MODELLING THE DEMAND FOR EMERGING MARKET ASSETS

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ABSTRACT

This paper addresses the problem of estimating the aggregate international demand schedule for emerging market (EM) securities as an asset class. The standard 'push-pull' model of capital flows is modified by reference to recent work on portfolio choice in the context of credit rationing leading to a simultaneous equation model that determines EM yield and capital flows together. Interaction effects include lagged flows and yields to reflect herding and asset bubbles, with a time-varying risk aversion variable affecting yields and flows. This model is then tested on monthly data for US bond purchases, using the General-to-Specific Approach (GETS) to find significant variables, lags, and shock dummies for yield spread and bond flows separately; followed by a Full Information Maximum Likelihood (FIML) estimation of the two equations together. The results are robust and give a very good fit for both yields and flows, contributing a valuable insight into the dominant impact of short-term shifts in the demand schedule on emerging markets.

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1. INTRODUCTION [*]

The expansion and contraction of portfolio capital flows from the global financial centres towards emerging markets over the past decade has generated considerable controversy over the underlying economic determinants of these flows, and by extension their instability. Most research has focused on the conditions in emerging markets themselves - often known as 'fundamentals'- rather than the determinants of the demand for emerging market securities as an asset class.[1] None the less, recent academic literature has begun to emphasise 'home market' factors such as US interest rates, changing risk appetite, herding behaviour and momentum trading as key determinants of flows.

However, attempts to model these flows have revealed difficulties in separating home from host factors - or 'push' and 'pull' effects as they are conventionally known – because aggregate flows and yield spreads do not simply reflect an underlying process of portfolio allocation based on known risk and return characteristics of emerging markets in relation to wealth and riskless return on the investors' own market. This is because: first, capital flows themselves affect asset prices both directly (asset bubbles) and indirectly (default risk); second, the changing level of investor risk appetite on the home market affects both asset prices and capital flows; and third, international capital markets

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[1] For a discussion of the role of these factors in the context of capital market instability during the late 1990's, see FitzGerald (2002).

do not fully clear – in the sense that at the unconstrained market price, some borrowers remain unsatisfied.[2]

In this paper, we attempt to encompass these three characteristics in an empirically testable model of capital flows. Section 2 reviews the recent literature which has found that home or 'international' factors are at least as significant as host factors or 'fundamentals' in determining not only capital flows themselves but also asset yields and credit ratings. The 'push-pull model' that underpins most econometric work in this field is discussed in Section 3, which suggests that the reduced form commonly used for estimation may fail to fully identify asset demand effects in a rationed market such as the observed inverse relationship between yields on EM assets and flows on the one hand, and of the correlation between these yields and those of other high-risk assets on home markets on the other. Moreover, only very recently have disequilibrium concepts been introduced to the push-pull model by Mody and Taylor (2002). Section 4 sets out our proposed model of the asset demand schedule based on a simultaneous equation system that determines yield spreads and capital flows with explicit inclusion of interaction effects. The two equations include lagged flows and yields to reflect herding and asset bubbles, with a risk aversion variable in both yield spread (to reflect asset pricing) *and* capital flows (to reflect credit rationing). This model is then tested on data for monthly bond flows from the US to emerging markets over the 1993-2001 period in Section 5. The results of a general-to-specific (GETS) econometric approach to the separate time series for yield spreads and bond flows, and of full information maximum likelihood (FIML) estimation of the two equations together, are robust and support the proposed

[2] See Stiglitz and Weiss (1992).

model. Section 6 concludes with some suggestions for further research, and draws some tentative policy implications in relation to the stabilization of fluctuations in demand for emerging market assets.

2. CAPITAL FLOWS AND THE IMPLICIT ASSET DEMAND SCHEDULE

The macroeconomic theory of international capital markets is still in its infancy, in marked contrast to the sophistication of the microeconomics of portfolio choice. Sticky prices, market segmentation, heterogeneous investors, persistent currency misalignments despite arbitrage and the cost of scarce information all need to be accounted for if the model is even to approximate the real world in a useful way (Dumas, 1994). In consequence, the relatively simple framework which combines international (push) and domestic (pull) factors in determining the capital flow to any one country still dominates empirical work. This approach reflects, in essence, a simple microeconomic portfolio composition rule based on given relative returns and risks of various assets, but without significant macroeconomic interaction at the aggregate level.

The relevant literature starts in the early 1990s, when the surge of capital flows to emerging markets got underway. On the basis of the observed comovement of Latin American reserves and exchange rates (as a proxy for capital flows), Calvo, Leiderman and Reinhart (1993) - using principal components analysis and structural VAR - conclude that common external shocks are a major determinant of capital inflows, which in turn lead to reserve accumulation and exchange rate appreciation.[3] Fernandez-Arias (1996) uses a panel of thirteen developing countries to address the determination of country risk as the channel through which exogenous shocks are transmitted to portfolio inflows, finding that external ('push') factors have a substantial impact on creditworthiness as reflected in the secondary market debt prices. Montiel and Reinhart (1999) employ fixed-effects panel data analysis for 15 emerging market countries and examine the volume and composition of capital inflows. They conclude that international interest rates have an important effect on not only the volume but also the asset composition of flows. Montiel and Reinhart (2001) confirm the influence of US interest rates but argue that there are also step effects at work due to the progressive integration of international capital markets, which go beyond separate 'push' and 'pull' factors. Finally, Mody, Taylor and Kim (2001) use a vector equilibrium correction model to forecast pull and push factors for inflows to 32 developing countries of bond, equity and syndicated loans. Push factors include US growth, US interest rates (short and long-term) and the US high-yield spread as a proxy for risk aversion. They conclude that in general, pull factors are more important in the long-run but that push factors are determinant in short-run dynamics.[4]

The country level approach in these articles has the disadvantage that the push factors may be underestimated because flows from *all* host countries are included but only US

[3] However, Chuhan, Claessens, Mamingi (1998) show that reserves are only weakly correlated with portfolio capital flows, and so should not be used as a proxy.
[4] However, they treat bond yields (i.e.the EMBI) as an exogenous variable, implicitly assuming that yields are unaffected by the capital flows themselves: this may lead to an underestimation of the strength of asset demand fluctuations.

factors are considered. In consequence, some authors have examined the capital outflows to emerging markets from the US alone. Taylor and Sarno (1997) examine the determinants of US portfolio capital outflows towards Latin America and Asia using cointegration techniques. They find that global ('push') and domestic ('pull') factors have similar importance in explaining short-run equity flows to Asia and Latin America. However, for the short-run dynamics of bond flows, global factors (particularly U.S. interest rates) are found to be more important than domestic factors. Chuhan, Claessens, Mamingi (1998) model US portfolio flows to Latin American and Asian markets using panel data method. They find, in contrast, that push factors (the slowdown in US industrial production and the drop in US interest rates) are the main determinants of portfolio flows to Latin America and Asia. However, while equity flows are more sensitive to global 'push' factors, bond flows are found to react more to credit ratings and secondary market price of debt.

The only attempt to model asset demand and supply effects in conjunction is an innovative disequilibrium model of capital flows to four emerging markets – Brazil, Mexico, Thailand and Korea - in Mody and Taylor (2002). They derive this model from the Stiglitz-Weiss (1981) theory of credit rationing, which allows for such market disequilibria explicitly. Using the maximum likelihood estimation technique, they estimate supply and demand functions for capital flows jointly for each country. The technique estimates the probability of the demand for capital exceeding the supply at any one point in time, which the authors term a 'capital crunch'. The global 'push' factors include: short-term and long-term US interest rates, the US high yield spread (to proxy the default risk in the US), a measure of industrialized country economic activity (proxied by an index of US industrial production), and the cost of capital (EMBI of spreads over the US risk-free rate). Pull factors (the 'demand for capital') considered include the international cost of capital as proxied by the EMBI, domestic stock market indices and reserve levels. They find that the supply of capital (i.e. push effect) operates through two distinct channels: first, US industrial production growth raises the supply of capital; second, increased US high-yield spreads reduce the supply of capital to emerging markets. This second effect is interpreted by the authors as reflecting an increase in the cost of risk capital, which in turn is expressed in the EM yield spread (proxied by the EMBI).

This model marks a significant step forward from the single-equation push-pull model, particularly the explicit handling of capital rationing. However, there are two aspects where our approach differs from that of Mody and Taylor. First, the negative impact of the US high yield spread on flows to emerging markets indicates that what is being captured is changes in risk aversion, not US default risk as such, because in portfolio theory increased risk in one asset should *increase* demand for other assets. Second, the inclusion of yield spread as an independent variable in their capital demand function overlooks the fact that flows can clearly affect spreads inversely. In other words, flows and spreads should be modelled simultaneously.

As we have seen, the literature on bond flows takes the yield spread itself to be an exogenous factor. However, there is also a recent literature on the determination of EM bond spreads themselves. Eichengreen and Mody (1998) use a 'standard model 'of spreads as a function of global economic conditions (proxied by the rate on ten-year U.S. treasuries), issuer characteristics such as the region of the borrower and whether it is sovereign, and country characteristics. They find that a rise in U.S. interest rates is associated with a lower probability of a bond issue (i.e primary supply estimates) while reducing spreads. In contrast, Min (1998) finds no effect of U.S. T-bill rates on yield spreads for EM dollar bonds, but points out that bond rates (unlike syndicated bank debt) are not tied to US short rates. The International Monetary Fund introduces market expectations in suggesting that "the stance and predictability of U.S. monetary policy is important in explaining fluctuations in developing country interest rate spreads" (IMF 2000: 68). Arora and Cerisola (2000) estimate the influence on country risk (proxied by sovereign bond spreads) of U.S. monetary policy, host fundamentals, and world capital market conditions. They point out that the ambiguous results in the literature may be due to proxying U.S. monetary policy by the yield on Treasury securities. When the U.S. Federal Funds target rate is used, they find direct positive effects on sovereign bond spreads, as theory anticipates. However, this particular literature does not seem to take into account the effect of capital flows themselves as asset prices and debt levels, and thus yield spreads.

