Reversals in Global Market Integration: A Funding Liquidity Explanation*

Amir Akbari

McGill University

Abstract

This paper provides an explanation for reversals in time–varying market integration through the funding liquidity channel, consistent with limits to arbitrage and home bias dynamics. I show that the existing measure of market segmentation increases as funding constraints bind more strongly. Moreover, during global funding distress periods, Betting Against Beta portfolios that load on funding liquidity commove less across markets. This implies that at these times, funding liquidity shocks are local in nature and their risk is borne by local investors, hence market segmentation. This result is consistent with implications of an international-margin CAPM with both *investor-specific* and *asset-specific* margin constraints, where under the null of no segmentation, local shadow prices of the margin constraints comove globally. I construct a Funding-liquidity Segmentation Indicator (FSI) of equity markets based on the differentials of these shadow prices. The FSI not only fits with the existing measures of market segmentation but also explains reversals in integration after liberalization, when barriers to investment are lifted.

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1 Introduction

The literature of international finance has intensively studied global market integration and its dynamics through time. It has been documented that markets are becoming more integrated due to the progressive reduction of barriers to international investment and regulatory restrictions. However, at times we also have observed reversals, for which the literature has failed to provide convincing explanations. This paper provides empirical evidence that partly explains these reversals via the role of financial intermediaries and funding liquidity.

Market integration is a central concept in international finance mainly because it is a critical factor for international diversification benefits, more than other measures such as cross-market correlations. For instance, if international investment opportunities can be fully replicated at home, then low cross-market correlation does not necessarily imply the existence of diversification opportunities for domestic investors, whereas low values of market integration is a more informative indicator of diversification opportunity (see Errunza, Hogan, and Hung (1999), Pukthuanthong and Roll (2009)). Moreover, understanding market integration also sheds lights on the contagion mechanism across markets via investment or shared discount factor channel. One strand of the literature argues that by force of arbitrage local credit shocks in a market, for instance the US, could be transmitted across the global markets via the SDF channel (Dedola and Lombardo (2012)). However, if markets become segmented during these periods, then international assets are not governed by one common pricing kernel, hence shared SDF cannot be a valid contagion channel.

As a result of its important role in asset pricing, the literature of international finance has explored different dimensions and implications of market integration.[1]. Research shows that markets differ in their degree of integration, and these cross-sectional differences are justified by the severity of the barriers to international investment in each market.[2] Moreover,

[1] Among many see Bekaert and Harvey (1995), Carrieri, Errunza, and Hogan (2007), Pukthuanthong and Roll (2009), Bekaert, Harvey, Lundblad, and Siegel (2011) and Eiling and Gerard (2014)

[2] Barriers take many forms including capital controls, restrictions/taxes on repatriation, and limits on ownership, market regulation, investor protection, and information.

research documents that market integration is a time-varying process with an upward trend and few reversals. This upward trend is linked to progressive reduction of explicit and implicit barriers of investment. However, persistent reduction of these barriers stands at odds with the occurrence of reversals. Analysis of graphs of measures of market integration in this literature confirms that the reversals mainly occur during global financial crisis (see Figure 1). Yet, to my knowledge, no paper has directly explained these patterns and there is no study on the dynamics of market integration conditional on financial crises. In fact, the mechanisms and channels that affect market segmenation during crisis periods have not been fully explored, especially in the post-liberalization period, when most barriers to investment have been lifted. Moreover, the role of institutional investors, who are responsible for most cross-country investments, has not been clearly defined in this process.

[Place Figure 1 about here]

Bekaert et al. (2011) point out that market segmentation increases in recessions and periods of market stress and relate it to the increase in global risk aversion in these periods. However, it is not clear why investors perceive international assets riskier than local assets, as a result of the increase in their risk aversion. Moreover, why do we observe that some countries suffer more severely during these periods? More importantly, the propagation channel of local distress across markets and investors is not clearly defined and needs to be explored in depth. Drawing analogy to the domestic setting, I conjecture that the frictions in borrowing market can provide a potential explanation for the occurrence of reversals during financial crisis. In addition, if local investors liquidate their foreign investments during funding distress periods, we expect to observe an increase in market segmentation. Less international investment leads to more local risk to be borne by local investors, which translates to local pricing factors, hence, market segmentation increases. In fact, empirical analysis shows that measure of market segmentation increases during funding liquidity drought, as proxied by multiple measures of funding liquidity. Figure 1 shows that almost all reversals are contemporaneous with worsening of funding conditions as measured by the TED spread as a frequently used proxy of funding conditions for global investors. This explanation of reversals during financial crisis is supported by the evidence documented in the limits to arbitrage literature and dynamic of home bias.

In domestic settings, the literature of limits to arbitrage provides theoretical and empirical evidence that funding illiquidity and frictions in markets could result in deviations from the Law of One Price (LoOP).[3] This matches the definition of segmented markets, where similar assets with identical cash flows could be priced differently across international markets (Chen and Knez (1995)). For instance, a financially constrained arbitrageur, as the liquidity provider in two isolated markets, would fail to trade simultaneously in the two markets and close the price gap of similar assets during crisis periods (Gromb and Vayanos (2002, 2010)). Similarly, as funding conditions worsen legal constraints of institutional investors[4] might bind more and prevents them from undertaking arbitrage activities, hence deviation from LoOP and segmentation occur.

Empirical research on the dynamics of the home bias also suggests a potential link to market segmentation, documenting that the home bias of institutional investors increases following funding shocks.[5] This "flight home" effect, as Giannetti and Laeven (2012) frame it, affects on the free flow of capital across markets, which consequently influence global risk sharing and diversification benefits. Moreover, this effect can potentially affect trading capacity of international investors and prohibit them to fully provide liquidity as an arbitrageur in both markets *a la* Gromb and Vayanos (2002). In addition, the "flight home" phenomenon effectively acts as a portfolio constraint which is shown by Basak and Croitoru (2000) can lead to mispricing between similar (international) assets. In short, when funding liquidity

[3] Influential research in this literature includes Shleifer and Vishny (1997), Basak and Croitoru (2000), Gromb and Vayanos (2002), Brunnermeier and Pedersen (2009), Duffie (2010), Geanakoplos (2010), Gârleanu and Pedersen (2011), He and Krishnamurthy (2012, 2013), Adrian and Shin (2014).

[4] Some institutional investors are legally prohibited to take short positions or are allowed only limited positions in derivatives. Others may lose their external fundings if their net wealth depreciates significantly.

[5] This pattern is documented in different asset markets across different investors, see for example Jotikasthira, Lundblad, and Ramadorai (2012), Giannetti and Laeven (2012), and Ahrend and Schwellnus (2013).

is scarce, investors, unable to execute their international trading strategies, “fly home,” as if local funding illiquidity were to represent as a barrier to international investment. The inability to share occasional local funding liquidity risk internationally translates to more risk that should be borne by local investors. Thus, market segmentation would increase during funding distress. Related to this phenomenon, Warnock and Warnock (2009) show that foreign inflows into the U.S. Government Bonds drop following the 1987 Black Monday, 1998 LTCM default, East Asia crashes, and tech-bubble burst in 2001. Giannetti and Laeven (2012) focusing on global syndicated loans market provide convincing evidence that the “flight home” effect is distinguished from “flight to quality”, where investors rebalance their portfolios toward less riskier assets. Jotikasthira et al. (2012) study global equity funds and find that regardless of the size of their cash holdings, global funds substantially alter portfolio allocations in emerging markets in response to funding shocks from their investor base.

The literature of intermediary asset pricing studies the frictions faced by institutional investors, such as agency problems and leverage constraints, to explain asset price comovements. These intermediaries are responsible for most cross-country investments and when the frictions they face increase, international prices might be consequently affected. Inability to borrow, as in Frazzini and Pedersen (2014), is one of these frictions that have attracted growing attention of researchers, especially in the aftermath of the 2008 financial crisis. Frazzini and Pedersen (2014) show that financially constrained investors, who cannot buy on margin, overweight high-beta securities to lever up their portfolios. This consequently reduces the premium of these securities, because of their efficiency as liquidity providers. The authors show that a beta-neutral portfolio that longs the low-beta portfolio and shorts the high-beta portfolio has a positive premium, which is increasing in the ex-ante tightness of constraints. They call this portfolio the Betting Against Beta or BAB.

Extending their paper, in order to study the impact of borrowing frictions on global market integration and to explore the role of institutional investors, I propose a simple asset pricing framework that incorporates heterogeneity both among securities, and among investors.[6] The assumptions of the international-margin CAPM are supported by research and practice. *Ceteris paribus*, it is more difficult to borrow against highly volatile stocks from emerging markets, as they require higher margins, comparing to large stable stocks from developed markets. Comparing to retail investors, institutional investors are less financially constrained and are able to lever up their portfolios more easily. In fact, research has shown that more volatile assets require higher margins (see Fostel and Geanakoplos (2008) and the references therein) because of the devaluation risk of the underlying. For instance, Chicago Mercantile Exchange (CME) Group's approach is to adjust margin requirements based on historical, intraday, and implied volatilities (see Figure 2).[7] Since, emerging markets have persistently higher volatilities than developed markets, it is expected to observe heterogeneity of margin requirements among international assets.[8] In a similar setting, Gârleanu and Pedersen (2011) also study *asset-specific* margins and show that high-margin assets have higher expected returns, especially during funding liquidity droughts.

[Place Figure 2 about here]

Constructing market beta-neutral portfolios from local assets, we observe that during funding distress periods, these portfolios comove less across markets, relative to local market portfolios. These portfolios, as shown by the international-margin CAPM, load on funding liquidity factor. Therefore, their low correlation implies that local funding liquidity shocks do not fully diversify out internationally. Existence of local asset pricing factors (shocks) directly lead to market segmentation. That is, in these periods there is no global representative investor and we have different margin constraints for different markets, hence market segmentation increases. On the other hand, during periods of less market stress, when capi-

[6] For different applications, this setting has been studied in Chen and Lu (2014) and Malkhozov, Mueller, Vedolin, and Venter (2014).

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

[8] From personal discussions with portfolio managers of institutional investors, they confirm that in practice margins are also set based on location of assets, due to differences in perceived foreign investment risk of securities, such as political or corruption risk. In domestic market, Gorton and Metrick (2010) provide evidence on time variation and cross-sectional differences of Repo Haircuts backed by different securities.

tal flows freely, these shadow prices comove more strongly across markets, as if all investors are constrained by one aggregated margin constraint, hence market integration increases. Interestingly, the correlations of shadow prices of funding constraints are higher for developed markets, comparing to emerging markets, consistent with the previously documented empirical evidence. In addition, I show that there is an upward trend in these correlations, consistent with the effect of market liberalizations on global market integration.

The effect of funding liquidity on capital mobility is different from asset liquidity, although the two are linked via liquidity spirals (Brunnermeier and Pedersen (2009)). Many authors have pointed out the role of liquidity risk in international investments and have shown liquidity risk as a priced local factor may lead to valuation differentials (see Bekaert, Harvey, and Lundblad (2007) and references therein). However, in fully integrated markets without investment barriers, local liquidity factors will aggregate out as a global liquidity factor and local liquidity factor is not priced. On the other hand, margin constraints may lead to local funding liquidity shocks, which persist in international markets even after full market liberalization.

The outline of the article is as follows. Section 2 reviews the related literature of global market integration and limits to arbitrage. In Section 3, I introduce the model and the Funding-liquidity Segmentation Indicator. Dataset and the empirical methodology, as well as the estimation results, are presented in Section 4. Section 5 discusses the implications of the model and concludes.

2 Related Literature

In this section I review the main ideas of market integration introduced in international finance and limits to arbitrage literatures.

Integrated market is defined as an economy where all assets, irrespective of their origin, are priced by a unique (common) pricing kernel. In other words, in this economy similar assets have identical prices across markets. Conversely, in segmented market there exists a different pricing kernel for each market; that is, local asset pricing factors, as opposed to global factors, price local assets, consequently, prices of similar assets may diverge. As markets become more integrated, the investment opportunity set expands for investors across markets and the cost of capital drops. In addition, integration enables the investors to better hedge the idiosyncratic risk of their holdings by reducing the local impact of country-specific shocks. The international finance literature has introduced numerous measures that quantify market integration and has proposed factors that can explain the dynamics of market integration through time.

