Global Market Integration Reversals and Funding Liquidity*

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Abstract

This paper shows the role of the funding liquidity in global financial integration reversals. First, we construct a segmentation indicator based on funding liquidity differences across countries as measured by the performance of local betting-against-beta strategies. Second, we find that funding liquidity shocks help explain recent integration reversals in the absence of any new explicit foreign investment barriers. These findings are consistent with tighter limits to arbitrage and increased home bias during funding distress periods. Our empirical analysis is guided by a margin-CAPM model extended to an international setting.

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1 Introduction

Financial markets became more integrated internationally over the past decades. Researchers attributed this long-run trend to the progressive reduction of barriers to foreign investment around the world, such as capital controls or taxes on repatriation.[1] However, reversals in market integration, i.e. transitory increases in market segmentation, are at odds with the permanent removal of such impediments. Reversals occur, for instance, during financial crises when cross-border investment activity becomes severely disrupted, despite no notable increase in explicit investment barriers.[2] Moreover, fundamental shocks tend to become more correlated during crisis periods, which further challenges the analysis of market integration dynamics.[3]

In this paper, we shed new light on the dynamics of global market integration by considering the role of leverage- and margin-constrained investors in international financial markets. Our contribution is twofold. First, we construct a new market segmentation indicator based on the dispersion in the returns of the country betting-against-beta (BAB) portfolios. Our approach is to infer the degree of market segmentation from the differences in country-level funding liquidity that drives the performance of BAB strategies. Second, we find that reversals in market integration are related to funding liquidity shocks, suggesting that the ease with which investors can fund their international positions is an important driver of market integration, in addition to the level of other investment barriers.

As a first step, we build a simple international asset pricing model in which investors have to fund a fraction of their position in each asset with their own capital. Capital requirements are assumed to be not only investor-specific but also country-specific. This results in potential heterogeneity in investors' ability to access different markets by taking on leveraged positions.[4] In equilibrium, each security commands a premium proportional to its exposure to market risk, as well as a compensation for the capital required to maintain the position in this security. In turn, BAB portfolios, that are long the low-beta assets and short the high-beta assets in their respective countries, are constructed to have zero exposure to global market risk and load on the country funding component only. In perfectly integrated financial markets, BAB returns depend on the shadow price of the funding constraint of

[1]See Bekaert and Harvey (1995), Carrieri, Errunza, and Hogan (2007), Bekaert, Harvey, Lundblad, and Siegel (2011, 2013), Carrieri, Chaieb, and Errunza (2013), and Eiling and Gerard (2014), among others.

[2]Lehkonen (2014) directly tests and documents lower market integration levels during the East Asia crisis, dot-com crash, and sub-prime crisis.

[3]See Carrieri et al. (2007) and Pukthuanthong and Roll (2009) who discuss empirical and theoretical issues with using market-wide correlations across countries as a measure of market integration.

[4]The model builds on Frazzini and Pedersen (2014). Chen and Lu (2014) and Malkhozov, Mueller, Vedolin, and Venter (2014) also consider a similar setting but for different applications.

the representative international investor. Therefore, they should be highly correlated across countries. In contrast, when it is more difficult to take on leveraged positions in foreign assets, funding shocks to a given investor have differential impact on this investor's home and foreign markets. As a result, BAB returns become more dispersed.

We construct the BAB portfolios across 62 countries (25 developed markets and 37 emerging markets) at monthly frequency from daily firm-level stock prices for the period from 1973 to 2014. The average returns of these country BAB portfolios are large and positive for most countries. BAB portfolios correlate more strongly among developed markets, compared to emerging markets. In crisis periods, BAB portfolios tend to comove less across countries, in stark contrast to country market indices that have been shown in previous research to comove more.[5]

Building on these results, we construct a Funding-liquidity Segmentation Indicator (FSI) based on the measures of global funding liquidity extracted from countries' BAB portfolio returns. Specifically, we use Bayesian methods to estimate the shadow price of the funding constraint for the marginal investor in each market. In the context of the model and under the null of no segmentation, all the shadow prices measure the global representative investor's funding liquidity and are the same across markets. However, they differ if capital markets are not perfectly integrated. We measure segmentation for a given country as the aggregate distance of its shadow price from those of the other markets.

This newly introduced segmentation indicator fits the previously documented evidence on market segmentation. First, the FSIs of developed markets are 30 percent smaller than those of emerging markets. In addition, the FSIs of all markets exhibit downward trends. Such trend is larger for the emerging markets, consistent with the impact of the progressive reductions of foreign investment barriers around the world.

More interestingly, FSI also indicates substantial market integration reversals. These reversals coincide with periods of tight global funding constraints and cannot be accounted for by the existing explanations in the literature. Indeed, we find a positive and statistically significant association between FSI and commonly used measures of global funding liquidity, even after controlling for the previously studied explanatory factors of market segmentation. The association with funding liquidity holds when we use an alternative measure of market segmentation based on the difference in monthly price-to-earnings ratios of industry portfolios across countries proposed by Bekaert et al. (2011, 2013) (BHLS hereafter). Finally, for each country we also find a positive association between local funding liquidity and both the FSI and BHLS measures of that country.

[5] See Huang, Lou, and Polk (2014) and Bali, Brown, Murray, and Tang (2014) for additional evidence on the performance of BAB portfolios through time.

Our analysis carefully distinguishes funding and market liquidity. Research has demonstrated the role of liquidity risk in international investments and has shown that liquidity risk as a priced local factor may lead to valuation differentials (see for example Bekaert, Harvey, and Lundblad (2007) and Lee (2011)). However, the effect of funding liquidity due to constraints on intermediaries' capital is different from the effect of asset liquidity, although the two could potentially be linked (Brunnermeier and Pedersen (2009)). We control for local market liquidity and find an insignificant relationship between market liquidity and FSI, consistent with the results of Goyenko and Sarkissian (2014).

Our findings of increased segmentation during funding shocks are supported by the recent research on cyclicality of international capital flow (for example see Rey (2015)). During periods of high market volatility, when the VaR (capital) constraints of large financial institutions are more binding, international credit inflows and portfolio debt inflows drop significantly across markets. In contrast, during periods of low volatility, inflows grow across all markets increasing market integration. Gârleanu, Panageas, and Yu (2015) show that small variations in market access costs across different locations may cause abrupt deleveraging and portfolio-flow reversals in bad times. In this case, the resulting outflows from the leveraged strategies reduce aggregate market integration and depress the prices of risky securities.

While providing an explanation for reversals in market integration, this paper contributes to the literature on international asset pricing by linking it to the one on limits to arbitrage and home bias. The literature of intermediary asset pricing and limits to arbitrage shows that frictions, such as funding liquidity, could result in deviations from the Law of One Price (LOP).[6] Influential theoretical research in this literature includes Shleifer and Vishny (1997), Basak and Croitoru (2000), Gromb and Vayanos (2002), Brunnermeier and Pedersen (2009), Geanakoplos (2010), Gârleanu and Pedersen (2011), Ashcraft, Gârleanu, and Pedersen (2011), Duffie and Strulovici (2012), He and Krishnamurthy (2012, 2013), Fostel and Geanakoplos (2013), Adrian and Shin (2014). There is extensive empirical research on funding constraints and asset prices confirming the findings of these theoretical explanations (for a short list of recent research see Hameed, Kang, and Viswanathan (2010), Ang, Gorovyy, and van Inwegen (2011), Hu, Pan, and Wang (2013), Adrian, Muir, and Etula (2014), Pasquariello (2014), Frazzini and Pedersen (2014), and Fleckenstein, Longstaff, and Lustig (2014)). Temporary deviations from the LOP match the definition of reversals, where similar assets with identical cash flows are priced differently across international markets (Chen and Knez (1995)). Literature on the dynamics of home bias, such as Warnock and

[6] As Pontiff (2006) shows, this effect is larger for more volatile assets, such as those in emerging markets, where idiosyncratic risk reduces demand for a mispriced asset and dampens arbitrage activity due to the hedging demand.

Warnock (2009), Hoggarth, Mahadeva, and Martin (2010), Jotikasthira, Lundblad, and Ramadorai (2012), and Giannetti and Laeven (2012, 2015) also suggests a link between funding liquidity and reversals in market integration, documenting that the home bias of institutional investors increases following funding shocks.[7] These investors are responsible for most cross-country investments; therefore, the frictions they face directly affect international asset prices and the global integration process. As they "fly home" more risk should be borne by local investors, which would increase market segmentation.

The dynamics of financial integration matter for international risk sharing and the cost of capital across countries. Thus reversals can be costly. The funding liquidity channel explored in this paper adds a new dimension to the existing research on those dynamics (see for instance, Carrieri et al. (2007), Pukthuanthong and Roll (2009), Bekaert et al. (2011), and Carrieri et al. (2013)). This strand of research, building on the theoretical international finance models, characterizes the role of explicit and implicit barriers in foreign investments.[8] This paper argues that short-term reversals in the level of market integration, contrary to the long-term trend and cross-sectional differences, are difficult to explain by the decreasing severity of the barriers that we have observed in the last few decades. On the other hand, these dynamics can be partially explained by short-term funding frictions, which are contemporaneous with most of the reversals.

The rest of the paper is organized as follows. Section 2 introduces the Funding-liquidity Segmentation Indicator. The data and the estimation results are presented in Sections 3 and 4. Section 5 concludes.

2 Funding-implied Segmentation Indicator

2.1 A Model with Funding Barriers to International Investment

We consider an economy with two dates $t = 0, 1$ and two countries indexed by j.[9] In each country there exist a set of stocks $k \in \mathcal{K}_j$ and a set of competitive investors $i \in \mathcal{I}_j$. We denote the set of all stocks by $\mathcal{K}$ and the set of all investors by $\mathcal{I}$.

Each stock k is in fixed supply and its gross return between dates 0 and 1 is denoted by R_k. Agents also have access to a global riskless asset with gross return R_0 given exogenously. Finally, we assume that purchasing power parity holds and all prices are expressed in US dollars.[10]

[7] See Coeurdacier and Rey (2013) for a recent survey on the research on home bias.

[8] Early work includes Black (1974), Stulz (1981), and Errunza and Losq (1985).

[9] We can think about the second country as the rest of the world.

[10] See, e.g., Bekaert et al. (2007) who make a similar assumption.

Each investor i can invest in all assets of the world economy. She maximises

$$\max_{\{x_{i,k}\}_{k\in\mathcal{K}}} \mathrm{E}_0\left[W_{i,1}\right] - \frac{\alpha_i}{2}\mathrm{Var}_0\left[W_{i,1}\right]$$

subject to her budget constraint

$$W_{i,1} = W_{i,0}R_0 + \sum_{k\in\mathcal{K}}\left(R_k - R_0\right)x_{i,k},$$

where $W_{i,0}$ is investor's initial wealth and $x_{i,k}$ is the dollar amount investor i holds in stock k at time 0.

Furthermore, investors' leverage is limited through some combination of regulatory constraints and market discipline.[11] Specifically, investing in or shorting securities requires investor i to commit the amount of her capital equal to the multiple $m_{i,k}$ of the position size:

$$\sum_{k\in\mathcal{K}} m_{i,k}\left|x_{i,k}\right| \leq W_{i,0} + \zeta_i, \tag{1}$$

where ζ_i is a shock that tightens or relaxes the leverage constraint before investor chooses her optimal portfolio. These shocks are a reduced form way to model changes in investors' capital position through past investment gains/losses and any exogenous shocks to their funding liquidity. Stock $k \in \mathcal{K}_j$ capital requirement is given by

$$m_{i,k} = \begin{cases} m, & \text{if } i \in \mathcal{I}_j \\ \kappa m, & \text{if } i \notin \mathcal{I}_j. \end{cases}$$

When $\kappa > 1$, it is more costly (in terms of committed capital) for investors to take foreign leveraged positions relative to domestic leveraged positions. Thus, in the model $\kappa - 1$ measures the funding barriers to international investments.[12]

Finally, we focus on the case in which investors are primarily concerned with funding their long positions in the international stock market, in line with evidence in Frazzini and Pedersen (2014), and assume $x_{i,k} > 0$.

Conditional on the realisations of funding liquidity shocks ζ_i, we have

[11] Investors who are active in international financial markets can be subject to bank capital requirements, participation constraints imposed by debtholders, margin requirements, etc.

[12] In practice, it could be more difficult to borrow against assets in more volatile emerging markets. Similarly, investors differ in their borrowing ability given that some investors, such as large institutional investors, are able to lever up their portfolios more easily. Allowing capital requirements to be $m_i m_k$ for domestic and $\kappa m_i m_k$ for foreign positions has no bearing on our result.

Proposition 1. *The equilibrium expected return on a self-financing market-neutral portfolio that is long in low-beta securities and short in high-beta securities in country j is*

$$\mathrm{E}_0\left(R_{BAB,j}\right) = \left(\frac{1}{\beta_L} - \frac{1}{\beta_H}\right)\Psi_j,$$

where

$$\begin{aligned}\Psi_j &= m\sum_{i\in\mathcal{I}_|}\frac{\alpha}{\alpha_i}\psi_i + \kappa m\sum_{i\notin\mathcal{I}_|}\frac{\alpha}{\alpha_i}\psi_i \\ &= m\sum_{i\in\mathcal{I}}\frac{\alpha}{\alpha_i}\psi_i + (\kappa-1)\,m\sum_{i\notin\mathcal{I}_|}\frac{\alpha}{\alpha_i}\psi_i,\end{aligned} \tag{2}$$

β_L, β_H are global market betas of the long and short legs of the portfolio, respectively, ψ_i are Lagrange multipliers associated with Equation (1), and $\frac{1}{\alpha} = \sum\limits_{i\in\mathcal{I}}\frac{1}{\alpha_i}$.

The proof, shown in the appendix, follows Frazzini and Pedersen (2014). Proposition 1 states that the expected return on country j betting-against-beta portfolio reflects the compensation required by investors for capital tied down in holding country j stocks.

The realisation of funding liquidity shocks ζ_i determines the shadow prices of capital ψ_i, and thereby the expected performance of betting-against-beta portfolios. We have

Proposition 2. *Assuming ζ_i independent across investors and denoting $Var_\zeta\left(\psi_i\right) = \sigma_i^2$,*

$$\begin{aligned}\mathrm{Corr}_\zeta\left(\Psi_j, \Psi_{j'}\right) &= \frac{1}{\sqrt{1 + \left(\frac{1}{\kappa} - \kappa\right)^2 \frac{\sum\limits_{i\in\mathcal{I}_j}\frac{\alpha^2}{\alpha_i^2}\sigma_i^2 \sum\limits_{i\in\mathcal{I}_{j'}}\frac{\alpha^2}{\alpha_i^2}\sigma_i^2}{\left(\sum\limits_{i\in\mathcal{I}_j}\frac{\alpha^2}{\alpha_i^2}\sigma_i^2 + \sum\limits_{i\in\mathcal{I}_{j'}}\frac{\alpha^2}{\alpha_i^2}\sigma_i^2\right)^2}}}, \\ \frac{\partial\mathrm{Corr}_\zeta\left(\Psi_j, \Psi_{j'}\right)}{\partial\kappa} &< 0 \quad \textit{for } \kappa > 1.\end{aligned}$$

Proposition 2 follows from Equation (2). It has two implications that motivate our Funding-implied Segmentation Indicator. First, funding liquidity shocks introduce commonality in the performance of of betting-against-beta portfolios, even when these shocks are uncorrelated across investors. In particular, when $\kappa = 1$, expected returns on all betting-against-beta portfolios depend on the overall global funding liquidity and are perfectly correlated. Second, when $\kappa > 1$, the correlation between the expected performance of betting-against-beta portfolios is decreasing in the funding barrier to international investment measured by $\kappa - 1$. This is because the funding liquidity of domestic investors and that of foreign investors have a different weighting in the expected betting-against-beta portfolio returns as investors have to tie down additional capital for their foreign positions.

