.82	0.87	0.86	0.83	0.92

Note: The table shows properties of the investment degree for private equity portfolios where the current commitments are set equal to current distributions plus uncalled commitments divided by the investment degree, for specific portfolios only consisting of European, US, venture capital, buy-out capital, follow-on or first time funds. Reported is the mean investment degree based on 1,000 simulated portfolios (excluding the first three years of the portfolios' life). In each simulation, the initial portfolio is composed of 16 randomly selected funds from the relevant vintage year. Quarterly recommitments in subsequent years are equally distributed among four randomly selected new funds from that year. The results for vintage years 2001-2005 are not reported as these portfolios are too immature to illustrate the effectiveness of the strategies, while the first 4 years for Europe and 5 years for buy-out are missing because not enough funds are available.

The average investment degree for BO (0.87) and VC (0.86) portfolios are similar to the unrestricted portfolios (0.85), while the probability of liquidity shortfall is marginally higher than the unrestricted strategy. The strategies only differ in the volatility of the investment degree, which is equal to 7.9 and 21.2 percent for BO and VC portfolios, respectively. From Figure 6.5, panel (a) it can be seen that the average investment degrees for unrestricted and VC portfolios are most similar. This close resemblance can be explained by the distribution of funds over the two investment types: VC-funds constitute two-thirds of the TVE data set. The difference in investment degree between VC and BO portfolios is particularly clear during the dot-com bubble in 2000 and 2001. In those years venture capital funds made historically large distributions while the buy-out distributions were less extreme.

The results for US portfolios closely resemble those for the unrestricted portfolios, although the average investment degree for all vintage years is slightly lower (0.82). The average for European portfolios (0.92) is closer to 1, but at the cost of an increased probability of liquidity shortfall.

Given that the results for VC and BO portfolios as well as the US and Europe portfolios resemble the results for unrestricted portfolios, we conclude that our strategy III can also be applied successfully to such specialised private equity portfolios.

Fund access

Typically, first-time funds are not in the position to turn away new investors, while established private equity fund managers may restrict access to their follow-on funds. Access to follow-on funds is in fact often limited to the shareholders that already participate in a current fund. As a result fund investors are required to invest some part of their assets in first-time funds from new managers. It has been documented that expected returns on first-time funds are lower on average than expected returns on follow-on funds, see Kaplan and Schoar (2005). Therefore, we examine the applicability of our strategy restricting the sample either to first-time funds or to follow-on funds. Our sample holds 1,529 (58%) follow-on funds and 1,089 (42%) first-time funds. Panel (b) in Figure 6.5 shows the average investment degree for the unrestricted portfolios as well as the portfolios consisting of first-time and follow-on funds only for vintage year 1986. The last two columns in Table 6.4 show the corresponding summary statistics for all vintage years.

The average investment degree for follow-on funds (0.83) portfolios is similar to the unrestricted portfolios (0.85), while the average investment degree for first-time fund portfolios (0.92) is higher. From Figure 6.5, panel (b) it can be seen that the average investment degrees for unrestricted and first-time portfolios deviate most, with the difference being most clear during the dot-com bubble in 2000–2001. During this period many first-time venture capital funds were raised. Second the volatility of the investment degree of the follow-on fund portfolios (8 percent) is similar to the total sample (9 percent), while the investment degree of the first-time fund portfolios is more volatile (12 percent).

Given that the results for first-time and follow-on portfolios resemble the results for unrestricted portfolios, we conclude that our strategy III can also be applied successfully to such private equity funds with different degrees of accessibility.

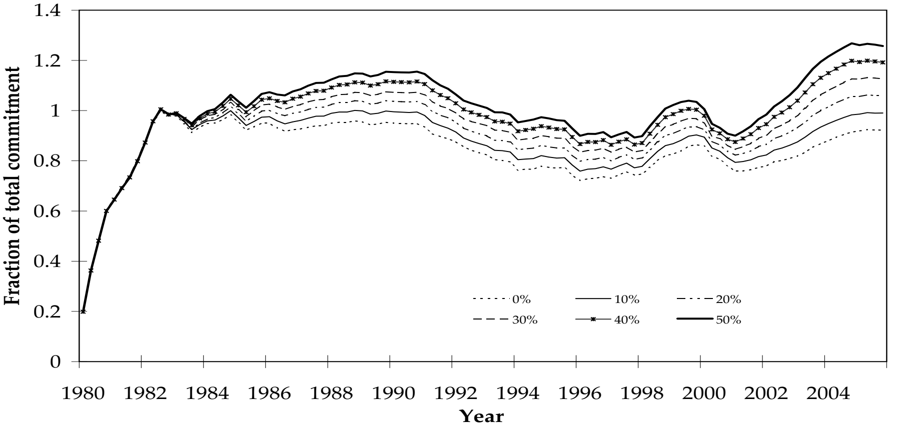
6.5.3 More aggressive overcommitment

The analysis so far has demonstrated that making use of overcommitment with a dynamic percentage based on the investment degree of the current private equity portfolio leads to a successful recommitment strategy with stable performance. Nevertheless, the resulting private equity exposure is still below the target level by 15% on average as the average investment degree is equal to 0.85. This finding can be understood intuitively from (6.2), which shows that new commitments become equal to current distributions and uncalled capital that was committed six years before. The slow and incomplete calls for capital then put downward pressure on the investment degree in subsequent quarters, as discussed before. Obviously, the average investment degree can be brought further up by more aggressive overcommitment, but this necessarily comes at a greater risk of liquidity shortfall. In this section we examine the balance between these two aspects, by reconsidering our strategy III, but now increasing the overcommitment with a constant percentage OC equal to $10, 20, \ldots, 50$ percent in each quarter:

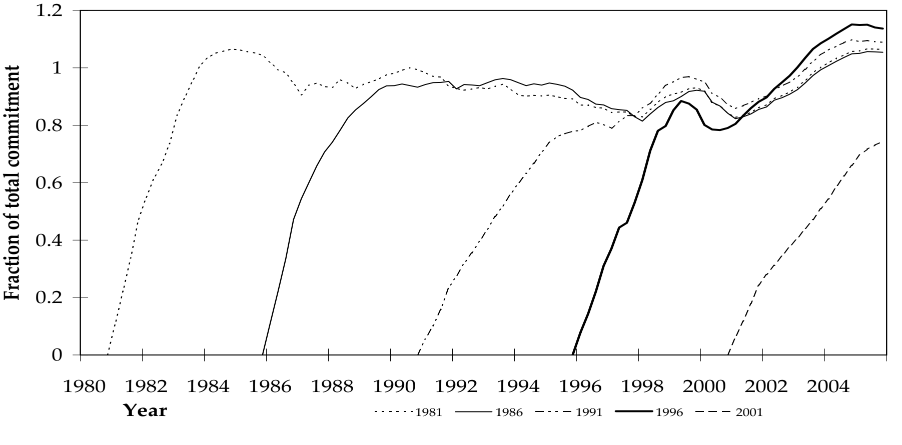
$$C_t = \frac{1 + OC}{ID_t} \left(D_t + UC_{t-P} \right) \tag{6.3}$$

Panel (a) in Figure 6.6 shows the average investment degrees resulting from these strategies for the 1980 portfolios, with summary statistics provided for all vintage years in Table 6.5. Inflating the overcommitment percentage appears to be successful, in the sense that the average investment degree moves closer to the target level of one as OC increases. The increase in the investment degree that we observe for 1980 in Figure 6.6 is also prevalent for the other vintage years, see Table 6.5. The average investment degree goes up from 0.85 for strategy III with dynamic overcommitment only, to 0.89, 0.92, 0.95,

Figure 6.6: Evolution of the investment degree and overcommitment.



(a) Strategy III with varying additional overcommitment $(0, 10, \ldots, 50\%)$ for vintage year 1980



(b) Strategy III with 20% additional overcommitment for vintage years 1981, 1986, 1991, 1996 and 2001

The figure shows the average investment degree of private equity fund portfolios maintained with recommitment strategy III with varying degrees of additional fixed overcommitment for vintage year 1980 (a) and 20% overcommitment for vintage years 1981, 1986, 1991, 1996 and 2001 (b).

Table 6.5: Summary statistics of the investment degree in recommitment strategies with additional fixed overcommitment across vintage years

Vintage	Mean					$P_{(ID>1)}$				
year	10%	20%	30%	40%	50%	10%	20%	30%	40%	50%
1980	0.90	0.94	0.97	1.01	1.05	0.16	0.30	0.42	0.52	0.62
1981	0.91	0.94	0.98	1.01	1.04	0.16	0.26	0.39	0.52	0.64
1982	0.92	0.95	0.99	1.02	1.05	0.21	0.32	0.45	0.56	0.67
1983	0.91	0.95	0.98	1.02	1.05	0.20	0.30	0.40	0.51	0.62
1984	0.92	0.95	0.98	1.02	1.05	0.26	0.35	0.45	0.54	0.63
1985	0.92	0.95	0.98	1.01	1.05	0.22	0.30	0.38	0.47	0.56
1986	0.89	0.92	0.96	0.99	1.02	0.08	0.18	0.28	0.39	0.51
1987	0.88	0.92	0.95	0.98	1.01	0.12	0.20	0.29	0.36	0.44
1988	0.88	0.92	0.95	0.98	1.01	0.14	0.22	0.30	0.38	0.45
1989	0.86	0.90	0.93	0.96	0.99	0.08	0.16	0.24	0.31	0.37
1990	0.89	0.92	0.95	0.98	1.02	0.16	0.25	0.33	0.41	0.47
1991	0.86	0.90	0.93	0.96	1.00	0.14	0.23	0.33	0.39	0.45
1992	0.86	0.89	0.92	0.96	0.99	0.07	0.15	0.24	0.32	0.39
1993	0.87	0.90	0.94	0.97	1.00	0.15	0.25	0.33	0.40	0.45
1994	0.88	0.91	0.95	0.98	1.01	0.13	0.23	0.34	0.41	0.46
1995	0.89	0.93	0.97	1.00	1.04	0.17	0.26	0.37	0.45	0.52
1996	0.91	0.97	1.00	1.06	1.11	0.27	0.40	0.46	0.54	0.61
1997	0.89	0.92	0.95	0.99	1.03	0.15	0.25	0.35	0.47	0.54
1998	0.91	0.93	0.96	0.98	1.00	0.16	0.24	0.30	0.38	0.45
1999	0.87	0.89	0.91	0.92	0.93	0.11	0.13	0.19	0.22	0.27
2000	0.82	0.83	0.83	0.84	0.83	0.11	0.12	0.12	0.13	0.13
Average	0.89	0.92	0.95	0.98	1.01	0.16	0.24	0.33	0.41	0.49

Note: The table shows properties of the investment degree for private equity portfolios where the current commitments are set equal to current distributions plus uncalled commitments divided by the investment degree multiplied by varying levels of additional fixed overcommitment (10, 20, 30, 40 and 50%). Reported are the mean investment degree and the fraction of observations with an investment degree higher than 1 ($P_{(ID>1)}$). Vintage year statistics are based on 1,000 simulated portfolios (excluding the first three years of the portfolios' life). In each simulation, the initial portfolio is composed of 16 randomly selected funds from the relevant vintage year. Quarterly recommitments in subsequent years are equally distributed among four randomly selected new funds from that year. The results for vintage years 2001-2005 are not reported as these portfolios are too immature to illustrate the effectiveness of the strategies.

0.98 and 1.01 with additional fixed overcommitment equal to $10, \ldots, 50\%$. Unfortunately, the accompanying increase in the probability of being overinvested is substantial. In fact, this probability rises faster than the average investment degree, and becomes equal to 16, 24, 33, 41 and 49%, while it is only 9% for strategy III without additional overcommitment. Hence, it seems that a more aggressive overcommitment strategy is suitable only when liquidity shortfall is not a serious problem for our institutional investor. This may be the case when private equity is part of a larger investment portfolio that also includes public equity, which can be sold (temporarily) to provide the capital necessary for the private equity investments. For these investors it seems that a 20% additional overcommitment is optimal as this brings the average investment ratio to 0.92 while the probability of being overinvested is 24%. Panel (b) in Figure 6.6 shows the average investment degrees resulting from strategy III including a 20% fixed overcommitment for different vintage years. From this graph it is clear that the average investment degrees are close to one. Again we observe that the investment degree develops similarly for different vintage years after the portfolios have matured. All portfolios show a decline in the investment degree in 2000 and a sharp increase in the years afterwards.