3. PUSH-PULL MODELS OF CAPITAL FLOWS

The standard model used in the empirical literature[5] states that the portfolio capital flow (F_{ij}) from any one country of origin (i) to a country of destination (j) is the result of 'push' and 'pull factors', or 'capital supply' and 'country characteristics'. For a vector of known home country (or international market) variables $\boldsymbol{w}$ and host country variables $\boldsymbol{h}$ then ,

$$F_{ij}=F(\boldsymbol{w}_i,\boldsymbol{h}_j)$$

Push factors ($\boldsymbol{w}$) conventionally include: home country wealth (e.g. GDP); home monetary policy (e.g. money supply); riskless home interest rate (e.g. US treasury yield); and home asset risk (e.g. US bond yield spread) The econometric literature indicates that roughly half of the observed flow variance can be explained by these factors. Pull factors ($\boldsymbol{h}$) usually include: EM yield spreads (or EMBI prices); risk ratings; host country growth rates and debt levels etc. One of these country characteristics (such as credit rating) may have a separate estimation equation involving further exogenous variables –such as Fernandez-Arias (1996).

At first sight, single-equation 'push-pull' models might seem to be the reduced form of a simultaneous equation model where demand (F_d) is a function of host characteristics ($\boldsymbol{w}$)

[5] See Jeanneau and Micu (2002) for an excellent literature survey of these models and Fernandez-Arias and Montiel (1996) for the microeconomic theory underpinning the expected returns and risk factors that determine creditworthiness.

and the return or 'price' (P), while supply (F_s) of these assets is a function of host characteristics ($\boldsymbol{h}$) and price (P).

$$
\begin{aligned}
F_d &= a_1 + b_1\mathbf{w} + c_1 P \\
F_s &= a_2 + b_2\mathbf{h} + c_2 P \\
F_d &= F_s = F \\
F &= f_0 + f_1\mathbf{w} + f_2\mathbf{h} \\
\\
f_0 &= (a_1 c_2 - a_2 c_1)/(c_2 - c_1) \\
f_1 &= b_1 c_2 /(c_2 - c_1) \\
f_2 &= b_2 c_1 /(c_1 - c_2)
\end{aligned}
$$

The existence of exogenous variables ($\boldsymbol{w}$,$\boldsymbol{h}$) in the two equations means that there would be no identification problem as such.[6] However, the three coefficients (f) in the reduced form that is usually estimated do not in fact correspond to the original response coefficients (b) for the supply and demand functions and should not be interpreted as such.[7] Specifically, the price response from the *demand* schedule (c_1) is included in the measured effect (f_2) of host characteristics on flows. In our context, the observed inverse correlation between yield spreads and capital flows indicates that the risk information included in yield is more important than the underlying expected return information, and the valuation of this risk depends on risk appetite in the *home* market as well as default risks as such. The implication is that it is necessary to estimate the flow and yield schedules separately and then handle the simultaneity problem explicitly, if we are to determine the 'push' factors ($\boldsymbol{w}$) correctly.

More seriously, the implicit F_s equation is not in fact a supply schedule for assets as such because the decisions of primary issuance (e.g. by EM treasuries) in response to price are unknown, and in any case as much affected by market access as by yield spreads as such, as Eichengreen and Mody (1998) point out. The 'pull' factors (***h***) contain information about the quality of the asset (expected return, default risk etc.), *not* the quantity supplied. Indeed, as there is an active secondary market, EM bond purchases by (say) US investors may be 'supplied' by (say) Japanese disinvestors. Moreover, the fundamentals (***h***) such as debt overhang and growth rates are not truly independent variables but are in fact affected by flows themselves through debt accumulation and asset bubbles; so default probabilities depend on past and present flows. In other words, $\boldsymbol{h} = \boldsymbol{h}(F)$.

Finally, EM bond markets are rationed at equilibrium in the sense that prices are unconstrained but the market does not clear because EMs would like to borrow more (i.e. supply more assets) at the going price than investors are willing to lend (i.e. purchase assets). The implications of this are clearly set out by Folkerts-Landau (1985), who extends the familiar model of rationed credit markets to international debt. Higher lending rates have an adverse selection effect on borrowers, increasing the default risk along with higher levels of indebtedness. With imperfect information, full pricing of assets to reflect risk is impossible, and entire asset classes are thus 'rationed out' of the debt market. In consequence, there is a backward-sloping supply curve of funds beyond a certain interest rate; and in this range the lenders' profit-maximising level of credit is lower than developing countries' demand for external finance.

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[6] See Pindyck and Rubinfeld (1991, chapter 11) 'Simultaneous-equation estimation'.
[7] Nor, indeed, can they be derived again from the reduced form.

In sum, the macroeconomic ‘push-pull’ model is in effect a representation of shifts in the demand schedule for EM assets, with the ‘fundamentals’ reflecting asset quality. This notion informs the model we estimate below.

4. PROPOSED MODELLING APPROACH

The microeconomic logic of investment behaviour in response to particular financial incentives also has consequences for the pricing of developing country assets, quite independently of the underlying fundamentals.[8] Moreover, asset valuation methods and portfolio composition rules used by investors in practice tend to be rather crude, being largely based on considerations of liquidity and exit possibilities (Clark, Levasseu and Rousseau, 1993). The resulting asset bubbles can have a serious impact on the real economy in both developed and developing countries even in the presence of low inflation, fiscal balance and monetary rectitude (IMF, 2000).

There are thus severe limitations to the use of yield spreads on emerging market bonds as evidence of markets perception of asset quality in the form of underlying default risk: “care is needed in interpreting yield spreads, since they are influenced by a variety of factors other than the perceived creditworthiness of the borrower including investors’

[8] See IMF (1995) – in particular Section 5 (pp. 37-44) ‘Institutional investor behaviour and the pricing of developing country stocks’. Recent work on herding by investors indicates that three causes can be involved. First, payoff externalities where payoff to an agent adopting an action is positively related to the number of agents adopting the same action. Second, principle-agent considerations such that a manager, in order to maintain or gain reputation when markets are imperfectly informed, may prefer either to ‘hide in the herd’ to avoid evaluation or ‘ride the herd’ in order to improve reputation. And third, information cascades where later agents, inferring information from the actions of prior agents, optimally decide to ignore their own information (Devenow and Welck, 1996).

appetite for risk and the liquidity of particular instruments" (Cunningham, Dixon and Hayes, 2001, p.175). Moreover, despite the fact that yield dispersion has increased over time as well as increasing after crises, which can be interpreted as growing investor discrimination in a cumulative learning process, it is still the case that beyond investment grade[9], the relationship between risk (as reflected in ratings) and price (reflected in yield spreads) tends to break down – particularly during droughts when credit rationing reduces transactions volume severely.

Clearly higher home interest rates, lower volatility in home assets, higher covariance between these and emerging market assets, and higher risk aversion will all reduce demand for emerging market assets independently of the supply conditions (Disyatat and Gelos, 2001). Further, pervasive herding behaviour causes a 'momentum' effect in which demand for an asset becomes a positive function of the quantity (capital flow) itself. There is thus good reason to see risk aversion (or 'risk appetite') as a variable in itself which is not only changing but also path dependent, varying with past experience of yields and bubbles and thus potentially strongly pro-cyclical. For instance, the IMF recognises that risk appetite changes over time in practice, and uses for this purpose the JP Morgan 'Global Risk Aversion Index (IMF 2001) which measures monetary liquidity and credit premia.[10]

[9] According to the Bank of England, the spread/rating curve tends to the origin, moves through 250 basis points at Moody's A2 and 500 basis points at B3, becoming asymptotic to infinity beyond B3 (Cunningham, Dixon and Hayes, 2001).
[10] The Bank of England, however, warns that "it is difficult to construct robust indicators of risk appetite" because of the problem of separating out the effects of pure contagion and underlying fundamentals in aggregate indicators (Cunningham, Dixon and Hayes, 2001, p.185).

Econometric analysis of US mutual fund portfolios shows that their momentum trading in emerging market equities is positive – they systematically buy winners and sell losers (Kaminsky *et al.* 2000). Contemporaneous momentum (buying winners and selling losers) is stronger during crises; lagged momentum trading (buying past winners and selling past losers) is stronger during non-crises. Investors also engage in contagion trading: that is they sell assets from one country when asset prices fall in another. In a similar vein, Disyatat and Gelos (2001) find that benchmarking explains observed behaviour of dedicated US mutual funds better than a rebalancing rule implied by the standard mean-variance optimisation model, but do not explore variations in risk aversion over time.