2.2 Empirical Implementation

This section introduced the Funding-implied Segmentation Indicator (FSI). This measure is constructed from the discrepancies of the shadow price of the funding constraints, estimated from the BAB portfolios and Equation (2).

We follow Frazzini and Pedersen's methodology in estimating BAB portfolios. That is, at each period t and in each country j, all assets are ranked based on their betas with respect to global market portfolio and are grouped in two categories (high- and low-beta). In each group, securities are weighted by the beta ranks in that group. The BAB portfolio for country j is then formed by longing the low-beta portfolio, leveraged to beta one, and shorting the high-beta portfolio, de-leveraged to a beta of one.[13]

Under the null of integration, i.e. $\kappa = 1$, Equation (2) shows that, once such portfolios are constructed, one can extract the funding liquidity of the global representative investor, ψ, from the BAB portfolio in market j, while controlling for both the beta spread and margins. We control for the cross-sectional differences in margin requirement, m, assuming that the *country-specific* margins in country j, m^j are well approximated by local market volatility, $m_t^j = a + b\sigma_{j,t-1}$. We rewrite Equation (2) as below:

$$E_t\left[R^j_{BAB,t+1}\right] = \psi_t \;\; Z_t^j,$$

where, Z_t^j is the product of global beta spread of assets in country j, $\left(1/\beta^j_{L,t} - 1/\beta^j_{H,t}\right)$, and lagged local market realized volatility, $\sigma_{j,t-1}$. Since funding liquidity is a persistent variable, in this paper, we employ latent variable methods, more specifically Markov Chain Monte Carlo (MCMC) and Gibbs Sampling, to estimate ψ_t. In a similar setting, Jostova and Philipov (2005) and Ang and Chen (2007) implement this methodology to estimate conditional market betas for a single-factor CAPM. With simulation analysis, they show that their approach generates significantly more precise beta estimates than several competing models. Our specification is:

$$r^j_{BAB,t+1} = \psi_t \;\; \hat{Z}_t^j + \sigma_b\, \varepsilon_t \tag{3}$$

$$\psi_t = \phi_0 + \phi_1(\psi_{t-1} - \phi_0) + \sigma_\psi \epsilon_t. \tag{4}$$

We assume that ψ_t follows a stationary AR(1) process with mean reversion and we estimate $\phi_0, \phi_1, \sigma_\psi, \sigma_b$ with MCMC and Gibbs Sampler with normal distributions for priors of the

[13] Methodological details of the procedure are in Appendix B.

unknowns. To ensure stationarity, prior for ϕ_1 is a truncated normal between (-1,1). By Bayes law, posterior distributions are proportional to the priors times the likelihoods, which are defined by Equation (3). Thus, we randomly draw 10,000 samples from the posteriors and take the average to estimate the mean of the parameters. The first 1,000 draws are excluded as they are considered the training set. We acknowledge the "error-in-variable" issue from the estimation of the beta spread and market volatility (since $\hat{Z}_t^j$ is estimated in the previous step), however implementing the Gibbs Sampler reduces such concerns. Detail of the estimation is in Appendix C.[14]

Following Equation (2), under the null of no segmentation, the estimates of ψ_t from each market (ψ^j) are the same. In contrast, in a segmented world these estimates diverge from each other with respect to κ. Therefore, the distance between ψ_t^j and ψ_t^c can be interpreted as an indicator of how market j is segmented from market c. To construct the Funding-implied Segmentation Indicator (FSI), we estimate value-weighted discrepancies among ψ_t pairs, and construct

$$FSI_t^c = \sum_{j=1}^{J} w_t^j \;\; |\psi_t^j - \psi_t^c|, \tag{5}$$

where, w_t^j is the weight of country j in the world market portfolio.

3 Data

We collect the dollar denominated daily total return index, the market capitalization, and the Price-Earning ratio for all individual stocks that are available in DataStream and World-Scope databases. For country market data and global market portfolio, we use the DataStream market indexes that are available for 52 countries.[15] According to the classification by Standard and Poor's (S&P), 22 of these countries are developed (Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Hong Kong, Ireland, Israel, Italy, Japan, Luxembourg, Netherlands, New Zealand, Norway, Singapore, South Korea, Spain, Sweden, Switzerland, the U.K., and the U.S.), and 30 countries are emerging (Argentina,

[14] As an alternative methodology we could estimate ψ_t with rolling-windows (Lewellen and Nagel (2006)). However, with this methodology the estimates only speak for the average funding liquidity over the window period and it is difficult to mark their variations to business dates. Moreover, rolling-window estimations are sensitive to outliers. Nonetheless, this methodology produces similar dynamics for ψ_t and our results are robust.

[15] DataStream also provides market portfolio returns for Bahrain, Bulgaria, Croatia, Cyprus, Jordan, Kuwait, Malta, Nigeria, Oman, and Qatar. The time series for these markets are less than 10 years that we require to robustly estimate the rolling betas and MCMC parameters. The market capitalization of these countries are less than 0.01% of the global economy and thus their exclusion have negligible effect on our results.

Brazil, Chile, China, Colombia, Czech Republic, Egypt, Greece, Hungary, India, Indonesia, Malaysia, Mexico, Morocco, Pakistan, Peru, Philippines, Poland, Romania, Russian Federation, Slovenia, South Africa, Sri Lanka, Taiwan, Thailand, Turkey, Venezuela). DataStream provides daily asset return data for 226,239 assets for the period from January 1973 to October 2014. We follow Karolyi, Lee, and van Dijk (2012) in cleaning the data. In DataStream we choose Equity as Data type and exclude depositary receipts (DRs), real estate investment trusts (REITs), preferred stocks, investment funds, and other stocks with special features.[16] Moreover, we ensure each asset in the sample has at least 750 trading days of non-missing return data in a window of five years, required to estimate the asset beta (for details on beta estimation see Appendix B). To limit the effect of survivorship bias, the dead stocks are also included in the sample. The final sample (clean) includes 58,405 stocks. For the risk-free rate, we use one-month T-bill rates from Kenneth French's website.

As a measure for funding liquidity, we consider five proxies widely used in recent research, since there is no single agreed upon measure in the literature. Specifically, we consider proxies of funding liquidity in the U.S. market: the TED spread (calculated as the spread between the three-month LIBOR based on the U.S. dollars and the three-month Treasury Bill from Federal Reserve Bank of St. Louis), the VIX index (implied volatility of the S&P 500 market index from CBOE website), the broker-dealer leverage (calculated using total financial assets divided by the total financial liabilities of security broker-dealers as captured in Table L.128 of the Federal Reserve Flow of Funds), and the fixed income-implied funding liquidity (from Jean-Sébastien Fontaine's website). The literature frequently uses the TED spread to proxy borrowing cost as it captures the difference between collateral and uncollateral borrowing rates (Gârleanu and Pedersen (2011)). The VIX index is not theoretically linked to the funding liquidity; however, it is considered informative of the state of the credit market because of the link between aggregate uncertainty (proxied by the VIX index) and the funding conditions (Ang et al. (2011)). The intermediary asset pricing literature provides convincing arguments suggesting that the balance sheet and asset holding of large institutional investors are informative of the funding conditions of the whole market. More specifically, Adrian and Shin (2010) suggest that the broker-dealers' asset growth corresponds to changes in their debt capacity. Since financial intermediaries manage their value-at-risk, asset growth is immediately followed by active balance sheet adjustments that result in a higher overall

[16] The exclusion of these stocks is done manually by examining the names of the individual stocks, as neither DataStream nor WorldScope provide codes for discerning non-common shares from common shares. We drop stocks with names including "REIT," "REAL EST," "GDR," "PF," "PREF," or "PRF" as these terms may represent REITs, Global DRs, or preferred stocks. We drop stocks with names including "ADS," "RESPT," "UNIT," "TST," "TRUST," "INCOME FD," "INCOME FUND," "UTS," "RST," "CAP.SHS," "INV," "HDG," "SBVTG," "VTG.SAS," "GW.FD," "RTN.INC," "VCT," "ORTF," "HI.YIELD," "PARTNER," "HIGH INCOME," "INC.&GROWTH," and "INC.&GW" due to various special features.

leverage. Adrian et al. (2014) follow this idea by proposing the broker-dealers' leverage factor, which indicates the financial difficulty the intermediaries face in funding their daily trades. Fontaine and Garcia (2012) similar to Hu et al. (2013) measure funding liquidity from the cross-section of Treasury securities. Increases in the TED spread, the VIX index and the fixed income-implied measure imply worsening in the funding conditions. Conversely, decreases in the broker-dealer leverage imply decreases in funding liquidity of the economy. Although these proxies of funding liquidity generally comove with each other, they also have shown differences, as arguably some of them measure funding liquidity of the supply side and some others measure that of the demand side (see Boguth and Simutin (2015)). These measures are available with different frequencies and time periods. The TED spread and VIX index are available at a daily frequency, respectively from 1986 and from 1990. The broker-dealer balance sheet data is available at a quarterly frequency from 1968, while the fixed income-implied funding liquidity is available from 1986 with a monthly frequency. To match the datasets we take the last observations of the month (or quarter) to transform daily data to monthly (or quarterly) data.

Data for control variables are from DataStream, S&P IFCI/IFCG, IMF e-Library, Oxford Economics, the World Bank WDI database, and the OECD National Accounts data files. For more details on these variables see Appendix 2 of Bekaert et al. (2011). Annual data are linearly interpolated to access higher frequency data when missing. As these macroeconomic variables are very persistent, the interpolation method should not have a large impact on the results.

4 Empirical Results

In this section, we study the effect of funding liquidity on market segmentation. First, we analyze the BAB portfolios across markets, and we then introduce a Funding-liquidity Segmentation Indicator (FSI) based on these BAB portfolios. We separately study the FSI with respect to global and to local funding liquidity shocks to provide supportive evidence of reversals that can be linked to borrowing frictions of intermediaries. The results of our analysis are then compared with the results using the BHLS measure of market segmentation.

4.1 BAB Analysis

We construct the betting against beta portfolio (BAB) that longs the low-global beta assets and shorts the high-global beta assets from each market's security-level returns, with a methodology similar to Frazzini and Pedersen (2014). Table 1 presents the descriptive statistics of these portfolios together with some other relevant statistics for the countries in the dataset. In the sample, developed markets have on average more firms in their cross-section (almost three times more firms), and lower monthly realized market volatilities (4.66% versus 5.71%), compared to emerging markets. The world market beta spreads, the difference between the reciprocal of the aggregate beta of high global beta portfolios and low global beta portfolios, are around 0.60 across developed markets. For emerging markets the beta spreads are instead in a much wider range, from 0.24 to 1.44. This is possibly due to smaller exposure to the global market risk, lower cross-section of assets, and similar characteristics of the assets covered by the data vendor in emerging markets. For instance, the table shows that for some emerging markets DataStream provides return data only on a small cross-section of large companies. These companies have similar betas and therefore the beta spread is very small for these countries. On the other hand, for markets that have smaller exposure to the global market risk, both high-beta and low-beta are small and their beta spread is larger.

The table also presents the monthly average of BAB portfolio returns. Following Proposition 1, the expected value of BAB portfolios in each country is equal to the beta spread times the shadow price of the leverage constraints for that country. Therefore, we expect that the historical average of BAB portfolios, as a proxy for expected value of BAB portfolios, to be positive. Consistent with the findings of Frazzini and Pedersen (2014), in almost all countries the premium for the betting against beta is estimated positive.

More interestingly, Proposition 1 and Equation (1) show that the expected return of the BAB portfolios are increasing with respect to the funding barriers to international investments, as modeled by κ in our setting. Ψ_j, the shadow price of the leverage constraint, in countries with higher κ is higher. As a result, there is a higher permium for the BAB portfolio in these countries. The funding barriers to foreign investment are shown to be higher for emerging markets, mostly due to differences in perceived foreign investment risk of securities, such as political, corruption, or exchange rate risk.[17] Therefore, our model predicts that the mean of the BAB portfolio returns for these markets to be higher than those of the developed markets. This is in line with the tabulated results in Table 1. In our sample, the mean of the BAB portfolio returns in emerging markets, on average, is 1.25% per month, whereas the BAB portfolios in developed markets only yield 0.84% monthly returns.

Table 1 also presents the cross-sectional correlations of global BAB portfolio returns. For the sake of comparison, we also report cross-sectional correlations of market portfolios countries in our sample. Following Proposition 2, in the presence of foreign funding barriers

[17]From personal discussions with portfolio managers of institutional investors, they confirm that in practice margins are also set based on the location of assets.

(i.e. $\kappa > 1$), BAB portfolios are imperfectly correlated. As shown in Table 1, when compared to the market-wide correlations, BAB portfolios comove less than their market portfolio counterparts. But more importantly, consistent with Proposition 2 that shows countries with more sever funding barriers (as captured with higher values of κ) have lower correlations, we observe that these correlations are lower in the sample of emerging markets, compared with the developed markets. The average correlations of BAB portfolios in emerging markets is 0.08, whereas this value is 0.22 for developed markets.

[Place Table 1 about here]

In addition to the cross-sectional implications, our model also suggests that the dynamics of the correlations of the BAB portfolios can characterize how funding shocks comove across international markets. For instance, if during global financial distress, funding foreign investment becomes more scarce (for example due to investors' "fly home" and international capital immobility in the aftermath), then funding liquidity shocks do not diversify across markets. That is, following Proposition 1 and Equation (1) we predict that during these periods correlations of BAB portfolios decrease. However, this is in contrast with empirical evidence on market portfolio returns' correlation. Previous research in international finance has documented how correlations of market-wide country indices increase during financial distress (see for example Longin and Solnik (2001)).

Figure 1 plots market portfolio return and BAB correlations across developed and emerging markets. We implement a 2-year rolling window correlation estimation and mark large global financial distresses on the graphs.[18] The BAB and market return portfolios correlations differ noticeably. We observe that comovements between market returns increases during almost all large financial crisis. The literature on contagion shows that this pattern is also observed among other portfolios such as industry or size portfolios. However, BAB comovements seem to decrease, or increase negligibly, during the distress periods.

[Place Figure 1 about here]

In Table Appendix.1, we test this prediction more formally. We estimate the time-varying correlations of the BAB portfolios of each market with that of value weighted average of BAB portfolios (BAB Global) with the Dynamic Conditional Correlations (DCC) specification as proposed by Engle (2002).[19] There we provide statistical evidence for the implication of

[18]These market crashes are Black Monday on October 1987, withdrawal of the pound sterling from the European Exchange Rate Mechanism (ERM) on September 1992, East Asia Stock Market Crash on July 1997, Long-Term Capital Market (LTCM) collapse on September 1998, and Subprime Crisis on September 2008.

[19] The moving window correlations, while producing similar patterns with DCC, are difficult to mark to business dates.