6.5.4 Using the future investment degree

Using the current investment degree of the existing private equaty portfolio to determine the overcommitment percentage in quarter t, as in strategy III according to (6.2), might be sub-optimal because part of the previously committed but yet uncalled capital will be invested in the near future. Using the current investment degree might lead to an overestimate of the required commitments in quarter t. On the other hand, distributions from the current investments will likely continue in the future such that we may be underestimating the required overcommitment percentage. The results in Section 6.5.1 suggest that this second effect dominates.

The performance of the recommitment strategy may be improved by using the future investment degree of the current portfolio to set the current commitments. Implementing this in practice requires a cash flow prediction model, see Takahashi and Alexander (2002) and De Malherbe (2004) for examples. The performance of the recommitment strategies is then, to a considerable extent, determined by the quality of these forecasting models. In order to focus on the merits of our recommitment strategy as such, we use perfect foresight instead. Obviously this implies that our results have to be treated with caution, as they may be overly optimistic about the ability of the strategies to achieve the goal of a full and constant exposure to private equity. On the other hand, we do not aim to select private equity funds having a pattern of commitments that matches the pattern of distributions from the portfolio as closely as possible. Instead, funds are selected randomly. Hence, we consider strategy III but now applying the actual investment degree of the current portfolio in quarter $t + Q$ for determining the overcommitment percentage to be applied in quarter t. That is, we replace the current investment degree ID_t in (6.2) by ID_{t+Q}, where we consider values of Q equal to $4, 8, \ldots, 20$:[11]

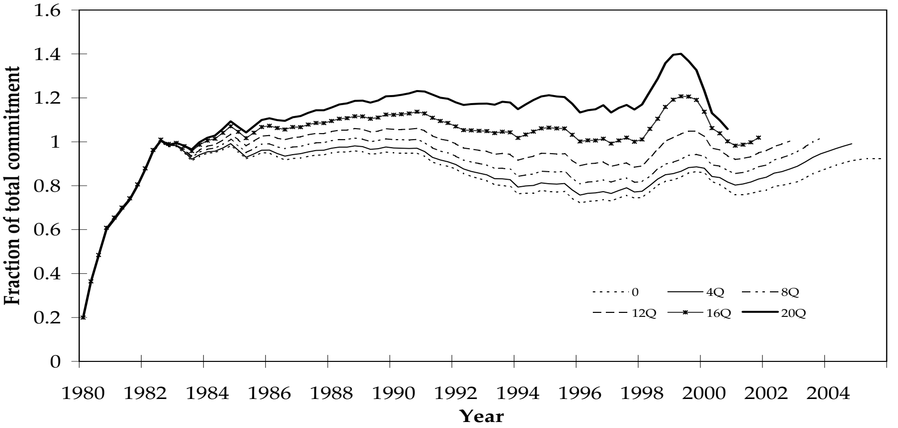
$$C_t = \frac{1}{ID_{t+Q}} \left(D_t + UC_{t-P}\right) \tag{6.4}$$

The average investment degrees resulting from these strategies for the 1980 portfolios are shown in panel (a) in Figure 6.7. Clearly, applying the future investment degree in the recommitment strategy becomes effective only five years after inception of the portfolio as the investment degrees do not differ much during the first years. It also appears that looking ahead too far into the future, that is, four and five years, results in being overinvested. This is probably caused by the fact that the investment degree of the current portfolio will be quite low after four and five years, such that the level of new commitments becomes too high. On the other hand, the investment degree does not rise that much if we use the investment degree for one or two years ahead. This leads us to conclude that our strategy can benefit most from a cash flow forecasting model with a three year horizon. This conclusion is confirmed by the summary statistics for the other vintage years shown in Table 6.6. Using a three year horizon in our recommitment strategy leads to an increase of the average investment degree to 0.92 and a probability of being overinvested of 23%. Panel (b) in Figure 6.7 shows the average investment degrees resulting from strategy III including three-year perfect foresight for different vintage years. From this graph it is clear that the investment degrees are close to 1. Again we observe that the investment degree develops similarly for different vintage years after the portfolios have matured.

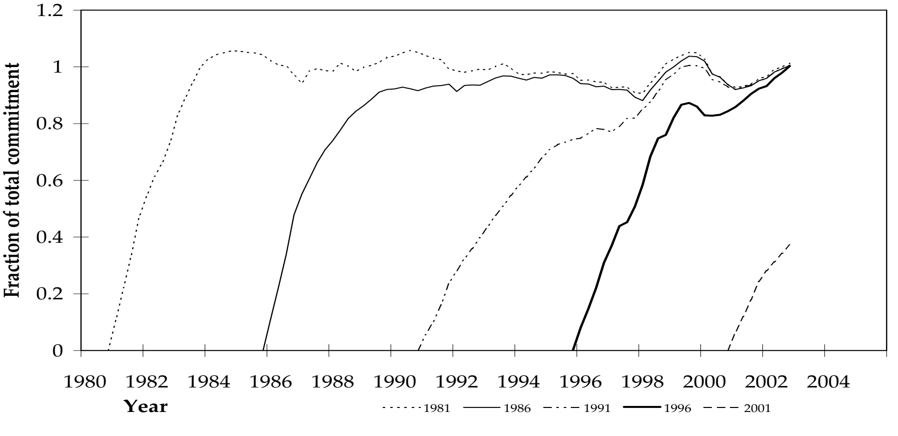
In sum, an investor who has a cash flow prediction model at her disposal can improve our recommitment strategy by using the expected future investment degree of the current portfolio to determine the appropriate overcommitment percentage. It is advisable to employ investment degree forecasts for an horizon of three years.

[11]We stress that ID_{t+Q} is the investment degree in quarter $t + Q$ of the private equity portfolio held in quarter t, that is, we do not use information about new commitments made between t and $t + Q$.