Kumar and Persaud (2001) point out that changes in risk appetite (and the implications for contagion) have received comparatively little attention in the academic literature, even though discussed in market and policy circles. They argue that most of the indicators used to proxy risk aversion in the empirical literature confuse the level of risk itself with risk appetite: spreads are a function (K) of risk, where K reflects risk appetite, itself containing structural components (the underlying utility function and financial market structure) and a time varying element reflecting shorter-term factors such as so-called 'wake-up calls'. In their model, risk is proxied by the variance of the asset price (σ^2) and the expected return is then:

$$E(R) = \alpha + K \log (\sigma^2)$$

where *E(R)* is the expected return, α is a measure of 'global' risk, and *K* is risk aversion. They define the expected excess return as the difference between the long price *LR(P)* and the current price of the asset:

$$LR(P) - P = \alpha + K \log(\sigma^2) \qquad \text{or}$$

$$P = LR(P) - \alpha - K \log \sigma^2$$

Clearly, not only does a fall in risk appetite[11] (increased *K*) cause a fall in asset price *(P)* for a given risk level *(σ)*, but also the impact on price will be greater for riskier asset classes (higher σ). Applying this argument to our context, to the extent that home risk aversion is reflected in US risk spreads, then the same change in risk appetite would be reflected in EM spreads, as well as in the aggregate flows due to the capital market rationing effect. As we have seen, the empirical literature does report this effect, but without a clear explanation.

In sum, therefore, we propose an approach where shifts in the asset demand function dominate, and thus our model for empirical testing should have the following five characteristics:

[11] Kumar and Persaud estimate risk appetite *(K)* from this model by calculating excess returns (the difference between spot rates and forward rates from the previous period) on seventeen emerging market currencies over ten years. Their risk appetite index exhibits marked quarterly and annual cycles, and troughs that appear to be correlated with major market discontinuities.

1. Spreads impact flows negatively because of the risk information they contain; while flows impact spreads negatively because increased demand drives up the price;
2. Risk aversion varies over time, and affects flows negatively due to asymmetric rationing, and yield spreads positively due to risk pricing;
3. There are lagged effect of past on present flows due to momentum trading, and past on present spreads due to asset bubbles;
4. The familiar home variables such as riskless return and wealth (or liquidity) and host variables to reflect fundamentals such as real return and probability of default, are included;
5. A simultaneous equation system to capture the interaction of price (yield spread) and quantity (capital flow) in equilibrium.

This leads us to a proposed model structure of the following form. Capital flows *(F)* depend upon its lagged self (with a structure to be determined empirically); the EM yield spread *(S)*; wealth/liquidity *(L),* riskless return *(I)* and risk aversion *(R)* in the home market; with expected coefficient signs:

$$F_t = \alpha_0 + \alpha_1 F_{t-1} + \alpha_2 S_t + \alpha_3 L_t + \alpha_4 I_t + \alpha_5 R_t$$
$$\alpha_1 > 0$$
$$\alpha_2 < 0$$
$$\alpha_3 > 0$$
$$\alpha_4 < 0$$
$$\alpha_5 < 0$$

Yield spread *(S)* depends upon its lagged self; capital flows *(F);* home risk aversion *(R)* and host risk fundamentals *(D)*; with the following coefficient signs:

$$S_t = \beta_0 + \beta_1 S_{t-1} + \beta_2 F_t + \beta_3 R_t + \beta_4 D_t$$
$$\beta_1 > 0$$
$$\beta_2 < 0$$
$$\beta_3 > 0$$
$$\beta_4 > 0$$

5. EMPIRICAL ESTIMATION OF THE MODEL

5.1. Data

The main two variables in our study are total US bond flows to developing countries and EMBI Sovereign Spread. The data for the first variable was taken from the US Treasury Department (TIC: the Treasury's International Capital Reports) and reconsolidated so as to yield an aggregate of [(Asia less Japan)+Africa+(Latin America less Caribbean)]. EMBI Sovereign Spread was taken from Bloomberg. The data for explanatory variables come from various sources: International Financial Statistics (US Industrial Production Index), Bloomberg (US High-yield Spread), US Federal Reserve System (M3 US Money Stock, US Federal Funds Rate), and Cross Border Capital (Emerging Market Liquidity Index). All data are on a monthly basis from 1993:02 to 2001:12. Table 1 below shows the detailed information about the data:

Table 1 Data Description

Transformation	Mnemonic	Description of the variable
logTBDC	LTBDC	Bond Flows to Developing Countries
Spread_EM/100	Spread_EM	EMBI Sovereign Spread
Spread_HY/100	Spread_HY	US High-yield Spread
σ(Spread_EM)	SD(Spread_EM)	EMBI Sovereign Spread
Δ Spread_HY	DSpread_HY	US High-yield Spread
σ(Spread_HY)	SD(Spread_HY)	US High-yield Spread
Spread_HY/σ(Spread_HY)	R(Spread_HY)	Risk Aversion
Δlog(IIP)	DLIIP	US Industrial Production Index
Δlog(M3)	DLM3	M3 US Money Stock

$\Delta x_t = x_t - x_{t-1}$ $\sigma(x_t)$ = standard deviation of x_t over the previous 12 months

Visual examination of the main data trends (see Appendix 2) reveals some of the main characteristics accounted for by the model. The extreme variability of monthly bond flows (Figure A.1) and yield spreads (Figure A.2) is clear and well known. The bond flows have a rising trend into the crisis of the late 1990s, and seem to have stabilised at a lower (but still highly volatile) level thereafter. The inverse relationship between yields and flows is clear from Figure A.3 where the two graphs are combined.

Our source for risk aversion is the US High-Yield Spread (HYS)[12]. This is plotted against bond flows in Figure A.4, where the inverse relationship is evident. The direction of causality is presumably from the US home market to EM bond flows and spreads, given the relative size of the two asset classes. Similarly the direct relationship between HYS and EM spread is evident from Figure A.5. In common with other authors (e.g. IMF 2001; Mody and Taylor, 2002), we interpret this as reflecting changes in risk aversion which are shown in both the yield (the price of risk) and the flow (credit rationing).

[12] The difference between the yield on sub-investment grade ('junk') bonds and 10 year US Treasuries.

The exact formulation of the proxy variable for risk aversion from the HYS data is complicated. The microeconomic formulation in Kumar and Persaud (2001) would imply that the ratio of HYS to its standard deviation would be appropriate, and it is shown in Figure A.6. This also has the advantage of reflecting the 'Sharpe Ratio' used as a rule of thumb by investors,[13] as well as displaying a regular cyclical structure. However, we explain below, this proxy for risk aversion does not perform well econometrically. In fact, we find as Mody and Taylor (2002) do, that the change in the High-Yield Spread gives the best results.

5.2. Methodology and Empirical Results

In our model, since the effect of exogeneous variables on the dependent variables is spread over a period of time, we use *Autoregressive Distributed Lag* (ADL) model. Using *PcGets* (see Hendry and Krolzig, 2001), a general, dynamic, unrestricted, linear model of LTBDC and Spread_EM was constructed that incorporates the variables from the theoretical discussion above, and applies a *general-to-specific approach* in order to determine an undominated congruent model. We apply *PcGets* to two general, dynamic, unrestricted linear models of LTBDC and Spread_EM separately and obtain a congruent reduction of the two mentioned equations. Finally, we take account of the simultaneity of LTBDC and Spread_EM by collecting the two equations to Simultaneous Equations model and estimate the system by Full Information Maximum Likelihood (FIML) using *PcGive* (Hendry and Doornik, 2001).

[13] See Caouette, Altman and Narayanan (1998), p.242.

The lag order selected by *PcGets* is two for the first model and one for the second model (see Hendry and Krolzig, 2001);lag-order preselection results are shown in the Appendix.

General, 1993(2)-2001(12):

$$\begin{aligned}
\widehat{LTBDC}_t = &+ \underset{(0.101)}{0.47}\,LTBDC_{t-1} + \underset{(0.0958)}{0.135}\,LTBDC_{t-2} - \underset{(0.0206)}{0.033}\,Spread_EM_t - \underset{(0.029)}{0.033}\,Spread_EM_{t-1} \\
&+ \underset{(0.0245)}{0.008}\,Spread_EM_{t-2} + \underset{(0.852)}{3.51} + \underset{(0.124)}{0.154}\,SD(Spread_EM)_t - \underset{(0.195)}{0.161}\,SD(Spread_EM)_{t-1} \\
&+ \underset{(0.112)}{0.054}\,SD(Spread_EM)_{t-2} + \underset{(0.0103)}{0.0038}\,R(Spread_HY)_t + \underset{(0.0151)}{0.0029}\,R(Spread_HY)_{t-1} \\
&- \underset{(0.00908)}{0.0026}\,R(Spread_HY)_{t-2} + \underset{(0.0576)}{0.15}\,DLIIP_t + \underset{(0.0672)}{0.0626}\,DLIIP_{t-1} - \underset{(0.0653)}{0.109}\,DLIIP_{t-2} - \underset{(0.182)}{0.303}\,FedFunds_t \\
&+ \underset{(0.277)}{0.181}\,FedFunds_{t-1} + \underset{(0.2)}{0.21}\,FedFunds_{t-2} + \underset{(0.0777)}{0.0297}\,DLM3_t - \underset{(0.0844)}{0.0566}\,DLM3_{t-1} + \underset{(0.081)}{0.0346}\,DLM3_{t-2} \\
&- \underset{(0.0705)}{0.00526}\,DSpread_HY_t - \underset{(0.0689)}{0.0302}\,DSpread_HY_{t-1} - \underset{(0.069)}{0.127}\,DSpread_HY_{t-2}
\end{aligned}$$

Figures in parentheses show estimated standard errors.