Proposition 1, and show that BAB comovements negatively relates to funding condition of the economy, suggesting that the funding liquidity risk is not fully diversified during distress periods. Therefore using market-wide correlations to infer market integration goes against our intuition that international markets become less integrated at these times.

4.2 Funding-liquidity Segmentation Indicator (FSI)

In light of the results in Section 4.1 and motivated by Equation 1, in this section we introduce and study the Funding-liquidity Segmentation Indicator (FSI). As described in Section 2, FSI is constructed from the shadow prices of the margin constraint in the International Margin-CAPM that are estimated from assets of each market.

In the absence of foreign funding barriers, i.e. when $\kappa = 1$, our model dictates equal ψ_t^j across markets at each period t. In this case, all these shadow prices, ψ_t^j, measure the global representative investor's funding liquidity, thus they are the same across markets. However, with segmentation, they diverge with respect to the foreign funding barrier κ. Following Equation 2, the discrepancies between the extracted shadow prices of any pair of markets, c and j, proxies κ. Thus these discrepancies can be interpreted as the severity of the constraints to unimpeded flows on funding capital across the two markets at time t. The larger the distance between these prices, the higher the degree of market segmentation of market c from k and vice versa. Analogously, FSI^c, as the value-weighted average of the discrepancies between market c and all other markets, can be an indicator of market segmentation for country c.

Figure 2 plots the average measure of FSIs of the developed markets (in blue) and emerging markets (in red). Comparing across the two subsets, the figure indicates that emerging markets are less integrated with the world, compared to developed markets. Overtime, we see that both measures have a downward slope suggesting that with the reduction of barriers to international investment markets are becoming less segmented.

[Place Figure 2 about here]

To save space, we report the summary statistics on this indicator in Table Appendix.2, which shows that the mean and maximum of the FSIs are statistically larger for emerging markets. On average, the FSI is estimated 0.30 for developed markets and 0.92 for emerging markets. In fact, all top 15 maxima belong to FSIs of emerging markets. Conversely, 14 out of 15 minima are observed for FSIs of developed markets.The smallest mean value of FSI is for the U.S. at 0.37, and the largest mean value of FSI is for Sri Lanka at 2.34. In addition, the standard deviations of the FSIs are smaller in developed markets compared to emerging markets. This finding is possibly related to the larger reduction in barriers to foreign investments experienced by emerging markets in recent years. The table also provides statistical analysis on the differences of the newly introduced segmentation indicator between emerging and developed markets. In line with the above observations, this analysis confirms that the FSI of developed markets are indeed smaller than those of the emerging markets, either in pooled or univariate analyses. Moreover, the table shows that for all markets there is a downward trend in FSIs, and that such trend is larger for the emerging markets.

In Table Appendix.3, we study the newly introduced measure with respect to the previously studied explicit and implicit barriers to foreign investment. In univariate analysis, our results show that countries with higher GDP per capita, more credit allocated to the private sector, longer life expectancy and better school enrollment are significantly less segmented. This evidence is consistent with the economic development literature, which argues that counties with better economic infrastructure provide a more attractive investment opportunity for international investments. In addition, our results show that countries with higher past market return, more liquid stock market and better legal environment are more integrated. The financial market in these countries is more apealing for internationl investors as they offer high return but in the meantime provide sufficient investment protections. lastly, we find that *de jure* measures of market openness, as measured by Capital and Current account openness of Quinn and Toyoda (2008) negatively relate with FSI, suggesting lower segmentation among countries with less barriers to foreign investment. In Table Appendix.4, we study these barriers in a pooled regression. The regression (1) studies all determinants jointly. These variables are highly correlated with each other and pooling them might challenge robustly estimating the coefficients. As a result, the literature commonly implements a multi-step approach to identify the important determinants and only study those variables. Since the focus of this paper is the reversals periods of market integration, therefore we abstract from this step and simply exclude variables that are not statistically significant in regression (1). The results are reported in regression (2). We observe that in multivariate analysis, higher past year stock market returns, larger GDP growth rates and GPD per capita statistically imply lower market segmentation. In the last regression, we include only the variables that Bekaert et al. (2011) find determine the market segmentation variations across countries in their sample. Overall, we confirm their findings.

In short, our newly introduced measure of market segmentation, FSI, fits the previously documented evidence in market segmentation. In addition, our measure points out to an interesting observation. As shown in Figure 2, reversals in FSI coincide with large global financial crises and tightening of funding conditions, as identified by increases in the TED spread (marked in black). This observation is consistent with the implications from the research on international capital flows. For instance, Warnock and Warnock (2009) show that foreign inflows into U.S. Government Bonds dropped following the 1987 Black Monday, 1998 LTCM default and East Asia crashes, and the tech-bubble burst in 2001. As a result of this limited capital mobility in international markets, the shadow prices of the funding liquidity, (ψ_t^js), diverge during funding crises and FSI. This further indicates higher level of market segmentation across markets. We study this pattern in more details in Section 4.3.

4.3 Segmentation and Global Funding Liquidity

If we observe that during some periods accessing to international capital is scarce and investors "fly home", as Giannetti and Laeven (2012) frame it, we can infer that at times investors across markets are unable to internationally share funding liquidity risk. Therefore, in these times, we expect larger international market segmentation. Conversely, when investors are not financially constrained and funding capital is freely accessible across international markets, risk sharing improves and market segmentation decreases.[20] To test this hypothesis, in this section we study the relationship between proxies of global funding liquidity and market segmentation.

We focus on developed markets and use the measures of funding liquidity in the U.S. market as proxies of the global funding liquidity, assuming the funding liquidity shocks in the U.S. propagate to other markets. Indeed research has documented that international institutional investors, as the main cross-market investors, mostly rely on the U.S. market for their borrowing activities. We test the comovements of the measure of market segmentation, FSI, with respect to these proxies of global funding liquidity in Table 2.

In Panel A, we present the main result of the paper. The newly introduced segmentation indicator positively and statistically relates to funding liquidity, suggesting that FSI is higher during tight global funding periods and is lower in relaxed periods. The coefficients for the TED spread, the VIX index, the broker-dealer leverage and the fixed-income funding liquidity are estimated to be positive and statistically significant. The regressions of Panel A include country intercepts and a time trend to capture the effect of time-invariant and time-varying barriers to investment but their estimates are not tabulated to save space. The untabulated results show that country intercepts are jointly significant and positive, implying that there exists heterogeneity in the level of market segmentation across these markets. We also observe that the coefficient of the time trend is estimated to be significant and negative, which is consistent with the progressive reduction of barriers in the recent

[20]Giannetti and Laeven (2012) provide convincing evidence that the "flight home" effect is different from "flight to quality", where investors rebalance their portfolios toward less risky assets. Moreover, Jotikasthira et al. (2012) also documents that investors tilt their holdings toward domestic assets in funding crisis periods.

period. The inclusion of country fixed effects and the time trend beside the global funding liquidity proxies helps us explain almost half of the variation of the measure of segmentation (the adjusted R^2 of the regression for the TED spread is 0.44 and for the VIX is 0.46).

In the panel regressions, to account for heteroskedasticity, serial autocorrelations and cross-correlations in error terms, p-values are calculated based on the double clustered standard errors, through time and country, as instructed by Petersen (2009).

[Place Table 2 about here]

Previous research on the dynamics of market integration has provided support for the explanatory power of a number of variables as proxies of explicit or implicit barriers to investment. In Panel B, we directly control for the previously studied barriers, such as equity and capital account openness, investment profile, market capitalization to GDP, U.S. corporate bond spread, and past year local market portfolio returns. The results also confirm the positive association between FSI and funding liquidity. The coefficients for the TED spread, the VIX index, the broker-dealer leverage are positive and significant while the estimate for the fixed-income funding liquidity is also of the correct sign but with a lower significance level.

Lee (2011) finds empirical evidence that local liquidity risks are priced in international financial markets. However, the effect of funding liquidity on capital mobility is different from the effect of asset liquidity, although the two are linked via liquidity spirals (Brunnermeier and Pedersen (2009)). We argue that the mechanism by which the funding channel affects market segmentation as explained in this paper is distinct from the previously studied barriers to investment. We control for local market liquidity and we show that reversals are not fully explained by local market liquidity. A comparison of Panel A and B reveals that substituting the country fixed effects and the trend with a set of control variables, as proxies of the barriers, does not substantially change the sign and magnitude of the coefficient estimates.

Besides the statistical link of the proxies of funding liquidity with the increases in the FSI, we argue that the funding channel can also rationalize reversals better than the previously studied factors already linked to segmentation measures. In fact, there are no *a priori* expectations for decreases in investment profile or in capital account openness to occur in global financial crisis periods.[21] Some implicit barriers such as information barriers, as measured by news coverage, are actually likely to decrease during financial crises, and thus they cannot provide a valid explanation for reversals. Neither can an increase in risk aversion,

[21] There is only evidence of a few increases in regulatory restrictions during financial crises, for example in Malaysia or Iceland.

because it symmetrically affects the demand of local and foreign assets. Moreover, the empirical evidence for the importance of U.S. risk aversion for global markets is weak, as shown in Bekaert et al. (2011). On the other hand, one can argue that the positive association observed in the data between the VIX Index, which is extensively used as a measure of funding liquidity (Ang et al. (2011)), and the U.S. credit spread is more likely related to the funding channel as opposed to the risk aversion explanation. Similar arguments hold for the negative association between segmentation and decreases in market-wide returns (or market capitalization to GDP). At a monthly frequency, large negative market returns or a decrease in market capitalization to GDP could possibly indicate a worsening of funding liquidity for financial intermediaries instead of deterioration in the financial development of markets, as argued by BHLS. This alternative explanation relies on the observation that most of these intermediaries are net long in the market and capital constraints are more likely to hit during market downturns (Brunnermeier and Pedersen (2009)).

The results of this section suggest that previously studied segmentation factors, which are mainly slow moving processes, can better explain the long-term downward trend in international market segmentation, whereas funding liquidity has stronger explanatory power for the periods of short-term deviations above this trend, i.e. the reversals. In fact, our analysis at higher frequencies enables us to explain the short-term dynamics of the market segmentation and capture some patterns that are more difficult to uncover at the lower frequencies.

To strengthen the evidence on the conditional association between market segmentation and funding liquidity, we directly identify tight and relaxed periods of funding condition study FSI in these periods. Table 3 presents the results. In Panel A, the explanatory variable is a dummy variable that takes a value of one if the proxies for funding liquidity are above their 90^{th} percentile and zeros otherwise. Thus, values of one for the dummy variable represents here the tight funding conditions. Similarly, the explanatory variable in Panel B is a dummy variable that takes a value of one if the proxies for funding liquidity are less than their 50^{th} percentile, and thus it identifies the relaxed funding conditions. The table shows that in Panel A, where we study the FSI conditional on the dummy of tight funding conditions, the coefficients are estimated to be always positive and statistically significant. Conversely, this association flips in relaxed funding periods. This is consistent with the hypothesis that affluent arbitrageurs, during the relaxed funding periods, trade more intensively internationally and close price gaps across markets.

[Place Table 3 about here]

The higher market segmentation observed in response to a funding shock aligns with the theoretical models in the literature of limits to arbitrage (e.g. Basak and Croitoru (2000), Gârleanu and Pedersen (2011)). This strand of literature shows that deviations from Law of One Price (LOP) can occur during periods when investors' holding restrictions on redundant assets bind more, preventing them from undertaking arbitrage activities.[22] Related to this research, Gromb and Vayanos (2002) show that when financial intermediaries who act as the liquidity providers in isolated markets are financially constrained, deviations from LOP occur. Such deviations match the definition of market segmentation, where assets of similar risk are priced differently across markets. That is, during funding liquidity peaks, asset prices are governed by local demand and supply, as opposed to aggregate demand and supply for global markets. The financial intermediaries fail to execute the arbitrage strategy and cannot close the gap across markets between similar assets. In Table 4, we test this prediction where we study FSI with respect to deviations of covered interest rate parity as a proxy LOP deviations.

More specifically, in this table we measure CIP deviations by absolute value of cross-currency basis for 3-month contracts averaged across 11 widely traded currencies.[23] Du, Tepper, and Verdelhan (2017) find that CIP deviations imply systematic arbitrage opportunities, which are not explained away by credit risk or transaction costs and are most likely related to banks' inability to trade.

Similar to Tables 2 and 3, we study FSI with respect to this proxy of funding liquidity. We observe that there is a positive and statistically significant relationship between CIP deviations and market segmentation. We observe a similar relationship studying the periods of large CIP deviations, as identified by a dummy variable that takes value of one if the CIP deviation is larger than its 90^{th} percentile. Conversely, during low CIP deviations, i.e. when the CIP deviation is in its 50^{th} percentile, we observe that FSI is lower.

[Place Table 4 about here]

The literature of CIP deviations point out to a causal effect of banking regulation in the aftermath of the financial melt down in 2008. In fact, CIP deviations tend to be larger after 2007, when large institutional investors are more constrained to implement freely in international markets. Figure 3 visualizes this pattern. In this figure, we also plot the TED spread to emphasize that CIP deviations tend to positively correlates with other proxies of funding liquidity.

[22] Regulatory restrictions may allow only limited positions in certain assets or prohibit investors from taking short positions.

[23] These currencies include Australian Dollar, Canadian Dollar, Danish Krone, Euro, Japanese Yen, Norwegian krone, New Zealand dollar, Pound Sterling, Swiss Frank and Swedish Krone currencies. The inception of the dataset is January 2000. We thank courtesy of Wenxin Du for sharing the dataset.

[Place Figure 3 about here]

Motivated by the patterns in Figure 3, we also perform subperiod analysis in regression 4 and 5. The results show that the link between FSI and CIP deviation is present in the periods following 2007 crisis but statistically we fail to reject the null in the first half of the sample.Focusing on the post 2007 period, in regression 6, we study FSI and CIP deviations with a set of previously studied proxies of investment barriers. These barriers are mostly negligible in the recent years and we observe that they are not estimated statistically significant. However, the coefficient for CIP deviation is estimated positive and highly significant.

We proceed with directly studying the banks and large institutional investors. The intermediary asset pricing literature provides convincing arguments suggesting that the balance sheet and asset holding of large institutional investors are informative of the funding conditions of the whole market. More specifically, Adrian and Shin (2010) suggest that the broker-dealers' asset growth corresponds to changes in their debt capacity. He and Krishnamurthy (2012, 2013) and Brunnermeier and Sannikov (2014) provide further theoretical support for the role of intermediary wealth. Therefore, in Table 5 we study the relationship between FSI and Total asset growth of broker-dealers and growth of the global banking industry as *noisy* proxies of the funding constraints that large institutional investors face.

In the table, these variables are signed such that an increase in them implies worsening the global funding conditions. Our results show that FSI positively and highly significantly correlates with the growth of global banking industry's market capitalization ($\text{Banks}^{\text{MCAP}}$). Similar relation is also observed between FSI and the growth of total asset of broker-dealers asset ($\text{Total Asset}^{\text{BD}}$), albeit at lower statistical significance. We observe a stronger statistical relationship studying tight periods of these proxy. A dummy variable that indicates periods when these variables are in their 90^{th} percentile is positively and statistically relates to FSI. Conversely, the dummy variable that indicates periods of low variability of total asset of broker dealers or size of global banking industry is estimated negative. Controlling for previously studied barriers, we observe a positive and statistically significant relationship between total asset of broker-dealers asset and banking industry size, although with higher p-value.