Bekaert and Harvey (1995) study the evolution of market integration induced by a single factor model (CAPM) within regime-switching framework. In their setting, measure of market integration is the time-varying probability that markets conform to one of the two polar extreme cases of full integration (i.e. when the pricing kernel is the global CAPM) and complete segmentation (i.e. when the pricing kernels are the local CAPM). Carrieri et al. (2007) introduce a measure of market integration based on the amount of risk explained by integrated model relative to segmented model. There, the polar cases of full integration and segmentation are modeled in the sprite of Errunza and Losq (1985) that takes into account infeasible assets. Focusing on an APT asset pricing model, Pukthuanthong and Roll (2009) introduce a measure of market integration based on the proportion of a country's returns that can be explained by global factors. More specifically, they take the R-squared of the regression of a country's market index returns on common global factors, which are extracted from principal components analysis. Similar to the other papers, they document that integration is increasing, possibly as a result of the reduction in the barriers. But more interestingly, they report higher global market integration in bear markets; however, they do not bring economic justifications for this pattern. Bekaert et al. (2011) introduce a measure of market segmentation based on price-earning ratio differentials of industry portfolios across market. They argue that industry portfolios have similar growth opportunities and similar systematic risk across markets, thus their PE ratios should be similar, under the null of no segmentation. Bekaert et al. (2011) point out that market segmentation increases in recessions and periods of market stress and relate it to increase in global risk aversion in these periods. However, since their market segmentation measure is "model-free," they cannot provide the exact mechanism or convincing explanation for increase in segmentation during those periods. This formulation of market segmentation is also studied in Bekaert, Harvey, Lundblad, and Siegel (2013, 2014b).

It is important to point out that the market index cross-correlation is a flawed measure of market integration. That is, higher correlations do not necessarily translate to more market integration and more integration does not necessarily lead to higher correlations. Formally, Pukthuanthong and Roll (2009) show that unless the underlying asset pricing model is a single-factor model, there is no link between market integration and market-wide correlations. Assets in perfectly integrated markets may exhibit low cross-correlation, if they have different loadings on the pricing factors. Moreover, correlations might increase simply because of increasing common factor variance, rather than increasing exposures to common factors (Forbes and Rigobon (2002)). In other words, market returns may exhibit common patterns simply because markets are increasingly hit by the similar shocks. Alternative argument against this link is provided via homemade diversification (Errunza et al. (1999), Carrieri et al. (2007)). Lastly, higher integration should yield less contagion due to higher risk sharing where we observe the opposite in these periods (Forbes (2012)).

The literature has also introduced explanatory variables that can explain time-series and cross-section of market segmentation across countries. These variables are mainly categorized as explicit or implicit barriers to investment. Explicit barriers are regulatory restrictions on capital movement and are measured by variables such as equity market openness, capital account openness and trade openness. These regulatory barriers that directly impede international investment are shown to be the most important explanatory variable of market segmentation. Implicit barriers to investment include a wide range of variables such as institutional environment, quality of information available to investors, corporate governance, political risk and legal environment. The recent market liberalizations and globalization trend suggest a progressive reduction of barriers to international investment and fail to explain reversals. However, the empirical proxies of these barriers may be imperfect and imply reversals. For instance, the literature uses ratio of equity market capitalization to gross domestic product as a proxy for financial development and institutions environment. This is supported by the observation that financially developed countries have higher equity market capitalization to GDP ratios. However, any drop in this ratio does not necessarily imply a decrease in institutional developments in the countries. More plausibly in higher frequencies, this drop can be attributed more to the frictions in financial markets and less to the real economy and institutions' development.

The literature of limits to arbitrage study deviations from the law of one price (LoOP) through the role of the arbitrageurs (see Gromb and Vayanos (2010) for detail literature review). This literature has documented how assets with claims to almost identical dividend streams (e.g. "Siamese-twin" stocks) can be traded at significantly different prices. The basic justification for this phenomenon is that these stocks are exposed to different risk factors, thus they have different prices. From this point of view, deviation of LoOP matches the market segmentation definition (Chen and Knez (1995)). In this strand of literature, deviations from LoOP are explained through the costs and constraints that arbitrageurs face. Basak and Croitoru (2000) study asset pricing implications of the constraints investors face in their portfolio holdings. In their model, investors face an upper bound on the proportion of wealth invested in assets and a no-short sales constraint. In this setting, portfolio constraints generate mispricing between similar securities. Gromb and Vayanos (2010) emphasize the following costs faced by arbitrageurs: (i) risk, both fundamental and non-fundamental, (ii) costs of short-selling, (iii) leverage and margin constraints, and (iv) constraints on equity capital. In the aftermath of the 2008 financial crisis, leverage and margin constraints have attracted a growing attention both among researchers and among policy makers. Brunnermeier and Pedersen (2009) study liquidity spirals, the link between investors funding liquidity and asset's market liquidity. Geanakoplos (2010) studies an equilibrium where variations in leverage cause fluctuations in asset prices. Gârleanu and Pedersen (2011) show that required returns of securities increase in their margin requirements. He and Krishnamurthy (2012, 2013) study the agency problem between retail investors and financial intermediaries, and point out to the role of the wealth of these intermediaries in determining asset prices. Similarly, Adrian and Shin (2014) study this agency problem from the leverage constraints. Adrian, Etula, and Muir (2014) explore the explanatory power of the leverage of financial intermediaries in explaining the cross-section of asset returns. Empirically they show a single-factor model based on shocks to broker-dealers' leverage outperforms standard multi-factor benchmarks in pricing the cross-section of size, book-to-market, momentum, and bond portfolios. Frazzini and Pedersen (2014)) consider mean-variance investors with different borrowing ability and show that investors, who cannot buy on margin, overweight high-beta securities in their portfolios for their embedded margin, comparing to CAPM prediction. This extra demand pressure drives the premium of these securities down, which results in a flatter capital market line. Therefore, betting against beta portfolio with zero market beta would have positive premium. Here, an investor holds a portfolio of low-beta assets, levering them up to beta of one, and shorts high-beta assets, levering them down to beta one.

In this paper, I extend Frazzini and Pedersen's framework to a more general setting where investors also face *asset-specific* margins in an international setting. For different applications, *asset-specific* and *investor-specific* margin constraints have been previously introduced and studied in the literature. For instance, Chen and Lu (2014) construct a market-based measure of funding constraint extracted from different classification of stocks and show this measure helps explain the cross-section of hedge fund returns. The intuition, similar to Frazzini and Pedersen (2014), is that the constrained investors are willing to pay a higher price for stocks with embedded leverage and this effect is stronger for stocks with higher margin requirements. Malkhozov et al. (2014) introduce an international liquidity asset pricing model and construct a measure of funding liquidity based on fixed income market data for six developed market, in the spirit of Hu, Pan, and Wang (2013). Empirically, they show that funding liquidity has strong pricing implications on cross-section of international stock.

3 Model

In this section, I describe the model setting and introduce the measure of international market segmentation.

Extending Frazzini and Pedersen's framework, I consider an overlapping-generations (OLG) economy with I $(i = 1, \dots, I)$ mean-variance optimizer agents in K $(k = 1, \dots, K)$ countries and J $(j = 1, \dots, J)$ risky securities. In each period t, agents are born with wealth $W_{i,t} \geq 0$, and they invest internationally subject to their margin constraints. In the next period, $t+1$, agents consume and exit the economy. The risky securities are in total supply of θ_t^j, and each pay real dividends D_t^j in the unique consumption good in period t. Their ex-dividend price is denoted by P_t^j. Investors maximize their utility by choosing a portfolio of risky assets and investing the rest of their wealth at the risk-free rate r^f. In matrix notation, each investor maximizes:

$$\max_{\mathrm{x_{i,t}}} \quad {x_{i,t}}^\top \left(E_t[P_{t+1} + D_{t+1}] - (1 + r^f)P_t\right) - \frac{\gamma_i}{2}\, x_{i,t}^\top\, \Omega_t\, x_{i,t}, \tag{1}$$

where $x_{i,t} = [x_{i,t}^1, \dots, x_{i,t}^J]$ is the vector of portfolio choice of investor i and includes the number of shares she invests in each asset. γ_i denotes the agent i's coefficient of risk aversion and Ω is the covariance matrix of asset prices. Investors are margin constrained, that is they must finance a fraction of their investment, $m_{i,t}^j$, by their own capital and cannot fully borrow.[9]

$$\sum_{j=1}^{J} m_{i,t}^j \, |x_{i,t}^j| \, P_t^j \leq W_{i,t}. \tag{2}$$

The constraint requires that sum of the total dollar (*investor-specific* and *asset-specific*) margins invested by agent i to be less than her wealth. Here, it is assumed that long and short positions require similar margin deposits. In Black (1972) setting, where investors cannot borrow, $m_{i,t}^j = 1$. Margin requirements less than one implies that investors can borrow $(1 - m_{i,t}^j)$ portion of the underlying price, using it as the collateral. Margin requirements greater than one implies that investors should hold portion of their wealth in cash, such as the case for the mutual funds or insurance companies, which hold cash to meet daily redemptions or to pay claims. Both long and short positions on the underlying require margins and for simplicity I assume the margin requirements are the same for long and short trades. $\psi_{i,t}$ is the shadow price of the margin constraint of each investor at time t.

Under the null of no segmentation, all assets, irrespective of their origin, are priced by a unique pricing kernel. Thus, a subgroup of investors (e.g. the U.S. investors) cannot face barriers to investment, in the form of higher margin requirements, for a subgroup of assets (e.g. Indian stocks). That is, all foreign and domestic investors are equally constrained with respect to assets in country k. As a result, for asset j we have $m_i^j = m_i \, m^j$; which means *asset-specific* margins are set irrespective of the location of the investor and *investor-specific* margins are set irrespective of the assets they purchase.

This setting fully nests traditional barriers to investments as discussed in the international finance literature; if an asset in a country k is totally inaccessible to investor i, then the required margin for that asset from investor i is infinite.[10] Formally, in a fully segmented world, we have $m_i^j = \kappa_i^k \, m_i \, m^j$; where κ_i^k is equal to one if investor i resides in country k and is infinite otherwise. This discontinuity in margins across markets results in multiple pricing

[9] Ashcraft, Gârleanu, and Pedersen (2011) study in more detail the relationship between investors' ability to borrow and margin constraints and they argue that investors' leverage is mainly constrained due to required margins.

[10] See Black (1974) and Stulz (1981) for similar argument with infinite taxes.

kernels, therefore, this formulation matches the textbook definition of segmented world where assets of each market are priced by a different pricing kernel, and consequently local factors, as opposed to global factors, price local assets. Similarly, cases of mild segmentation, where part of the local investment opportunity set is accessible to foreign investors assets, or where foreign investors face higher costs to international investments are attainable in this setting by proper choice of κ. Consequently, with any non-infinite (finite) value of κ for foreign investors, local and global factors jointly price local assets together, as in Errunza and Losq (1985). This paper focuses on the post-liberalization period, where traditional barriers to investment (explicit or implicit) are fully lifted, and introduces funding illiquidity as barrier to investment.

Under these assumptions and under the null of no segmentation, I derive the following international-margin CAPM:[11]

$$E_t\left[r_{t+1}^j\right] - r^f = \beta_t^j \lambda_t + \psi_t\left(m_t^j - \beta_t^j\ m_t^G\right). \tag{3}$$

Here, the betas are with respect to the global market return, and the risk premium, λ_t, is for the global market risk. ψ_t is the shadow price of the funding constraint of the representative investor and m_t^G is the aggregated margin required for the global market portfolio.

If margin constraints are not binding, i.e. when $\psi_t = 0$, then the model reverts to the basic single-factor CAPM. However, assuming investors are financially constrained, assets that require higher margins, relative to the average asset, command extra premiums.[12] Specifically, high margin assets command an additional premium, $\psi_t m_t^j$, since more capital is required to hold a position in those assets. Similarly, a higher global margin increases required return on the global market portfolio, which decreases the expected excess return of assets by $-\psi_t\ \beta_t^j\ m_t^G$. Assuming similar *asset-specific* margins internationally, i.e. where $m_t^j = 1$, we have $m_t^G = 1$ and thus international-margin CAPM reverts to the Frazzini and

[11] Detail mathematical derivations are in the appendix

[12] I assume purchasing power parity holds; thus, there is no exchange risk premium.