Figure 6.7: Evolution of the investment degree and the future investment degree.



(a) Vintage year 1980



(b) Vintage years 1981, 1986, 1991, 1996, and 2001

The figure shows the average investment degree of private equity fund portfolios maintained with recommitment strategy III with perfect foresight concerning the future investment degree at varying horizons for vintage year 1980 (panel (a)) and three-year perfect foresight for vintage years 1981, 1986, 1991, 1996, and 2001 (panel (b)).

Table 6.6: Summary statistics of the investment degree in recommitment strategies that include the future investment degree across vintage years

Vintage	Mean					$P_{(ID>1)}$				
year	$+4Q$	$+8Q$	$+12Q$	$+16Q$	$+20Q$	$+4Q$	$+8Q$	$+12Q$	$+16Q$	$+20Q$
1980	0.89	0.93	0.98	1.06	1.16	0.10	0.21	0.43	0.79	0.93
1981	0.90	0.94	0.99	1.07	1.18	0.14	0.21	0.47	0.84	0.95
1982	0.91	0.95	1.00	1.08	1.19	0.17	0.25	0.49	0.82	0.91
1983	0.91	0.94	1.00	1.07	1.18	0.18	0.24	0.44	0.79	0.96
1984	0.91	0.94	0.99	1.06	1.15	0.21	0.26	0.43	0.76	0.92
1985	0.91	0.95	1.00	1.07	1.16	0.20	0.25	0.41	0.71	0.90
1986	0.88	0.90	0.95	1.02	1.10	0.04	0.06	0.20	0.54	0.73
1987	0.87	0.90	0.94	1.01	1.09	0.08	0.10	0.21	0.50	0.74
1988	0.87	0.90	0.95	1.01	1.09	0.10	0.13	0.26	0.51	0.75
1989	0.85	0.88	0.91	0.97	1.04	0.06	0.08	0.17	0.36	0.53
1990	0.88	0.91	0.94	1.00	1.08	0.13	0.17	0.28	0.47	0.63
1991	0.83	0.84	0.86	0.89	0.93	0.07	0.08	0.15	0.31	0.40
1992	0.85	0.87	0.90	0.96	1.03	0.04	0.05	0.14	0.33	0.49
1993	0.84	0.85	0.86	0.90	0.95	0.01	0.08	0.09	0.22	0.38
1994	0.85	0.85	0.87	0.89	0.91	0.05	0.05	0.07	0.14	0.25
1995	0.86	0.87	0.89	0.93	0.98	0.11	0.11	0.13	0.25	0.40
1996	0.88	0.89	0.89	0.92	0.95	0.18	0.18	0.13	0.21	0.29
1997	0.86	0.87	0.86	0.85	0.84	0.08	0.08	0.05	0.04	0.02
1998	0.87	0.87	0.86	0.85	-	0.09	0.07	0.07	0.08	-
1999	0.84	0.83	0.81	-	-	0.07	0.04	0.02	-	-
2000	0.78	0.73	-	-	-	0.07	0.07	-	-	-
Average	0.87	0.89	0.92	0.98	1.06	0.10	0.13	0.23	0.46	0.62

Note: The table shows properties of the investment degree for private equity portfolios where the current commitments are set equal to current distributions plus uncalled commitments divided by the future investment degree (+4, +8, +12, +16 and +20 quarters perfect foresight). Reported are the mean investment degree and the fraction of observations with an investment degree higher than 1 ($P_{(ID>1)}$). Vintage year statistics are based on 1,000 simulated portfolios (excluding the first three years of the portfolios' life). In each simulation, the initial portfolio is composed of 16 randomly selected funds from the relevant vintage year. Quarterly recommitments in subsequent years are equally distributed among four randomly selected new funds from that year. The results for vintage years 2001-2005 are not reported as these portfolios are too immature to illustrate the effectiveness of the strategies.

6.5.5 Existing commitment strategies

CCK-rule

The literature on (re)commitment strategies in private equity is very scarce; in fact only two relevant papers were found. Cardie *et al.* (2000) suggest a commitment rule (denoted as CCK-rule), which states that an investor should commit her entire private equity allocation target to new investments every other year or one half of the target each year. Although frequently making new private equity commitments is certainly necessary to maintain the desired exposure, the CCK-rule seems somewhat naive. In particular, it does not to take into account the development of the existing private equity investments in the portfolio when making new commitments.

Here we examine the first variant of the CCK-rule, setting new commitments equal to the private equity target times the current market value of the portfolio (the sum of the portfolio's NAV and cash) every other year. The annual number of funds that is selected (randomly) in each round of new commitments is set equal to 16 and the target is set at 100 percent. The average investment degree over 1,000 simulated portfolios is shown in panel (a) of Figure 6.8 for vintage years 1981, 1986, 1991, 1996, and 2001. Clearly, the private equity investment degrees are not kept constant at 100 percent over time. Instead, they remain permanently and substantially above target and fluctuate wildly. It is clear that the CCK-rule does not succeed in keeping the investment degree constant at the allocation target. Not taking into account the characteristics of the current portfolio results in a high and volatile investment degree.

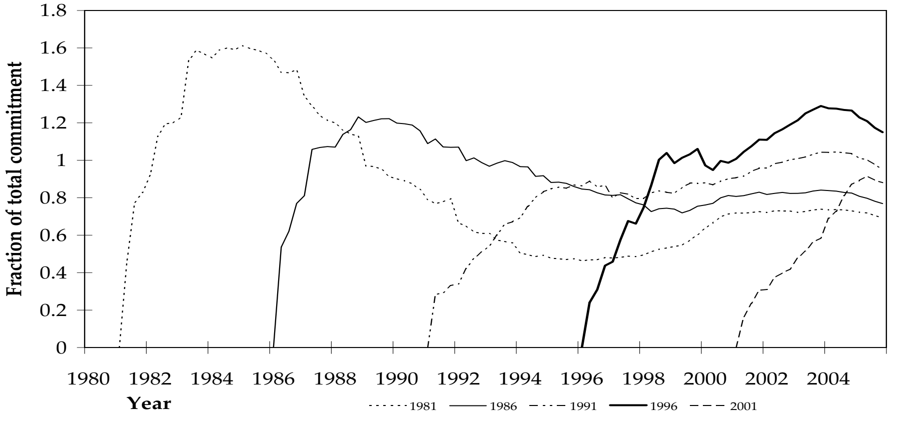
NCM-rule

Nevins *et al.* (2004)'s commitment strategy, denoted as the NCM-rule, states that an investor should make new commitments when actual committed capital falls below its target C^*, equal to the difference between the two. For a 100 percent allocation target for private equity, the target level of committed capital according to the the NCM-rule is defined as:

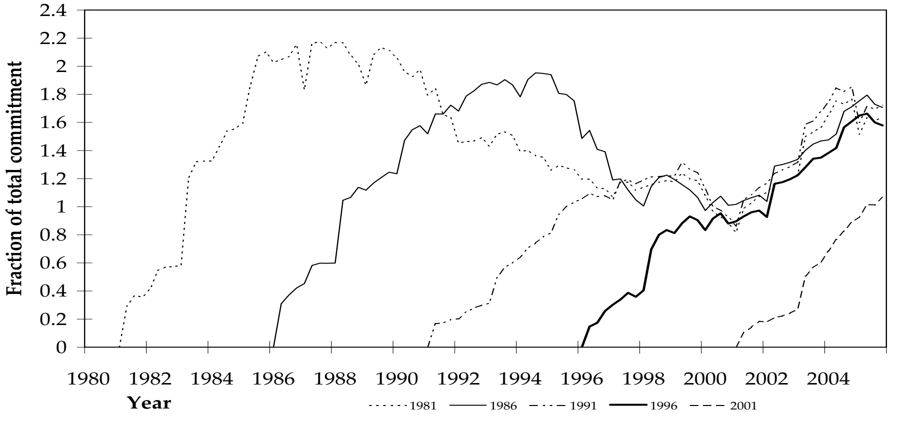
$$C^* = 1 + \frac{r_{DI}}{r_{IN}}, \tag{6.5}$$

where r_{DI} is the rate at which distributions are paid from the private equity investments (expressed as a percentage of the value of invested capital (NAV)) and r_{IN} is the rate at which capital commitments are invested, expressed as percentage of remaining (not (yet)

Figure 6.8: Evolution of the investment degree for earlier documented strategies.



(a) CCK-rule



(b) NCM-rule

The figure shows the average investment degree of private equity fund portfolios maintained with (a) the CCK-rule and (b) the NCM-rule for vintage years 1981, 1986, 1991, 1996, and 2001.

invested) commitments. In case r_{DI} is large, more capital needs to be committed to compensate for the reduction in investment degree due to large distributions. If r_{IN} is small, more capital is required for new commitments, because existing commitments are called relatively slowly. For computing r_{DI} and r_{IN} Nevins *et al.* (2004) suggest using information on capital calls and distributions from liquidated funds only, and find that 70 percent overcommitment as a result.[12]

The NCM-rule rests on two crucial assumptions. First, investors make commitments according to the computed allocation target for committed capital. Second, the rate of distributions and investments r_{DI} and r_{IN} in (6.5) are assumed to be constant over time and across private equity funds.[13] When these two assumptions hold, the ratio of committed capital to invested capital converges to a steady-state level. However, especially the second part of the second assumption seems to be unrealistic. As discussed in Section 6.2, the rates of distributions and investments vary over time, while in addition they likely vary across private equity funds according to characteristics such as size and investment orientation (Ljungqvist and Richardson, 2003b). Of course this dependence will diminish if multiple private equity funds are combined in a portfolio (or fund-of-funds), but it will not disappear completely given that the number of included funds is typically fairly small (up to 20, say).

The NCM-rule is assessed using the same framework as before. Investors make new commitments if the amount of actual committed capital falls short of its target (170 percent), equal to the difference between the two. The average investment degree over 1,000 simulated portfolios is shown in panel (b) of Figure 6.8 for the vintage years 1981, 1986, 1991, 1996, and 2001. Clearly, the investment degrees are not kept constant at 100 percent over time. For example, the 1981 portfolio starts substantially above target in the 1980s and falls back to 0.5 in the mid-1990s. In contrast to our strategy III the NCM-portfolios do not converge to the same investment degree as they mature. The wide range in the investment ratios for mature portfolios can for example be seen in 2005, where the degrees range between 0.69 for the 1981 portfolio and 1.15 for the 1996 portfolio. This illustrates that the NCM strategy is not able to deal with the dynamics of a specific portfolio. Finally,

[12]Based upon the 536 liquidated funds in our TVE database, r_{DI} is equal to 24.36 percent and r_{IN} is equal to 20.36 percent. With these figures, the target for committed capital as determined according to (6.5) is equal to 2.19, which is equivalent to 119 percent overcommitment. We find a percentage in the same order of magnitude as the 70 percent reported by Nevins *et al.* (2004) if we only take into account capital calls during the first six years of the fund's lifetime for estimating r_{IN}, when nearly all committed capital is called.

[13]This assumption is reflected in the way Nevins *et al.* (2004) estimate r_{DI} and r_{IN}, namely by aggregating the characteristics of the liquidated funds of their dataset on a life cycle basis.

we remark that excessive commitments are made in 2000 due to the difference between the actual amount of committed capital and its target, and the value of the total portfolio (NAV + cash). This could be caused by differences in sample period used to estimate r_{DI} and r_{IN}, as Nevins *et al.* (2004) only consider liquidated funds for vintage years between 1980 and 2000.

We conclude that the NCM-strategy is not capable to keep the private equity investment degree constant at one for a prolonged period. This is most likely due to the fact that the assumption of constants rates of distribution and investment do not hold in practice.