[Place Table 5 about here]

4.4 Segmentation and Local Funding Liquidity

In integrated markets, local funding liquidity shocks diversify internationally, by means of global capital mobility. In this case, if a market is hit by a local funding shock, international intermediaries would instantaneously intervene to arbitrage out any mispricing resulting from the shock. On the other hand, in segmented markets, foreign investors are restricted in providing capital, and local funding distress will persist. Therefore, the severity of the financial constraints of the local investors can be an indicator of the magnitude of barriers to investment in that market. In this section, we study the relationship between FSI and proxies of local funding liquidity.

To empirically test this hypothesis, first we need to estimate the local funding liquidity for every market in the cross-section, since these measures are not readily available for large cross-section of countries. As opposed to the U.S. market, data for the TED spread, the broker-dealer balance sheet and implied volatilities are not available in most emerging markets. Similarly, the fixed income-implied measure can only be constructed for a small cross-section of developed markets.[24] In the light of the evidence in Tables 4 and 5, we proxy the local funding liquidity with CIP deviations for each country of the currency and the size of the local banking industry. The results are presented in Table 6.

More specifically, we exclude the U.S. market as consider the absolute value of cross-currency basis for 3-month contracts as a proxy of local funding liquidity for the countries that use that currency. This includes the 15 Euro region countries in our sample as well as Australia, Canada, Denmark, Japan, New Zealand, Norway, Sweden, Switzerland and UK. DataStream provides time-series data for market capitalization of the local banking industry for the whole cross-section of 52 countries in our sample. We acknowledge that these are *noisy* measures of local funding liquidity

Our results show that there is a positive and statistically significant relationship between these proxies of local funding liquidity and FSI, suggesting that the local sources of risk are not fully diversified during distress periods. Similar to the previous tests, in these regressions we include country fixed effect and a time trend to capture the effects of country-specific differences between markets and the reduction of barriers to investment during time. We also specifically control for the previously studied barriers and show that during tighter funding periods markets are indeed more segmented. For $\text{Banks}^{\text{MCAP}}$ we exclude market returns as they are highly correlated with the changes in market capitalization of the local banking industry.

[**Place Table 6 about here**]

Lastly, we include the TED spread as a proxy of global funding liquidity. We observe that the effect the local CIP deviations is not fully subsumed by the TED spread. The coefficient

[24] Malkhozov et al. (2014) construct this measure for a set of six developed markets, with similar methodology to Fontaine and Garcia (2012) and Hu et al. (2013).

is still estimated positive and significant but now at a lower magnitude. Similar result is observed for the local banking industry, $\text{Banks}^{\text{MCAP}}$, although at a lower statistical level. This is possibly as a result of higher noise in the later as a proxy of local funding liquidity.

The evidence documented in this section is aligned with the research on international banks' lending behavior (see Holmstrom and Tirole (1997), Morgan, Rime, and Strahan (2004), Kalemli-Ozcan, Papaioannou, and Peydró (2013)). This strand of literature argues that if firms in a certain country are hit by unfavorable shocks to their collateral, banks rebalance their lending in order to decrease lending in this country and increase lending in the non-affected countries. This contributes to further disconnect the affected country from the rest of the world.

4.5 Robustness Checks

To validate the interpretation of our findings, we broadly replicate the analysis of Table 2 with the BHLS measure of market segmentation, the SEG index. While the analysis in Bekaert et al. (2011) is with annual frequency, we work with monthly and quarterly frequencies to capture the effect of short-term funding liquidity.

We formally test for the relationship and present in Table 7 the results for the BHLS measure of developed markets, similar to the previous analysis. Panel A shows the results of a pooled panel regression with country fixed effects and a time trend to incorporate the effect of time-invariant and time-varying (implicit or explicit) barriers to investment across markets. In Panel A, the estimated coefficients of proxies of global funding liquidity in all regressions are positive and significant. As stated above, these proxies of funding liquidity are in a different range and scale, therefore, the magnitude of the coefficients are not closely comparable. However, the sign of the estimated coefficients provides supportive evidence for a positive association of funding liquidity with segmentation.

In Panel B of Table 7, we control for previously studied barriers to investment, such as investment profile, trade to GDP, market returns and liquidity. We confirm that the positive association between market segmentation observed in Panel A is robust to the inclusion of these factors. All the estimated coefficients for the liquidity proxies retain the sign and significance observed in the previous panel, albeit at lower statistical level for fixed income-implied funding liquidity.

[**Place Table 7 about here**]

In a not reported result, we study the SEG index in tight and relaxed periods of funding. These results confirm the above findings. We find that the periods of short-term increases in the BHLS measure (in other words, the reversal periods) coincide with periods of tighter funding constraints. More interestingly, we also observe that including factors related to the funding liquidity in the regressions of Table 7, considerably increases the explanatory power of the regression in the reversal periods. We find that for the periods when the BHLS measure is high, the coefficient of determination ($adj.R^2$) of the regression almost doubles, increasing from 0.13 to 0.24.

In Table 7, we also include the FSI as determinant of SEG and we find a positive and statistically significant relationship between the two. This link even hold after controlling for the effect of barriers. This provides further support for our FSI as an indicator of market segmentation.

We are concerned that the results in the above pooled panel regression could be driven by the link between the U.S. market segmentation and the U.S. proxies of funding liquidity, or that they are sample specific. We then run a few checks. At first, we exclude the U.S. market segmentation from the test assets. This exclusion has minuscule effect on the coefficient estimates, their t-stats, and the coefficient of determination (adj.R^2). Furthermore, excluding from the estimation observations of the years 2007-2009, we confirm that the positive association between the FSI and funding liquidity is not solely driven by the considerable worsening of the funding conditions during the subprime mortgage crisis in 2008. However, the coefficient for funding liquidity are estimated at a lower magnitude. For instance, the coefficient for the TED spread drops from 0.1623 to 0.0974. Finally, we exclude from the test the early periods as it has been argued that explicit barriers to investment were in place and effective, at least partly, till the early Nineties. This does not alter the conclusions of Panel A as we find that market segmentation loads positively and significantly on all proxies of funding liquidity. In fact, the size of the coefficients of the funding liquidities are estimated at a larger magnitude. For instance, the coefficient for the TED spread for this subsample increases from o.1623 to 0.1966.[25]

To further confirm that the results of local funding liquidity and FSI, in Table 8 we focus on the U.S. market. We choose the U.S. market because of the large population of active international institutional investors residing in the U.S. and data availability necessary to construct multiple measures of funding liquidity. The table shows that we observe larger FSI for the U.S. market (i.e. higher U.S. market segmentation) as the funding condition in the U.S. economy worsen. Using the FSI as dependent variable, the broker-dealer's total asset and leverage, and the TED spread are estimated to be positive and significant while the VIX index and the fixed income-implied funding liquidity are also estimated to be positive but at a lower statistical significance.

[25] Results of the subsample tests are not tabulated to save space and are available upon request.

[Place Table 8 about here]

5 Conclusion

This paper links the literature on limits to arbitrage and intermediary asset pricing with the international finance literature and offers an explanation for reversals in international market integration via the role of institutional investors and funding liquidity.

We show that during global funding distress, betting against beta portfolios (the BAB factors), which load on funding liquidity, comove less across markets. Inspired by these findings, we study the segmentation implications of an International CAPM with Leverage constraints that incorporates borrowing frictions of investors in international markets. We show that periods when funding constraints of intermediaries are not binding correspond to higher integration among international financial markets. Periods of tightening constraints that follow relaxed ones, correspond to reversals and increase in segmentation among countries.

A Funding-implied Segmentation Indicator (FSI), extracted from countries' BAB portfolios not only fits the previously documented evidence of market segmentation but also explains reversals in market integration during global funding shocks. We argue that withholding investments by global investors in certain markets during periods of tight funding constraints, as implied by the FSI, is consistent with the "flight home" effect and the deviations from the Law of One Price documented in other literature. Moreover, we show that markets that experience more severe local funding shocks are on average more segmented. This is consistent with the notion that local funding shocks which persist where the access of intermediary capital is somewhat restricted, lead to inefficient risk sharing, as more local risk will be borne by local investors.

Previous research has explained cross-sectional differences and time-variation in integration across countries through the presence of barriers to foreign investment. However, there is no *a priori* expectation to observe increases in the severity of such barriers that would be necessary to explain reversals in integration during crisis periods. In fact, empirically, most of these barriers are slow-moving processes that are a better explanation of the long-term dynamics of international market integration than its short-term reversals. We argue that the funding channel provides a plausible explanation for reversals. This channel adds a new dimension to the understanding of the dynamics of international market integration especially in the post-liberalization period, when most explicit barriers to foreign investment have been eliminated.

References

Adrian, T., T. Muir, and E. Etula. 2014. Financial Intermediaries and the Cross-Section of Asset Returns. *The Journal of Finance* .

Adrian, T., and H. S. Shin. 2010. Liquidity and leverage. *Journal of Financial Intermediation* 19:418–437.

Adrian, T., and H. S. Shin. 2014. Procyclical Leverage and Value-at-Risk. *Review of Financial Studies* 27:373–403.

Ang, A., and J. Chen. 2007. CAPM over the long run: 1926–2001. *Journal of Empirical Finance* 14:1–40.

Ang, A., S. Gorovyy, and G. B. van Inwegen. 2011. Hedge fund leverage. *Journal of Financial Economics* 102:102–126.

Ashcraft, A., N. Gârleanu, and L. H. Pedersen. 2011. Two Monetary Tools: Interest Rates and Haircuts. *NBER Macroeconomics Annual* 25.

Bali, T. G., S. Brown, S. Murray, and Y. Tang. 2014. Betting Against Beta or Demand for Lottery. SSRN Scholarly Paper ID 2408146, Social Science Research Network, Rochester, NY.

Basak, S., and B. Croitoru. 2000. Equilibrium mispricing in a capital market with portfolio constraints. *Review of Financial Studies* 13:715–748.

Bekaert, G., and C. R. Harvey. 1995. Time-Varying World Market Integration. *The Journal of Finance* 50:403–444.

Bekaert, G., C. R. Harvey, and C. Lundblad. 2007. Liquidity and Expected Returns: Lessons from Emerging Markets. *Review of Financial Studies* 20:1783–1831.

Bekaert, G., C. R. Harvey, C. T. Lundblad, and S. Siegel. 2011. What Segments Equity Markets? *Review of Financial Studies* 24:3841–3890.

Bekaert, G., C. R. Harvey, C. T. Lundblad, and S. Siegel. 2013. The European Union, the Euro, and equity market integration. *Journal of Financial Economics* 109:583–603.

Black, F. 1974. International capital market equilibrium with investment barriers. *Journal of Financial Economics* 1:337–352.

Boguth, O., and M. Simutin. 2015. Leverage Constraints and Asset Prices: Insights from Mutual Fund Risk Taking. Tech. Rep. working paper.

Brunnermeier, M. K., and L. H. Pedersen. 2009. Market Liquidity and Funding Liquidity. *Review of Financial Studies* 22:2201–2238.

Brunnermeier, M. K., and Y. Sannikov. 2014. A Macroeconomic Model with a Financial Sector. Tech. Rep. 2.

Carrieri, F., I. Chaieb, and V. Errunza. 2013. Do Implicit Barriers Matter for Globalization? *Review of Financial Studies* 26:1694–1739.

Carrieri, F., V. Errunza, and K. Hogan. 2007. Characterizing World Market Integration through Time. *The Journal of Financial and Quantitative Analysis* 42:915–940.

Chen, Z., and P. J. Knez. 1995. Measurement of market integration and arbitrage. *Review of Financial Studies* 8:287–325.

Chen, Z., and A. Lu. 2014. A Market-Based Funding Liquidity Measure. Tech. Rep. working paper.

Coeurdacier, C., and H. Rey. 2013. Home Bias in Open Economy Financial Macroeconomics. *Journal of Economic Literature* 51.

Du, W., A. Tepper, and A. Verdelhan. 2017. Deviations from Covered Interest Rate Parity. Working Paper 23170, National Bureau of Economic Research.

Duffie, D., and B. Strulovici. 2012. Capital Mobility and Asset Pricing. *Econometrica* 80:2469–2509.

Eiling, E., and B. Gerard. 2014. Emerging Equity Market Comovements: Trends and Macro-Economic Fundamentals. *Review of Finance-forthcoming* .

Engle, R. 2002. Dynamic Conditional Correlation: A Simple Class of Multivariate Generalized Autoregressive Conditional Heteroskedasticity Models. *Journal of Business & Economic Statistics* 20:339–350.

Errunza, V., and E. Losq. 1985. International Asset Pricing under Mild Segmentation: Theory and Test. *The Journal of Finance* 40:105–124.

Fleckenstein, M., F. A. Longstaff, and H. Lustig. 2014. The TIPS-Treasury Bond Puzzle. *The Journal of Finance* 69:2151–2197.

Fontaine, J.-S., and R. Garcia. 2012. Bond Liquidity Premia. *Review of Financial Studies* 25:1207–1254.

Fostel, A., and J. Geanakoplos. 2008. Leverage Cycles and the Anxious Economy. *American Economic Review* 98:1211–1244.

Fostel, A., and J. Geanakoplos. 2013. Reviewing the Leverage Cycle. Tech. Rep. Working Paper.

Frazzini, A., and L. H. Pedersen. 2014. Betting against beta. *Journal of Financial Economics* 111:1–25.

Gârleanu, N., and L. H. Pedersen. 2011. Margin-based Asset Pricing and Deviations from the Law of One Price. *Review of Financial Studies* 24:1980–2022.

Geanakoplos, J. 2010. The Leverage Cycle. *NBER Macroeconomics Annual* 24:213–233.

Giannetti, M., and L. Laeven. 2012. Flight Home, Flight Abroad, and International Credit Cycles. *The American Economic Review* 102:219–224.

Giannetti, M., and L. Laeven. 2015. Local Ownership, Crises, and Asset Prices: Evidence from US Mutual Funds. *Review of Finance* forthcoming.

Gorton, G. B., and A. Metrick. 2010. Haircuts. Tech. Rep. working paper.

Goyenko, R., and S. Sarkissian. 2014. Treasury Bond Illiquidity and Global Equity Returns. *Journal of Financial and Quantitative Analysis* 49:1227–1253.

Gârleanu, N., S. Panageas, and J. Yu. 2015. Financial Entanglement: A Theory of Incomplete Integration, Leverage, Crashes, and Contagion. *The American Economic Review* 105:1979–2010.

Gromb, D., and D. Vayanos. 2002. Equilibrium and welfare in markets with financially constrained arbitrageurs. *Journal of Financial Economics* 66:361–407.

Hameed, A., W. Kang, and S. Viswanathan. 2010. Stock Market Declines and Liquidity. *The Journal of Finance* 65:257–293.

He, Z., and A. Krishnamurthy. 2012. A Model of Capital and Crises. *The Review of Economic Studies* 79:735–777.

He, Z., and A. Krishnamurthy. 2013. Intermediary Asset Pricing. *The American Economic Review* 103:732–770.

Hoggarth, G., L. Mahadeva, and J. H. Martin. 2010. Understanding International Bank Capital Flows During the Recent Financial Crisis. Tech. rep., Financial Satability Paper No. 8, Bank of England.

Holmstrom, B., and J. Tirole. 1997. Financial Intermediation, Loanable Funds, and The Real Sector. *The Quarterly Journal of Economics* 112:663–691.