Pedersen's model (Eq. 21). Note that under the null of no segmentation, we have a representative investor and no variable has the index i, and only global factors are in the pricing kernel. In a segmented world, there is no representative investor and both local and global factors price assets. In fact, it can be shown that with barriers to investment (i.e. $\kappa_i^k \neq 1$) we have segmented markets:

$$E_t\left[r_{t+1}^j\right] - \ r^f \ = \ \beta_t^j \lambda_t + \phi_t^k - \beta_t^j \ \phi_t^G, \tag{4}$$

where, $\phi_t^k = f(\kappa_i^k)$ is a market-specific factor that captures investors funding constraints for investing in assets in country k, and ϕ_t^G is a global factor that captures the aggregate funding constraints of the investors across markets.

In what follows I focus on Equation (3), which enables us to extract the funding liquidity of the global representative investor, ψ_t from any zero beta portfolio. Under the null of no segmentation, if we form the BAB portfolio as in Frazzini and Pedersen (2014), and assume the *asset-specific* margins of the securities in each market is the same, the international-margin CAPM implies that the expected return of the country k's BAB is:

$$E_t\left[r_{BAB,t+1}^k\right] - r^f \ = \frac{\beta_{H,t}^k - \beta_{L,t}^k}{\beta_{H,t}^k \ \beta_{L,t}^k} \ m_t^k \ \psi_t. \tag{5}$$

This expected return is determined by three components: the beta spread for country k, the level of margins for country $k's$ assets, and the shadow price of funding constraint for the global representative investor. If we control for the first two country-k-specific components, the extracted funding liquidities of the global representative investor from each market should be comoving perfectly across markets. This of course is the case only under the null. If markets were segmented, investors in different countries would have their own shadow price of funding constraint. Thus, one can construct a measure of market integration based on the conditional correlations of estimates of ψ_t^k of any country pair. The intuition here is that, in an integrated world capital flows freely across markets and by the force of arbitrage, prices of similar assets are set close to each other. This ensures that local funding illiquidity either does not occur, as investors (international intermediaries) would meddle in to provide liquidity and to arbitrage out any deviation of the Law of One Price, or would spill over and result in comovements in funding liquidities across markets. In either case, only global funding liquidity enters in the pricing kernel. Whereas, in a segmented world, capital cannot move freely and local funding liquidities persist. Hence, shadow prices of funding constraint may diverge. Therefore, any discrepancies between the estimated ψ_t^k across markets imply that investors face market-specific frictions that cannot be diversified out; hence it would be interpreted as a measure of market segmentation.

4 Empirical Results

In this section, I introduce the identification methodology and the dataset. The empirical results are then presented.

4.1 Methodology

I follow Frazzini and Pedersen's methodology in estimating BAB portfolio. For this purpose, I compute market beta of each asset by estimating volatilities and correlations separately with rolling-window estimations, which permits to overcome non-synchronous trading. Beta of asset j at each period is computed by the correlation of this asset's return and the global market portfolio's, in the last five years, multiplied by the ratio of asset volatility to market volatility, in the last year.[13] Then betas are shrunk toward the cross-sectional mean to reduce the influence of outliers. For volatility estimation, I use one-day log returns and use overlapping three-day log returns for correlation estimation to control for nonsynchronous trading.

To form the BAB portfolio, at each period t and in each country k, all assets are ranked

[13] Since correlations appear to move more slowly than volatilities, a smaller window is assigned for volatility estimation.

based on their betas and are grouped in two categories (high- and low-beta). In each group, securities are weighted by the beta ranks in that group. BAB portfolio 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:

$$r^k_{BAB,t+1} = \frac{1}{\beta^k_{L,t}}\left(r^k_{L,t+1} - r^f\right) - \frac{1}{\beta^k_{H,t}}\left(r^k_{H,t+1} - r^f\right). \tag{6}$$

Hence, Equation (5) enables us to extract funding liquidity of the global representative investors from securities in market k, controlling for both the beta spread and margins. Assuming *country-specific* margins are well approximated by market volatility, $m^k_t = a + b\sigma_{k,t-1}$, we can rewrite Equation (5) as below:

$$E_t\left[r^k_{BAB,t+1}\right] = \psi_t \ \ Z^k_t,$$

where, Z^k_t is the product of local beta spread, $\left(\beta^k_H - \beta^k_L\right)/\beta^k_H\beta^k_L$ and local market realized volatility. Since funding liquidity is a persistent variable, we can estimate it with rolling-window estimation or latent variable methods.[14] In this paper, I exploit the latter method and implement Markov Chain Monte Carlo (MCMC) and Gibbs Sampling because it permits to mark the variations to business dates.[15]

$$r^k_{BAB,t+1} = \psi_t \ \ Z^k_t + \sigma_b\,\varepsilon_t \tag{7}$$

$$\psi_t = \phi_0 + \phi_1(\psi_t - \phi_0) + \sigma_\psi\epsilon_t. \tag{8}$$

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

[14]In a similar setting, for estimating conditional market beta for single-factor CAPM, Lewellen and Nagel (2006) implement rolling window estimation and Jostova and Philipov (2005) and Ang and Chen (2007) implement latent variable estimation.

[15]Rolling-window estimation results in similar dynamic for ψ_t, however, the estimates only speak for the average funding liquidity over the window. Results are available from the author upon request.

unknowns. Prior for ϕ_1 is a truncated normal between (-1,1) to ensure stationarity. By Bayes law, posterior distributions are proportional to the priors times the likelihoods, which are defined by Equation (7). Then, I 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. Detail of the estimation is in the Appendix.

Under the null of no segmentation, the estimates of ψ_t from each market should comove perfectly. On the other hand, in a segmented world these estimates diverge from each other. Thus, I estimate value-weighted discrepancies among ψ_t pairs to construct Funding-liquidity Segmentation Indicator (FSI).

$$FSI_t^c = \sum_{k=1}^{K} w_t^k \ \ |\psi_t^k - \psi_t^c|, \tag{9}$$

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

4.2 Data

I collect daily total return index, market capitalization and Price-Earning ratio for all individual stocks that are available in DataStream and WorldScope database, dollar denominated. The final sample (cleaned) includes 58,405 stocks from 62 countries for the period January 1973 to October 2014. According to the classification by Standard and Poor's (S&P), 25 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 37 countries are emerging (Argentina, Bahrain, Brazil, Bulgaria, Chile, China, Colombia, Croatia, Cyprus, Czech Republic, Egypt, Greece, Hungary, India, Indonesia, Jordan, Kuwait, Malaysia, Malta, Mexico, Morocco, Nigeria, Oman, Pakistan, Peru, Philippines, Poland, Qatar, Romania, Russian Federation, Slovenia, South Africa, Sri Lanka, Taiwan, Thailand, Turkey, Venezuela). I follow Karolyi, Lee, and van Dijk (2012) in cleaning data. In the DataStream I 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]

To limit the effect of survivorship bias, the dead stocks are also included in the sample. For country market data and global market portfolio, I use the DataStream market index. For risk-free rate, I use one-month T-bill rates from Kenneth French website.

Following the literature and due to data availability, I consider the following proxies of funding liquidity in the U.S. market: TED spread (calculated as the spread between three-month LIBOR based on the U.S. dollars and the three-month Treasury Bill from Federal Reserve Bank of St. Louis), VIX index (implied volatility of the S&P 500 market index from CBOE website), log of Broker–Dealer total asset (from Table L.128 of the Federal Reserve Flow of Funds), 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), fixed income–implied funding liquidity (from Jean-Sébastien Fontaine 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, Gorovyy, and van Inwegen (2011)). Intermediary asset pricing literature provide convincing arguments suggesting that the balance sheet and asset holding of large institutional investors are informative of funding conditions of the whole market (see Boguth and Simutin (2015)). More specifically, Adrian and Shin (2010) suggest that broker–dealers' asset growth

[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. I 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.

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 leverage. Adrian et al. (2014) follow this idea by proposing the broker–dealers' leverage factor, which indicates the financial difficulty the intermediaries face for funding their daily trades. Fontaine and Garcia (2012) similar to Hu et al. (2013) measure funding illiquidity from the cross-section of Treasury securities. Increases in the TED spread, VIX index and the fixed income–implied measure imply worsening in the funding conditions. Conversely decreases in the Broker–Dealer total asset and leverage imply decreases in funding liquidity of the economy. Broker–Dealer balance sheet is available at quarterly frequency, however, other proxies are accessible at higher frequencies. These measures are available with different frequencies and time period. The TED spread is available at daily frequency since 1986. The VIX index is available at daily frequency since 1990. Broker–Dealer balance sheet data is available at quarterly frequency since 1968. Fixed income–implied funding liquidity is available since 1986 with monthly frequency. To match the datasets I take the last observations of the month (or quarter) to transform daily data to monthly (or quarterly) data.

4.3 Results

In this section, first I study the effect of funding liqudity on measure of market segmentation. Motivated by the results of this section, I analyze the BAB portfolios across markets, and show that these portfolios comove less during crisis periods comparing to market portfolio returns. Then, I introduce the Funding-liquidity Segmentation Indicator (FSI) based on these portfolios. Lastly, I show this indicator comove with funding difficulty in each market. This evidence supports the claim that funding illiquidity can be an effective barrier to investment, and worsening of local funding conditions can possibly explain the reversals in global market integration.

4.3.1 Segmentation and Global Funding Liquidity.

In this section I study the relationship between global funding liquidity and market segmentation. Here, I take the measure of market segmenation that is introduced and studied in Bekaert et al. (2011, 2013, 2014b). This is a "model-free" measure and is based on price-earning ratio differentials of industry portfolios across market. The authors argue that industry portfolios have similar growth opportunities and similar systematic risk across markets, thus their PE ratios should be similar, under the null of no segmentation. Define the weight of industry j in country k at time t by $IW_{k,j,t}$ and denote industry j's earnings yield in country k as $EY_{k,j,t}$. Then, the degree of market segmentation for country k at t is computed as:

$$SEG_{k,t} = \sum_{j=1}^{N} IW_{k,j,t} |EY_{k,j,t} - EY_{w,j,t}|. \tag{10}$$

Following their methodology I aggregate the firm-level data according to the 38 industry classification employed by DataStream to construct industry portfolios. Then, for each industry and country, I calculate local earnings yield and portfolio weights to construct the measure of market segmentation. Focusing on the U.S. market, I proceed to study the comovement of this measure and the funding liquidity. The choice of the U.S. market is justified by the large population of active international institutional investors residing in the U.S. market and data availability necessary to construct multiple measures of funding liquidity. Following the literature, I consider the following proxies of funding liquidity in the U.S. market: TED spread, VIX index, log of Broker–Dealer total asset, Broker–Dealer leverage, fixed income–implied funding liquidity.

Table 1 presents the result of the U.S. segmentation test conditional on funding liquidity in the U.S. market. Panel A reports the regression results of the U.S. segmentation on the U.S. funding liquidity proxies. Panel B and C study the link between segmentation and funding liquidity in the fifth and first quantile regressions respectively. Results in Panel A show that all variables are estimated positive, consistent with the hypothesis that the funding illiquidity in the U.S. market increase degree of market segmentation of this market from the rest of the world. TED spread, total asset and leverage of the Broker–Dealer are estimated statistically significant. The VIX index and fixed income–implied funding liquidity are estimated with correct sign but at lower statistical significance. Panel B reports the regression estimates of the U.S. segmentation on a dummy variable that takes value 1 when the proxy of the funding liquidity is at its 75 percentile. The dummy variable captures the peak periods of funding illiquidity. As funding constraints bind more, capital flows less freely in these periods and risk sharing is inefficient. Moreover, due to funding constraints arbitrageurs fail to execute their arbitrage activities and close price gaps across markets. In addition, in these periods according to the "flight home" effect investors liquidate their international investments, which results in further increase in market segmentation. This is supported with the evidence reported in Panel B where the estimates for all proxies of funding liquidity is positive. TED spread, leverage of the Broker–Dealer, and fixed income–implied funding liquidity are estimated statistically significant. The VIX index and total asset of Broker–Dealer are estimated with correct sign but at lower statistical significance. However, during relax funding periods, capital flows more freely across markets and risk sharing is improved. Moreover, intermediaries have the sufficient resources to execute arbitrage activity to bring the price of similar assets close across markets. Therefore, market segmentation reduces. Results in Panel C bring supports for this argument as all coefficient are consistently estimated negative. Note that because of high correlations of funding variables, the dummy variables in each of the regressions in Panel B and C are similar in size and pattern. As a result the estimated coefficients in these panels are close in size.