6.6 Conclusion

This paper provides a (re)commitment strategy for long term institutional investors, such as insurance companies, pension funds or endowments, which aim to have a constant private equity exposure in their strategic asset allocation. Investors need this strategy because private equity is illiquid such that it, in general, cannot be bought instantaneously in the primary or secondary market. Given the high level of expertise and experience required for investing, managing and divesting of private equity, most investments take place through private equity funds. Our heuristic recommitment strategy makes new fund commitments every quarter and explicitly takes into account characteristics of the existing private equity portfolio for determining the level of new commitments. Commitments in a particular quarter are set equal to current distributions plus uncalled capital from commitments made six years ago, with an dynamice overcommitment percentage determined by the investment degree of the current portfolio. The reason for recommitting uncalled capital is to prevent 'leakage' of capital due to the fact that on average 10 percent of the commitments are not invested. The investment degree is used to determine an overcommitment percentage to counter the fact that committed capital is actually invested only gradually, with a delay that can extend to several years, with distributions already starting to occur before all commitments are called.

The recommitment strategy is evaluated by means of historical simulations using the Thomson Venture Economics database. We consider portfolios composed of investments in 16 private equity funds diversified across venture capital and buy-out capital and across the US and Europe. Furthermore we use a 30% overcommitment to initialize the portfolio in the first year. We find that our recommitment strategy is capable of maintaining a stable investment degree that is close to the target level, while keeping the probability of being overexposed within reasonable bounds. Sensitivity analyses show that our strategy remains successful when the portfolio is restricted to a certain type of private equity capital, to a specific region or to fund managers with varying experience. Furthermore, we show that the quality of the strategy can be improved if an investor can use the three-year future investment degree of the current portfolio to scale up or down her new commitments. An investor that can permit herself a higher allocation could consider more aggressive overcommitment as this will bring the portfolio exposure closer to the target, but at the cost of a higher risk of being overexposed. In addition, we find that the commitment strategies of Cardie *et al.* (2000) and Nevins *et al.* (2004) are both not capable to keep the investment degree stable for a prolonged period of time. In particular, the investment degree remains permanently above its target.

The concept of our private equity recommitment strategy can be expanded further to other illiquid asset classes that involve commitments, like some specific real estate funds or infrastructure funds. Further research could also consider the use of more accurate intermediate valuations of the portfolio investments. Driessen *et al.* (2007) present a methodology to estimate the intermediate net asset values by estimating the CAPM beta on the fund's cash flows when the fund is matured. We expect that the average exposure to private equity over time will not be affected much, but that the volatility of the investment degree will rise because the value of private equity investments will become more volatile. Furthermore, our current strategy is limited to 100% private equity, but it can be expanded in a straightforward manner to private equity in a broader strategic asset allocation with e.g. public equity, bonds and hedge funds, taking into account the returns on these asset classes. Finally more research on cash flow prediction, see Takahashi and Alexander (2002) and Ljungqvist and Richardson (2003b), is necessary to make the recommitment strategy based on the future investment degree operational.

Data Appendix

The data set obtained from Thomson Venture Economics contains information on 2,786 private equity funds over the period 1980Q1-2005Q4, and includes the regional focus (US/Europe), the type of investment (venture capital, buy-out capital, mezzanine finance and fund-of-funds), the vintage year, quarterly contributions and distributions, and quarterly information on the net asset value (NAV). Reported cash flows are given in US dollars and are net of (management) fees as well as carried interest. In total 168 funds are excluded on the following grounds:

1. Total commitments: The fund's cash flows and NAVs are expressed relative to its total commitment, which makes funds of different sizes comparable. One fund reports a zero commitment and has been excluded from the data set.

2. Geographic orientation: 1 fund was included in both the European and US sample. The double counting has been excluded and the fund is characterized as 'global'.

3. Type of investment: Mezzanine funds (65 funds) are removed, since their structures differ from private equity funds. As this research focuses on private equity fund investors, data on fund-of-funds (direct investing (13 funds) and secondaries (7 funds)) are excluded as well.

4. Missing observations: Two funds report cash flows equal to zero over the entire period and are therefore excluded.

5. Visual inspection: 71 funds are removed on visual inspection of the data.

The Thomson Venture Economics database reports a fund's contributions, distributions and estimated NAVs. The contributions and distributions, if any, are assumed to take place at the end of the month and information on the NAVs is given on a quarterly basis. The following adjustments were made to these cash flow variables:

1. 157 funds report negative contributions, which have been changed to distributions.

2. Negative distributions of 14 funds have been adjusted by subtracting them from the fund's earlier distributions.

3. 8 funds report a negative NAV. As the NAVs of funds are highly unlikely to become negative, these funds have been removed.

Nederlandse samenvatting (Summary in Dutch)

Dit proefschrift bestaat uit een bundeling van vijf empirische studies naar financiële markten. Iedere studie staat op zichzelf en heeft betrekking op een specifieke markt: opkomende markten, bedrijfsobligaties, of private equity. Deze Nederlandse samenvatting geeft een overzicht van de belangrijkste bevindingen.

Opkomende markten

De uitdrukking 'opkomende markten' of 'emerging markets' is geïntroduceerd door de International Finance Corporation (IFC) van de Wereld Bank. De term 'opkomend' verwijst naar de ontwikkelingsfase van een economie tussen onderontwikkeld en ontwikkeld. De opkomende markten omvatten landen met lage en midden-inkomens, waarvan de aandelenmarkten openstaan voor buitenlandse beleggers, zoals Mexico en Zuid-Afrika. Hiernaast worden ook ontwikkelde economieën met een hoog politiek risico of beperkte regulering, zoals respectievelijk Israel en Zuid-Korea, aangemerkt als opkomende markten.

De economieën en financiële markten van opkomende landen zijn uitgebreid bestudeerd. Het onderzoek nam een grote vlucht sinds het begin van de jaren negentig door de beschikbaarheid van relevante data door onder andere IFC. Een goed overzicht van het onderzoek naar opkomende markten wordt gegeven door Bekaert en Harvey (2002, 2003). Hiernaast hebben de hoge rendementen en sterke economische groei sterk bijgedragen aan de interesse van beleggers voor opkomende markten.