Hu, G. X., J. Pan, and J. Wang. 2013. Noise as Information for Illiquidity. *The Journal of Finance* 68:2341–2382.

Huang, S., D. Lou, and C. Polk. 2014. The Booms and Busts of Beta Arbitrage .

Jostova, G., and A. Philipov. 2005. Bayesian Analysis of Stochastic Betas. *Journal of Financial and Quantitative Analysis* 40:747–778.

Jotikasthira, C., C. Lundblad, and T. Ramadorai. 2012. Asset Fire Sales and Purchases and the International Transmission of Funding Shocks. *The Journal of Finance* 67:2015–2050.

Jurek, J. W., and E. Stafford. 2010. Haircut dynamics. Working Paper.

Kalemli-Ozcan, S., E. Papaioannou, and J.-L. Peydró. 2013. Financial Regulation, Financial Globalization, and the Synchronization of Economic Activity. *The Journal of Finance* 68:1179–1228.

Karolyi, G. A., K.-H. Lee, and M. A. van Dijk. 2012. Understanding commonality in liquidity around the world. *Journal of Financial Economics* 105:82–112.

Lee, K.-H. 2011. The world price of liquidity risk. *Journal of Financial Economics* 99:136–161.

Lehkonen, H. 2014. Stock Market Integration and the Global Financial Crisis. *Review of Finance* p. rfu039.

Lewellen, J., and S. Nagel. 2006. The conditional CAPM does not explain asset-pricing anomalies. *Journal of Financial Economics* 82:289–314.

Longin, F., and B. Solnik. 2001. Extreme Correlation of International Equity Markets. *The Journal of Finance* 56:649–676.

Malkhozov, A., P. Mueller, A. Vedolin, and G. Venter. 2014. Funding Liquidity CAPM: International Evidence. Tech. Rep. working paper.

Morgan, D. P., B. Rime, and P. E. Strahan. 2004. Bank Integration and State Business Cycles. *The Quarterly Journal of Economics* 119:1555–1584.

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

Pasquariello, P. 2014. Financial Market Dislocations. *Review of Financial Studies* 27:1868–1914.

Petersen, M. A. 2009. Estimating Standard Errors in Finance Panel Data Sets: Comparing Approaches. *The Review of Financial Studies* 22:435–480.

Pontiff, J. 2006. Costly arbitrage and the myth of idiosyncratic risk. *Journal of Accounting and Economics* 42:35–52.

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

Quinn, D. P., and A. M. Toyoda. 2008. Does Capital Account Liberalization Lead to Growth? *The Review of Financial Studies* 21:1403.

Rey, H. 2015. Dilemma not Trilemma: The global Financial Cycle and Monetary Policy Independence .

Shleifer, A., and R. W. Vishny. 1997. The Limits of Arbitrage. *The Journal of Finance* 52:35–55.

Stulz, R. M. 1981. On the Effects of Barriers to International Investment. *The Journal of Finance* 36:923–934.

Warnock, F. E., and V. C. Warnock. 2009. International capital flows and U.S. interest rates. *Journal of International Money and Finance* 28:903–919.

Appendix

A International CAPM with Leverage Constraints

Investor $i \in \mathcal{I}_j$ first order conditions for stocks $k \in \mathcal{K}_j$ and $k \notin \mathcal{K}_j$ are respectively

$$\mathrm{E}_0\left(R_k - R_0\right) - \alpha_i \mathrm{Cov}_0\left(R_k, \sum_{h \in \mathcal{K}} R_h x_{i,h}\right) - \psi_i m = 0 \tag{6}$$

$$\mathrm{E}_0\left(R_k - R_0\right) - \alpha_i \mathrm{Cov}_0\left(R_k, \sum_{h \in \mathcal{K}} R_h x_{i,h}\right) - \psi_i \kappa m = 0 \tag{7}$$

where the shadow price of investor's leverage constraint ψ_i. Combining (6) and (7) with market clearing, we find that stock $k \in \mathcal{K}_j$ equilibrium expected stock return is given by

$$\mathrm{E}_0\left(R_k - R_0\right) = \beta_k \mathrm{E}_0\left(R_m - \Psi_m - R_0\right) + \Psi_j, \tag{8}$$

where

$$\Psi_j = m \sum_{i \in \mathcal{I}_|} \frac{\alpha}{\alpha_i}\psi_i + \kappa m \sum_{i \notin \mathcal{I}_|} \frac{\alpha}{\alpha_i}\psi_i, \tag{9}$$

$\beta_k = \frac{\mathrm{Cov}_0(R_k, R_m)}{\mathrm{Var}_0(R_m)}$, $R_m = \sum\limits_{h \in \mathcal{K}} R_h \theta_h$, $\Psi_m = \sum\limits_{j} \sum\limits_{h \in \mathcal{K}_|} \Psi_j \theta_h$, $\frac{1}{\alpha} = \sum\limits_{i \in \mathcal{I}} \frac{1}{\alpha_i}$, and θ_k is the share of stock k in the global market capitalisation. Finally, using (8), the expected return on a self-financing market-neutral portfolio that is long in low-beta securities and short in high-beta securities in country j is

$$\mathrm{E}_0\left(R_{BAB,j}\right) = \left(\frac{1}{\beta_L} - \frac{1}{\beta_H}\right)\Psi_j,$$

where β_L and β_H are betas of the long and short legs of the portfolio, respectively.

B BAB Portfolio

We follow Frazzini and Pedersen's methodology in estimating BAB portfolios. For this purpose, we compute beta of each asset by estimating volatilities and correlations separately:

$$\beta_j^{TS} = \widehat{\rho_{jm}} \frac{\widehat{\sigma_j}}{\widehat{\sigma_m}} \tag{10}$$

Beta of asset j at each period is computed by the correlation of this asset and the global market portfolio in the last five years, multiplied by the ratio of asset volatility to market volatility, in the last year. Since correlations appear to move more slowly than volatilities, a smaller window is assigned for volatility estimation. For volatility estimation, we use one-day log returns and use overlapping three-day log returns for correlation estimation to control for nonsynchronous trading. Moreover, at least 120 trading days of non-missing data is required to estimate volatilities. Similarly at least 750 trading days of non-missing return data is required for correlations estimation. After calculating the betas, they are shrunk toward the cross-sectional mean (i.e. 1) to reduce the influence of outliers: $\beta_j = 0.6\beta_j^{TS} + 0.4$.

To form the BAB portfolio, at each period, assets are ranked based on their ex-ante betas in ascending order and grouped in two categories (high- and low-beta) based on the median of the betas. In each portfolio, securities are weighted by the ranked betas (i.e., lower-beta securities have larger weights in the low-beta portfolio and higher-beta securities have larger weights in the high-beta portfolio). The portfolios are rebalanced every calendar month. BAB is then formed by longing the high beta portfolio, de-leveraged to beta one, and shorting the low beta portfolio, leveraged to a beta of one. This results in a zero beta portfolio, ex-ante. More formally if $\boldsymbol{r_t}^\top$ is the vector of monthly asset returns and $\boldsymbol{\beta_t}^\top$ we have:

1. $r_{H,t+1} = \boldsymbol{r}_{\boldsymbol{t+1}}^\top \boldsymbol{w_{H,t}}$, and $r_{L,t+1} = \boldsymbol{r}_{\boldsymbol{t+1}}^\top \boldsymbol{w_{L,t}}$.
2. $\beta_{H,t+1} = \boldsymbol{\beta}_{\boldsymbol{t+1}}^\top \boldsymbol{w_{H,t}}$, and $\beta_{L,t+1} = \boldsymbol{\beta}_{\boldsymbol{t+1}}^\top \boldsymbol{w_{L,t}}$.
3. $r_{BAB,t+1} = \frac{1}{\beta_{L,t}} \left(r_{L,t+1} - r^f\right) - \frac{1}{\beta_{H,t}} \left(r_{H,t+1} - r^f\right)$

C MCMC and Gibbs Sampler

Research has shown that more volatile assets require higher margins (see Fostel and Geanakoplos (2008), Jurek and Stafford (2010) and the references therein) because of the devaluation risk of the underlying asset. In practice, the Chicago Mercantile Exchange (CME) Group's approach is to adjust margin requirements based on historical, intraday, and implied volatilities (see Figure Appendix.1).[26] In domestic market, Gorton and Metrick (2010) provide evidence on time variation and cross-sectional differences of Repo Haircuts backed by different securities.

[Place Figure Appendix.1 about here]

Ceteris paribus, it is more difficult to borrow against highly volatile stocks from emerging markets compared to large stable stocks from developed markets. Therefore, we control for the cross-sectional differences in margin requirement, m, assuming that the *country-specific*

[26] Reference: www.cmegroup.com/clearing/files/cme-clearing-margins-quick-facts-2011.pdf

margins in country j, m^j are well approximated by local market volatility, $m_t^j = a + b\sigma_{j,t-1}$. We rewrite Equation (2) as below:

$$E_t\left[R_{BAB,t+1}^j\right] = \psi_t \;\; Z_t^j,$$

where, Z_t^j is the product of global beta spread of assets in country j, $\left(1/\beta_{L,t}^j - 1/\beta_{H,t}^j\right)$, and lagged local market realized volatility, $\sigma_{j,t-1}$.

we implement Markov Chain Monte Carlo (MCMC) and Gibbs sampler to draw samples from the conditional distributions, following Jostova and Philipov (2005) and Ang and Chen (2007), who implement a similar methodology to estimate conditional beta of a single-factor CAPM. The Bayesian estimation includes the following steps. First we impose a dynamic for the global funding liquidity, ψ_t. Then we choose prior distributions for the model parameters. Here, we assume the joint prior distribution is the product of the independent priors of each unknown parameter. Then, the likelihood function is derived from the dynamics of the BAB returns and the shadow price of the funding constraints (see below). By Bayes's Law, we find the posterior distributions and the conditional posterior distributions for each parameter given the rest of the unknown parameters. In the last step, we draw random samples from these conditional posterior distributions and take the averages of these samples, to obtain the expected value of the joint distribution of the unknown parameters.

$$r_{BAB,t+1} = \psi_t \;\; \hat{Z}_t + \sigma_b\, \varepsilon_t \tag{11}$$

$$\psi_t = \phi_0 + \phi_1(\psi_{t-1} - \phi_0) + \sigma_\psi \epsilon_t \tag{12}$$

The unknown parameters are $\phi_0, \phi_1, \sigma_\psi, \sigma_b$. Since ψ_t is a persistent variable, here we assume it follows a stationary AR(1) process with unconditional mean ϕ_0 and mean reversion speed ϕ_1. For ϕ_0, we choose a normal prior with mean $\hat{\psi}$ and standard deviation 10. $\hat{\psi}$ is the OLS estimate of ψ_t, assuming time-invariant process in Equation (11). For ϕ_1, we consider a truncated normal prior with mean 0.5 and standard deviation 10 that lies in the interval $(-1, 1)$. This range of values for ϕ_1 ensures stationarity of ψ_t. For the variance of the shadow price of the funding constraint, σ_ψ, I suggest an inverse gamma (IG) prior (typically used in the literature to model the distribution of unknown variances) with shape and scale parameters equal to 0.001. Similarly, for the variance of the BAB returns, σ_b , we select an IG prior with shape and scale parameters equal to 0.001. Based on the above dynamics and assumptions, ψ_t and BAB returns follow conditional normal distributions:

$$\begin{aligned}\psi_t|\psi_{t-1} \quad &\sim \mathcal{N}\big(\phi_0 + \phi_1(\psi_{t-1} - \phi_0), \sigma_\psi^2\big)\\ r_{BAB,t}|\psi_t, Z_t &\sim \mathcal{N}\big(\psi_t Z_t, \sigma_b^2\big)\end{aligned}$$

Therefore, the likelihood function is:

$$L(\boldsymbol{\psi}, \phi_0, \phi_1, \sigma_\psi, \sigma_b|\mathbf{r_{BAB}}, \mathbf{Z}) \propto \prod_{t=1}^{T} \mathcal{N}\left(\phi_0 + \phi_1(\psi_{t-1} - \phi_0), \sigma_\psi^2\right) \times \prod_{t=1}^{T} \mathcal{N}\left(\psi_t Z_t, \sigma_b^2\right)$$

where, $\boldsymbol{\psi} = [\psi_1, \ldots, \psi_T]$, $\mathbf{r_{BAB}} = [r_{BAB,1}, \ldots, r_{BAB,T}]$, and $\mathbf{Z} = [Z_1, \ldots, Z_T]$. By Bayes' Law we have that the Posterior Distribution, $p(\boldsymbol{\theta}|\boldsymbol{y})$, is proportional to the prior distribution times the likelihood function. Formally, $p(\boldsymbol{\theta}|\boldsymbol{y}) \propto p(\phi_0, \phi_1, \sigma_\psi, \sigma_b) \times L(\boldsymbol{\theta}|\boldsymbol{y})$, where, $\boldsymbol{\theta}$ is defined as a vector of $(\boldsymbol{\psi}, \phi_0, \phi_1, \sigma_\psi, \sigma_b)^\top$ and $\boldsymbol{y}$ is the vector of $(\mathbf{r_{BAB}}, \mathbf{Z})^\top$. Since the prior distribution is not a well-defined joint distribution, we implement the Gibbs Sampler which enables us to draw samples from the conditional posterior distributions,$p(\theta_k|rest)$, instead. In each iteration $i = 1, \cdots, I$ of the Gibbs Sampler, and for each model parameter $k = 1, \cdots, K$ we draw samples iteratively from the conditional prior distributions. More specifically, we draw the current sample of θ_k conditional on the current samples of $\theta_1, \cdots, \theta_{k-1}$ and the previous samples of $\theta_{k+1}, \cdots, \theta_K$, where K is the number of unknown parameters.

$$p(\theta_k^{(i+1)}|\theta_1^{(i+1)}, \cdots, \theta_k^{(i+1)}, \theta_{k+1}^{(i)}, \cdots, \theta_K^{(i)}, \boldsymbol{y})$$

We randomly draw 10,000 samples from the posteriors and exclude the first 1,000 draws, since they are considered as the startup phase.

Figures and Tables

A Tables

Table 1. Summary Statistics of BAB portfolios

The table presents descriptive statistics for the Betting-Against-Beta (BAB) portfolios constructed from securities in each market. The sample includes 22 developed markets, identified with DM, and 29 emerging market, identified with EM, from 1973 to 2014 (Data source: DataStream). The table reports the number of firms in each market, and number of monthly observations, average monthly return of the BAB portfolio in percentage and average Beta spread of the BAB portfolios. In addition, the table reports the correlation of the BAB portfolio of each market with that of the Global BAB portfolio as well as the market wide correlations.

