

International Liquidity CAPM^{*}

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Abstract

In this paper we study how funding constraints affect asset prices internationally. We build an equilibrium model with multiple countries where investors face margin constraints, and derive an international funding-liquidity-adjusted CAPM. In particular, the model has implications for (i) the global and local liquidity effect on asset prices in the time series, and (ii) for the pricing of global and local liquidity risk in the cross-section of international assets beyond market risk. To test the model, we construct daily funding liquidity proxies for six different countries and decompose them into one global and six country-specific indices. We then assess whether funding risk is priced in the cross-section of international stock returns. In line with the theoretical predictions, we find that holding betas constant, stocks with higher illiquidity earn higher alphas and Sharpe ratios. A trading strategy that is long high illiquidity to beta ratio stocks and short low illiquidity to beta ratio stocks (BAIL) earns significant positive risk-adjusted returns and outperforms a simple betting-against beta strategy. In the time-series we find that global funding risk is an economically and statistically highly significant predictor of BAIL.

Keywords: Margin, CAPM, Funding Risk, Liquidity

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^{*}We warmly welcome comments.

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This paper studies both theoretically and empirically the effect of funding constraints of specialized institutional agents, such as brokers, hedge funds, and investment banks, across different countries. As it was starkly illustrated during the last financial crisis, the level of institutional capital is an important factor in the healthy operations of capital markets: The large losses financial institutions incurred in the subprime market has led them to cut their activities in many, otherwise unrelated, markets, too. Because financial institutions are responsible for most cross-country investments, it is natural to think that when their funding constraints tighten, it can lead to (il)liquidity comovements across the world, driving the prices of assets in many countries.

We consider a world economy where investors have access to financial assets from several countries. When investing, agents are subject to margin constraints that can vary across both agents and countries; a form of mild segmentation. As a result, we show the existence of an international liquidity-adjusted CAPM, where expected excess returns do not only depend on the global market risk of assets but on local and global liquidity, too. We construct a new measure of funding liquidity in six different countries, and test how and whether funding risk is priced in the cross-section of a large panel of international stocks. Consistent with each of the theoretical predictions, we find that (i) more illiquid stocks earn higher returns, (ii) a market-neutral trading strategy that is long high illiquidity stocks and short low illiquidity stocks earns significant positive risk-adjusted returns and (iii) funding risk significantly predicts future returns to this trading strategy.

We start by presenting a simple overlapping-generations international asset pricing model with funding liquidity. We think about agents as levered investors, who are subject to margin constraints that impose limits on investors' use of leverage. We allow for investor-specific and country- or asset-specific margins, and derive an international liquidity-adjusted CAPM. In particular, in our model, the expected excess return on any security depends on the market beta of this asset with respect to the global market portfolio, and two additional terms representing local and global illiquidity: On one hand, a higher average margin on the country j asset, interpreted as local illiquidity, increases the expected excess return of asset j . This is because a higher margin implies

that more capital has to be committed to maintain the position in this country, which commands an additional premium and drives up expected returns. On the other hand, a higher average margin across the world, interpreted as global illiquidity, decreases the expected excess return of asset j , because it increases the required return on the world portfolio.

To study empirically the effect of funding constraints in a global setting, we construct country-specific measures for funding constraints. We follow the approach of Hu, Pan, and Wang (2013) who calculate price deviations in the U.S. Treasury market. The bond market is particularly useful to study funding constraints for several reasons. First, many types of investors actively trade in this market not only for investment but also funding needs. Second, the variation of government bonds can usually be explained by a few factors which keeps the information content easily tractable. Third, the Treasury market is one of the most liquid markets and represents a safe haven during crisis periods, hence, price deviations contain a very strong signal about the overall funding liquidity in the market.

Using daily bond data for six different countries (US, Germany, UK, Canada, Japan, and Switzerland), we construct country-specific funding measures by first backing out, each day, a smooth zero-coupon yield curve. We then use this yield curve to price the available bonds. With each bond, we obtain both the market and model price. By aggregating the deviations across all bonds and calculating the mean squared error, we obtain a funding measure for each country. We then decompose the country-specific funding measures into a single global and six local measures. The overall correlation of the six country-specific funding proxies is quite high, especially during crisis periods like 2008. However, we also find distinct periods of heightened country-specific funding risk which can be traced back to specific political or economic events. For example, we see a large spike in the German and UK funding proxies during the period of the British Pound dropping out of the Exchange Rate Mechanism while at the same time the corresponding US measure remains relatively calm.