[**Place Table 1 about here**]

Local funding liquidity measures, similar to the U.S. market are not available for large cross-section of countries. Data for the TED spread, broker–dealer balance sheet and implied volatilities are not accessible. Sufficient data of the fixed income market to construct this measure for larger cross-section is not available.[17] However, to the extend the proxies of funding liquidity in the U.S. are approximates of the global funding liquidities, we expect to observe segmentation increases across markets during funding droughts in the U.S. market.Table 2 studies this hypothesis for developed markets, assuming the U.S. proxies of funding liquidity shocks propagates internationally in these markets. Consistent with the previous results, Panel A provide supportive evidence for the increase in segmentation as funding liquidity becomes more scarce. As a robustness check, I exclude the recent crisis observations from the estimation (years 2007, 2008, 2009). Panel B presents the estimation results for this subsample. These results show that our main results are not driven by the extreme events in the 2008 sub-prime crisis.

[Place Table 2 about here]

In the next section I proceed my analysis of the effect of funding liquidity on segmentation by studying the BAB portfolios. The international-margin CAPM imply that the expected return of the BAB portfolios are increasing in funding tightness in the economy (Equation (5)).

4.3.2 BAB Analysis. Table 3 presents the summary statistics of the countries in the dataset and the BAB portfolio returns constructed from each market security-level data. In our sample, developed markets on average, have more firms in the cross-section comparing to emerging markets, and have lower monthly market volatilities, as measured by the realized squared market returns in each month. *Ceteris paribus* lower cross-section of assets results in convergence of beta estimates. This is consistent with the observed larger beta spread for emerging markets. In addition, the beta spread across developed markets fall in the vicinity of 0.60, whereas for emerging market the beta spreads fall in a large range, from 0.24 to 1.44.The table also presents average of BAB portfolio returns, as well as their correlations

[17]Malkhozov et al. (2014) construct a measure similar to the fixed income–implied funding liquidity introduced by Fontaine and Garcia (2012) and Hu et al. (2013) for a set of six developed markets.

with the BAB portfolio return extracted from the U.S. market. Consistent with findings of Frazzini and Pedersen (2014) in almost all countries the premium for the betting against beta is positive. Equation (5) implies that high correlations of BABs translate to high comovements of ψ_t^k, when margins and beta spreads are similar across markets. This is consistent with the summary statistics of the BAB portfolios presented in Table 3. There, we observe that the correlations of BAB portfolio returns of developed market with that of the U.S. are higher than the correlations in emerging markets. High correlations of BABs translate to higher comovements of ψ_t^k, because of similar observed market volatility, as a proxy of margins, and beta spread among developed markets. This observation is consistent with the previously documented evidence that developed markets are more integrated into the U.S. market comparing to the emerging markets.

[**Place Table 3 about here**]

If during financial distress investors fly home and capital mobility drops internationally, then funding liquidity shocks do not diversify across markets. Consequently, as Equation (5) implies, we expect to observer that the correlations of the BAB portfolios across markets drop during financial distress periods, whereas previous research has documented that correlations of international portfolios increase during financial distress (see for example Longin and Solnik (2001)). Table 4 tests this hypothesis and studies the correlations of BAB portfolios conditional on funding liquidity. Similar to Table 2 I focus on developed markets and use U.S. market funding liquidity as global funding liquidity proxies. I estimate the correlations of BAB portfolios of each market with that of the U.S. market with Dynamic Conditional Correlations (DCC) introduced in Engle (2002). I control for the correlation of the equity markets in the regression. Correlation of developed market portfolios with the U.S. market portfolio is similarly estimated using the DCC specification. Results in Table 4 shows that correlations of BAB portfolios drop as funding constrains tighten. This evidence support the implication of Equation (5) and show that inefficient diversification of funding liquidity risk during happens during distress periods. The TED spread, total asset of Broker–Dealer and the fixed income–implied funding liquidity are estimated significantly negative. The VIX index and the leverage of Broker–Dealer are correctly estimated negative but at lower statistical level.

[Place Table 4 about here]

Analysis of the BAB portfolio returns is in line with the analysis of the measure of market segmentation introduced by Bekaert et al. (2011). As a result, I conjecture a segmentation indicator implied from these portfolio also support the role of funding liquidity during integration reversals. Therefore, in this section, I extract and study the shadow price of the margin constraint of the global representative investor from each market BAB. Then, I construct the Funding–implied Segmentation Indicator (FSI) based on bivariate discrepancies of these shadow prices. Lastly, I provide regression results on comovement of FSI with local funding liquidity.

Analysis of the shadow prices of the margin constraints supports the results of Table 3. Controlling for the heterogeneity in the margins and beta spread, I extract the information of global funding liquidity shocks from the BAB portfolios (i.e. estimate the ψ_t^k), with MCMC and Gibbs sampler as described in section Methodology. Under the null of no segmentation ψ_t^k should convey the same information across markets as all ψ_t^k are estimates of funding constraints of the global representative investor. Figure 3 plots correlations of these estimates with that of the U.S. market. Developed markets are marked in red and emerging markets are marked in blue. The figure shows that the funding liquidity of the global representative investor extracted from the developed markets comove more strongly with that of the U.S. market, comparing with the emerging markets. This is consistent with the null of integration that capital mobility is higher among these markets and local funding liquidity diversifies out by global influx of capital.

[Place Figure 3 about here]

4.3.3 Funding-liquidity Segmentation Indicator (FSI). The results in Figure 3 and Table 3 are also supported by the analysis of Funding–liquidity Segmentation Indicator (FSI). Under the null of no segmentation, international-margin CAPM dictates that the shadow price of the global representative investor extracted from any zero beta portfolio should be the same. Therefore, the discrepancies between the extracted prices of any pair of markets, c and k, can be interpreted as the severity of the barriers to capital flow across the two markets. Thus, the larger the distance between these prices implies higher degree of market segmentation of market c from k and vice versa. Analogously, a value-weighted average of the discrepancies between market c and all other markets can be an indicator of market segmentation for country c.

Table 5 presents test on statistical significance of the newly introduced segmentation indicator (FSI) in an unbalancced pooled panel regression for All sample, only Developed markets, and only emerging markets. Since data coverage of our data source, DataStream, is different across markets and initial observations start at different dates the panel length varies across samples. Regressions include only one intercept (no country fixed effect), however, to incorporate the heteroskedasticity, serial autocorrelations and cross-correlations in error terms, in the panel regression, p-values are calculated based on the double clustered standard errors, through time and country, as instructed by Petersen (2009). The table also presents test results for average of the developed market and average of emerging markets. In these univariate regressions, p-values are calculated with Newey and West (1987) heteroskedasticity and autocorrelation robust standard errors. The table shows that in both panel estimation and univariate regressions, FSI is statistically significant for all sample, emerging markets, and developed markets. Moreover, in all cases coefficients of the time trend is estimated statistically negative, consistent with the reduction of barriers to international investment in the post-liberalization period. The one-way t-test confirms that the segmentation indicator is statistically larger for the emerging markets, consistent with the previously documented evidence in the literature that emerging markets are more segmented from the world due to larger barriers to investment.

[Place Table 5 about here]

Figure 4 plots the average measure of market segmentation of the developed and emerging markets. The figure visualized the results in Table 5. Both measures have a downward slope consistent with reduction of barriers to international investment. More interestingly, the plot shows that reversals in the newly introduced measure of market segmentation coincide with large global financial crisis, although this measure by construction is controlled for the increase in the volatility during crisis periods.

[Place Figure 4 about here]

4.3.4 Segmentation and Local Funding Liquidity. As discussed before, due to data availability, we do not have access to measure of local funding liquidity for international markets. Therefore, in this section I first estimate local funding liquidity and then I proceed to study the comovement of market segmentation conditional on local funding liquidity in a pool panel regression. However, since we have access to other proxies of local funding liquidity for the U.S. market, similar to the analysis in Section 4.3.1, I study the U.S. market separately.

I estimate local funding liquidities from a domestic Margin–CAPM, in the spirit of Frazzini and Pedersen (2014). That is, I estimate BAB portfolios in each market with respect to the local market portfolio, as oppose to the global market portfolio. Then, I extract the shadow price of the margin constraint of the local representative investor, Ψ_t^k with MCMC and Gibbs sampler. Frazzini and Pedersen (2014) with time-series analysis for the U.S. market show that the shadow price of the margin constraint is well proxied by the TED spread.

Constructing proxies of local funding liquidity measures, I proceed to the analysis of our reversal hypothesis. If markets are integrated, local funding illiquidity diversifies out by global capital mobility. However, in segmented markets with high barriers to free flow of capital local funding illiquidity persists. Table 6 studies this hypothesis in three subsamples; all markets, developed markets, and emerging markets in a cross-sectional regression. Panel A of the table, presents the regression results of the average of the measure of market segmentation introduced in Bekaert et al. (2011) on the average of the estimated local funding liquidity, Ψ^k. Panel B reports the results of similar regression where I use the FSI as a measure of market segmentation. The results bring support to our claim that in all cases, countries with tighter funding constraint, as measured by the high average Ψ^k, are more segmented from the world. For all subsamples in the two panels we observe positive and significant estimates for the local funding liquidity. However, this results are estimated at higher statistical significant level for the developed market. Larger loadings for the emerging market is consistent with the previously documented evidence, showing that emerging markets face higher barriers to free flow of capital.

[Place Table 6 about here]

Table 7 study the same hypothesis with time-series analysis. If markets become more segmented during funding liquidity droughts, then the severity of the financial constraints of the local investors can be interpreted as a barrier to investment in that market. In fact, because of these barriers in the first place we observe local shocks, otherwise we these shocks would have been diversified fully and we would have observed only global shocks. Similar to Table 6, I study both SEG measure introduced in Bekaert et al. (2011) and FSI conditional on the estimated local funding liquidity Ψ^k. In Panel A, table presents the estimates of the SEG and in the Panel B, present the estimates of the FSI regression, for three cases of all markets, only developed markets, and only emerging markets. In Panel B for all subsamples, the measure of market segmentation positively and statistically comoves with local funding illiquidity. That is, market segmentation is higher in periods when investors are more financially constraints and it is smaller in periods when investors face less difficulty obtaining required funding. Results in Panel A convey the same message, albeit with lower statistical power. In all subsamples segmentation increases as funding condition worsen. We expect to observe relatively stronger explanatory power in developed markets, as explicit barriers to foreign investment in these markets has been reduced significantly. These barriers are effective in the emerging markets, at least partly throughout the sample period. Previous research has documented that these barriers have high explanatory power in explaining the dynamic of segmentation. This pattern is consistent with the “flight home” effect (Giannetti and Laeven (2012)); If investors liquidate their international investments during local funding shocks, eventually capital mobility decreases and assets in local market are priced by local demand, which leads to local pricing factors in the pricing kernel, hence markets become segmented.

[**Place Table 7 about here**]

I acknowledge the error-in-the-variable bias in this analysis, resulted in estimating explanatory variable, the local funding liquidity time-series. To confirm that the main result of this paper is not driven by this bias, in this section, I focus on the U.S. market. The choice of the U.S. market is justified by the large population of active international institutional investors residing in the U.S. market and data availability necessary to construct multiple measures of funding liquidity.

Table 8 presents the result of U.S. segmentation test conditional on funding liquidity in the U.S. market. The table also tabulates the results of first and fifths quantile regressions. In Panel B the explanatory variable is a dummy variable that takes value of one if the proxies for funding liquidity in the U.S. are above their 75 percentile and zeros otherwise. Here, values of one for the dummy variable represents the tight funding conditions. Similarly, the explanatory variable in Panel C is a dummy variable that takes value of one if the proxies for funding liquidity in the U.S. are below their 25 percentile and zeros otherwise. Here, values of one for the dummy variable identifies the most relax funding periods. Results in

Panel A show that all variables are estimated positive at monthly frequency, consistent with the hypothesis that the local funding liquidity in the U.S. market segments this market from the rest of the world. The TED spread and the funding liquidity of the local representative investor, implied by the margin-CAPM, Ψ_t^k, are statistically significant at 5% and 1% levels. Results in Panel B are consistent with those of Panel A. As funding condition of the economy worsen, as identified by different measures, we observe that the U.S. market segmentation indicator increases. These results are consistent with lower international capital mobility and "flight home" effect. Conversely, Panel C reports the results for periods of relax funding condition. During these periods the U.S. market segmentation indicator decreases, supporting the hypothesis that affluent arbitrageurs trade more intensively internationally and close price gaps across market. This increases global market integration.