(1)

Estimation statistics

RSS	3.9999	$\hat{\sigma}$	0.21953	R^{2}	0.84301	$R^{adj\,2}$	0.79951
LogLik	175.8308	AIC	-2.83796	HQ	-2.59492	SC	-2.23845
T	107	P	24	F_{pNull}	0.00000	F_{pConst}	0.00000

Misspecification tests

$F_{Chow(1997:7)}(54,29)$	= 1.880	[0.0342]	$F_{ar(1\text{-}4)}(4,79)$	= 1.685	[0.1617]
$F_{Chow(2001:2)}(11,72)$	= 1.769	[0.0756]	$F_{arch(1\text{-}4)}(4,99)$	= 0.870	[0.4851]
$\chi^2_{nd}(2)$	= 1.945	[0.3781]	$F_{het}(46,60)$	= 1.813	[0.0153]

Chow tests indicate that the model is structurally stable, with no structural breaks. The normality test is only marginally accepted (fat tails), but there is no autocorrelation in the error terms. There is some indication of heteroscedasticity, but this is to be expected with financial time series.

In general, the estimated coefficients of (1) are statistically insignificant and therefore not of great interest. Using *PcGets* reduction process, we eliminate the statistically insignificant variables while ensuring that all the information contained in (1) is retained in the reduced model. Standard testing procedures are applied to the unrestricted, congruent general model in order to arrive at an undominated, parsimonious representation of the data, with diagnostic tests to confirm the validity of the reductions (see Hendry and Krolzig, 2001). The *PcGets* model reduction process reduced the number of coefficients from 24 to 7 and yields the following ADL model of LTBDC:

Specific, 1993 (2) - 2001 (12)

$$\begin{aligned}\mathrm{LTBDC}_t^{\wedge} &= +\underset{(0.0609)}{0.584}\,\mathrm{LTBDC}_{t-1} - \underset{(0.0107)}{0.0484}\,\mathrm{Spread\_EM}_t + \underset{(0.555)}{3.71} + \underset{(0.0498)}{0.171}\,\mathrm{DLIIP}_t - \underset{(0.0696)}{0.228}\,\mathrm{FedFunds}_t \\ &+ \underset{(0.0765)}{0.316}\,\mathrm{FedFunds}_{t-2} - \underset{(0.0551)}{0.151}\,\mathrm{DSpread\_HY}_{t-2}\end{aligned} \tag{2}$$

Estimation statistics

RSS	4.6000	σ^	0.2145	$R^{\wedge 2}$	0.8195	$R^{adj\wedge 2}$	0.8086
LogLik	168.3522	AIC	-3.0159	HQ	-2.9450	SC	-2.8411
T	107	P	7	F_{pNull}	0.0000	F_{pGUM}	0.7612

Diagnostics

$F_{Chow(1997:7)}(54,46)$	= 1.379	[0.1328]	$F_{ar(1\text{-}4)}(4,96)$	= 1.981	[0.1035]
$F_{Chow(2001:2)}(11,89)$	= 1.396	[0.1887]	$F_{arch(1\text{-}4)}(4,99)$	= 2.065	[0.0911]
$\chi^2_{nd}(2)$	= 1.257	[0.5335]			

The specific model is able to explain 82% of the variation in the capital flows and the F-test of the specific against the general model rejects only at a marginal rejection probability of 0.7612, so the reduction cannot be rejected. Figure 1 shows the properties of the estimated model (2). The first (upper LHS) and second (upper RHS) graphs indicate the fit of the model over time and the fit against the actual values of LTBDC, respectively. The third (lower LHS) and fourth (lower RHS) graphs indicate the residuals and the squared residuals, respectively. Diagnostic tests confirm that (2) is a valid congruent reduction of the general model in (1) (See Hendry and Krolzig, 2001).

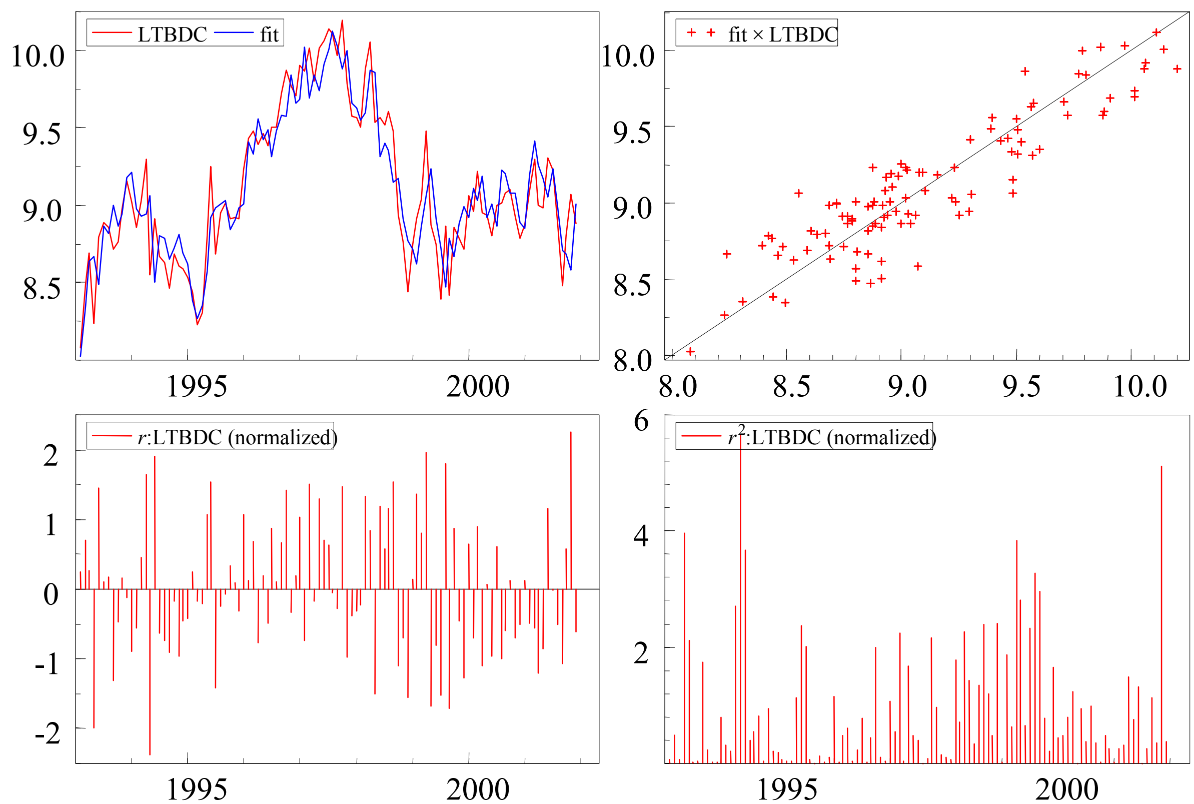

Figure 1. Model of LTBDC

Our second model is as follows:

General, 1993(2)-2001(12)

$$\widehat{Spread\_EM}_t = +\underset{(4.20)}{10.1} + \underset{(0.0884)}{0.758}\,Spread\_EM_{t-1} - \underset{(0.556)}{0.0449}\,SD(Spread\_EM)_t + \underset{(0.532)}{0.190}\,SD(Spread\_EM)_{t-1}$$
$$- \underset{(0.0505)}{0.024}\,R(Spread\_HY)_t + \underset{(0.0511)}{0.006}\,R(Spread\_HY)_{t-1} + \underset{(0.297)}{0.6893}\,DLIIP_t - \underset{(0.339)}{0.352}\,DLIIP_{t-1} - \underset{(0.535)}{0.497}\,LTBDC_t$$
$$- \underset{(0.494)}{0.482}\,LTBDC_{t-1} - \underset{(0.983)}{0.469}\,FedFunds_t + \underset{(1.026)}{0.588}\,FedFunds_{t-1} + \underset{(0.403)}{0.102}\,DLM3_t + \underset{(0.427)}{0.059}\,DLM3_{t-1}$$
$$+ \underset{(0.318)}{1.308}\,DSpread\_HY_t - \underset{(0.337)}{0.081}\,DSpread\_HY_{t-1} - \underset{(0.493)}{0.121}\,LiqEM_t + \underset{(0.485)}{0.100}\,LiqEM_{t-1} \quad (3)$$

Estimation statistics

RSS	122.36817	σ^	1.17257	$R^{\wedge 2}$	0.83761	$R^{adj\wedge 2}$	0.80659
LogLik	-7.17999	AIC	0.47065	HQ	0.65293	SC	0.92029
T	107	P	18	F_{pNull}	0.00000	F_{pConst}	0.00000

Misspecification tests

$F_{Chow(1997:7)}(54,34)$	= 0.704	[0.8777]	$F_{ar(1\text{-}4)}(4,84)$	= 0.889	[0.4743]
$F_{Chow(2001:2)}(11,77)$	= 1.198	[0.3030]	$F_{arch(1\text{-}4)}(4,99)$	= 2.854	[0.0276]
$\chi^2_{nd}(2)$	= 7.624	[0.0221]	$F_{het}(35,71)$	= 1.863	[0.0134]

There are two potential problems: the Chow test is only marginally accepted, possibly due to structural breaks; there is also evidence of heteroscedasticity, although not of the ARCH type. A centered impulse dummy, I(1998:8), was included to reflect the very large outlier ($\varepsilon_t > 3\sigma$) reflecting the Russian collapse in August 1998.