We then ask how global and local funding risk affects international asset returns. As a first way to illustrate the cross-sectional asset pricing implications of funding risk,

we consider illiquidity to beta sorted portfolios. Our model predicts that assets which have high illiquidity and low beta should earn higher expected returns than stocks with low illiquidity and high beta. Using a large cross-section of international stocks, we find our theoretical predictions confirmed in the data. Holding beta constant, both alphas and Sharpe ratios increase considerably with illiquidity. Holding illiquidity constant, lower beta stocks earn higher alpha and Sharpe ratios than higher beta stocks. We then construct a trading strategy that is long in high illiquidity to beta stocks and short in low illiquidity to beta stocks. We call this trading strategy BAIL (betting-against-international-liquidity). We find that this trading strategy earns a monthly return of 0.827% (t-statistic of 3.53), an annualized Sharpe ratio of 0.73, and a CAPM alpha of 0.8% per month (t-statistic of 3.53). Interestingly, this strategy outperforms the betting-against-beta (BAB) strategy suggested by Frazzini and Pedersen (2013): If we had invested \$1 in January 1990 in BAIL, we had earned \$8 by December 2012 compared to \$6.5 in BAB.

A time-series prediction of our model implies that lower margins imply higher returns on BAIL and BAB. We test this prediction by running predictive regressions from returns to the BAIL and BAB strategy onto the global funding proxy. We find that global funding risk is not only a statistically highly significant predictor but also economically relevant: For any one standard deviation change in global funding risk, there is a 0.6% monthly drop in the BAIL strategy. We also show that other common proxies of funding risk such as the TED spread or the VIX predict neither BAIL nor BAB.

Related Literature: There exists a large theoretical literature that studies how funding constraints affect asset prices; see e.g., Kiyotaki and Moore (1997), Xiong (2001), Kyle and Xiong (2001), Gromb and Vayanos (2002), Krishnamurthy (2003), Brunnermeier and Pedersen (2009) and Fostel and Geanakoplos (2012). The papers closest to us are Gârleanu and Pedersen (2011) and Frazzini and Pedersen (2013). Gârleanu and Pedersen (2011) show that high-margin assets have higher expected returns, especially during times of funding illiquidity, and show empirically that deviations of the Law of One Price can arise between assets with the same cash flows but different margins.¹ Frazzini and

¹In a similar vein, Chabakauri (2013) and Rytchkov (2014) study theoretically how a tightening of margin constraints affects prices in equilibrium. They both find that binding margin constraints reduce

Pedersen (2013) present a model where investors face agent-specific margin constraints. Those who cannot lever up invest in more risky assets which causes returns to decline. The authors test a betting-against-beta strategy in bond, stock, and credit markets and find overwhelming empirical evidence. While our model is similar to theirs, we allow for both country- and agent-specific margins, and interpret them as proxies for local and global illiquidity, which have different signs in the margin-augmented CAPM. We also test our predictions using a novel dataset on international funding constraints. Chen and Lu (2013) present empirical evidence that the betting against beta factor is linked to funding conditions using a difference-in-difference approach. The intuition is that constrained investors are willing to pay a higher price for stocks with embedded leverage and that this effect is stronger for stocks with higher margin requirements. Different from their paper where they focus on asset specific margins, we study both agent and asset specific margins. Empirically, the authors proxy stock-level margin constraints by different proxies and then construct betting-against-beta strategies within the different margin groups.

We also speak to the literature that studies liquidity risk in an international context. Karolyi, Lee, and van Dijk (2012) study commonality in stock market liquidity for 40 different countries and ask whether the time variation in commonality is mainly driven by supply- or demand-side sources. The authors find little evidence that commonality in liquidity is higher when intermediaries hit their capital constraints and conclude that commonality is mainly driven by demand-side factors. Amihud, Hameed, Kang, and Zhang (2013) measure illiquidity premia in 45 different countries and find that a portfolio which is long illiquid stocks and short liquid stocks earns more than 9% per year even when controlling for different global risk factors. Bekaert, Harvey, and Lundblad (2007) investigate different definitions of liquidity risk and assess their pricing ability for emerging market portfolios. Motivated by Acharya and Pedersen (2005), Lee (2011) studies how liquidity risk is priced in the cross-section of different stock returns. Our approach is different from his the way we measure liquidity. He defines liquidity to

the volatility of returns but increases expected returns. In particular, the latter author also shows that in the presence of margin constraints, it becomes optimal to overweight the asset with the highest beta, i.e. having a portfolio with the highest possible leverage, in line with Frazzini and Pedersen (2013).

be the ratio of zero stock return days over the total number of trading days given per month. We on the other hand derive funding measures from the bond market which is more liquid than the market for individual stocks.

Related to funding and leverage risk, Adrian, Etula, and Muir (2013) and Adrian, Moench, and Shin (2013) study how intermediary leverage affects the time-series and cross-section of different assets. They find that intermediary leverage is highly procyclical, has a positive price of risk in the cross-section of asset returns, and high leverage growth predicts low future returns. The pricing kernel the authors derive is similar to an economy where the price of risk is the Lagrange multiplier on margin constraints. The tight relationship between leverage and margin constraints is also studied in Ashcraft, Gârleanu, and Pedersen (2011) who argue that investors' leverage is mainly constrained due to margins that prevail in the market (see also Adrian and Etula (2011)).

The rest of the paper is organized as follows. In the next section, we present a model of the margin-augmented CAPM which includes both local and global constraints. Section 2 describes the data and the construction of the funding proxies. Section 3 studies the pricing of global and local funding risk in the cross-section of different assets and finally, we conclude in Section 4.