[**Place Table 8 about here**]

4.3.5 Global Institutional Investors and Market Segmentation. Gromb and Vayanos (2002) show that when financial intermediaries, as the liquidity providers, are financially constraints, deviation from LoOP occurs, as intermediaries cannot close the gap between similar assets across markets. In their setting, barriers to investment prohibits the domestic investors to invest abroad, however, the financial intermediary has access to both markets. As a result, if local prices diverge from their intrinsic value, the intermediary simultaneously bids in the two market to arbitrage out the price mismatch. This ensures that price of assets are governed by aggregate demand and supply of the two markets, as oppose to local demands and supplies. However, if the intermediary is financially constrained and fails to deposit sufficient margins required to execute the two trades, deviation from LoOP is possible. I test this hypothesis on the newly introduced indicator of global equity market segmentation, FSI. Consistent with the assumptions of Gromb and Vayanos's model, research has shown that global institutional investors are responsible for most cross-country investments. Since these investors mostly rely on the U.S. market for their borrowing activities, it is plausible to assume U.S. funding liquidity highly affects these investors' ability to borrow. Identifying global funding periods by the U.S. measures is also supported by the relative size of the U.S. market. Table 9 present the results of a pool panel regression for two cases of developed market, reported in Panel A, and emerging market, reported in Panel B. Here, the global funding periods are identified as periods when the proxies of the funding conditions in the U.S. market are at their peak (i.e. the fifth percentile). Time trend is also included in these regressions to approximate any reduction in barriers to investment through time. In Panel A, the results show that FSI increases during tight funding conditions for the developed market, except for the case of Broker–Dealer leverage, for which we fail to reject the null at 10% significant level. Results presented in Panel B for the emerging market are convey the same message, however at weaker statistical power. Effect of the U.S. funding liquidity on local funding liquidities should be stronger for more integrated markets, such as developed markets. Therefore, we expect to observe stronger explantory power of the global funding factor for these markets. For the emerging markets, on the other hand, it is documented that the barriers for international investment explain much of their market segmentation. Many of the emerging market in our sample during the first part of the sample period have high levels of explicit barriers to investment in the form of legal restrictions to foreign ownership.

[**Place Table 9 about here**]

Since during global funding drought local investors liquidate their foreign investments, in these periods more local risk is borne by local investors, which translates to local pricing factors, hence, market segmentation increases. The critical point here is that the "flight home" effect is essentially different from "flight to quality" phenomena, where risky securities become especially illiquid during market downturns (Giannetti and Laeven (2012)).

5 Conclusion and Discussion

The analysis in this paper provides further evidence against early research on market integration that relates it to market-wide correlations. Empirical research presents ample evidence that cross-correlations of market index returns increase after large systematic shocks (Longin and Solnik (2001)). Therefore, based on the arguments of early research on market integration, one should expect that market integration increase, not decrease, after large international crashes. As Brunnermeier and Pedersen (2009) reports, most financial intermediaries are net long in the market. Therefore, capital constraints are more likely to be hit during market downturns and to force these investors to "fly home," which leads to inefficient international risk sharing and market segmentation. Previous research also provides convincing arguments against the link between correlations and integration, some of which are reviewed in the Section 2.

The argument of this paper is also in line with the previously documented empirical evidence of the importance of implicit barriers (see Carrieri, Chaieb, and Errunza (2013)). In this literature the ratio of market capitalization to GDP and ratio of private credit to GDP, as proxies of financial development and banking development of markets, positively correlates with market integration. The underlying argument is that countries with larger market capitalization or larger credit markets are more financially developed and they have higher quality financial institutions. These variables could explain the cross-sectional deferences among countries; however, they do not necessarily represent changes in quality of institutions and financial developments in high frequencies, especially during market downturns. During these periods, short term funding liquidity shocks in the *asset* market, most likely do not affect the real economy and GDP. However, these shocks affect asset market capitalization, liquidity and credit markets in the same direction as the argument of this paper. I argue these variables partly proxy the local funding liquidity shocks during the stress periods and from this channel affect market integration.

This paper also shed more light on the contagion mechanisms during financial crisis (see Forbes (2012) for detailed categorization of contagion channels) and brings evidence against contagion explanations that are based on market integration assumption. In the aftermath of the 2008 crisis, investment and portfolio channel (Kyle and Xiong (2001)) has gained considerable attentions as credible contagion channels. In this regard, some researchers argue that the international exposure of highly leveraged financial intermediaries to subprime-related assets in the U.S. was the central contagion channel in that period. Intermediaries that were affected by the downturn in the subprime market, to repair their balance sheet were forced to liquidate other assets, which further contracted lending and investment across the board, and further deepened the financial crisis (Krugman (2008)). However, Dedola and Lombardo (2012) argue that the high degree of home bias in international financial markets suggests that the cross-border propagation via balance sheet effects would be relatively small. In response, they propose a contagion channel, where borrowing costs are synchronized across markets by force of no arbitrage, in an integrated markets framework with investors that are restricted to borrow locally. Optimality of investors' decisions and portfolio choices require that the returns on domestic and foreign capital be equalized to the domestic cost of raising funds. Consequently, local credit spread shocks in the U.S. market would be globally transmitted across markets. However, if markets become less integrated during market, as is shown in this paper, asset prices and investors' decisions are not governed by a unique common SDF across markets. Moreover, there is ample documented evidence in failure of no arbitrage mechanism in these periods. As a result, this paper draw further doubts on the role of investment channel in contagion, consistent with the empirical evidence in Bekaert, Ehrmann, Fratzscher, and Mehl (2014a) that confirms the "wake-up call" hypothesis, with markets focusing more on country-specific characteristics during the crisis.

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Appendix

A Mean-Variance Optimization

Investors optimize the following utility subject to margin constraints. In equilibrium, market clears.

$$\max_{\mathrm{x_{i,t}}} \quad {x_{i,t}}^{\top} \left(E_t[P_{t+1} + D_{t+1}] - (1 + r^f)P_t \right) - \frac{\gamma_i}{2} x_{i,t}^{\top}\, \Omega_t\, x_{i,t} \tag{11}$$

$$\sum_j m^j_{i,t}\, x^j_{i,t}\, P^j_t \leq W_{i,t} \tag{12}$$

$$\sum_i x^j_{i,t} = \theta^j_t \tag{13}$$

First order condition of the above optimization problem results in:

$$\text{FOC} : 0 = E_t[P_{t+1} + D_{t+1}] - (1 + r^f)P_t - \gamma_i\, \Omega_t\, x_{i,t} - \psi_{i,t}\, M_{i,t} \tag{14}$$

Where $\psi_{i,t}$ is agent i's shadow price of margin constraint and $M_{i,t} = (m^1_{i,t} P^1_i,\ \ldots,\ m^J_{i,t} P^J_i)$ is a vector of dollar margins. Rearranging Eq (A), we have the portfolio choice of investor i:

$$x_{i,t} = \frac{1}{\gamma_i} \Omega_t^{-1} \left(E_t[P_{t+1} + D_{t+1}] - (1 + r^f)P_t - \psi_{i,t} M_{i,t} \right) \tag{15}$$

Under the null hypothesis of market integration, a subgroup of investors cannot face higher margin requirements for a subgroup of assets, that is we have $m^j_{i,t} = m_{i,t} m^j_t$. In equilibrium market clears. Aggregating asset demands for asset j over all investors, i, and rearrangement of Eq (15) we get the price of asset j:

$$P^j_t = \frac{E_t[P_{t+1} + D_{t+1}] - \gamma 1_j^{\top} \Omega_t \theta_t}{1 + r^f + \psi_t m^j_t} \tag{16}$$

Where $1_j^\top$ is a $J \times 1$ vector of zeros with one in column j, $\frac{1}{\gamma} = \sum_i \frac{1}{\gamma_i}$ and $\psi_t = \sum_i \frac{\gamma}{\gamma_i} \psi_{i,t} m_{i,t}$ are the coefficient of risk aversion and the shadow price of margin constraint for the representative agent. Thus, the expected return of asset j follows:

$$E_t[r_{t+1}^j] = \frac{E_t[P_{t+1}^j + D_{t+1}^j]}{P_t^j} - 1 = \ r^f + \psi_t m_t^j + \gamma \frac{1}{P_t^j} 1_j^\top \Omega_t \theta_t \tag{17}$$

Labeling global market return r^G and expanding the covariance matrix, we have:

$$\frac{1}{P_t^j} 1_j^\top \Omega_t \theta_t = \frac{1}{P_t^j} \ cov_t \left(P_{t+1}^j + D_{t+1}^j, \theta_t^\top \left[P_{t+1} + D_{t+1} \right] \right) = cov_t(r_{t+1}^j, r_{t+1}^G) \theta_t^\top P_t \tag{18}$$

So, Eq (17) simplifies to

$$E_t[r_{t+1}^j] = r^f + \psi_t m_t^j + \gamma \ cov_t(r_{t+1}^j, r_{t+1}^G) \ \theta_t^\top P_t, \tag{19}$$

Aggregating Eq (19) by market portfolio weights, i.e. $\frac{\theta_t^j P_t^j}{\sum_j \theta_t^j P_t^j}$, and choosing $m^G = \sum_j m^j \frac{\theta^j P^j}{\sum_j \theta^j P^j}$ we obtain

$$E_t[r_{t+1}^G] = r^f + \psi_t m_t^G + \gamma \ var_t(r_{t+1}^G) \ \theta_t^\top P_t \tag{20}$$

Define the market risk premium $\lambda_t = E_t[r_{t+1}^G] - r^f$ and $\beta_{j,t} = \frac{cov_t(r_{t+1}^j, r_{t+1}^G)}{var_t(r_{t+1}^G)}$, and substitute Eq (20) into Eq (19), we have the international-margin CAPM:

$$E_t[r_{t+1}^j] - r^f = \beta_t^j \lambda_t + \psi_t \left(m_t^j - \beta_t^j \ m_t^G \right) \tag{21}$$

Now if we assume assets-specific margins, m^j are the same for all assets in market k and form beta neutral portfolio, then Eq (21) implies the expected return of this portfolio is related to the beta spread in that market, shadow price of funding constraint of representative agent and market specific margins. To form the BAB portfolio, r_{BAB}, in each market k we long local low beta portfolio,r_H, levered to beta one and short local high beta portfolio, r_L, delevered to beta one.

$$E_t\left[r^k_{BAB,t+1}\right] - r^f = \frac{1}{\beta^k_{L,t}}(r^k_{L,t} - r^f) - \frac{1}{\beta^k_{H,t}}(r^k_{H,t} - r^f) \tag{22}$$

$$= \frac{\beta^k_{H,t} - \beta^k_{L,t}}{\beta^k_{H,t}\beta^k_{L,t}}\psi_t m^k_t \tag{23}$$

B BAB Portfolio

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

$$\beta^{TS}_j = \widehat{\rho_{jm}}\frac{\widehat{\sigma_j}}{\widehat{\sigma_m}} \tag{24}$$

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, I 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: $\beta_j = 0.6\beta^{TS}_j + 0.4$.