Twee aspecten maken empirisch onderzoek naar opkomende markten interessant. Allereerst bieden deze een natuurlijke test voor gevestigde en nieuwe theorieën die in eerste instantie meestal worden toegepast op ontwikkelde markten. De studie naar aandelenselectiestrategieën in hoofdstuk 2 is hiervan een goed voorbeeld. Ten tweede hebben opkomende markten hun eigen kernmerken zoals regelmatig terugkerende financiële crises en beperkte reguleringen. Dit rechtvaardigt dan ook specifieke (nieuwe) modellen voor opkomende markten. De studie in hoofdstuk 3 naar de winstvoorspellingen van analisten in opkomende markten is hiervan een goed voorbeeld. Uiteindelijk biedt de studie naar de valuta markt van de opkomende markten in hoofdstuk 4 een nieuw perspectief op valuta beleggingsstrategieën voor zowel opkomende als ontwikkelde markten.

Hoofdstuk 2 onderzoekt twee tegenstrijdige verklaringen voor de winstgevendheid van aandelenselectiestrategieën in opkomende markten. De studie laat zien dat de significante excess rendementen van aandelenselectiestrategieën, gebaseerd op waarde, momentum en winstrevisie indicatoren, niet verklaard kunnen worden door zowel het marktrisico als wereldwijde risico factoren. Onze bevindingen voor de waarde en momentum strategieën zijn consistent met bestaande resultaten voor ontwikkelde markten die wijzen op een 'behavioral' verklaring. Onze resultaten voor de waarde strategie zijn in overeenstemming met overreactie-verklaring omdat we zien dat de winstgroei van deze aandelen bovengemiddeld blijft na de portefeuilleformatie. Voor de momentum strategie zien we zowel een onderreactie (kort na portefeuilleformatie) en een overreactie (op langere termijn). De hoge opwaartse winstrevisies vlak na de portefeuilleformatie wijzen op een initiele onderreactie-verklaring, terwijl we vijf jaar na de portfefeuilleformatie zien dat het aandeel zijn sterke performance niet heeft weten vast te houden. Dit laatste wijst op een overreactie-verklaring. Bovendien vinden we dat de belangrijkste 'behavioral' verklaring voor waarde aandelen gerelateerd is aan de onderschatting van de lange termijn groei vooruitzichten. Dit blijkt uit de bovengemiddelde afwijkingen in de winstvoorspellingen en winstrevisies op lange termijn en door de snel verbeterende winstgroeiverwachtingen. Ten slotte vinden we dat overreactie effecten een beperkte rol spelen voor de winstrevisie strategie. Hierin verschilt deze strategie van de momentum strategie.

Hoofdstuk 3 presenteert empirisch bewijs dat financieel analisten inefficiënt gebruik maken van beschikbare macro-economische informatie in hun winstvoorspellingen voor bedrijven in opkomende markten. Analisten blijken informatie over de politieke stabiliteit volledig over het hoofd te zien. Daarentegen verwerken zij economische groeivoorspellingen wel in hun winstschattingen, maar helaas blijkt uit ons onderzoek dat deze groeivoorspellingen geen relevante informatie voor winstgroei bevat. Het zou dus beter zijn dat analisten deze informatie niet meenemen in hun winstvoorspellingen. Inflatie voorspellingen blijken op de juiste manier verwerkt te worden in de winstvoorspellingen. Verder blijkt dat de transparantie van ondernemingen cruciaal is voor de kwaliteit van winstvoorspellingen in opkomende markten. Onze resultaten wijzen erop dat analisten de macro-economische informatie beter verwerken in hun winstvoorspellingen voor meer transparante bedrijven dan voor minder transparante bedrijven.

Hoofdstuk 4 meet de economische waarde van macro-economische informatie en technische handelsregels voor de valutamarkten in opkomende landen. Op basis van wisselkoersgegevens van 23 opkomende landen met een zwevend wisselkoers regime over de periode 1995-2007 laten we zien dat beide informatiebronnen benut kunnen worden voor winstgevende valuta beleggingsstrategieën. In overeenstemming met de conclusies van enquêtes onder valutamarkt professionals betreffende het gebruik van fundamentele en technische analyse, vinden we dat de combinatie van de informatiebronnen in een beleggingsstrategie een verbeterd, voor risicogecorrigeerd, rendement laat zien.

Bedrijfsobligaties

Ondernemingen gebruiken doorgaans een combinatie van verschillende financieringsbronnen om een optimale kapitaal structuur te bewerkstelligen. Meestal komt dit neer op een combinatie tussen eigen vermogen en vreemd vermogen. Vandaag de dag halen veel ondernemingen, zonder de tussenkomst van banken, zelf geld op in de kapitaalmarkt door hun eigen obligaties uit te geven. In principe komen deze bedrijfsobligaties neer op een financiële verplichting van de onderneming om rente te betalen op vooraf vastgestelde data gedurende de looptijd van de obligatie en om aan het eind van de looptijd de hoofdsom terug te betalen. Vanwege het risico dat een onderneming niet aan deze verplichting kan voldoen eisen beleggers een hogere rentevergoeding op deze bedrijfsobligaties dan op staatsobligaties. In het geval van faillissement hebben de houders van bedrijfsobligaties overigens voorrang boven de claims van aandeelhouders.

In de afgelopen 15 jaar is het onderzoek naar bedrijfsobligaties sterk gegroeid, hoewel de eerste studie naar bedrijfsobligaties door Fisher (1959) al veel langer teruggaat. De toegenomen interesse is te danken aan de enorme groei van de markt voor bedrijfsobligaties in zowel de V.S als Europa en aan de introductie van afgeleide instrumenten op bedrijfsobligaties zoals ‘credit default swaps’. Desalniettemin is het aantal empirische onderzoeken vanuit het perspectief van een belegger in bedrijfsobligaties beperkt vanwege het gebrek aan betrouwbare historische data van rendementen en prijzen. Voor zover bekend, is hoofdstuk 5 de eerste studie naar anomalieën in bedrijfsobligatierendementen die data van individuele bedrijfsobligaties met beleggingsfondsen in bedrijfsobligaties combineert. Voorgaande studies richten zich of alleen op de individuele bedrijfsobligaties (zie bijvoorbeeld Gebhardt et al. (2005)) of op beleggingsfondsen in bedrijfsobligaties (zie bijvoorbeeld Elton et al. (1995) of Huij and Derwall (2007)).