1 Model

In this section we present a simple international asset pricing model with liquidity, based on Frazzini and Pedersen (2013). We think about agents as levered investors, who borrow and invest in a portfolio of global assets while being subject to margin constraints. Margins determine the fraction of the investment that must be financed by an agent's own capital, and thus, margin constraints impose limits on investors' use of leverage. These limits can depend on the agent, or the composition of the agent's portfolio. In our model, we allow for investor-specific and country-specific margins. The former may result from regulatory requirements that apply only to investors from a certain country, or represent the variation in funding conditions in case investors rely on local borrowing. The latter may result from the difference in the perceived risk of

securities of certain countries. Finally, (il)liquidity is understood as the impact that these margin constraints have on the price of a given asset.

We consider an overlapping-generations world economy with I agents, indexed by $i = 1, \dots, I$, and J countries, indexed by $j = 1, \dots, J$. Agents are born in each period t with wealth $W_{i,t}$, and live for two periods: they invest in period t , then consume and exit in period $t + 1$. Agents of all generations have access to $J + 1$ securities, the first J of them being risky. Each country j has one representative security in total supply θ_t^j that pays a real dividend D_t^j in the unique consumption good in period t , and whose ex-dividend price is denoted by P_t^j . We think about the asset of country j as being a broad index of all the securities available in country j , and could easily extend our model to have multiple (risky) securities in each country. The $(J + 1)$ th asset is a riskless one, with the risk-free rate r^f given exogenously.

At each time period t , young agents choose a portfolio of holdings $x_{i,t} = (x_{i,t}^1, \dots, x_{i,t}^J)^\top$ and invest the rest of their wealth in the riskless asset to maximize mean-variance preferences over next-period consumption. If γ_i denotes agent i 's risk aversion, the optimization problem can be written as

$$\max_{x_{i,t}} x_{i,t}^\top (\mathbb{E}_t [D_{t+1} + P_{t+1}] - (1 + r^f) P_t) - \frac{\gamma_i}{2} x_{i,t}^\top \Omega_t x_{i,t},$$

where P_t is the vector of prices at time t , and Ω_t is the conditional variance-covariance matrix of $D_{t+1} + P_{t+1}$.

Agents are also subject to margin constraints. In particular, we assume that agent i has to post a proportional margin of $m_{i,t}^j$ on asset j , when spending $x_{i,t}^j P_t^j$ on asset j , i.e.

$$\sum_j m_{i,t}^j x_{i,t}^j P_t^j \leq W_{i,t}.$$

This constraint depends on both the agent i and the security j , i.e. combines both investor-specific and country-specific components. Holding asset j fixed, the differences in the margin $m_{i,t}^j$ capture the cross-sectional differences across agents: if agent i faces a lower margin than agent i' , $m_{i,t}^j < m_{i',t}^j$, she can take a larger position in the same asset with the same dollar wealth. On the other hand, keeping agent i fixed, the differences

in $m_{i,t}^j$ capture the cross-sectional differences across countries: if agent i faces a lower margin on country j assets compared to country j' assets, $m_{i,t}^j < m_{i,t}^{j'}$, she can take a larger position in country j with the same amount of capital.²

Finally, in equilibrium, market clearing in the country j asset's market requires

$$\sum_i x_{i,t}^j = \theta_t^j. \quad (1)$$

Equilibrium pricing is obtained from the first-order condition of agents, which, after rearranging, gives the optimal position

$$x_{i,t} = \frac{1}{\gamma_i} \Omega_t^{-1} [\mathbb{E}_t [D_{t+1} + P_{t+1}] - (1 + r^f) P_t - \psi_{i,t} M_{i,t}], \quad (2)$$

where $\psi_{i,t}$ is the Lagrange multiplier associated with the margins constraint of agent i , and $M_{i,t}$ is a column vector of $m_{i,t}^j P_t^j$.

Combining (1) and (2), we obtain the vector of equilibrium security prices:

$$P_t = \mathbf{M}_t^{-1} (\mathbb{E}_t [D_{t+1} + P_{t+1}] - \gamma \Omega_t \theta_t), \quad (3)$$

where $\mathbf{M}_t$ is a diagonal matrix with the j th diagonal term equal to $1 + r^f + \sum_i \frac{\gamma}{\gamma_i} \psi_{i,t} m_{i,t}^j$, and γ is defined as aggregate risk aversion: $\frac{1}{\gamma} = \sum_i \frac{1}{\gamma_i}$. Denoting the net return on security j by r_{t+1}^j and the net return on the global market portfolio by r_{t+1}^G , that is

$$r_{t+1}^j = \frac{D_{t+1}^j + P_{t+1}^j - P_t^j}{P_t^j} \text{ and } r_{t+1}^G = \sum_j r_{t+1}^j \frac{\theta_t^j P_t^j}{\sum_j \theta_t^j P_t^j},$$

equation (3) implies the following augmented CAPM:

Proposition 1. *The equilibrium excess return of any security j is*

$$\mathbb{E}_t [r_{t+1}^j] - r^f = \beta_t^j \lambda_t + m_t^j - \beta_t^j m_t^G, \quad (4)$$