Country		#Firms	#Obs.	$\overline{(\text{BAB})}\%$	$\sigma_{(\text{BAB})}\%$	$\overline{\beta Sprd}$	$\rho_{(\text{BAB}^j,\text{BAB}^G)}$	$\rho_{(r^j,r^G)}$
Argentina	EM	107	191	3.25	6.11	0.37	0.14	0.52
Australia	DM	2,525	438	2.98	4.77	0.79	0.27	0.66
Austria	DM	161	438	3.03	5.79	0.44	0.19	0.56
Belgium	DM	243	438	2.42	4.10	0.52	0.38	0.70
Brazil	EM	258	180	3.06	5.39	0.38	0.01	0.70
Canada	DM	3,815	438	3.22	6.03	0.78	0.39	0.77
Chile	EM	258	240	2.88	6.01	0.70	0.12	0.49
China	EM	2,578	192	5.54	13.04	1.00	0.11	0.45
Colombia	EM	81	188	4.58	11.63	0.24	0.10	0.41
Czech	EM	85	188	7.32	15.64	0.92	0.19	0.57
Denmark	DM	312	438	3.34	5.73	0.47	0.31	0.64
Egypt	EM	128	153	4.78	9.06	0.77	0.07	0.42
Finland	DM	203	256	2.71	5.07	0.58	0.44	0.69
France	DM	1,599	438	2.31	4.09	0.53	0.51	0.74
Germany	DM	1,390	438	2.21	3.44	0.59	0.47	0.73
Greece	EM	374	234	2.80	7.88	0.50	0.08	0.53
Hong Kong	DM	1,078	438	2.39	4.35	0.55	0.24	0.55
Hungary	EM	62	205	3.72	6.84	0.43	0.18	0.67
India	EM	2,672	234	4.45	11.77	0.88	0.19	0.40
Indonesia	EM	538	231	4.07	6.65	0.43	0.11	0.49
Ireland	DM	104	438	4.22	7.53	0.72	0.24	0.68
Israel	EM	487	198	2.59	4.33	0.56	0.33	0.58
Italy	DM	506	438	1.95	3.59	0.50	0.37	0.60
Japan	DM	4,823	438	2.31	3.82	0.53	0.54	0.70

Continued on next page

Table 1 – continued from previous page

Country		#Firms	#Obs.	$\overline{\text{(BAB)}}\%$	$\sigma_{(\text{BAB})}\%$	$\overline{\beta Sprd}$	$\rho_{(\text{BAB}^j,\text{BAB}^G)}$	$\rho_{(r^j,r^G)}$
Malaysia	EM	1,178	282	2.42	3.91	0.55	0.22	0.46
Mexico	EM	207	242	3.32	5.61	0.85	0.10	0.61
Morocco	EM	79	171	5.98	11.15	0.57	0.10	0.29
Netherlands	DM	293	438	2.70	4.28	0.52	0.52	0.83
New Zealand	DM	200	258	3.64	5.91	0.46	0.16	0.65
Norway	DM	437	354	3.28	5.46	0.51	0.31	0.69
Pakistan	EM	210	204	6.40	11.01	0.83	-0.002	0.17
Peru	EM	168	186	6.14	13.47	1.53	-0.07	0.46
Philippines	EM	241	262	3.67	7.85	0.46	0.20	0.49
Poland	EM	541	184	2.53	4.08	0.38	0.31	0.64
Portugal	EM	132	234	4.09	7.64	0.77	0.25	0.67
Romania	EM	142	151	4.43	14.17	0.53	0.22	0.49
Russia	EM	500	138	3.70	9.32	0.64	0.27	0.63
Singapore	DM	811	438	2.29	3.86	0.54	0.20	0.66
Slovenia	EM	58	127	5.55	9.80	0.38	0.17	0.52
South Africa	EM	681	438	4.09	9.73	0.65	0.19	0.58
South Korea	EM	2,116	262	3.03	7.48	0.56	0.19	0.58
Spain	DM	270	268	2.44	3.74	0.58	0.46	0.78
Sri Lanka	EM	221	248	8.08	63.33	1.02	0.01	0.14
Sweden	DM	703	330	2.66	5.06	0.48	0.49	0.77
Switzerland	DM	372	438	2.19	3.79	0.60	0.40	0.74
Taiwan	EM	1,914	254	3.07	6.31	0.56	0.28	0.47
Thailand	EM	698	270	2.86	5.51	0.77	0.24	0.55
Turkey	EM	386	258	2.88	9.45	0.43	-0.02	0.41
UK	DM	3,916	438	2.25	3.92	0.56	0.63	0.76
US	DM	16,406	438	1.70	2.83	0.69	0.81	0.86
DM		1,912	403	2.68	4.63	0.57	0.40	0.70
EM		589	218	4.18	10.49	0.64	0.15	0.50

Table 2. FSI and Global Funding Liquidity: Panel A reports the regression results of the FSI with respect to proxies of global funding liquidity measures, where we include country intercepts and time trend to capture the effect of country-specific differences and the reduction of barriers to investment during time. In Panel B we explicitly control for barriers to foreign investment. P-values are double clustered (standard errors are reported in parenthesis).

$$\text{Panel A: } FSI_t^j = \alpha^j + \delta \ \ FL_t + \theta t + \varepsilon_t^j, \qquad j \in DM$$

$$\text{Panel B: } FSI_t^j = \alpha + \delta \ \ FL_t + \gamma \text{Cont.Var.} + \varepsilon_t^j, \qquad j \in DM$$

Panel A	(1)	(2)	(3)	(4)
TED Spread	0.1623 ***			
	(0.0376)			
VIX Index		0.0126 ***		
		(0.0020)		
Lev.^{BD} $\times -1$			0.0022 **	
			(0.0010)	
FL^{FixedIncome}				0.0734 **
				(0.0358)
Trend	Yes	Yes	Yes	Yes
Country Fixed Effect	Yes	Yes	Yes	Yes
Observations	6,943	6,092	8,453	6,372
adj. R^2	0.22	0.36	0.13	0.14
Panel B	(1)	(2)	(3)	(4)
TED Spread	0.1519 **			
	(0.0515)			
VIX Index		0.0127 ***		
		(0.0026)		
Lev.^{BD} $\times -1$			0.0017 **	
			(0.0008)	
FL^{FixedIncome}				0.0363 *
				(0.0192)
<u>Control Variables:</u>				
Market Liquidity	0.2248 *	0.3630 ***	0.1953 *	0.1658
	(0.1357)	(0.1346)	(0.1044)	(0.1186)
Investment Profile	-0.0045	-0.0028	-0.0009	-0.0047
	(0.0073)	(0.0078)	(0.0068)	(0.0071)
Trade	0.0007	0.0007	0.0002	0.0003
	(0.0005)	(0.0005)	(0.0006)	(0.0005)
Market Cap.			-0.0001	-0.0001
			(0.0002)	(0.0002)
Market Returns	0.1281	0.2793 *	-0.1292	-0.0552
	(0.1557)	(0.1590)	(0.0978)	(0.1071)
Credit Spread	0.0164	-0.0684 *	0.0293	0.0370
	(0.0296)	(0.0369)	(0.0471)	(0.0508)
Observations	5,117	4,925	5,117	5,117
adj. R^2	0.21	0.34	0.16	0.15

Table 3. FSI and Global Funding Liquidity - Tight vs. Relaxed Periods: The table reports the regression results of the FSI of the developed markets in tight and relaxed periods of funding constraints. In Panel A, tight funding periods are identified by a dummy variable that takes value of one if the proxy of the global funding liquidity is in its 90 percentile. Similarly, in Panel B the relaxed funding periods are identified by a dummy variable that takes values of one if the proxies are below their 50 percentile. These regressions include country intercepts and time trend to capture the effect of country-specific differences between markets and the reduction of barriers to investment during time. Leverage of the broker-dealers is signed such that increase in the proxies of the funding liquidity implies worsening of the funding condition in the economy.

$$\text{Panel A: } FSI_t^j = \alpha^j + \delta \;\; I[FL_t > 0.90^{th}] + \theta t + \varepsilon_t^j, \qquad j \in DM$$
$$\text{Panel B: } FSI_t^j = \alpha^j + \delta \;\; I[FL_t \in 0.50^{th}] + \theta t + \varepsilon_t^j, \qquad j \in DM$$

Panel A	(1)	(2)	(3)	(4)
$\mathbb{1}_{\text{TED Spread}>90^{th}}$	0.1432 ***			
	(0.0527)			
$\mathbb{1}_{\text{VIX Index}>90^{th}}$		0.2116 ***		
		(0.0543)		
$\mathbb{1}_{\text{Lev.}^{BD}\in 10^{th}}$			0.1271 ***	
			(0.0439)	
$\mathbb{1}_{\text{FL}^{FixedIncome}>90^{th}}$				0.1151 **
				(0.0514)
Trend	Yes	Yes	Yes	Yes
Country Fixed Effect	Yes	Yes	Yes	Yes
Observations	6,943	6,092	8,453	6,372
adj. R^2	0.13	0.19	0.14	0.16

Panel B	(1)	(2)	(3)	(4)
$\mathbb{1}_{\text{TED Spread}\in 50^{th}}$	-0.0927 ***			
	(0.0233)			
$\mathbb{1}_{\text{VIX Index}\in 50^{th}}$		-0.1404 ***		
		(0.0179)		
$\mathbb{1}_{\text{Lev.}^{BD}>50^{th}}$			0.0022	
			(0.0133)	
$\mathbb{1}_{\text{FL}^{FixedIncome}\in 50^{th}}$				-0.0474 **
				(0.0191)
Trend	Yes	Yes	Yes	Yes
Country Fixed Effect	Yes	Yes	Yes	Yes
Observations	6,943	6,092	8,453	6,372
adj. R^2	0.13	0.22	0.10	0.14

Table 4. FSI and CIP Deviations: The table reports the regression results of FSI with respect to CIP deviations, as measured by absolute value of cross-currency basis for 3-month contracts averaged across AUD, CAD, CHF, DKK, EUR, GBP, JPY, NOK, NZD, SEK currencies (Source: Wenxin Du). Regression 1 is from inception of this dataset (Jan. 2000). We control for cross-sectional differences and the long term dynamics of market segmentation using country fixed effects and a time trend. In regression 2 (3), we model tight (relaxed) period of funding constraints with a dummy variable that takes one if CIP deviations are greater than their 90 percentile (in their 50 percentile). Regression 4 and 5, we study CIP deviations as a measure of funding liquidity in subsamples (before and after year 2007). Regression 6, studies FSI and CIP deviations with a set of previously studied proxies of investment barriers.

$$FSI_t^j = \alpha^j + \delta \ \ CIP_t^{World} + \gamma Cont.Var._t^j + \varepsilon_t^j, \qquad j \in DM$$

	(1)	(2)	(3)	(4)	(5)	(6)
	2000-2014			pre-2007	post-2007	post-2007
CIP Deviation	0.8643***			−2.6308	0.8499***	0.9313***
	(0.2532)			(2.1012)	(0.1890)	(0.3436)
$\mathbb{1}_{\text{CIP}>90^{th}}$		0.2532**				
		(0.1058)				
$\mathbb{1}_{\text{CIP}\in 50^{th}}$			−0.2406***			
			(0.0743)			
Control Variables:						
Market Liquidity						0.0724
						(0.1642)
Investment Profile						0.0241
						(0.0167)
Trade						−0.0005
						(0.0001)
Market Cap.						−0.0001
						(0.0001)
Market Returns						−0.1549
						(0.3023)
Capital Account Openness						0.0008
						(0.0024)
Trend	Yes	Yes	Yes	Yes	Yes	No
Country Fixed Effect	Yes	Yes	Yes	Yes	Yes	No
Observations	3,675	3,675	3,675	1,764	1,890	1,002
adj. R^2	0.35	0.19	0.16	0.22	0.51	0.48

Table 5. FSI and Funding constraints of the Institutional Investors: The table reports the regression results of FSI with respect to the market capitalization of the global banking industry and total asset of broker-dealers as proxies for the funding constraints of the institutional investors. These variables are signed such that an increase in them implies worsening of the funding condition.

$$FSI_t^j = \alpha^j + \delta \ \ Insi.FL_t + \gamma Cont.Var._t^j + \varepsilon_t^j, \qquad j \in DM$$

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\text{Banks}^{\text{MCAP}} \times -1$	0.0032***						0.0034	
	(0.0012)						(0.0022)	
$\text{Total Asset}^{\text{BD}} \times -1$		0.0045*						0.0109**
		(0.0023)						(0.0044)
$\mathbb{1}_{\text{Banks}^{\text{MCAP}} \in 10^{th}}$			0.1318***					
			(0.0417)					
$\mathbb{1}_{\text{Total Asset}^{\text{BD}} \in 10^{th}}$				0.0954**				
				(0.0430)				
$\mathbb{1}_{\text{Banks}^{\text{MCAP}} > 50^{th}}$					−0.0232*			
					(0.0129)			
$\mathbb{1}_{\text{Total Asset}^{\text{BD}} > 50^{th}}$						−0.0096		
						(0.0127)		
Control Variables:								
Market Liquidity							−0.0039	−0.0157
							(0.0691)	(0.0638)
Investment Profile							0.0225***	0.0201***
							(0.0042)	(0.0042)
Trade							0.00004	0.00003
							(0.0002)	(0.0001)
Market Cap.							−0.0001	−0.0001
							(0.0001)	(0.0001)
Market Returns							−0.0588	−0.1917
							(0.1903)	(0.1338)
Capital Account Openness							0.0006	0.0006
							(0.0008)	(0.0008)
Trend	Yes	Yes	Yes	Yes	Yes	Yes	No	No
Country Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	No	No
Observations	8,453	8,453	8,453	8,453	8,453	8,453	5,117	5,117
adj. R^2	0.14	0.13	0.15	0.10	0.12	0.10	0.15	0.22

Table 6. FSI and Local Funding Liquidity: The table reports the regression results of FSI with respect to proxies of local funding constraints. We use local CIP deviations, as measured by the absolute value of cross-currency basis for 3-month contracts, as well as decreases in market capitalization of the local banking industry.

$$FSI_t^j = \alpha + \delta \ \ Local\_FL_t^j + \gamma Cont.Var._t^j + \varepsilon_t^j$$

	(1)	(2)	(3)	(4)	(5)	(6)
CIP Deviations	0.3979***	0.3080***	0.2279***			
	(0.0871)	(0.1100)	(0.0730)			
$\text{Banks}^{\text{MCAP}} \times -1$				0.0011**	0.0011**	0.0006
				(0.0005)	(0.0005)	(0.0005)
Control Variables:						
Market Liquidity		0.2364**	0.2893***		0.0485	0.0047
		(0.0955)	(0.1027)		(0.1053)	(0.0619)
Investment Profile		0.0070	−0.0015		0.0188***	0.0263***
		(0.0129)	(0.0115)		(0.0051)	(0.0039)
Trade		−0.000003	0.00002		0.0001	−0.00002
		(0.0002)	(0.0002)		(0.0001)	(0.0001)
Market Cap.		−0.0002	−0.0002		−0.0007***	−0.0002
		(0.0002)	(0.0002)		(0.0002)	(0.0002)
Market Returns		−0.2630*	−0.0468			
		(0.1510)	(0.1391)			
Capital Account Openness		0.0011	0.0019		−0.0032***	0.0009
		(0.0012)	(0.0012)		(0.0007)	(0.0007)
TED			0.1445***			0.1558***
			(0.0399)			(0.0387)
Trend	Yes	No	No	Yes	No	No
Country Fixed Effect	Yes	No	No	Yes	No	No
Observations	3,627	2,544	2,268	13,984	8,032	4,624
adj. R^2	0.23	0.13	0.22	0.10	0.05	0.21

Table 7. SEG and Global Funding Liquidity: The table presents test results on the SEG index, the measure of market segmentation introduced in Bekaert et al. (2011), for developed markets conditional on proxies of global funding liquidity, as well as our newly introduced segmentation measure, FSI. In Panel A, regressions include country intercepts and time trend to capture the effect of country-specific differences between markets and the reduction of barriers to investment during time. Leverage of the broker-dealers is signed such that increase in the proxies of the funding liquidity implies worsening of the funding condition in the economy. In Panel B, the table includes a set of explanatory factors that Bekaert et al. (2011) show explain market segmentation. P-values are calculated with double clustered standard errors (standard errors are in parenthesis).