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. $r_{H,t+1} = \boldsymbol{r_{t+1}^\top w_{H,t}}$, and $r_{L,t+1} = \boldsymbol{r_{t+1}^\top w_{L,t}}$.
2. $\beta_{H,t+1} = \boldsymbol{\beta_{t+1}^\top w_{H,t}}$, and $\beta_{L,t+1} = \boldsymbol{\beta_{t+1}^\top w_{L,t}}$.
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

In this paper, I 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. Taking the averages of these samples, we obtain the expected value of the joint distribution of the unknown parameters. By Bayes law, posterior distributions are proportional to the prior distributions times the likelihood function. Here, I assume the joint prior distribution is the product of the independent priors of each unknown parameter, which are assumed normally distributed. Likelihood function is derived from the dynamics of the BAB returns and the shadow price of the funding constraints (see below). Then, I 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, since they are considered as the training set.

$$r_{BAB,t+1} = \psi_t \;\; Z_t + \sigma_b \, \varepsilon_t \tag{25}$$

$$\psi_t = \phi_0 + \phi_1(\psi_t - \phi_0) + \sigma_\psi \epsilon_t \tag{26}$$

The unknown parameters are $\phi_0, \phi_1, \sigma_\psi, \sigma_b$. Since ψ_t is a persistent variable, here I assume it follows a stationary AR(1) process with unconditional mean ϕ_0 and mean reversion speed

ϕ_1. For ϕ_0, I 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 (25). For ϕ_1, I 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 , I select an IG prior with shape and scale parameters equal to 0.001. Based on the above dynamic and assumptions, ψ_t and BAB returns follow conditional normal distributions:

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

Therefore, the likelihood function is:

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

where, $\boldsymbol{\psi} = [\psi_1, \ldots, \psi_T], \mathbf{r_{BAB}} = [r_{BAB,1}, \ldots, r_{BAB,T}], \mathbf{Z} = [Z_1, \ldots, Z_T]$

D Figures and Tables

D.1 Tables

Table 1. U.S. Segmentation and Funding Liquidity

Panel A

	(1)	(2)	(3)	(4)	(5)
(1) TED Spread	0.7455 **				
	(0.3693)				
(2) VIX Index		0.0068			
		(0.0073)			
(3) $\text{TA}^{BD} \times -1$			0.1211 *		
			(0.0631)		
(4) $\text{Lev.}^{BD} \times -1$				0.0120 *	
				(0.0063)	
(5) $\text{FL}^{FixedIncome}$					0.2564
					(0.2147)
α	Yes	Yes	Yes	Yes	Yes

Panel B

	(1)	(2)	(3)	(4)	(5)
(1) TED Spread	0.8198 ***				
	(0.2763)				
(2) VIX Index		0.0478			
		(0.0911)			
(3) $\text{TA}^{BD} \times -1$			0.4024		
			(0.3339)		
(4) $\text{Lev.}^{BD} \times -1$				0.4653 *	
				(0.2620)	
(5) $\text{FL}^{FixedIncome}$					0.5642 *
					(0.3118)
α	Yes	Yes	Yes	Yes	Yes

Continued on next page

Panel C					
	(1)	(2)	(3)	(4)	(5)
(1) TED Spread	-0.2720				
	(0.3200)				
(2) VIX Index		-0.0102			
		(0.0772)			
(3) $\text{TA}^{BD} \times -1$			-0.2029		
			(0.4736)		
(4) $\text{Lev.}^{BD} \times -1$				-0.2038	
				(0.4760)	
(5) $\text{FL}^{FixedIncome}$					-0.2764
					(0.3386)
α	Yes	Yes	Yes	Yes	Yes

Panel A: $SEG_t^{US} = \alpha + \delta \ \ FL_t + \varepsilon_t^{US}$,
Panel B: $SEG_t^{US} = \alpha + \delta \ \ I[FL_t \in 0.75^{th}] + \varepsilon_t^{US}$,
Panel C: $SEG_t^{US} = \alpha + \delta \ \ I[FL_t \in 0.25^{th}] + \varepsilon_t^{US}$,

Panel A reports the regression results of the U.S. measure of market segmentation (introduced in Bekaert et al. (2011)). Panel B and Panel C respectively report the results of the fifth and first quantile regression, implemented with a dummy variable. P-values are calculated with Newey and West (1987) standard errors (standard errors are reported in parenthesis). Total asset and Leverage of Broker–Dealers are signed such that increase in the proxies of the funding liquidity imply worsening of the funding condition in the economy. The estimates for the intercepts are not reported for the sake of brevity.

Table 2. DM Segmentation and Funding Liquidity

Panel A

	(1)	(2)	(3)	(4)	(5)
(1) TED Spread	0.5474 ***				
	(0.1294)				
(2) VIX Index		0.0617 ***			
		(0.0062)			
(3) $\text{TA}^{BD} \times -1$			2.7422 ***		
			(0.5702)		
(4) $\text{Lev.}^{BD} \times -1$				-0.0006	
				(0.0062)	
(5) $\text{FL}^{FixedIncome}$					0.1704 ***
					(0.0489)
α^k	Yes	Yes	Yes	Yes	Yes
Trend	Yes	Yes	Yes	Yes	Yes
adj. R^2	0.17	0.18	0.20	0.19	0.18

Panel B

	(1)	(2)	(3)	(4)	(5)
(1) TED Spread	0.3609 ***				
	(0.1362)				
(2) VIX Index		0.0235 ***			
		(0.0054)			
(3) $\text{TA}^{BD} \times -1$			1.0915 ***		
			(0.3692)		
(4) $\text{Lev.}^{BD} \times -1$				0.0222 ***	
				(0.0084)	
(5) $\text{FL}^{FixedIncome}$					0.0919 **
					(0.0455)
α^k	Yes	Yes	Yes	Yes	Yes
Trend	Yes	Yes	Yes	Yes	Yes
adj. R^2	0.17	0.16	0.21	0.21	0.17

$$SEG_t^k = \alpha^k + \theta t + \delta FL_t + \varepsilon_t^k, \qquad k \in DM$$

Table presents test results on the measure of market segmentation introduced in Bekaert et al. (2011) for developed markets conditional on proxies of funding liquidity in the U.S. market. Panel A reports the estimation for the full sample period and Panel B excludes the observations for the 2008 sub-prime crisis (i.e. years 2007, 2008, 2009). P-values are calculated with double clustered standard errors (standard errors are in parenthesis) as instructed by Petersen (2009). Total asset and Leverage of Broker–Dealers are signed such that increase in the proxies of the funding liquidity imply worsening of the funding condition in the economy. Estimates for the country intercepts and time trend are excluded for the sake of brevity.

Table 3. Summary Statistics of BAB portfolios

Country		#Firms	$\overline{R.Vol.\%}$	$\overline{r_{BAB}\%}$	$\overline{\beta Spread}$	$\rho(r^{k}_{BAB}, r^{US}_{BAB})$
Argentina	EM	107	7.56	-0.05	0.38	0.19
Australia	DM	2525	5.61	1.27	0.77	0.28
Austria	DM	161	4.89	0.84	0.44	0.09
Bahrain	EM	38	4.90	4.27	0.75	0.12
Belgium	DM	243	4.83	0.81	0.53	0.35
Brazil	EM	258	8.46	0.85	0.39	0.02
Bulgaria	EM	230	6.68	2.41	0.50	-0.04
Canada	DM	3815	4.30	0.79	0.80	0.41
Chile	EM	258	4.82	-0.60	0.75	0.17
China	EM	2578	8.08	1.60	1.12	-0.04
Colombia	EM	81	5.52	-1.00	0.24	0.12
Croatia	EM	112	4.90	1.68	0.41	-0.38
Cyprus	EM	109	8.36	-86.35	0.62	0.10
Czech Republic	EM	85	6.80	4.50	0.96	0.07
Denmark	DM	312	5.10	0.73	0.49	0.30
Egypt	EM	128	6.27	0.68	0.78	0.04
Finland	DM	203	7.84	0.69	0.57	0.43
France	DM	1599	5.58	0.79	0.55	0.44
Germany	DM	1390	5.19	0.79	0.62	0.47
Greece	EM	374	7.75	0.37	0.52	0.05
Hong Kong	DM	1078	6.63	0.34	0.56	0.30
Hungary	EM	62	8.59	0.85	0.43	0.16
India	EM	2672	6.95	0.42	1.00	0.06
Indonesia	EM	538	9.15	0.56	0.43	0.08
Ireland	DM	104	5.54	0.34	0.75	0.17
Israel	EM	487	6.04	567.54	0.59	0.26
Italy	DM	506	6.33	0.59	0.51	0.39
Japan	DM	4823	5.49	0.69	0.55	0.16
Jordan	EM	151	3.07	0.29	0.73	0.16
Kuwait	EM	131	4.52	-3.60	0.63	0.22
Luxembourg	EM	50	4.99	0.48	0.79	-0.04
Malaysia	EM	1178	5.54	1.05	0.57	0.13
Malta	EM	16	4.25	-3.17	0.63	0.19
Mexico	EM	207	6.79	0.87	0.87	0.07
Morocco	EM	79	4.00	1.38	0.57	0.09
Netherlands	DM	293	4.93	1.28	0.52	0.49
New Zealand	DM	200	5.06	0.87	0.44	0.10
Nigeria	EM	112	3.92	2.24	0.91	-0.09
Norway	DM	437	6.76	0.88	0.53	0.39
Oman	EM	105	2.46	1.20	0.61	-0.27

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Table 3 – continued from previous page

Country		#Firms	$\overline{R.Vol.\%}$	$\overline{r_{BAB}\%}$	$\overline{\beta Spread}$	$\rho(r^k_{BAB}, r^{US}_{BAB})$
Pakistan	EM	210	6.96	1.84	0.85	0.00
Peru	EM	168	4.37	2.26	1.44	-0.02
Philippines	EM	241	6.12	0.51	0.46	0.10
Poland	EM	541	7.97	0.91	0.41	0.16
Portugal	EM	132	5.16	0.28	0.72	0.08
Qatar	EM	37	5.24	0.51	0.49	0.09
Romania	EM	142	8.42	2.56	0.50	0.05
Russian Federation	EM	500	8.91	1.29	0.60	0.36
Singapore	DM	811	5.24	0.90	0.55	0.21
Slovenia	EM	58	5.00	1.00	0.46	0.11
South Africa	EM	681	6.86	0.55	0.67	0.22
South Korea	EM	2116	8.69	0.27	0.59	0.10
Spain	DM	270	5.92	1.00	0.60	0.37
Sri Lanka	EM	221	4.69	38.02	1.02	0.07
Sweden	DM	703	6.80	1.21	0.49	0.60
Switzerland	DM	372	4.52	0.87	0.63	0.34
Taiwan	EM	1914	7.13	-0.27	0.53	0.27
Thailand	EM	698	7.97	0.15	0.77	0.13
Turkey	EM	386	12.43	0.17	0.43	0.00
United Kingdom	DM	3916	5.24	0.73	0.59	0.62
United States	DM	16406	4.28	0.77	0.67	1.00
Venezuela	EM	47	8.77	248.42	0.92	0.03

Table presents summary statistics for the BAB portfolios constructed from securities in each market. The sample includes 25 developed markets, identified with DM, and 37 emerging market, identified with EM, from 1973 to 2014 (Data source: DataStream). Table reports the number of firms in each market, average realized volatility in percentage, average 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 and the BAB of the U.S. market.

Table 4. Correlation of BAB portfolios

	(1)	(2)	(3)	(4)	(5)
(1) TED Spread	-3.7471 **				
	(1.7362)				
(2) VIX Index		-0.0876			
		(0.0929)			
(3) $\text{TA}^{BD} \times -1$			-1.8510 **		
			(0.8552)		
(4) $\text{Lev.}^{BD} \times -1$				-0.0839	
				(0.0530)	
(5) $\text{FL}^{FixedIncome}$					-3.0554 ***
					(0.4525)
$\rho(Rm^c, Rm^{US})$	0.3589 ***	0.3997 ***	0.3154 ***	0.3604 ***	0.4024 ***
	(0.0468)	(0.0497)	(0.0441)	(0.0471)	(0.0435)
α	Yes	Yes	Yes	Yes	Yes
adj. R^2	0.22	0.21	0.25	0.24	0.25

$$\rho_t(BAB_t^k, BAB_t^{US}) = \alpha + \delta FL_t + \rho_t(Rm_t^k, Rm_t^{US}) + \varepsilon_t^k, \qquad k \in DM$$

Table presents time-series analysis results on the correlation of BAB portfolios with the U.S. market for developed markets conditional on proxies of funding liquidity in the U.S. market. Conditional 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). Total asset and Leverage of Broker–Dealers are signed such that increase in the proxies of the funding liquidity imply worsening of the funding condition in the economy. Estimates for the Intercept are excluded for the sake of brevity.

Table 5. Funding-liquidity Segmentation Indicator

Panel A					
	Average of Samples		Pooled Panel		
	FSI_{DM}	FSI_{EM}	All Sample	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)
Sample Size:					
n	1	1	60	22	38
Time	439	439	38-439	211-439	38-439
Observations	439	439	15997	8706	7291

Panel B	
	Mean
$FSI_{EM} > FSI_{DM}$	0.4936 ***
	(0.6870)

$$FSI_t^l = \alpha + \theta t, \qquad l = [DM, EM, k = 1, ..., K]^\dagger$$

Table presents test results on the Funding-liquidity Segmentation Indicator. Panel A reports the results on the statistical significance of the FSI and the time trend in univariate and panel regressions. In the univariate regression, I study the average of FSI for developed and emerging markets separately. P-values are calculated with Newey and West (1987) standard errors (standard errors are in the parenthesis). In the panel regression, I study FSI for all the cross-section in an unbalanced pooled panel, where standard errors are double clustered (Petersen (2009)). Sample size in time and cross-section is also reported. Panel B presents the result of a one-way t-test for the size of the measure of market segmentation for emerging markets relative to developed markets.