²Black (1972) assumes a no-borrowing constraint on agents, $m_{i,t}^j = 1$ for all i and j , while Frazzini and Pedersen (2013) consider agent-specific margins, $m_{i,t}^j = m_{i,t}$ for all j . Brunnermeier and Pedersen (2009) derive margins endogenously. Gârleanu and Pedersen (2011) use asset-specific margins for the brave agent and no margin on the risk-averse agent, i.e. $m_{a,t}^j = 0$ and $m_{b,t}^j \geq 0$.

where $\beta_t^j = \text{Cov}_t(r_{t+1}^j, r_{t+1}^G) / \text{Var}_t(r_{t+1}^G)$ is the beta of the country- j asset with respect to the global market portfolio, $\lambda_t = \mathbb{E}_t[r_{t+1}^G] - r^f$ is the global market portfolio risk premium, and m_t^j and m_t^G are given by

$$m_t^j = \sum_i \frac{\gamma}{\gamma_i} \psi_{i,t} m_{i,t}^j \text{ and } m_t^G = \sum_j m_t^j \frac{\theta_t^j P_t^j}{\sum_j \theta_t^j P_t^j}. \quad (5)$$

Equation (4) implies that expected excess return on the country j asset depends on the usual CAPM term, and two additional liquidity terms.

The first additional term, m_t^j , is defined as the weighted average of the margins investors face on the asset of country j . The weights include the Lagrange multiplier of agent i , $\psi_{i,t}$, and her risk aversion relative to the aggregate risk aversion. The second additional term, m_t^G , represents the weighted average of margins both across agents and securities, where the margins are also weighted according to their market capitalization.

The term $m_t^j - \beta_t^j m_t^G$ measures the margin that has to be posted on country j asset relative to the average margin across countries. Higher margin on the country j asset implies that more capital has to be committed to maintain the position in this country and this commands an additional premium that lowers the price of the asset and increases expected returns there. The average global margin m_t^G appears in this expression because excess returns on the global market portfolio are themselves in part driven by liquidity.

Equation (5) shows that both liquidity terms depend on the Lagrange multipliers of investors, and the aggregation of these components across assets takes into account the degree to which investors on average are capital constrained. If the constraint does not bind for any of the agents, all the Lagrange multipliers $\psi_{i,t}$ are zero, leading to $m_t^j = 0$ for all j , and $m_t^G = 0$ naturally. In this case, the standard CAPM holds in the world economy. However, when at least one investor's constraint binds, $m_t^j, m_t^G > 0$, and the required return on all securities are affected. Because investors have access to all assets, i.e. asset markets are perfectly integrated, it is the aggregate tightness of the constraints that matters.

Equation (5) also shows that the liquidity terms always depend on the Lagrange multipliers through a normalization with risk aversion: keeping everything else constant, required returns are higher if the constraint binds for more risk-tolerant agents, i.e. in times when risk-tolerant agents have lower wealth due to recent losses.

In the special case where margins are only country-specific, i.e., $m_{i,t}^j$ only varies with j but not with i , all agents have to pay the same margin on trading, and both liquidity terms become linear in $\psi_t = \sum_i \frac{\gamma_i}{\gamma_i} \psi_{i,t}$, the risk-tolerance-weighted average Lagrange multiplier. In the polar opposite case, when margins are investor-specific, i.e., $m_{i,t}^j$ is the same for all j s when holding i fixed, we get $m_t^G = m_t^j$ for all j , and the liquidity terms together simplify to $(1 - \beta_t^j) m_t^G$; analogous to the result of Frazzini and Pedersen (2013). This is the case because, due to having perfectly integrated markets, investor-specific margins, unlike country-specific margins, affect all assets in the same way.

Finally, when we relate the model to our empirical analysis, we think about illiquidity as the impact of margin constraints on the price or return of a given asset. This is measured by m_t^j , which we refer to as local illiquidity, and m_t^G , which we call global illiquidity. Since both terms include an aggregation of constraint tightness $\psi_{i,t}$ across agents, this naturally induces a correlation between the time series of global and local liquidity measures. Moreover, country-specific differences in margins introduce cross-sectional dispersion in expected returns on assets in different countries, beyond the one due to the difference in betas.

Until now we have been assuming that each country has a representative risky asset. This assumption was mainly to keep our notation tractable, and Proposition 1 certainly holds even if j stands for an individual asset instead of a stock index. However, since our proxy for funding constraints will be at the country level, we do not need to consider asset-specific margins to derive model predictions. Therefore, from now on, with a slight abuse of notation, we understand β_t^j as security j 's beta with respect to the global market portfolio, while m_t^j , the local illiquidity measure, refers to the illiquidity of the country to which asset j belongs. That is, the local illiquidity will be the same for assets in the same country.

Rewriting (4) provides the following results:

Proposition 2. (i) A security's alpha with respect to the global market is $m_t^j - \beta_t^j m_t^G$. Holding margins constant, a higher beta means lower alpha. Holding beta constant, the alpha increases in the local illiquidity and decreases in the global illiquidity measure.