$$\text{Panel A: } SEG_t^j = \alpha^j + \delta FL_t + \theta t + \varepsilon_t^j, \qquad j \in DM,$$
$$\text{Panel B: } SEG_t^j = \alpha + \delta FL_t + \gamma \text{Cont.Var.} + \varepsilon_t^j, \quad j \in DM,$$

Panel A	(1)	(2)	(3)	(4)	(5)
TED Spread	0.8424***				
	(0.1616)				
VIX Index		0.0497***			
		(0.0113)			
$\text{Lev.}^{BD} \times -1$			1.2042**		
			(0.5580)		
$\text{FL}^{FixedIncome}$				0.0019***	
				(0.0007)	
FSI					0.0150***
					(0.0043)
Trend	Yes	Yes	Yes	Yes	Yes
Country Fixed Effect	Yes	Yes	Yes	Yes	Yes
Observations	6,793	5,900	9,033	6,249	7,941
adj. R^2	0.26	0.26	0.30	0.23	0.31

Continued on next page

Table 7 - continued from previous page

Panel B	(1)	(2)	(3)	(4)	(5)
TED	0.7538**				
	(0.3334)				
VIX		0.0508**			
		(0.0198)			
Lev.$^{BD} \times -1$			1.3669*		
			(0.7779)		
FL^{FixedIncome}				0.0013	
				(0.0012)	
FSI					0.0132*
					(0.0071)
Market Liquidity	0.0120	0.0107	0.0103	0.0134	0.0115
	(0.0103)	(0.0107)	(0.0102)	(0.0103)	(0.0103)
Investment Profile	−0.0003	−0.0008	−0.0005	−0.0003	−0.0007
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Trade	0.00005***	0.0001***	0.00005***	0.00005***	0.00005***
	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)
Market Cap.	−0.0001***	−0.0001***	−0.0001***	−0.0001***	−0.0001***
	(0.00002)	(0.00002)	(0.00002)	(0.00002)	(0.00002)
Market Returns	−0.0201*	−0.0081	−0.0283**	−0.0274*	−0.0240*
	(0.0105)	(0.0098)	(0.0134)	(0.0144)	(0.0132)
Capital Account Openness	−0.0001	−0.0001	−0.0001	−0.0001	−0.0001
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Observations	4,841	4,661	4,841	4,841	4,841
adj. R^2	0.23	0.25	0.22	0.20	0.22

Table 8. U.S. FSI and Funding Liquidity: The table reports the regression results of FSI of the U.S. market with respect to funding illiquidity measures in the U.S. market. P-values are calculated with Newey and West (1987) standard errors (standard errors are reported in parenthesis). Leverage of the broker-dealers is signed such that an increase in it implies worsening of the funding condition in the economy.

$$FSI_t^{US} = \alpha + \delta \ \ FL_t + \varepsilon_t^{US},$$

	(1)	(2)	(3)	(4)
TED Spread	0.1421**			
	(0.0661)			
VIX Index		0.0114***		
		(0.0031)		
Lev.^{BD} $\times -1$			0.0036***	
			(0.0008)	
FL^{FixedIncome}				0.0532**
				(0.0022)
Observations	343	295	146	316
adj. R^2	0.13	0.26	0.20	0.09

B Figures

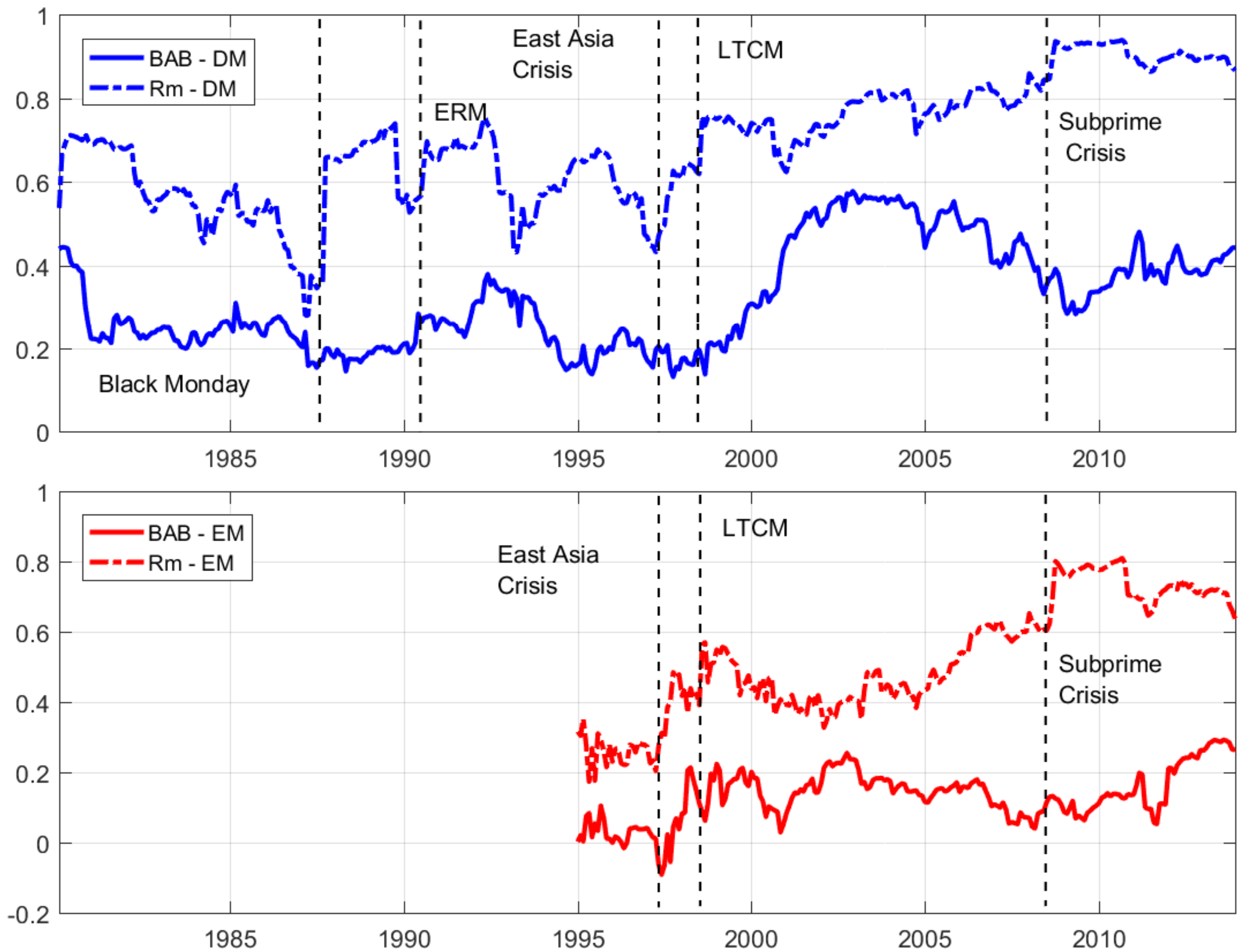

Figure 1. Market Return VS BAB correlations: In this plot, the top panel shows the average 2-year rolling window correlations for developed markets returns with global market portfolio return (in blue dashed line) and the average of BAB correlations with Global BAB portfolio (in blue solid line). The bottom panel plots a similar graph for the emerging markets (in red). Large global market crashes are marked: Black Monday on October 1987, withdrawal of the pound sterling from the European Exchange Rate Mechanism (ERM) on September 1992, East Asia Stock Market Crash on July 1997, Long-Term Capital Market collapse on September 1998, and Subprime Crisis on September 2008 .

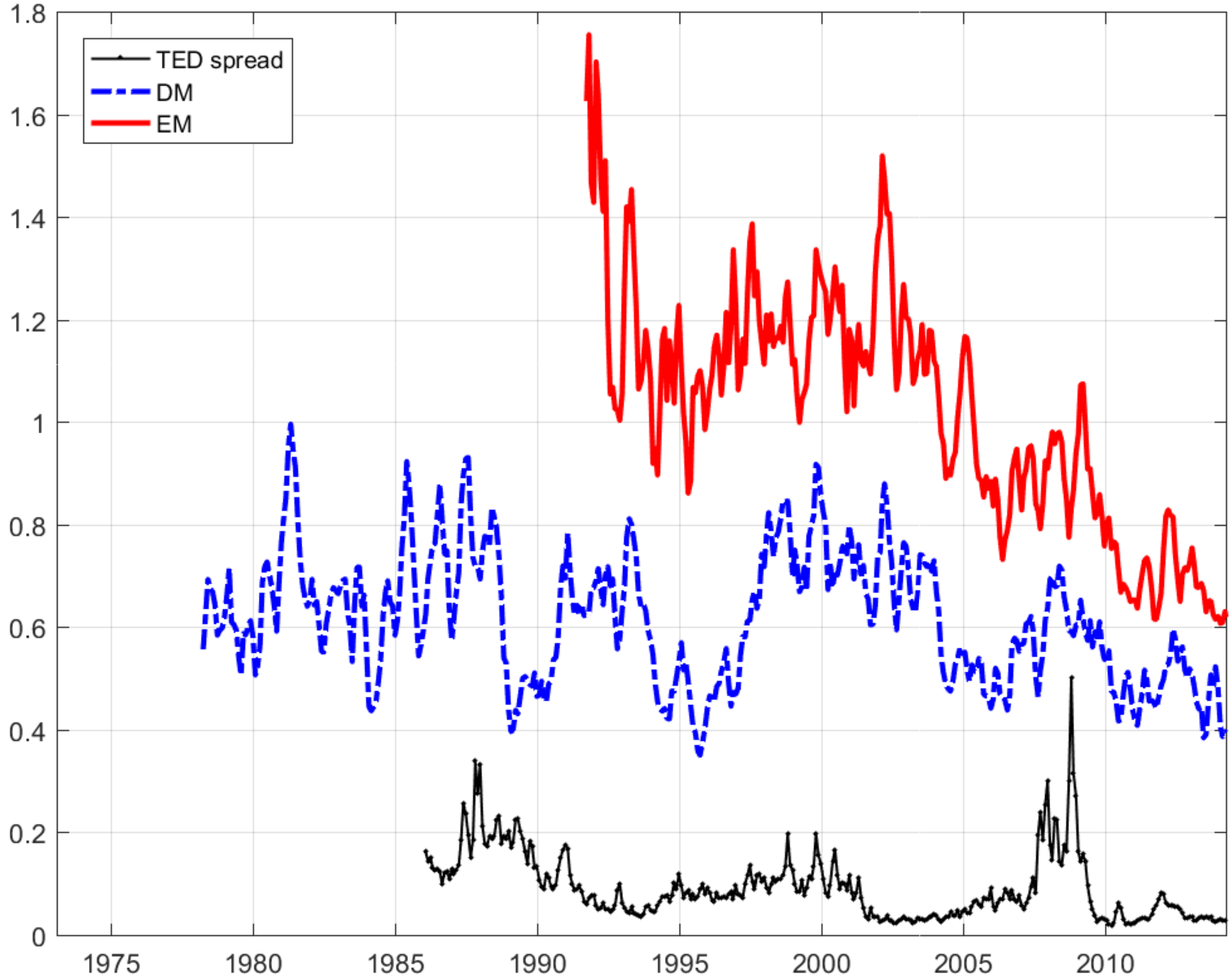

Figure 2. Funding-implied Segmentation Indicator: The plot shows the average of FSI for developed markets (in blue dash-dot line) and emerging markets (in solid red line). The measure is constructed based on the value-weighted discrepancies of the estimated shadow price of the funding constraint for the global representative investor, extracted from each market BAB portfolios. The TED spread is shown in black with asterisk marker.

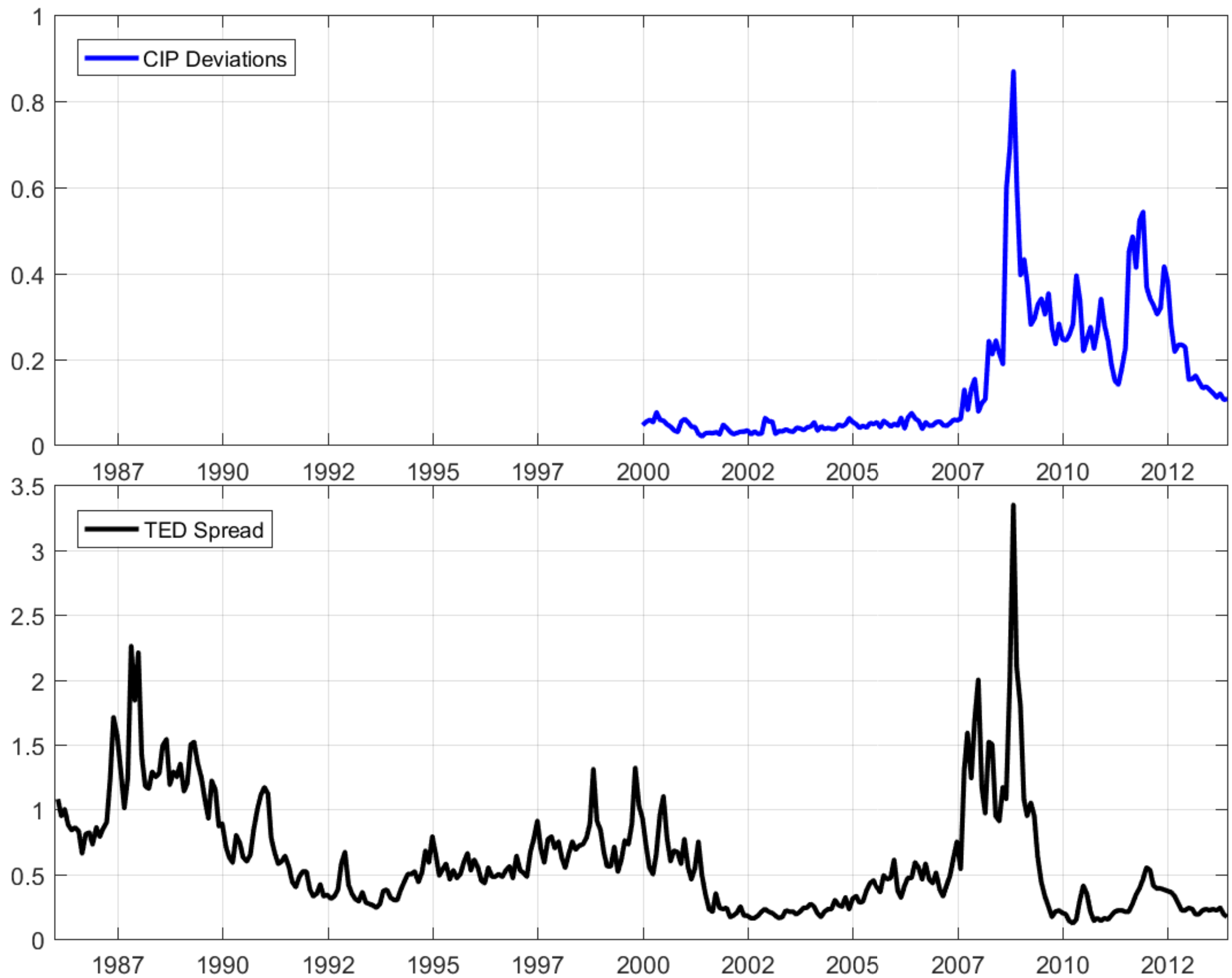

Figure 3. CIP Deviations: In the top panel, the plot shows Covered Interest rate Parity (CIP) Deviations,as measured by absolute value of cross-currency basis for 3-month contracts averaged across AUD, CAD, CHF, DKK, EUR, GBP, JPY, NOK, NZD, SEK currencies (Source: Wenxin Du). In the bottom panel we plot the TED Spread.