Table 6. Cross-section of Segmentation and Local Funding Liquidity

Panel A

	All Sample	DM	EM
$\overline{\Psi^k}$	0.0291 *	0.0063 ***	0.0392 **
	(0.0151)	(0.0016)	(0.0166)
α	0.0206 **	0.0257 ***	0.0190 *
	(0.0088)	(0.0022)	(0.0102)
adj. R^2	0.21	0.10	0.28

Panel B

	All Sample	DM	EM
$\overline{\Psi^k}$	0.4847 ***	0.3489 ***	0.5325 **
	(0.1468)	(0.0509)	(0.2001)
α	0.4972 ***	0.3925 ***	0.5767 ***
	(0.0977)	(0.0422)	(0.1373)
adj. R^2	0.32	0.60	0.34

$$\text{Panel A: } \overline{SEG^k} = \alpha + \delta \ \overline{\Psi^k} + \varepsilon^k,$$
$$\text{Panel B: } \overline{FSI^k} = \alpha + \delta \ \overline{\Psi^k} + \varepsilon^k,$$

Table presents cross-sectional test results on the measure of market segmentation and local funding liquidity. Panel A presents the estimates of the cross-sectional regression of the measure of market segmenation introduced in Bekaert et al. (2011) (SEG) on the average of the estimates of local funding liquidity (Ψ) in three subsamples (All Sample, Developed markets, and Emerging markets). Similarly, Panel B presents the estimated cross-sectional regression of the FSI on the average of the estimated local funding liquidity for the same subsamples.

Table 7. Time-series of Segmentation and Local Funding Liquidity

Panel A	All Sample	DM	EM
Ψ_t^k	0.6071	0.1665 **	0.8196
	(0.4224)	(0.0837)	(0.6220)
α^k	YES	YES	YES
adj. R^2	0.02	0.24	0.03

Panel B	All Sample	DM	EM
Ψ_t^k	0.4138 ***	0.3309 ***	0.4453 ***
	(0.0841)	(0.0571)	(0.1233)
α^k	YES	YES	YES
adj. R^2	0.20	0.30	0.19

$$\text{Panel A: } SEG_t^k = \alpha^k + \delta \ \ \Psi_t^k + \varepsilon_t^k,$$
$$\text{Panel B: } FSI_t^k \ = \alpha^k + \delta \ \ \Psi_t^k + \varepsilon_t^k,$$

Table presents time-series test results on the measure of market segmentation and local funding liquidity. Panel A presents the estimates of the time-series regression of the measure of market segmenation introduced in Bekaert et al. (2011) (SEG) on the estimated local funding liquidity (Ψ) in three unbalanced pool panel regressions (All Sample, Developed markets, and Emerging markets). Similarly, Panel B presents the estimates of the time-series regression of the FSI on the estimated local funding liquidity.

Table 8. U.S. FSI and Funding Liquidity

Panel A	(1)	(2)	(3)	(4)	(5)	(6)
(1) TED Spread	9.9135 **					
	(4.0248)					
(2) VIX Index		0.2127				
		(0.1448)				
(3) $TA^{BD} \times -1$			0.5188			
			(1.2615)			
(4) $Lev.^{BD} \times -1$				0.0556		
				(0.0871)		
(5) $FL^{FixedIncome}$					0.8361	
					(1.4905)	
(6) Ψ^{US}						12.2120 ***
						(2.1534)
α	Yes	Yes	Yes	Yes	Yes	Yes

Panel B	(1)	(2)	(3)	(4)	(5)	(6)
(1) TED Spread	10.7686 ***					
	(2.9569)					
(2) VIX Index		3.2807				
		(2.4840)				
(3) $TA^{BD} \times -1$			6.6645			
			(4.1071)			
(4) $Lev.^{BD} \times -1$				1.5329		
				(3.3685)		
(5) $FL^{FixedIncome}$					3.8198	
					(3.6044)	
(6) Ψ^{US}						12.3060 ***
						(2.1404)
α	Yes	Yes	Yes	Yes	Yes	Yes

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Panel C	(1)	(2)	(3)	(4)	(5)	(6)
(1) TED Spread	-6.1434 ***					
	(2.3462)					
(2) VIX Index		-4.7977 **				
		(2.2549)				
(3) $\text{TA}^{BD} \times -1$			1.7238			
			(3.8923)			
(4) $\text{Lev.}^{BD} \times -1$				-1.4015		
				(4.9138)		
(5) $\text{FL}^{FixedIncome}$					0.6850	
					(2.5065)	
(6) Ψ^{US}						-6.8496 ***
						(1.5952)
α	Yes	Yes	Yes	Yes	Yes	Yes

Panel A: $FSI_t^{US} = \alpha + \delta \;\; FL_t + \varepsilon_t^{US}$,
Panel B: $FSI_t^{US} = \alpha + \delta \;\; I[FL_t \in 0.75^{th}] + \varepsilon_t^{US}$,
Panel C: $FSI_t^{US} = \alpha + \delta \;\; I[FL_t \in 0.25^{th}] + \varepsilon_t^{US}$,

Table presents test results of FSI of the U.S. market conditional on proxies of funding liquidity in the U.S. market. Panel A reports the regression results of the U.S. FSI on the U.S. funding liquidity proxies. Panel B and Panel C respectively report the results of the fifth and first quantile regression, implemented with a dummy variable. P-values are calculated with Newey and West (1987) heteroskedasticity and autocorrelation robust standard errors (standard errors are reported in parenthesis). Total asset and Leverage of Broker–Dealers are signed such that increase in the proxies of the funding liquidity imply worsening of the funding condition in the economy. Each regression includes an intercept, however, the estimates for the intercepts are not reported for the sake of brevity.

Table 9. DM FSI and Funding Liquidity

Panel A	(1)	(2)	(3)	(4)	(5)	(6)
(1) TED Spread	7.7790 **					
	(3.6627)					
(2) VIX Index		9.9255 ***				
		(3.4856)				
(3) $\text{TA}^{BD} \times -1$			9.2743			
			(6.5783)			
(4) $\text{Lev.}^{BD} \times -1$				-2.7870		
				(4.2434)		
(5) $\text{FL}^{FixedIncome}$					1.0470	
					(3.0763)	
(6) Ψ^{US}						28.7775 ***
						(2.8169)
α	Yes	Yes	Yes	Yes	Yes	Yes
Trend	Yes	Yes	Yes	Yes	Yes	Yes
adj. R^2	0.07	0.01	0.04	0.02	0.00	0.00

Panel B	(1)	(2)	(3)	(4)	(5)	(6)
(1) TED Spread	2.4096					
	(4.8038)					
(2) VIX Index		0.3737				
		(3.5951)				
(3) $\text{TA}^{BD} \times -1$			9.3176 *			
			(5.3621)			
(4) $\text{Lev.}^{BD} \times -1$				-2.6042		
				(5.6401)		
(5) $\text{FL}^{FixedIncome}$					-3.2041	
					(3.9497)	
(6) Ψ^{US}						63.4594 ***
						(5.6156)
α	Yes	Yes	Yes	Yes	Yes	Yes
Trend	Yes	Yes	Yes	Yes	Yes	Yes
adj. R^2	0.07	0.03	0.04	0.03	0.00	0.00

$$FSI_t^k = \alpha + \theta t + \delta \ \ I[FL_t \in 0.75^{th}] + \varepsilon_t^k,$$

Table presents test results of FSI of the developed market (Panel A) and emerging market (Panel B) conditional on global funding liquidity. Global funding liqudity is identified by a dummy variable and takes value of one if the measure is in its fifth quantile. P-values are calculated with double clustering standard errors (standard errors are reported in parenthesis). Total asset and Leverage of Broker–Dealers are signed such that increase in the proxies of the funding liquidity imply worsening of the funding condition in the economy. The estimates for the intercepts and trend are not reported for the sake of brevity.

D.2 Figures

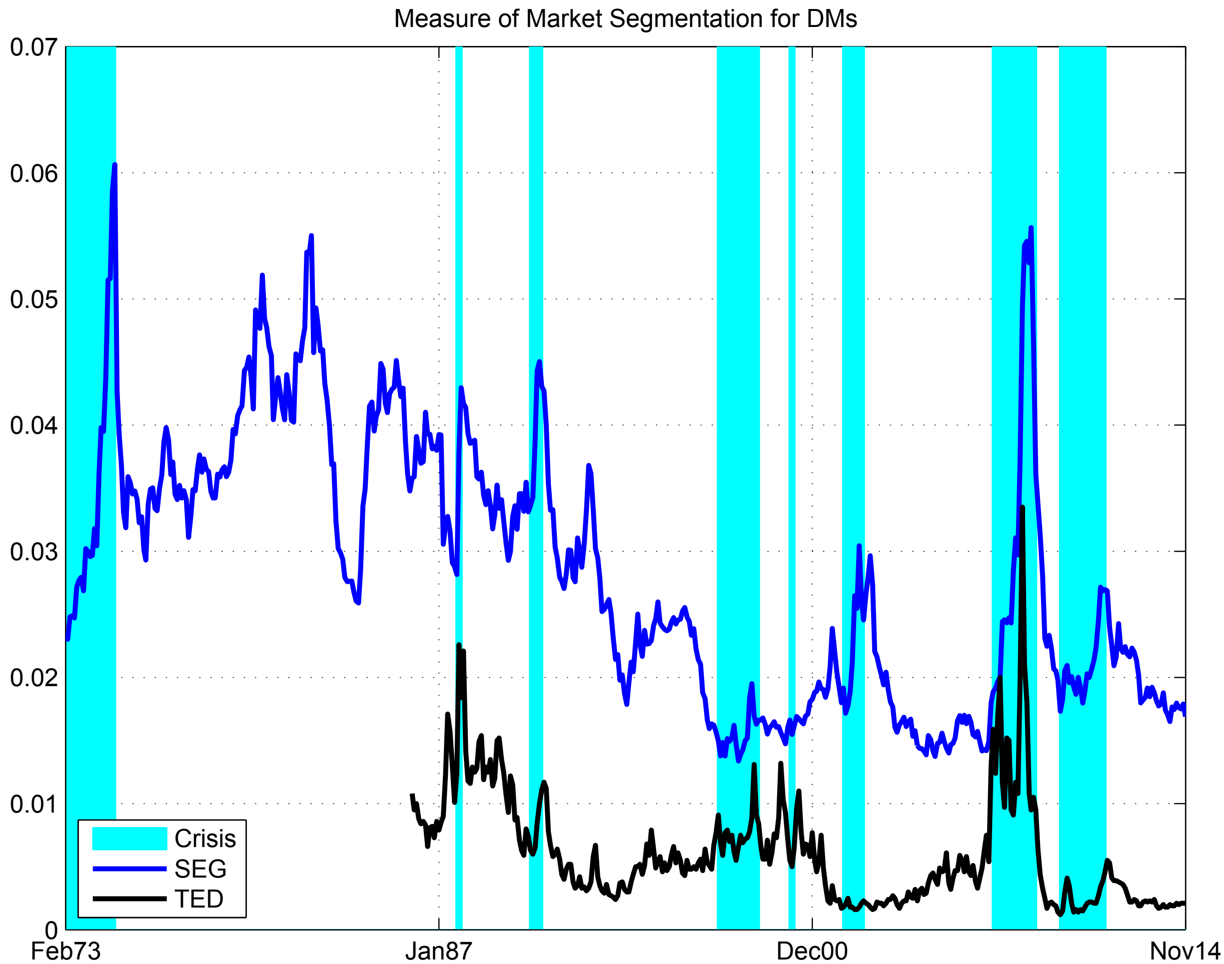

Figure 1. Market segmentation and global financial crises: Average measure of market segmentation of 20 developed markets, calculated from industry portfolios following the methodology proposed in Bekaert et al. (2011), in blue. TED spread, in black, is plotted since 1986, the beginning of the time-series. Large international market crashes are shown with gray bars. Reference: http://en.wikipedia.org/wiki/List_of_stock_market_crashes_and_bear_markets/