(ii) There is an 'average' security market line, but securities can be off the line due to the local illiquidity term m_t^j :

$$\mathbb{E}_t [r_{t+1}^j] = r^f + m_t^j + \beta_t^j (\mathbb{E}_t [r_{t+1}^G] - r^f - m_t^G). \quad (6)$$

Proposition 2 implies that the slope of the average security market line is given by $(\mathbb{E}_t [r_{t+1}^G] - r^f - m_t^G)$. Tighter portfolio constraints, and hence the global illiquidity m_t^G , flatten the security market line. However, assets do not necessarily line up on this security market line, if local illiquidity is not constant across countries. The difference is given by the country-specific illiquidity, m_t^j .

Next we apply the above results to consider the properties of a self-financing market-neutral portfolio that is long in assets with high m_t^j/β_t^j ratio and short in securities with low m_t^j/β_t^j . Let us denote the relative portfolio weights for the high illiquidity-to-beta securities by the vector w_1 —this portfolio has a return of $r_{t+1}^1 = w_1^\top r_{t+1}$, a beta of $\beta_t^1 = w_1^\top \beta_t$, and an average margin $m_t^1 = w_1^\top m_t$, where r_{t+1} , β_t , and m_t are the vectors of all security returns in the next period, betas, and margins. Similarly, consider a second portfolio consisting of securities with low illiquidity-to-beta ratios with weights w_2 , to obtain a return $r_{t+1}^2 = w_2^\top r_{t+1}$, a beta $\beta_t^2 = w_2^\top \beta_t$, and a margin $m_t^2 = w_2^\top m_t$. Applying a leverage $1/\beta_t^1$ to the first portfolio and going long in it (i.e. levering up if $\beta_t^1 < 1$ and down vice versa), and applying a leverage $1/\beta_t^2$ to the second portfolio and going short, we obtain a factor given by

$$r_{t+1}^{\text{BAIL}} = \frac{1}{\beta_t^1} (r_{t+1}^1 - r^f) - \frac{1}{\beta_t^2} (r_{t+1}^2 - r^f).$$

This portfolio has a beta of zero with respect to the global market, and it is self-financing, because it is the difference between excess returns. Combining (4) and the above definition immediately gives the following result about the factor we just created:

Proposition 3. *The expected excess return of the illiquidity portfolio is given by*

$$\mathbb{E}_t [r_{t+1}^{BAIL}] = \frac{m_t^1}{\beta_t^1} - \frac{m_t^2}{\beta_t^2} > 0. \quad (7)$$

Proposition 3 implies that if we create the long and short portfolios such that we go long in high m_t^j/β_t^j securities and short in low m_t^j/β_t^j securities, the portfolio earns a positive expected return on average. The size of the expected return depends on the spread in the ratio of the local illiquidity and the beta of the asset for the assets that we use for the portfolios. This result is a generalization of Proposition 2 in Frazzini and Pedersen (2013)—we obtain the original result if we assume investors pay the same margin on all assets.

Comparing the returns of the illiquidity portfolio to those of the betting-against-beta strategy leads us to our next result:

Proposition 4. *The return on the illiquidity portfolio is larger than on a similar long-short trading strategy that ignores sorting based on illiquidity:*

$$\mathbb{E}_t [r_{t+1}^{BAIL}] \geq \mathbb{E}_t [r_{t+1}^{BAB}], \quad (8)$$

where BAB goes long in low-beta assets and short in high-beta assets, with appropriately (de)levering: $r_{t+1}^{BAB} = 1/\beta_t^L (r_{t+1}^L - r^f) - 1/\beta_t^H (r_{t+1}^H - r^f)$.

Finally, we study the impact of changes in margin constraints on the returns of the trading strategy. Both the BAIL and BAB strategy lose when margin constraints tighten as investors need to de-lever their positions when funding becomes scarce. We summarize this in the following Proposition.

Proposition 5. *An increase in margin constraints m_t^j for $j = 1, 2$ leads to a loss in the future required return:*

$$\frac{\partial \mathbb{E}_t [r_{t+1}^{BAIL}]}{\partial m_t^j} < 0.$$

We provide empirical evidence for Propositions 2-5 in Section 3. Before that, in Section 2, we describe the data and how we construct the local and global illiquidity measures that we use as proxies for m_t^j and m_t^G .

2 Data

From Datastream, we collect the raw data for government bonds. Furthermore, we use daily stock return data, which is adjusted for stock splits and dividend payments, also from Datastream. The frequency is daily, running from 1 January 1990 to 31 December 2012, which leaves us with 6001 observations.