Specific, 1993(2)-2001(12)

$$\widehat{Spread\_EM}_t = +\underset{(2.4)}{7.43} + \underset{(0.0436)}{0.824}\,Spread\_EM_{t-1} - \underset{(0.237)}{0.659}\,LTBDC_t + \underset{(0.244)}{0.64}\,DSpread\_HY_t + \underset{(1.02)}{7.7}\,I1998:8_t \quad (4)$$

Estimation statistics

RSS	91.5499	σ^	0.9474	$R^{\wedge 2}$	0.8785	$R^{adj\wedge 2}$	0.87374
LogLik	8.3431	AIC	-0.0625	HQ	-0.0119	SC	0.06241
T	107	P	5	F_{pNull}	0.0000	F_{pGUM}	0.65903

Misspecification tests

$F_{Chow(1997:7)}(54,48)$	=	0.576	[0.9748]	$F_{ar(1-4)}(4,98)$	=	0.6605	[0.6209]
$F_{Chow(2001:2)}(11,91)$	=	0.415	[0.9456]	$F_{arch(1-4)}(4,99)$	=	1.7651	[0.1419]

With only 5 parameters, the model is able to explain 87.9% of the variation in the spread. The reduction is accepted at a marginal rejection probability of 0.659. Figure 2 shows the fit of the model and the plot of the estimation errors.

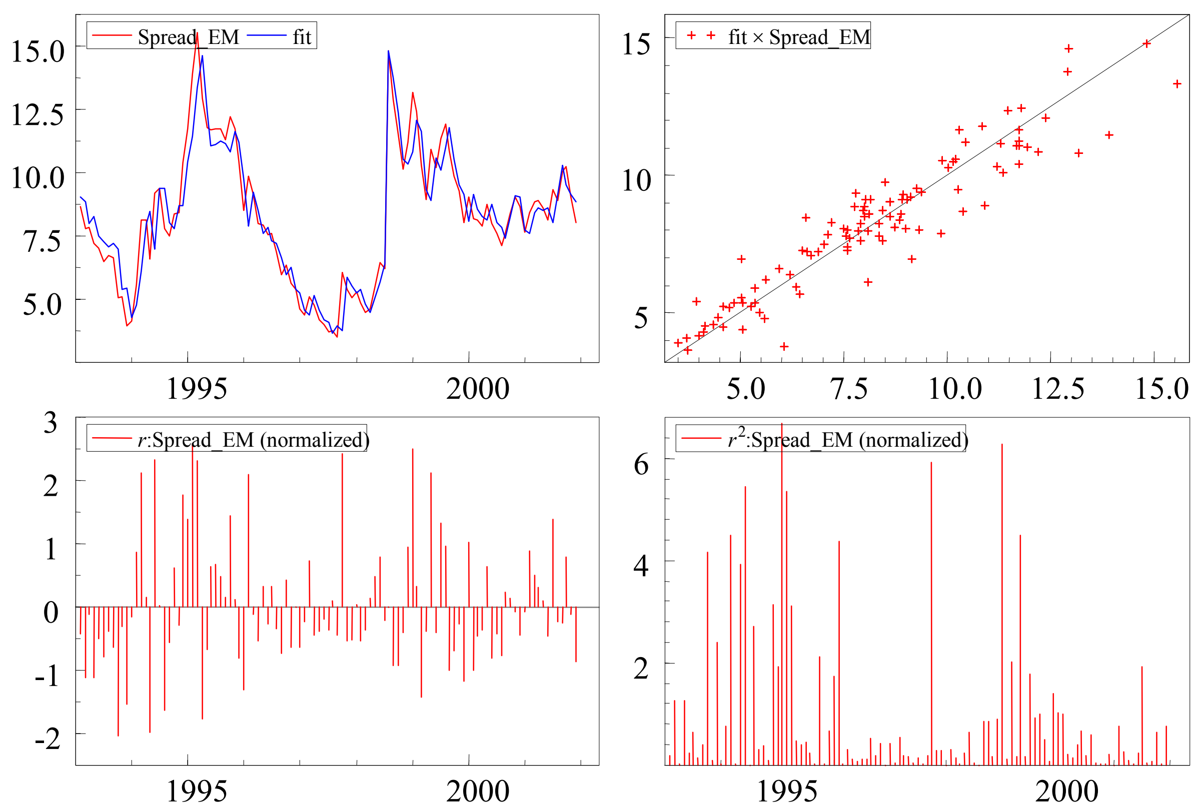

Figure 2. Model of Spread_EM

The Simultaneous Equations Model

The capital flows and interest rate spread dynamics of the system have so far been modelled by analyzing one equation at a time implicitly ignoring the simultaneity of equations (2) and (4). Due to the presence of instantaneous causality between LTBDC and Spread_EM, a single-equation model reduction approach is generally not efficient (Krolzig, 2001). We therefore check the restrictions imposed by *PcGets* in the previous subsection by combining the two equations in a simultaneous equation model

$$B\, y_t = \Gamma_1\, y_{t-1} + \Gamma_2\, x_t + \varepsilon_{t,}$$

where $y_t = (\text{LTBDC, Spread\_EM})'$ and x_t is the vector of the exogenous variables in the system. ε_t is a vector white noise process with $E[\varepsilon_t] = \Sigma$. Identification of the structural parameters is ensured by the null-restrictions set by *PcGets*.

FIML estimation[14] of the system yields almost identical parameter estimates (see Appendix 1) and a log-likelihood of the system of -128.84561. The standard error is 0.95304 in the first and 0.21355 in the second equation, while the correlation of structural residuals in the two equation is just 0.14775. The likelihood ratio (LR) test of the restrictions imposed by *PcGets* supports the empirical models (2) and (4): a χ^2(40) = 40.161 [0.4631] means that we can accept the reduction. The model reduction procedure used does not seem to be negatively affected by instantaneous non-causality.

5.3. Interpretation of the Results

In sum, this method yields the following two statistically robust simultaneous equations for our system (see again Appendix 1):

Flow determinants

$$\hat{LTBDC}_t = +\underset{(0.059)}{0.596}\,LTBDC_{t-1} - \underset{(0.011)}{0.0475}\,Spread\_EM_t + \underset{(0.555)}{3.62} + \underset{(0.048)}{0.163}\,DLIIP_t - \underset{(0.068)}{0.222}\,FedFunds_t + \underset{(0.074)}{0.304}\,FedFunds_{t-2} - \underset{(0.054)}{0.138}\,DSpread\_HY_{t-2}$$

Yield determinants

$$Spread\_\hat{EM}_t = +\underset{(2.804)}{6.44} + \underset{(0.046)}{0.836}\,Spread\_EM_{t-1} - \underset{(0.278)}{0.561}\,LTBDC_t + \underset{(0.244)}{0.656}\,DSpread\_HY_t + \underset{(1.021)}{7.48}\,I1998:8_t$$

In explaining aggregate bond flows, the lagged flow itself is the major explanatory variable, with a very high degree of persistence (60 percent) reflecting the widespread behaviour of momentum trading. The EM spread itself is significant and of the expected (negative) sign, but unexpectedly its standard deviation (to reflect volatility and thus risk) was not significant and thus discarded.

Our preferred measure of risk aversion (the ‘Sharpe Ratio’) was discarded as not significant either, but the alternative measure (change in U.S. HYS) is significant when lagged and of the expected (negative) sign, thus supporting our notion of risk aversion and credit rationing – the lag presumably reflecting portfolio adjustment delays. However, the outstanding bond stock, which we had included as a proxy for aggregate

[14] Using *PcGive10* (See Hendry and Doornik, 2001).

debt overhang, did not prove significant, which is unfortunate as this was our main 'pull' variable reflecting default risk.

Our measures of US wealth are US industrial production (as a proxy for monthly GDP) and liquidity (M3). The former was significant and with the correct sign; but the latter was not significant and thus discarded. However, although the current Federal Funds rate is significant and of the expected (negative) sign, the rate lagged by two months is also significant but with a positive sign. This could mean the presence of a difference operator[15] which might reflect the influence of *changes* in the Federal Funds rate at the six-weekly meeting of the Open Markets Committee.

The major explanator of yield spreads is lagged yield spread itself, with the expected (positive) sign reflecting asset bubbles and a very high degree of persistence (84 percent). As expected, bond flows are a significant variable, with the correct (negative) sign. Again, as in the case of flows, the change in HYS as a measure of home risk aversion itself is significant and has expected (positive) sign.

As in the case of the yields equation, the bond stock was discarded in earlier trials as not being significant. However, unlike the case of bond flows where no dummy term had been significant, one only was significant in the case of yields – that for the August 1998. This was the worst unexpected shock in the whole period: note that dummies did not seem significant for the Mexican or East Asian crises. It is of interest to note that the US

[15] Of the form ($-0.22FedFunds_t+0.304FedFunds_{t-2}$).

variables (funds rate, liquidity, output) did not turn out to be significant in explaining the yield spread – the effect of these variables being felt on the flow of bonds discussed above.

In sum, we have a high degree of persistence in the results, with risk aversion also affecting both yields and flows, all of which had been expected. Substituting the yield equation into the flow equation, it transpires that the 'full' lag coefficient for bond flows is of the order of 0.5. The unexpected result was that the two aggregate measures of host risk (debt stock and volatility of yields) did not turn out to be significant: this could be held to support the notion of two-stage portfolio allocation procedure, with host factors affecting country shares within the overall flow. The resulting fits are extremely good, as can be seen from Figures 1 and 2. However, the predictive power of the model should not be over-estimated: on the one hand, factors such as the US HYS are not forecastable; while on the other, the fitted function follows rather than anticipates turning-points.

6. CONCLUSIONS

This paper has set out to demonstrate how shifts in the demand schedule for emerging market assets affect prices (i.e. yield spreads) and quantities (flows). In doing so we have identified a number of points at which the macroeconomics of capital flows and the microeconomics of portfolio adjustment can be brought together to better define the key components of this demand schedule. We have also tried to establish how shifts in this demand schedule itself, independently of conditions in emerging markets, account for a large part of the changes in observed capital flows in the aggregate.