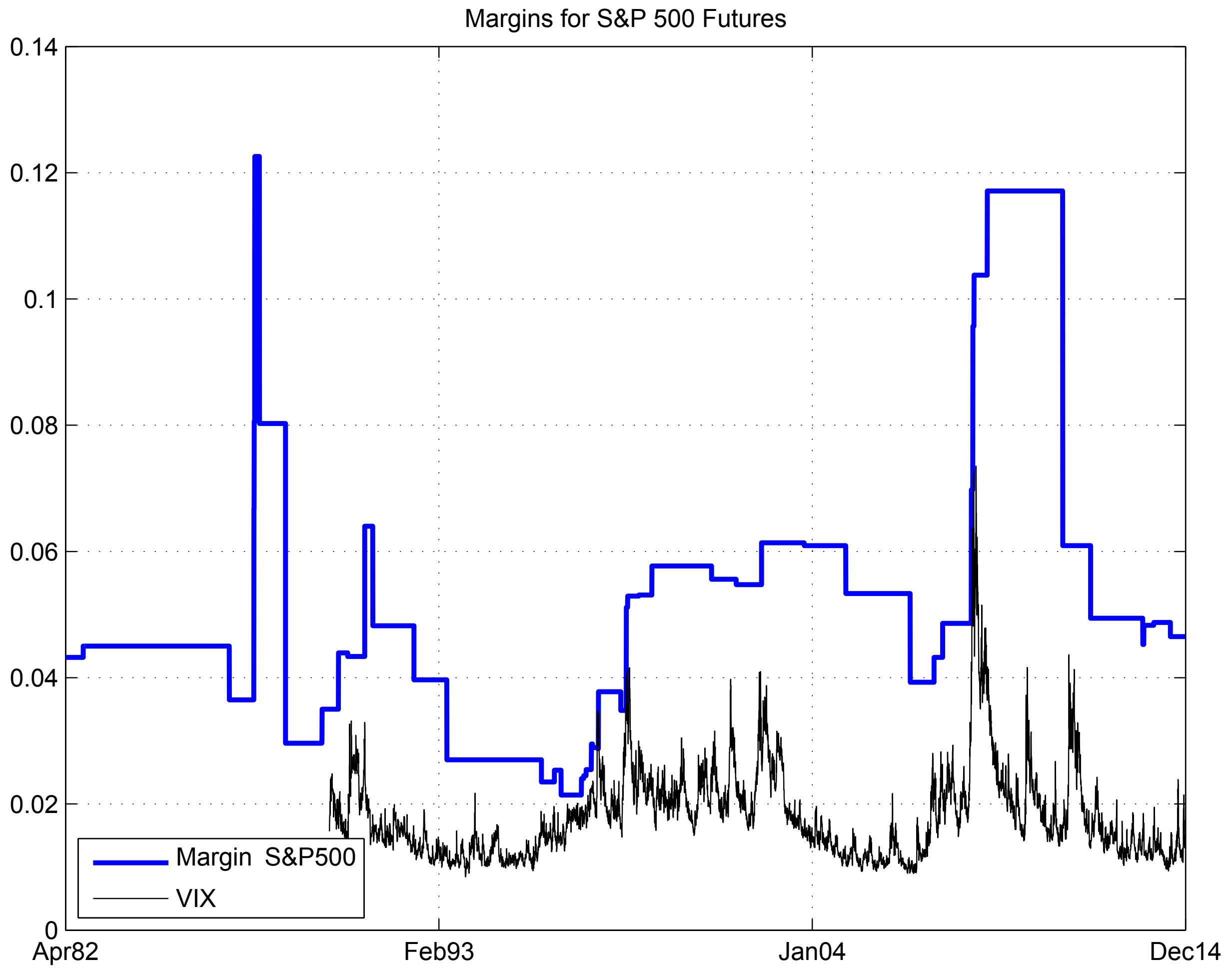

Figure 2. Margins for S&P 500 futures: The figure plots minimum performance bond requirement for S&P 500 stock index futures contracts for members of Chicago Mercantile Exchange. Here, the dollar value of the initial margin requirements are divided by the dollar value of a futures contract (value of 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

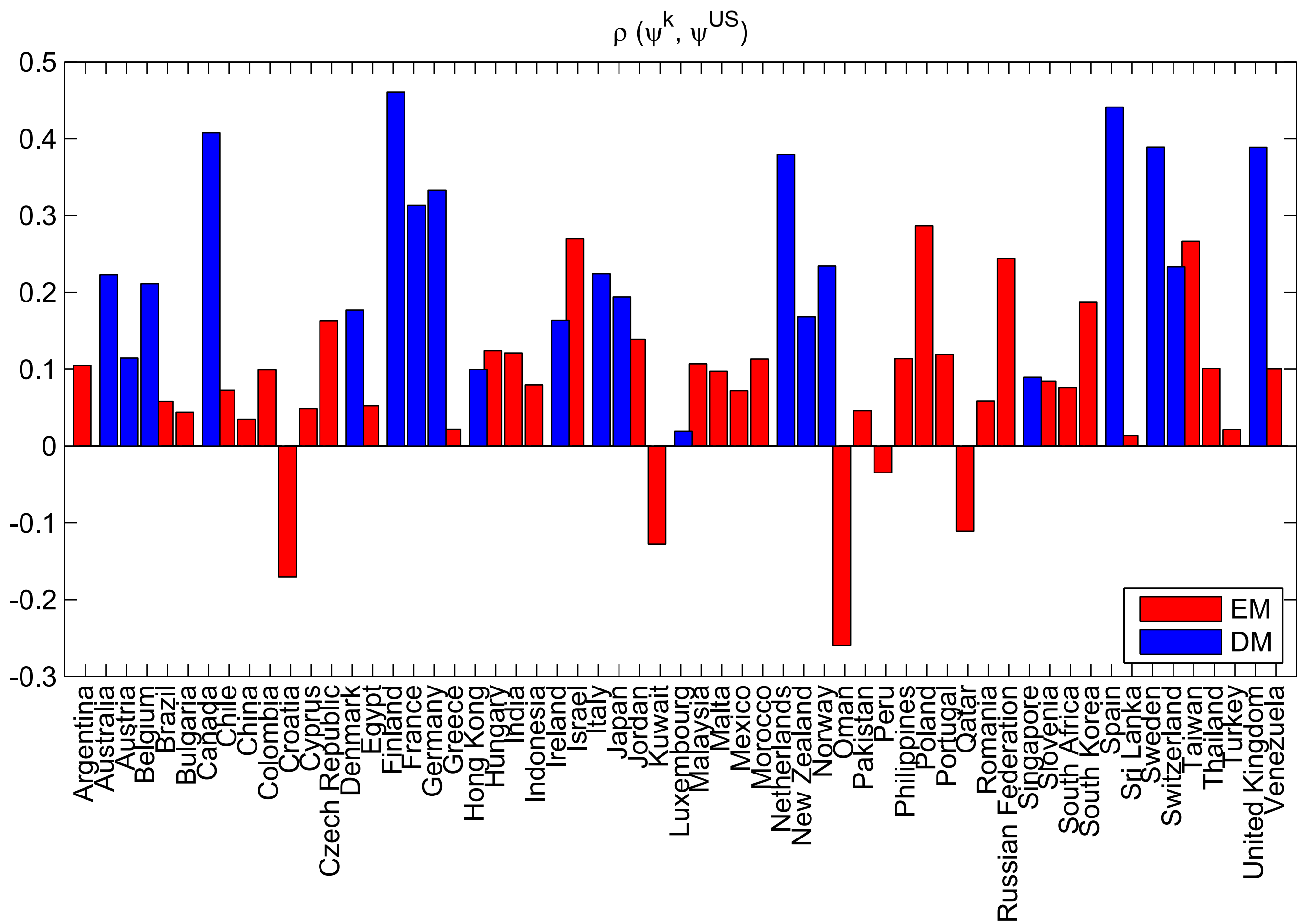

Figure 3. Measure of Market Integration with the U.S. Market: The plot shows the correlation of the estimated shadow price of funding constraint for each country with that of the U.S., controlling for *country-specific* margins and beta spreads. Developed markets are marked in blue and emerging markets are marked in red.

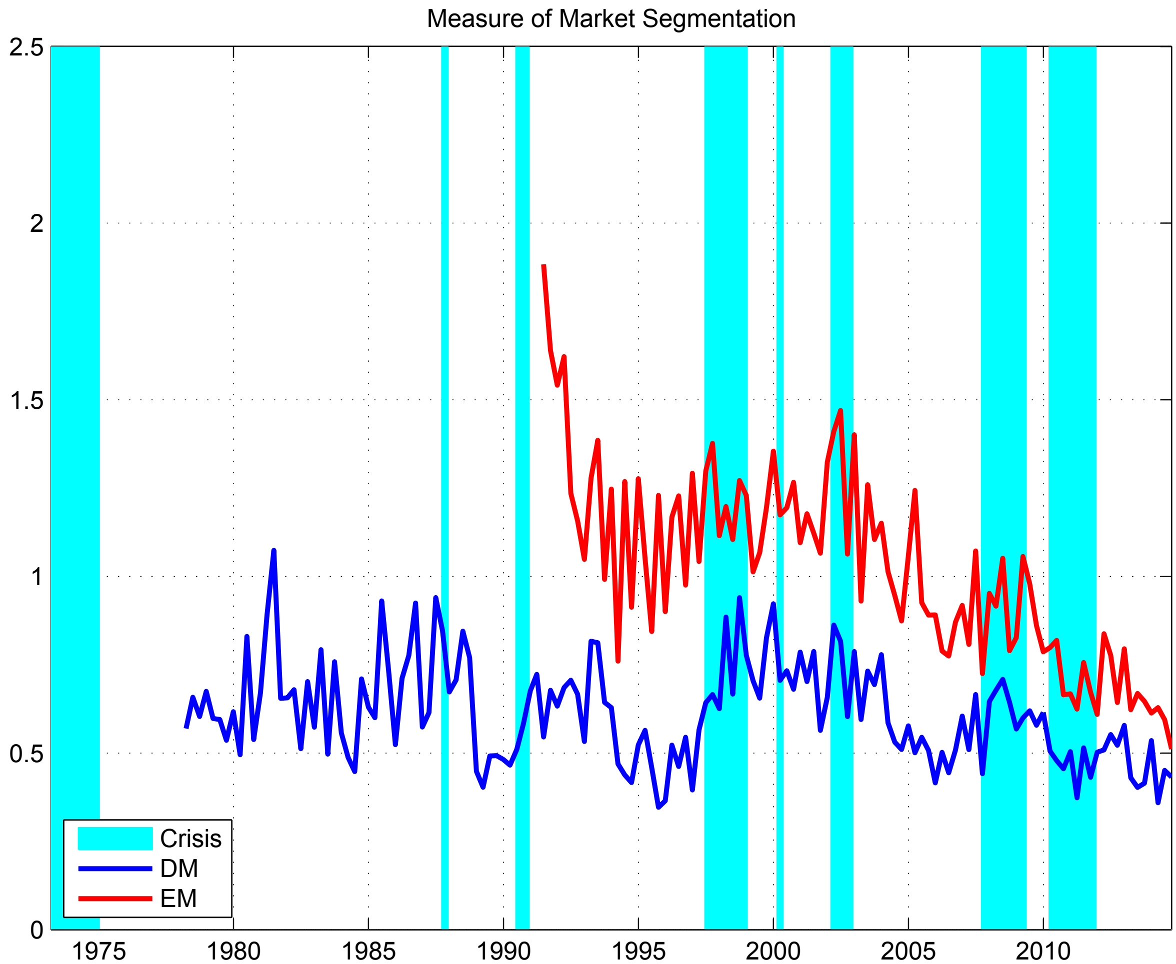

Figure 4. Measure of Market Integration: The plot shows the average measure of market segmentation for developed and emerging markets. The measure is constructed based on the value-weighted discrepancies of the estimated shadow price of the funding constraint for the global representative investor, extracted from each market BAB portfolios. The blue line represents developed markets and the red line represents the emerging markets. Large international market crashes are shown with gray bars. Reference:http://en.wikipedia.org/wiki/List_of_stock_market_crashes_and_bear_markets/