2.1 Bond Data

From Datastream we collect bond data for six different countries: Canada, Germany, Japan, the United Kingdom, the United States, and Switzerland. We obtain a daily cross-sections of end-of-day bond prices starting in January 1990 through December 2012 for all available maturities. We also collect information on accrued interest, coupon rates and dates, and issue and redemption. Following Gürkaynak, Sack, and Wright (2007), we apply several data filters in order to obtain securities with similar liquidity and avoiding special features. The filters can vary by country, but in general they are as follows: (i) We exclude bonds with option like features such as bonds with warrants, floating rate bonds, callable and index-linked bonds. (ii) We consider only securities with a maturity of more than one year at issue (this means that for example for the U.S. market we exclude Treasury bills). We also exclude securities that have a remaining maturity of less than three months. Yields on these securities often seem to behave oddly; in addition, excluding these short maturity securities may alleviate concerns that segmented markets may significantly affect the short-end of the yield curve.³ Moreover, short-maturity bonds are not very likely to be affected by arbitrage activity, which is the objective of our paper. (iii) We also exclude bonds with a remaining maturity of 15 years or more as in an international context they are often not very actively traded (see, e.g., Pegoraro, Siegel, and Tiozzo ‘Pezzoli’ (2013)). (iv) For the U.S. we exclude the on-the-run and first-off-the-run issues for every maturity. These securities often trade at a premium to other Treasury securities as they are generally more liquid than more

³Duffee (1996) for example shows that Treasury bills exhibit a lot of idiosyncratic variation and have become increasingly disconnected from the rest of the yield curve.

seasoned securities (see e.g., Fontaine and Garcia (2012)). Other countries either do not have on-the-run and off-the-run bonds in the strict sense, as they for example reopen existing bonds to issue additional debt, or they do not conduct regular auctions as the Treasury does. We therefore do not apply this filter to the international sample. (v) Additionally, we exclude bonds if the reported prices are obviously wrong. While the data quality for the U.S. is reasonably good, there are a lot of obvious pricing errors in the international bond sample, which requires substantial manual data cleaning.

Panel A of Table 1 provides details of our international bond sample. We note that on average we have 71 bonds every day to fit the yield curve and 60 bonds to construct the noise measure. Japan and the US are the most active markets, while the average number of bonds in Switzerland and the UK is rather low. The cross-section varies considerable over time: During the years 2001-2007, the number of bonds available dropped considerably for all countries except Japan which as a response to the banking crisis in the years 2000.

[Insert Table 1 here.]

We verify that our yield curve estimates are reasonable by comparing our term structures with the estimates published by central banks and the international yield curves used in Pegoraro, Siegel, and Tiozzo ‘Pezzoli’ (2013).

2.2 *Stock Returns*

We collect daily stock returns, volume, and market capitalization data for the six countries from Datastream. The initial sample covers more than 10,000 stocks. We only select stocks from major exchanges, which are defined as those in which the majority of stocks for a given country are traded. We exclude preferred stocks, depository receipts, real estate investment trusts, and other financial assets with special features based on the specific Datastream type classification. To limit the effect of survivorship bias, we include dead stocks in the sample. We use the following filtering procedure to secure a reliable data sample: To exclude non-trading days, we define days on which 90% or more

of the stocks are listed on a given exchange have a return equal to zero as non-trading days. We also exclude a stock if the number of zero-return days is more than 80% in a given month. Excess returns are above the US Treasury bill rate and the proxy for the global market is the MSCI world index. Panel B of Table 1 reports summary statistics.

2.3 Other Data

We also use the TED spread and the VIX as a further proxy for periods when constraints tighten. The TED spread is defined as the difference between the three-month Eurodollar LIBOR rate and the three-month U.S. T-Bill rate. From Andrea Frazzini’s webpage, we download global size, value, and momentum returns. The data construction is described in Asness and Frazzini (2013).

2.4 Equity Betas

We follow Frazzini and Pedersen (2013) to construct ex-ante betas from rolling regressions of daily excess returns on market excess returns. The estimated beta for any stock i is given by:

$$\hat{\beta}_i^{\text{TS}} = \hat{\rho} \frac{\hat{\sigma}_i}{\hat{\sigma}_m},$$

where $\hat{\sigma}_i$ and $\hat{\sigma}_m$ are the estimated volatilities for the stock and the market and $\hat{\rho}$ is their correlation. Volatilities and correlations are estimated separately. First, we use a one-year rolling standard deviation for volatilities and a five-year horizon for the correlation to account for the fact that correlations appear to move more slowly than volatilities. To account for non-synchronous trading, we use one-day log returns to estimate volatilities and three-day log returns for correlation. Finally, we shrink the time-series estimate of the beta towards the cross-sectional mean (β_i^{CS}) following Vasicek (1973):

$$\hat{\beta}_i = \omega_i \hat{\beta}_i^{\text{TS}} + (1 - \omega_i) \beta_i^{\text{CS}},$$

where we set $\omega = 0.6$ and $\beta^{\text{CS}} = 1$ for all periods across all stocks, in line with Frazzini and Pedersen (2013).