These are clearly initial results although they are clearly significant. The model could be tested on other markets, such as the UK bond flows towards emerging markets, or equity flows instead of bonds – although there are data limitations in both cases. The next proposed step is to test a similar model on flows to individual emerging markets.[16] This would involve including aggregate flows to EMs as a whole in the country-level models so as to reflect the two-stage process of portfolio construction. In this process, investors allocate funds to emerging markets as an asset class, and then between countries; where country characteristics and regional factors determine country shares.

Meanwhile, some tentative policy implications can be derived from our argument so far. To the extent that the greater part of the variance of flows and yields is determined by conditions within home financial markets, at the very least G3 governments could pay more attention to the negative effects on emerging markets of volatility within their own capital markets. As the IMF points out, “an approach to monetary policy that provides financial markets with clear indications of the US authorities' intentions is likely to reduce the impact of a US rate increase on developing countries” (IMF, 2000:68). However, the ability of the G3 to stabilise or even predict their macroeconomic cycles is clearly limited. Thus other measures in order to stabilise capital flows towards emerging markets from the ‘demand perspective’ might be considered. One possibility would be to

[16] The authors are currently engaged in this task.

encourage – by a combination of regulatory changes and tax incentives – G3 institutional investors to acquire and hold emerging market assets of a longer maturity than at present. This would in effect both shift the demand 'upwards' and reduce its volatility over the cycle by increasing risk appetite on a structural basis. The advantages to institutional investors would be higher long-term yields without the excess risk generated by the market instability of the past decade.

Another possibility would be to create greater liquidity in the market by encouraging 'market makers' (which could be the international financial institutions themselves or coordinated arrangements between regional central banks) to make an explicit commitment to counter-cyclical intervention so as to stand ready to buy assets from the private sector in the downswing of the cycle (when risk appetite declines) and sell in the upswing. This form of provision of liquidity would probably be more effective than the present practice of last-resort lending once crises have occurred, particularly since it would reduce the ex-ante volatility of emerging market assets and thus enhance their attractiveness to institutional investors.

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APPENDIX 1: ECONOMETRIC RESULTS

General-to-specific Modelling: bond flows

Lag-order preselection

lags	r	Diags	LogLik	Radj^2	AIC	HQ	SC	F-prob	max|t|	FpGUM
3	8	0	178.2131	0.7878	-2.7330	-2.4089	-1.9336	0.9014	0.2527	------
2	8	0	175.8308	0.7995+	-2.8380+	-2.5949	-2.2384	0.0241*	0.0696	0.9014
1	8	0	164.8484	0.7755	-2.7822	-2.6202+	-2.3825+	0.0000*	0.0000*	0.2021*
0	8	0	121.4851	0.5358	-2.1212	-2.0402	-1.9214	------	------	0.0000*

Selected lag order = 2.

GUM(115) Modelling LTBDC by GETS (using TICS.xls)
Estimation sample: 1993 (2) - 2001 (12)
Liberal strategy

	Coefficient	Std.Error	t-value	t-prob
LTBDC_1	0.46957	0.10067	4.665	0.0000
LTBDC_2	0.13457	0.09585	1.404	0.1641
Spread_EM	-0.03363	0.02059	-1.633	0.1063
Spread_EM_1	-0.03363	0.02899	-1.160	0.2495
Spread_EM_2	0.00844	0.02448	0.345	0.7312
Constant	3.50835	0.85195	4.118	0.0001
SD(Spread_EM)	0.15415	0.12360	1.247	0.2158
SD(Spread_EM)_1	-0.16109	0.19510	-0.826	0.4114
SD(Spread_EM)_2	0.05441	0.11230	0.485	0.6293
R(Spread_HY)	0.00382	0.01031	0.370	0.7122
R(Spread_HY)_1	0.00297	0.01514	0.196	0.8449
R(Spread_HY)_2	-0.00266	0.00908	-0.294	0.7698
DLIIP	0.15041	0.05756	2.613	0.0107
DLIIP_1	0.06259	0.06719	0.932	0.3542
DLIIP_2	-0.10868	0.06533	-1.663	0.1000
FedFunds	-0.30269	0.18213	-1.662	0.1003
FedFunds_1	0.18060	0.27676	0.653	0.5159
FedFunds_2	0.20988	0.20042	1.047	0.2981
DLM3	0.02967	0.07771	0.382	0.7036
DLM3_1	-0.05665	0.08437	-0.671	0.5038
DLM3_2	0.03465	0.08101	0.428	0.6700
DSpread_HY	-0.00526	0.07052	-0.075	0.9407
DSpread_HY_1	-0.03017	0.06892	-0.438	0.6627
DSpread_HY_2	-0.12682	0.06900	-1.838	0.0696

RSS	3.99991	Sigma	0.21953	R^2	0.84301	Radj^2	0.79951
LogLik	175.8308	AIC	-2.83796	HQ	-2.59492	SC	-2.23845
T	107	P	24	FpNull	0.00000	FpConst	0.00000

		value	prob	alpha
Chow(1997:7)	F(54, 29)	1.8797	0.0342	0.0050
Chow(2001:2)	F(11, 72)	1.7693	0.0756	0.0100
normality test	chi^2(2)	1.9452	0.3781	0.0100
AR 1-4 test	F(4, 79)	1.6850	0.1617	0.0100
ARCH 1-4 test	F(4, 99)	0.8696	0.4851	0.0100
hetero test	F(46, 60)	1.8131	0.0153	0.0000

MOD(115) Specific model of LTBDC (using TICS.xls)
Estimation sample: 1993 (2) - 2001 (12)

	Coefficient	Std.Error	t-value	t-prob	Split1	Split2	reliable
LTBDC_1	0.58437	0.06086	9.602	0.0000	0.0000	0.0000	1.0000
Spread_EM	-0.04839	0.01073	-4.510	0.0000	0.0000	0.0000	1.0000
Constant	3.71218	0.55476	6.692	0.0000	0.0000	0.0000	1.0000
DLIIP	0.17108	0.04979	3.436	0.0009	0.0051	0.0005	1.0000
FedFunds	-0.22773	0.06961	-3.271	0.0015	0.0317	0.0316	1.0000
FedFunds_2	0.31553	0.07654	4.122	0.0001	0.0003	0.0216	1.0000
DSpread_HY_2	-0.15055	0.05515	-2.730	0.0075	0.0003	0.0071	1.0000

RSS	4.60001	sigma	0.21448	R^2	0.81946	Radj^2	0.80862
LogLik	168.35220	AIC	-3.01593	HQ	-2.94504	SC	-2.84107
T	107	p	7	FpNull	0.00000	FpGUM	0.76122

		value	prob
Chow(1997:7)	F(54, 46)	1.3795	0.1328
Chow(2001:2)	F(11, 89)	1.3961	0.1887
normality test	chi^2(2)	1.2566	0.5335
AR 1-4 test	F(4, 96)	1.9809	0.1035
ARCH 1-4 test	F(4, 99)	2.0654	0.0911

Yield spread: Emerging Markets

Lag-order preselection

lags	r	diags	LogLik	Radj^2	AIC	HQ	SC	F-prob	max|t|	FpGUM
3	9	0	4.4460	0.8049	0.5898	0.9543	1.4891	0.5801	0.1349	------
2	9	0	-0.9809	0.8084+	0.5230	0.7964	1.1975	0.3781	0.1497	0.5801
1	9	0	-7.1800	0.8066	0.4707+	0.6529+	0.9203+	0.0000*	0.0000*	0.5163
0	9	0	-49.2190	0.6146	1.0882	1.1793	1.3130	------	------	0.0000*

Selected lag order = 1.

GUM(116) Modelling Spread_EM by GETS (using TICS.xls)
Estimation sample: 1993 (2) - 2001 (12)
Liberal strategy

	Coefficient	Std.Error	t-value	t-prob
Spread_EM_1	0.75844	0.08846	8.574	0.0000
Constant	10.10810	4.20204	2.406	0.0182
SD(Spread_EM)	-0.04491	0.55657	-0.081	0.9359
SD(Spread_EM)_1	0.19069	0.53270	0.358	0.7212
R(Spread_HY)	-0.02408	0.05056	-0.476	0.6350
R(Spread_HY)_1	0.00692	0.05113	0.135	0.8926
DLIIP	0.68932	0.29767	2.316	0.0229
DLIIP_1	-0.35249	0.33914	-1.039	0.3015
LTBDC	-0.49705	0.53538	-0.928	0.3557
LTBDC_1	-0.48236	0.49472	-0.975	0.3322
FedFunds	-0.46939	0.98319	-0.477	0.6342
FedFunds_1	0.58802	1.02692	0.573	0.5684
DLM3	0.10211	0.40357	0.253	0.8008
DLM3_1	0.05978	0.42778	0.140	0.8892
DSpread_HY	1.30881	0.31843	4.110	0.0001
DSpread_HY_1	-0.08188	0.33739	-0.243	0.8088
LiqEM	-0.12194	0.49357	-0.247	0.8054
LiqEM_1	0.10081	0.48542	0.208	0.8360

RSS	122.36817	sigma	1.17257	R^2	0.83761	Radj^2	0.80659
LogLik	-7.17999	AIC	0.47065	HQ	0.65293	SC	0.92029
T	107	p	18	FpNull	0.00000	FpConst	0.00000

		value	prob	alpha
Chow(1997:7)	F(54, 34)	0.7038	0.8777	0.0100
Chow(2001:2)	F(11, 77)	1.1977	0.3030	0.0100
normality test	chi^2(2)	7.6241	0.0221	0.0000
AR 1-4 test	F(4, 84)	0.8889	0.4743	0.0100
ARCH 1-4 test	F(4, 99)	2.8541	0.0276	0.0050
hetero test	F(35, 71)	1.8633	0.0134	0.0000