C Online Appendix

Table Appendix.1. Correlation of BAB portfolios: The table presents time-series analysis results on the time-varying correlations of BAB portfolios with respect to proxies of global funding liquidity. Time-varying correlations are generated with DCC Engle (2002) methodology. P-values are calculated with double clustered standard errors (standard errors are in parenthesis) as instructed by Petersen (2009). Leverage of the broker-dealers are signed such that an increase in it implies worsening of the funding condition in the economy. Estimates for the Intercept are excluded for the sake of brevity.

$$\rho_t(BAB_t^j, BAB_t^G) = \alpha^j + \delta FL_t + \rho_t(Rm_t^j, Rm_t^G) + \varepsilon_t^j, \quad j \in DM$$

	(1)	(2)	(3)	(4)
TED Spread	-7.9076^{***}			
	(2.2613)			
VIX Index		-0.0436		
		(0.1002)		
Lev.^{BD} $\times -1$			-0.0662	
			(0.1178)	
FL^{FixedIncome}				-0.0416^{***}
				(0.0094)
$\rho(Rm^c, Rm^G)$	0.2530^{***}	0.2861^{***}	0.2237^{*}	0.3385^{***}
	(0.0868)	(0.0948)	(0.1341)	(0.0942)
Country Fixed Effect	Yes	Yes	Yes	Yes
Observations	6,943	6,092	2,824	6,372
Adj. R^2	0.55	0.57	0.53	0.56

Table Appendix.2. Summary Statistics of FSIs

Panel A Country	EM/DM	#Obs.	Mean	Std.	Max	Min	AutoCorr
Argentina	EM	190	0.78	0.42	2.52	0.20	0.23
Australia	DM	433	0.64	0.34	2.06	0.15	0.27
Austria	DM	433	0.50	0.23	1.48	0.15	0.39
Belgium	DM	433	0.50	0.21	1.33	0.16	0.28
Brazil	EM	179	0.52	0.27	1.73	0.18	0.48
Canada	DM	433	0.92	0.60	3.87	0.16	0.16
Chile	EM	237	1.13	0.85	4.42	0.20	0.07
China	EM	191	1.08	0.81	4.37	0.18	0.17
Colombia	EM	187	1.28	1.51	8.42	0.22	0.94
Czech	EM	187	1.59	1.39	9.59	0.17	0.17
Denmark	DM	433	0.71	0.45	2.76	0.18	0.29
Egypt	EM	152	1.13	0.99	6.70	0.19	0.11
Finland	DM	253	0.49	0.18	1.23	0.18	0.31
France	DM	433	0.54	0.25	1.39	0.15	0.28
Germany	DM	433	0.52	0.24	1.51	0.15	0.31
Greece	EM	231	1.14	1.06	5.29	0.22	0.37
Hong Kong	DM	433	0.80	0.46	3.14	0.19	0.23
Hungary	EM	201	0.55	0.21	1.32	0.22	0.29
India	EM	231	1.00	0.72	4.45	0.23	0.17
Indonesia	EM	228	0.59	0.27	1.80	0.24	0.14
Ireland	DM	433	0.57	0.28	1.83	0.15	0.26
Israel	EM	197	0.56	0.26	1.73	0.18	0.27
Italy	DM	433	0.58	0.28	1.73	0.17	0.27
Japan	DM	433	0.52	0.29	1.66	0.11	0.40
Malaysia	EM	279	0.78	0.49	3.19	0.18	0.22
Mexico	EM	239	0.56	0.27	1.77	0.20	0.24
Morocco	EM	169	1.33	1.01	5.29	0.23	0.31
Netherlands	DM	433	0.53	0.21	1.21	0.15	0.40
New Zealand	DM	255	0.61	0.33	2.12	0.22	0.49
Norway	DM	351	0.51	0.23	1.49	0.17	0.36
Pakistan	EM	201	0.88	0.61	3.54	0.23	0.23
Peru	EM	185	0.64	0.36	2.09	0.18	0.29
Philippines	EM	259	0.76	0.52	2.99	0.23	0.32
Poland	EM	183	0.52	0.24	1.30	0.21	0.37
Portugal	EM	231	0.49	0.21	1.38	0.19	0.38
Romania	EM	150	1.22	1.03	4.99	0.23	0.23
Russia	EM	137	0.67	0.37	2.14	0.22	0.05
Singapore	DM	433	0.63	0.36	2.26	0.19	0.26
Slovenia	EM	126	0.58	0.20	1.12	0.23	0.46
South Africa	EM	433	1.24	1.06	6.43	0.15	0.19
South Korea	EM	259	0.75	0.50	2.52	0.22	0.32

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Table Appendix.2 – continued from previous page

Country	EM/DM	#Obs.	Mean	Std.	Max	Min	AutoCorr
Spain	DM	265	0.47	0.18	1.15	0.18	0.27
Sri Lanka	EM	244	2.34	2.10	11.58	0.31	0.06
Sweden	DM	327	0.60	0.33	1.96	0.18	0.18
Switzerland	DM	433	0.62	0.31	1.80	0.16	0.24
Taiwan	EM	251	1.04	0.72	4.23	0.20	0.15
Thailand	EM	267	0.61	0.28	1.73	0.18	0.28
Turkey	EM	255	0.79	0.48	2.63	0.21	0.21
UK	DM	433	0.68	0.39	2.17	0.16	0.18
US	DM	433	0.37	0.15	0.90	0.12	0.30
Venezuela	EM	230	1.14	0.89	5.29	0.24	0.15
Mean DM		399	0.30	1.86	0.16	0.29	0.47
Mean EM		217	0.92	3.88	0.21	0.26	0.26

Panel B	Average of Samples		Pooled Panel		
	FSI_{DM}	FSI_{EM}	All	DM	EM
α	0.6932***	1.3689***	0.8231***	0.7200***	1.9690 ***
	(0.0280)	(0.0707)	(0.0687)	(0.0466)	(0.1729)
θ (Time Trend)	-0.0003***	-0.0012***	-0.0001***	-0.0004***	-0.0026***
	(0.0001)	(0.0002)	(0.0002)	(0.0001)	(0.0004)
$H_0 : FSI_{EM} > 0$	0.001				
$H_0 : FSI_{DM} > 0$		0.001			
$H_0 : FSI_{EM} > FSI_{DM}$		0.001			
Nb Countries	1	1	52	22	30
Time	439	439	38-439	211-439	38-439
Observations	439	439	15997	8706	7291

$$FSI_t^c = \sum_{j=1}^{J} w_t^j \ |\psi_t^j - \psi_t^c|,$$

The table presents summary statistics for the Funding-liquidity Segmentation Indicators (FSI) constructed from BAB portfolios in each market. Panel A reports the number of monthly observations as well as mean, standard deviation, maximum, minimum and first order autocorrelations of FSI. Panel B studies the FSI and the progressively reducing barriers to investment, as proxied by the time trend, in univariate and panel regressions. In the univariate regressions, the average of FSI for developed and emerging markets are studied separately. P-values are calculated with Newey and West (1987) standard errors (standard errors are in the parenthesis). In the panel regressions, FSI for all the cross-section and subsamples of developed and emerging markets are studied in an unbalanced pooled panel, where standard errors are double clustered (Petersen (2009)). P-values of one-way t-tests for the statistical significance of the size of the measure of market segmentation for emerging markets relative to developed markets are also presented.

Table Appendix.3. FSI and Determinants of Market Segmentation-Univariate Regression Results

Panel A	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Market Returns	−0.2719***						
	(0.1003)						
Market Liquidity		0.1976***					
		(0.0668)					
Private Credit			−0.0006**				
			(0.0002)				
GDP per Capita				−0.0441***			
				(0.0091)			
Market Cap.					−0.0001		
					(0.0001)		
Trade						−0.0001	
						(0.0001)	
gGDP							−0.0018
							(0.0024)
Observations	15,052	15,052	14,215	14,768	12,823	14,775	14,763
Adjusted R^2	0.0059	0.0126	0.0091	0.0331	0.0016	0.0010	0.0004

Panel B	(1)	(2)	(3)	(4)	(5)	(6)	(7)
School Enrollment	−0.0020***						
	(0.0006)						
Life Expectancy		−0.4824**					
		(0.2405)					
Internet Users			−0.0053				
			(0.0040)				
Law & Order				−0.0397***			
				(0.0084)			
Investment Profile					0.0004		
					(0.0058)		
Capital Account Openness						−0.0021***	
						(0.0006)	
Current Account Openness							−0.0021***
							(0.0008)
Observations	13,140	14,798	12,150	13,635	13,635	14,750	14,750
Adjusted R^2	0.0201	0.0167	0.0028	0.0325	-0.0001	0.0274	0.0216

$$FSI_t^j = \alpha + \delta \ \ Determinants_t^j + \varepsilon_t^j,$$

The table reports the regression results of FSI with respect to previously studied determinants of market segmentation. P-values are calculated with double clustered standard errors (standard errors are reported in parenthesis).

Table Appendix.4. FSI and Determinants of Market Segmentation-Pooled Regression Results

	(1)	(2)	(3)
Market Returns	-0.2780^{*}	-0.2686^{**}	-0.2503^{***}
	(0.1512)	(0.1083)	(0.0871)
Market Liquidity	0.0661		0.1605^{*}
	(0.1228)		(0.0952)
Private Credit	-0.0004		
	(0.0003)		
GDP per Capita	-0.0447^{***}	-0.0668^{***}	
	(0.0170)	(0.0116)	
Market Cap.	-0.0001		-0.0001
	(0.0001)		(0.0001)
Trade	0.0001		0.0001
	(0.0001)		(0.0001)
gGDP	-0.0113^{***}	-0.0082^{***}	
	(0.0035)	(0.0025)	
School Enrollment	-0.0014		
	(0.0010)		
Life Expectancy	0.2534		
	(0.1642)		
Internet Users	0.0045		
	(0.0050)		
Law & Order	0.0091		
	(0.0113)		
Investment Profile	0.0204^{***}	0.0148^{***}	0.0081^{*}
	(0.0051)	(0.0057)	(0.0042)
Capital Account Openness	-0.0004		-0.0023^{***}
	(0.0006)		(0.0006)
Current Account Openness	-0.0023		
	(0.0016)		
Credit Spread			0.1516^{**}
			(0.0691)
Observations	9,008	13,374	11,616
Adjusted R^2	0.0773	0.0615	0.0924

$$FSI_t^j = \alpha + \sum_i \delta^i \ Determinants_t^{j,i} + \varepsilon_t^j,$$

The table reports the pooled regression results of FSI with respect to previously studied determinants of market segmentation. P-values are calculated with double clustered standard errors (standard errors are reported in parenthesis).

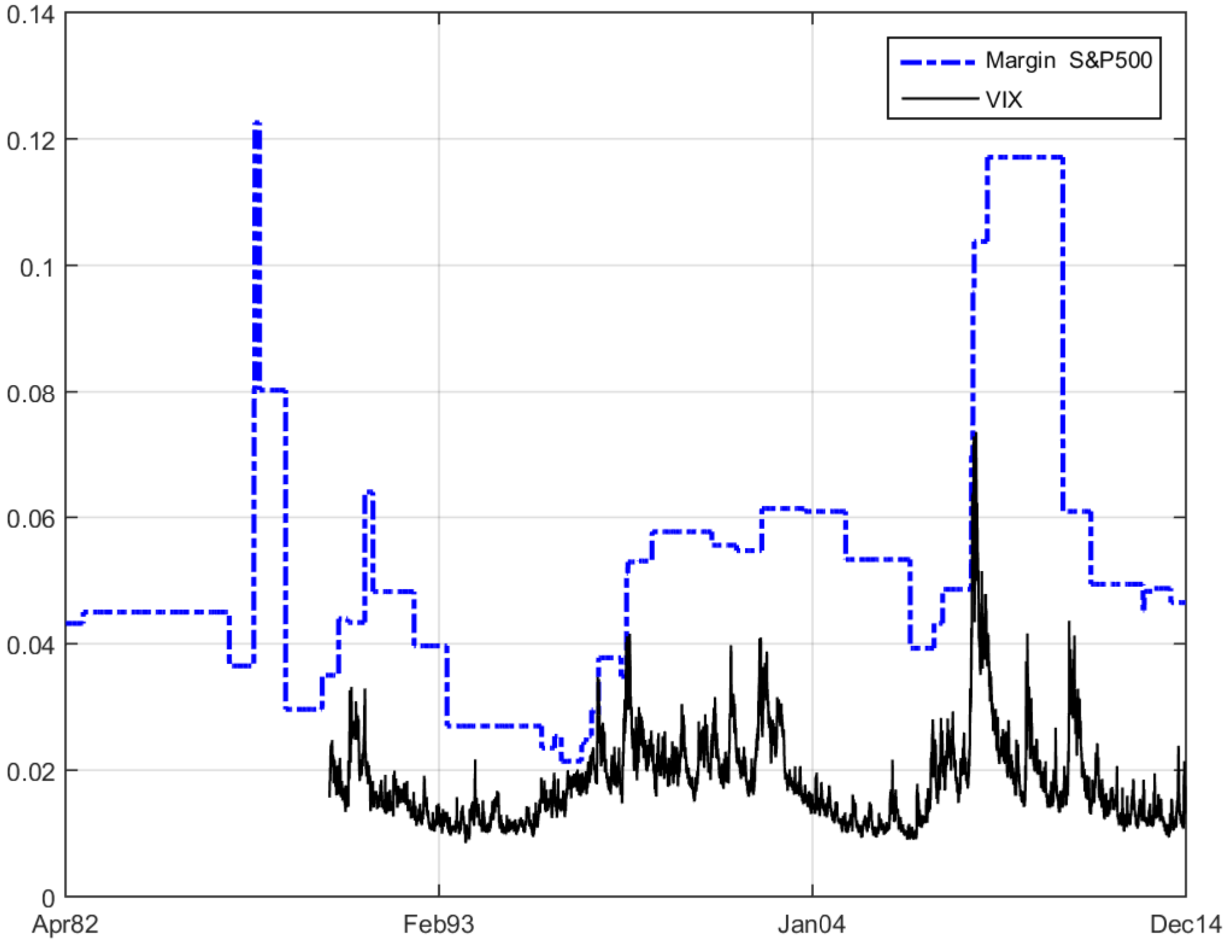

Figure Appendix.1. Margins for S&P 500 futures: The figure plots minimum performance bond requirement for S&P 500 stock index futures contracts for members of Chicago Mercantile Exchange with dash-dot line in blue. Here, the dollar value of the initial margin requirements are divided by the dollar value of a futures contract (value of the S&P 500 index times the contract size). The VIX index (implied volatility) is superimposed on the graph with dark solid line. Source: CME group website