2.5 Country-specific and Global Funding Proxies

To construct country-specific funding measures, we follow Hu, Pan, and Wang (2013) who employ the Svensson (1994) method to fit the term structure of interest rates.⁴

The Nelson and Siegel (1987) model assumes that the instantaneous forward rate f is given by:

$$f_m = \beta_{t,0} + \beta_1 \exp\left(\frac{-m}{\tau_1}\right) + \beta_2 \frac{m}{\tau_1} \exp\left(\frac{-m}{\tau_1}\right) + \beta_3 \frac{m}{\tau_2} \exp\left(\frac{-m}{\tau_2}\right),$$

where m denotes the time to maturity and $\beta_i, i = 0, 1, 2, 3$ are parameters to be estimated. By integrating the forward rate curve, we derive the zero coupon curve s_m :

$$\begin{aligned} s_m = & \beta_0 + \beta_1 \left(1 - \exp\left(-\frac{m}{\tau_1}\right)\right) \left(-\frac{m}{\tau_1}\right)^{-1} \\ & + \beta_2 \left(\left(1 - \exp\left(-\frac{m}{\tau_1}\right)\right) \left(\frac{m}{\tau_1}\right)^{-1} - \exp\left(-\frac{m}{\tau_1}\right)\right) \\ & + \beta_3 \left(\left(1 - \exp\left(-\frac{m}{\tau_2}\right)\right) \left(\frac{m}{\tau_2}\right)^{-1} - \exp\left(-\frac{m}{\tau_2}\right)\right). \end{aligned}$$

A proper set of parameter restrictions is given by $\beta_0 > 0, \beta_0 + \beta_1 > 0, \tau_1 > 0$, and $\tau_2 > 0$. For long maturities, the spot and forward rates approach asymptotically β_0 , hence the value has to be positive. $(\beta_0 + \beta_1)$ determines the starting value of the curve at maturity zero. (β_2, τ_1) and (β_3, τ_2) determine the humps of the forward curve. The hump's magnitude is given by the absolute size of β_2 and β_3 while its direction is given by the sign. Finally, τ_1 and τ_2 determine the position of the humps.

To estimate the set of parameters $b_t = (\beta_0, \beta_1, \beta_2, \beta_3, \tau_1, \tau_2)$ for each day, we minimize the weighted sum of the squared deviations between the actual and model-implied prices:⁵

$$b_t = \operatorname{argmax} \sum_{i=1}^{N_t} \left((P^i(b) - P_t^i) \times \frac{1}{D^i} \right)^2,$$

⁴We also use the Nelson and Siegel (1987) and a cubic spline method. All three approaches lead to qualitatively very similar results. As the Svensson (1994) method is the most widely used, we chose this one.

⁵Note that one could also minimize the the yield errors rather than the price errors. Since we are mainly interested in price deviations, rather than interest rates, we chose the latter.

where N_t is the number of bonds, $P^i(b)$ is the model-implied price for bond i , and D^i is the corresponding Macaulay duration for bond i . The illiquidity measure is then defined as the root mean square error between the market yields and the model-implied yields, i.e.

$$\text{Illiq}_t = \sqrt{\frac{1}{N_t} \sum_{i=1}^{N_t} (y_t^i - y^i(b_t))^2},$$

where y_t^i is the market yield corresponding to bond i , and $y^i(b_t)$ is the model-implied yield.

While we calculate the term structure using a wide range of maturities, we calculate the measure only using bonds with maturities ranging between one and ten years. Similar to Hu, Pan, and Wang (2013), we also apply data filters to ensure that funding measures are not driven by single observations. In particular, we exclude any bond whose associated yield is more than four standard deviations away from the model yield.

In a next step, we calculate a global funding proxy, henceforth denoted Illiq_t^G , by taking a GDP-weighted average of country-level funding proxies. Baker, Wurgler, and Yuan (2012) construct a global sentiment index from country-level sentiment indices by taking the first principal component. In a similar vein, Asness, Moskowitz, and Pedersen (2013) calculate a global funding risk factor using the first principal component from the TED spread, LIBOR minus term repo spread, and the spread between interest rate swaps and local short-term government rates from the US, UK, Japan, and Germany. Taking the first principal component from our country-level funding proxies leads to very similar results as taking an average (the unconditional correlation between the average and the first principal component is 95%), moreover, the principal component can be negative. For these reasons, we prefer to take an average.

2.6 International Funding Proxies Properties

The time-series of all country-specific funding measures together with the global measure are plotted in Figure 1. In Table 2, we report summary statistics (Panel A). We first note that there are certain spikes which are common to all series like the Lehman default

in summer 2008. There are, however, country-specific movements. For example, the Japanese measure is very volatile in the early 1990ies, especially around the Asian crisis of 1996-1997. It then spikes again around the dot-com bubble burst in 2001 and then again during the most recent financial crisis.

[Insert Figures 1 and 2 here.]

The German funding proxy is especially volatile after 1992 and during the most recent financial crisis. The heightened level of the funding proxy after 1990 can be explained by the large uncertainty surrounding the German reunification in October 1990. German interest rates had climbed relentlessly during 1991 and 1992 and then started to fall after the outbreak of the ERM crisis in September 1992 steadily through 1994. Moreover, the autumn of 1992 has witnessed massive speculative currency attacks (see e.g., Buiter, Corsetti, and Pesenti (1998)). The repercussions of the ERM crisis are also found in the funding proxies of the UK and Switzerland where during the year 1992 we see large jumps. Interestingly, these stark movements are completely absent in the US funding liquidity proxy which displays only moderate movements until 1997 (Asian crisis), except around the first Gulf War in 1991. The global measure is mainly characterized by four large spikes. The ERM crisis, the Asian crisis, the dot-com bubble burst, and the Lehman default.