MOD(116) Specific model of Spread_EM (using TICS.xls)
Estimation sample: 1993 (2) - 2001 (12)

	Coefficient	Std.Error	t-value	t-prob	Split1	Split2	reliable
Spread_EM_1	0.82430	0.04355	18.926	0.0000	0.0000	0.0000	1.0000
Constant	7.43229	2.39856	3.099	0.0025	0.0007	0.0001	1.0000
LTBDC	-0.65872	0.23730	-2.776	0.0066	0.0020	0.0003	1.0000
DSpread_HY	0.63981	0.24439	2.618	0.0102	0.0458	0.0046	1.0000
I1998:8	7.70355	1.02383	7.524	0.0000	0.0000	0.0000	1.0000

RSS	91.54985	sigma	0.94739	R^2	0.87851	Radj^2	0.87374
LogLik	8.34307	AIC	-0.06249	HQ	-0.01186	SC	0.06241
T	107	p	5	FpNull	0.00000	FpGUM	0.65903

		value	prob
Chow(1997:7)	F(54, 48)	0.5767	0.9748
Chow(2001:2)	F(11, 91)	0.4159	0.9456
AR 1-4 test	F(4, 98)	0.6605	0.6209
ARCH 1-4 test	F(4, 99)	1.7651	0.1419

Simultaneous Equation Model

MOD(1) Estimating the model by FIML (using TICS.xls)
The estimation sample is: 1993 (2) to 2001 (12)

Equation for: Spread_EM

	Coefficient	Std.Error	t-value	t-prob
Spread_EM_1	0.83659	0.04618	18.1	0.000
Constant	6.44060	2.804	2.30	0.024
LTBDC	-0.561045	0.2786	-2.01	0.047
DSpread_HY	0.656407	0.2440	2.69	0.009
I1998:8	7.48811	1.021	7.34	0.000

sigma = 0.95304

Equation for: LTBDC

	Coefficient	Std.Error	t-value	t-prob
LTBDC_1	0.596982	0.05992	9.96	0.000
Spread_EM	-0.0475242	0.01139	-4.17	0.000
Constant	3.62237	0.5554	6.52	0.000
DLIIP	0.163324	0.04890	3.34	0.001
FedFunds	-0.222525	0.06853	-3.25	0.002
FedFunds_2	0.304200	0.07499	4.06	0.000
DSpread_HY_2	-0.138531	0.05450	-2.54	0.013

sigma = 0.213547

log-likelihood	-128.84561	-T/2log|Omega|	174.807236
no. of observations	107	no. of parameters	12

LR test of over-identifying restrictions: Chi^2(40)= 40.161 [0.4631]
BFGS using analytical derivatives (eps1=0.0001; eps2=0.005):
Strong convergence

correlation of structural residuals (standard deviations on diagonal)