Hoofdstuk 5 laat zien dat de eerder gedocumenteerde risicofactoren uitstekend in staat zijn om de dwarsdoorsnede van de rendementen van bedrijfsobligaties met een middellange en lange looptijd te verklaren. De rendementen van korte termijn obligaties worden echter niet volledig verklaard en onderschat. Een aanzienlijk gedeelte van de rendementen op korte termijn bedrijfsobligaties is onafhankelijk van de premies voor marktrisico, looptijd en kredietrisico, de dynamiek van de rente curve, liquiditeitsrisico en premies gerelateerd aan macro-economische variabelen. Vergelijkbare aanwijzingen voor de korte termijn bedrijfsobligatie anomalie vinden we ook terug in portefeuilles van bedrijfsobligatie beleggingsfondsen. Dit duidt erop dat deze anomalie opgewassen is tegen belangrijke praktische beperkingen zoals transactiekosten, 'short-sell'-restricties en markt impact.

Private Equity

Private equity omvat het gehele spectrum van investeringen in deelnemingen in bedrijven die geen publieke notering aan een beurs hebben. Pas in de jaren tachtig werd deze beleggingscategorie bekend bij het grote publiek door de zeer grote private equity overnames die op dat moment plaatsvonden in de V.S. en veelvuldig in het nieuws kwamen. Desalniettemin gaat de geschiedenis van private equity in zowel Europa als de VS terug tot de jaren veertig. Sindsdien is de de private equity markt enorm gegroeid. Deze groei kwam tot stand door stimuleringsprogramma's van de overheid in de jaren vijftig, de introductie van de commanditaire vennootschap in de jaren zeventig en nieuwe regels voor pensioenfondsen en banken in de jaren tachtig. In deze laatste periode hebben institutionele beleggers, zoals pensioenfondsen en verzekeringsmaatschappijen, de hoofdrol overgenomen van particuliere investeerders. Hierdoor heeft private equity een extra impuls gekregen. Natuurlijk heeft het succes van verschillende bedrijven die oorspronkelijk gefinancierd waren door private equity investeerders, zoals Microsoft, Google, Starbucks, Apple Computers en Hewlett-Packard, hier ook aan bijgedragen. Eind jaren negentig zagen we een aanzienlijke groei van het aantal onafhankelijke private equity firma's. Dit kan deels verklaard worden door het succes van de private equity investeringen in internet start-ups aan het begin van de internet hype en de daaropvolgende succesvolle beursintroducties op de publieke aandelenmarkt. Private equity en speciaal venture capital ondervond een stevige correctie aan het eind van de internet hype, mede door de samenvallende wereldwijde macro-economische baisse. Het daaropvolgende macro-economische herstel leidde ook tot een herstel van de private equity rendementen. Gedreven door de lage rentes en de grote beschikbaarheid van liquide middelen ondergingen de buy-outs een sterke groei in de afgelopen drie jaar.

Heden ten dage is de interesse in private equity van institutionele belegger nog steeds groeiende. Zo blijkt uit een enquête van Cumming and Johan (2007) naar de opvattingen van Nederlandse institutionele beleggers met betrekking tot private equity dat 29% van de respondenten al belegt in private equity, terwijl nog eens 6% overweegt om in de komende twee tot vijf jaar in private equity te gaan beleggen. Verder overwegen de respondenten die nu al investeren in private equity om hun private equity portefeuille uit te breiden op de middellange termijn. Ondanks het enthousiasme van institutionele beleggers is er nog bijzonder weinig onderzoek gedaan naar beleggingsstrategieën voor private equity beleggers met een lange termijn beleggingshorizon. Hoofdstuk 6 vult deze hiaat.

Hoofdstuk 6 ontwikkelt een herbeleggingstrategie voor institutionele private equity beleggers. Deze strategie streeft ernaar om het gewicht van private equity in een beleggingsportefeuille constant te houden en bovendien rekening te houden met het illiquide karakter van private equity. Onze historische simulaties (1980 - 2005) laten zien dat deze dynamische strategie in staat is om een constant portefeuillegewicht dicht bij de gewenste allocatie in stand te houden. Dit resultaat vinden we niet alleen voor portefeuilles zonder restricties, maar ook voor portefeuilles die zijn beperkt tot alleen buy-out of venture capital, een specifieke regio (Europa of de VS), of de ervaring van de fondsmanager. Dit resultaat is van grote waarde voor institutionele beleggers zoals pensioenfondsen of verzekeringsmaatschappijen. In hun strategische asset allocatie streven zij immers dikwijls naar een constante allocatie naar verschillende beleggingscategorieën. De eindige looptijd van private equity investeringen in samenhang met de onzekere kasstromen maken het noodzakelijk dat deze beleggers hun portefeuille constant moeten onderhouden. Onze strategie kan hierbij van waarde zijn.

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EMPIRICAL STUDIES ON FINANCIAL MARKETS: PRIVATE EQUITY, CORPORATE BONDS AND EMERGING MARKETS

This dissertation consists of five empirical studies on financial markets. Each study can be read independently and covers a specific subject. The first three studies add to the literature on emerging markets. There are two aspects that make emerging markets research interesting. First, they provide a natural `out-of-sample' test for both established and new theories that initially are tested for developed markets. The study on stock selection strategies in emerging markets in Chapter 2 provides an example of this use of emerging markets data. Second, emerging markets have their own specific characteristics such as severe crises and limited regulations. The study on analysts' earnings forecasts, in Chapter 3, clearly looks at the specific characteristics of emerging markets. Finally, the study on emerging currency markets, in Chapter 4, gives a new perspective on investment strategies for both emerging as well as developed currency markets. The last two chapters cover corporate bonds and private equity respectively. To the best of our knowledge, Chapter 5 is the first study that incorporates both individual corporate bonds and US corporate bond mutual funds to address anomalous patterns in corporate bond returns. The last chapter aims providing guidance to institutional investors to maintain a constant portfolio allocation to private equity. Despite the enthusiasm from institutional investors for private equity, the formal research into private equity investment strategies for these investors appears to be limited. Chapter 6 fills this gap.

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