	Spread_EM	LTBDC
Spread_EM	0.95304	0.14775
LTBDC	0.14775	0.21355

APPENDIX 2: DATA CHARTS

FIGURE .A.1 MONTHLY BOND FLOWS

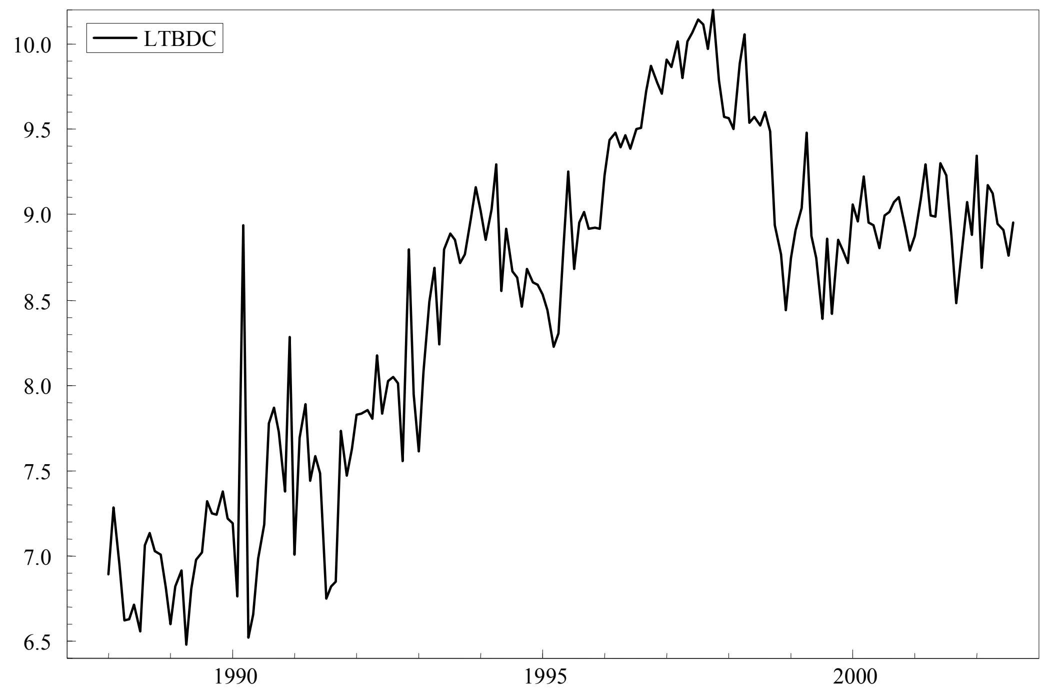


FIGURE A.2 EMERGING MARKET YIELD SPREAD

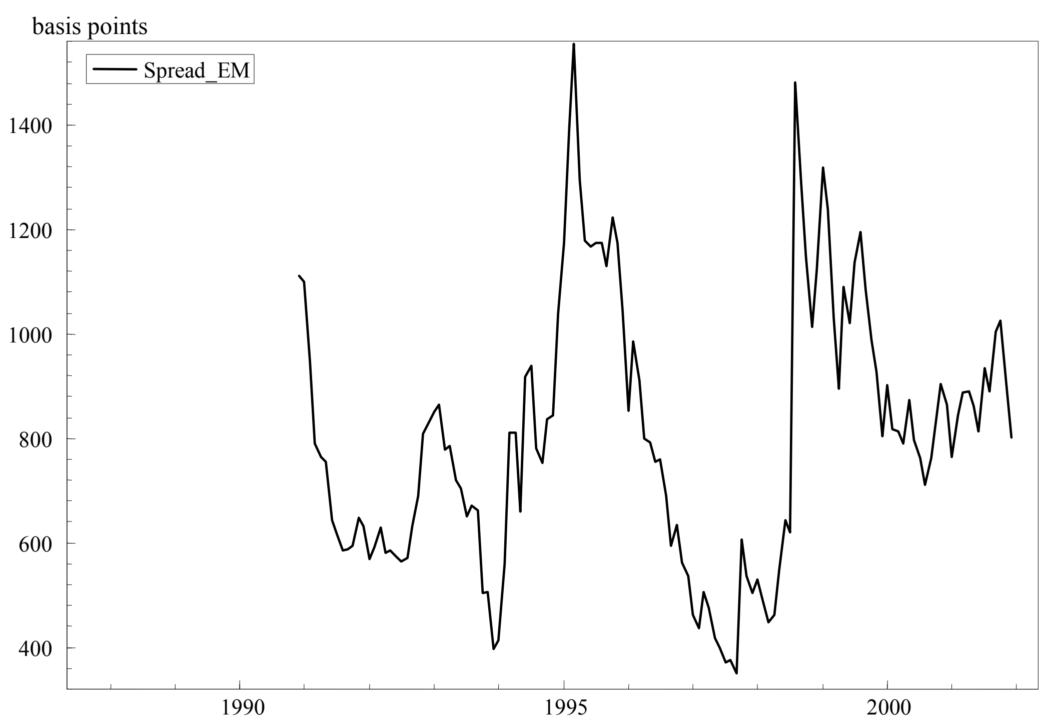


FIGURE A.3 BOND FLOWS AND YIELD SPREAD

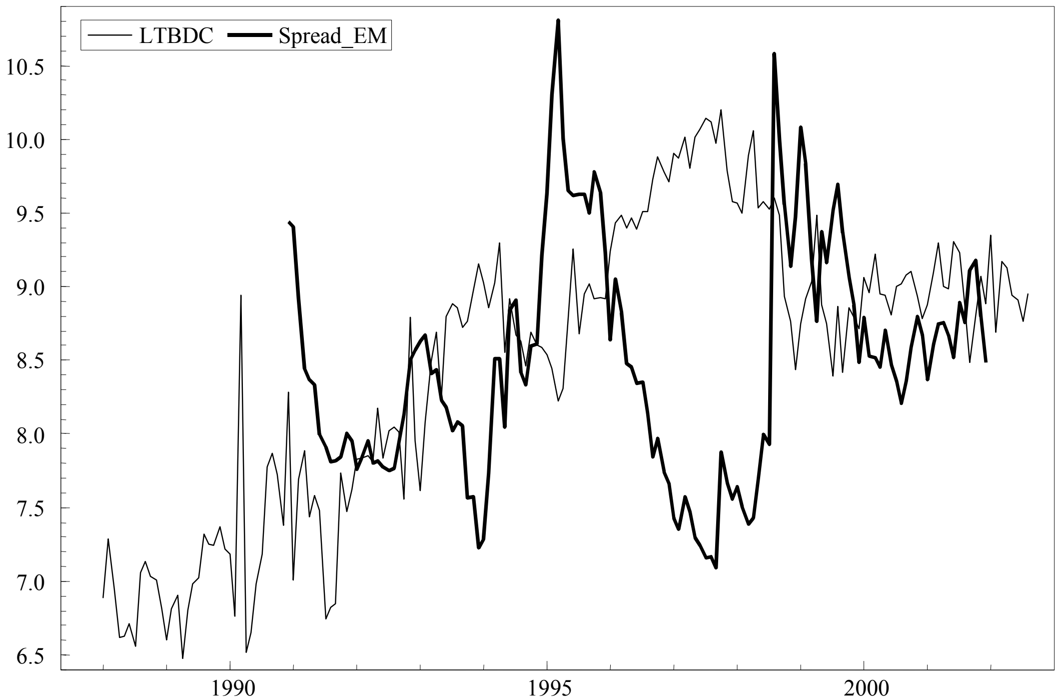


FIGURE A.4 BOND FLOWS AND US HIGH YIELD SPREAD

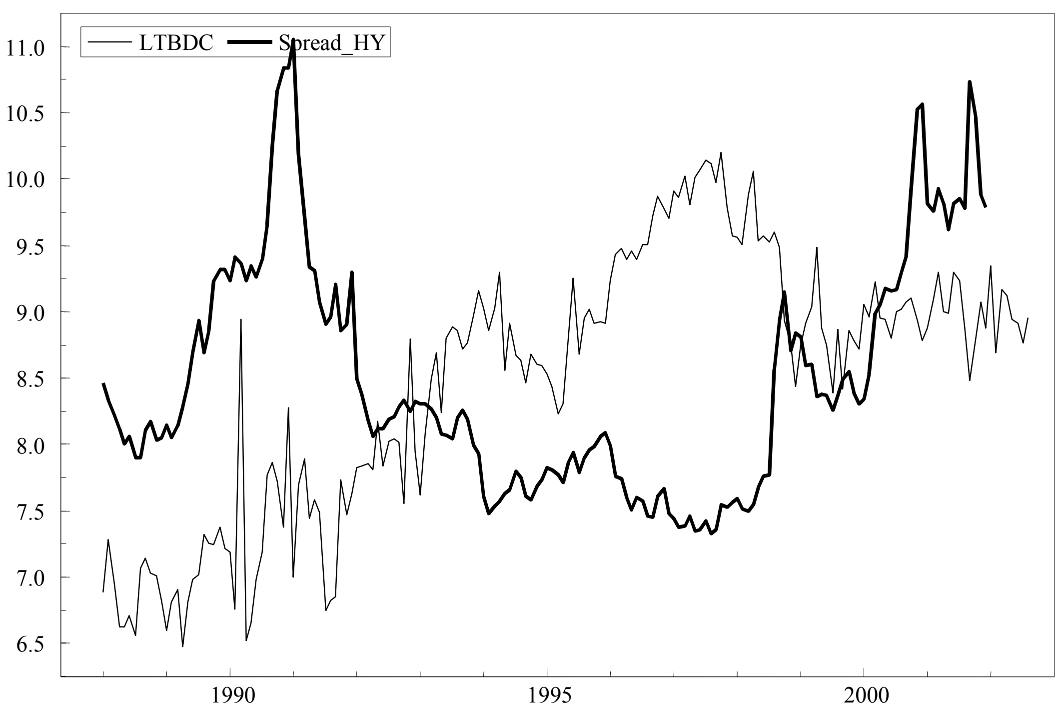


FIGURE A.5 EM YIELD SPREAD AND US HIGH YIELD SPREAD

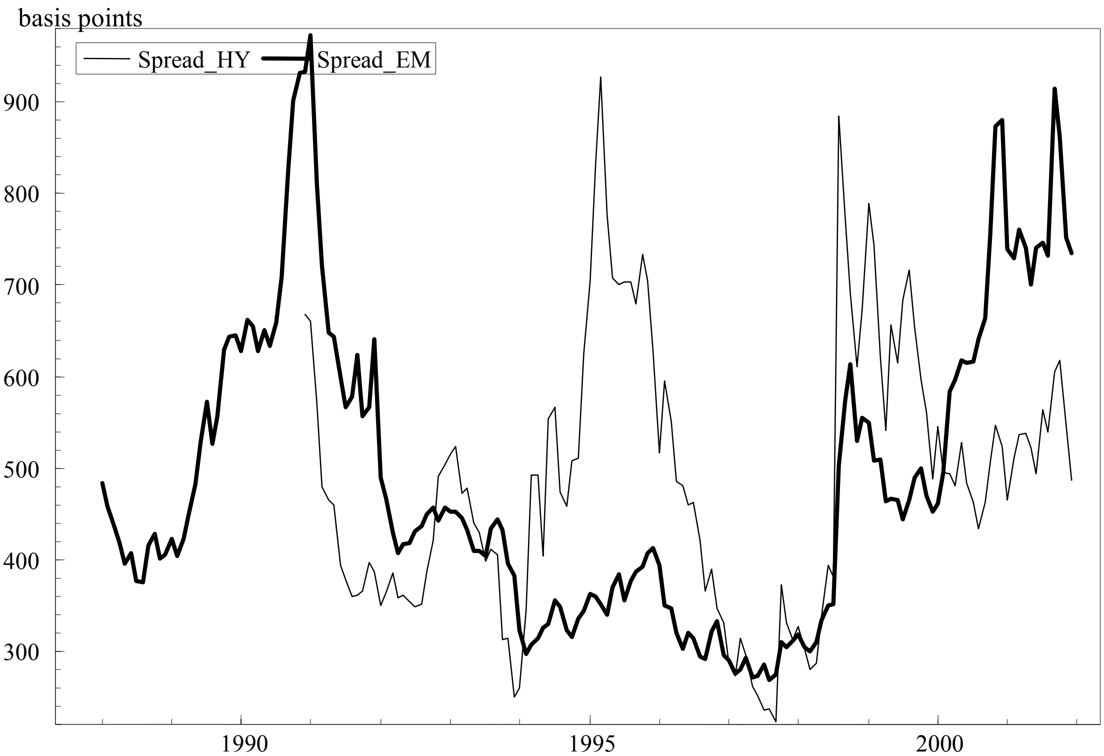
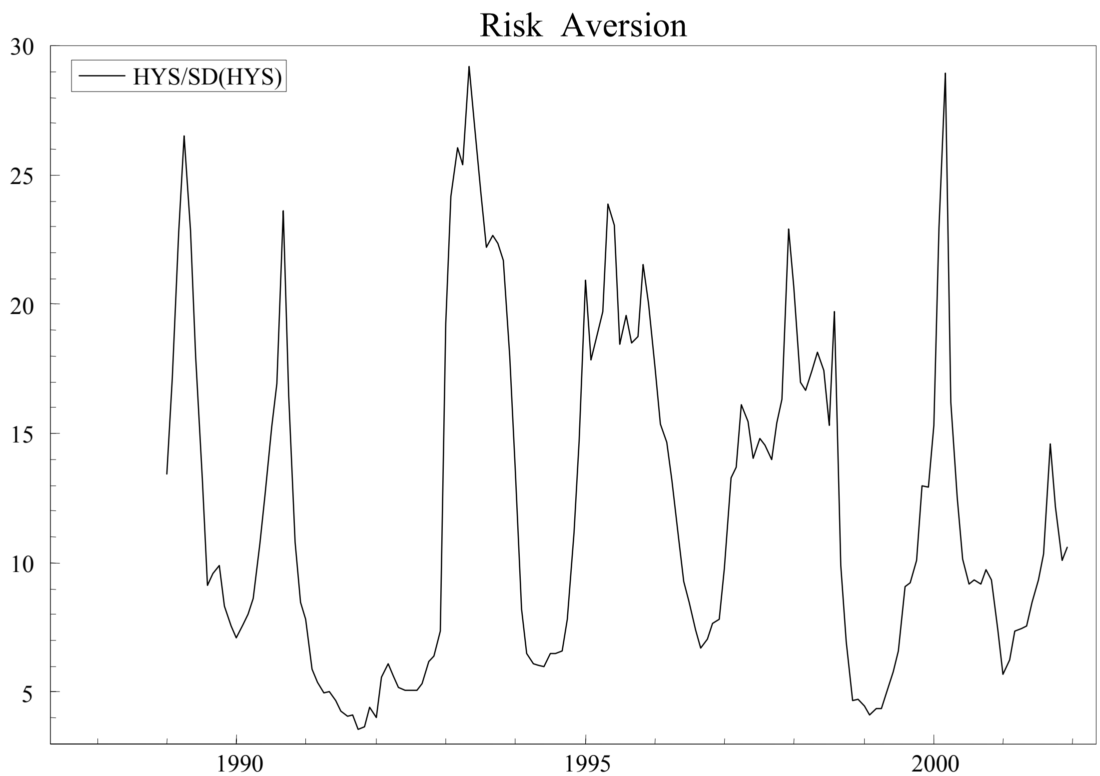


FIGURE A.6 A 'SHARPE RATIO" MEASURE OF RISK AVERSION



DATA SOURCES

US Bond Flows US Treasury Department (TIC: Treasury's International Capital Reports) (htpp://www.ustreas.gov)

EMBI Sovereign Spread Bloomberg (JPSS PRD)
<Index>

US High Yield Spread Bloomberg
(calculated as the difference between: J0A0 - GA10)
<Index> <Index>

US Industrial Production Index (seasonally adjusted) IFS 66..IZF

US Fed Funds Rate US Federal Reserve System (htpp://www.federalreserve.gov)

M3 US Money Stock (seasonally adjusted) US Federal Reserve System
(htpp://www.federalreserve.gov)

Emerging Market Liquidity Index Cross Border Capital