[Insert Table 2 and Figures 3 and 4 here.]

The summary statistics in Table 2, Panel A, reveal that overall, the average pricing errors are quite small, ranging from 2.8 basis points (US) to 6.2 basis points for Switzerland. The larger pricing errors for Switzerland can be explained by a smaller number of traded bonds which makes the estimation more difficult. This is also reflected in the overall larger volatility which ranges from 1.37 basis points (US) to 4.5 (Switzerland). The cross-correlation of the different country funding proxies is presented in Panel B of Table 2. The average correlation is quite high ranging from 20% (US and Japan) to 74% (Germany and Japan).

It is well known that markets usually correlate more during crisis periods and that illiquidity is particularly high in periods of distress (see e.g., Hameed, Kang, and Vishwanathan (2009)). We observe a similar pattern for the country-specific funding measures. Figure 2 plots the average conditional correlation among the different funding proxies.⁶ We note that the average correlation peaks during periods of distress such as the dotcom bubble burst or the most recent financial crisis where the correlation reaches almost 80%.

We can now explore how global funding risk is related to country-level funding proxies. Panel C of Table 2 reports loadings from the following regression:

$$\text{fund}_t^i = \beta_0 + \beta_1^i \text{fund}_t^G + \epsilon_t^i,$$

where fund_t^i is the funding proxy of country i and fund_t^G is the global funding proxy. We find, unsurprisingly, that all country-specific factors co-move positively with the global factor and that the global factors explains quite a large proportion of the variation in the country-specific funding measures with R^2 ranging between 30% to 66%. This is in line with the prediction from our model that the aggregate constraint tightness induces some correlation between global and local liquidity measures.

Figure 3 depicts the time-series of the global funding proxy. We note that the global measure summarizes the properties of country-level funding proxies. For example, the high volatility before 1995 can be attributed to rather Europe-specific events such as the British Pound leaving the ERM or the German elections in 1994 which were surrounded by large uncertainty. The downgrade of GM and Ford in May 2005 is a US specific event which is not reflected in the other five country-level funding proxies. Figure 4 plots the first difference of the global funding proxy together with first differences in the TED spread, another common proxy of funding constraints (see e.g., Brunnermeier and Pedersen (2009)). We first note the high correlation between the two series which is 45% over our data sample. Moreover, both the global funding proxy and the TED spread

⁶Conditional correlations are calculated using a rolling window of three years using daily data.

decline rapidly during major crashes in the stock market such as in October 1987, the dot com bubble burst in 2000, or the Lehman default in the summer of 2008.

2.7 Liquidity Trading Strategy

In the following, we construct a portfolio that is long high illiquidity to beta ratio stocks and we short sell low illiquidity to beta ratio stocks. We thereafter call this portfolio betting-against-international-illiquidity (BAIL). To make illiquidity proxies comparable across different countries, we standardize them using the following procedure. We first run regressions from each country's market index return onto the global return, the country's illiquidity proxy and the global illiquidity proxy:

$$rx_{t+1}^i = \alpha + \beta_g rx_{t+1}^G + \beta_t \text{Illiq}_t^i + \beta_G \text{Illiq}_t^G,$$

where rx_{t+1}^i is the excess return of country i , rx_{t+1}^G the global excess return, Illiq_t^i the country-level funding proxy, and Illiq_t^G the global funding proxy. The adjusted country-level funding proxy is then given by

$$\widetilde{\text{Illiq}}_t^i = \hat{\beta}_t \times \text{Illiq}_t^i,$$

where $\hat{\beta}_t$ is the estimated slope coefficient from the regression above. We then construct for each stock the ratio between $\widetilde{\text{Illiq}}_t^i$ and its estimated beta, $\hat{\beta}_g$, and rank them in ascending order. The ranked securities are then assigned into two different bins: High illiquidity to beta stocks and low illiquidity to beta stocks. We long the former and short the latter. In line with the portfolio construction in Proposition 3, we weight each stock in order for the portfolio to have a beta of zero. The BAIL strategy is then a self-financing zero-beta portfolio that is long a high illiquidity to beta portfolio and short a low illiquidity to beta portfolio:

$$r_{t+1}^{\text{BAIL}} = \frac{1}{\beta_t^1} (r_{t+1}^1 - r^f) - \frac{1}{\beta_t^2} (r_{t+1}^2 - r^f).$$

3 Empirical Analysis

In this section, we empirically test the theoretical propositions derived before. Propositions 2 and 3 focus on the cross-section of stocks with different liquidity, while Proposition 4 compares the return of the BAIL with the BAB strategy. The prediction of Proposition 5 is in the time-series dimension. We first test how returns vary in the cross-section of illiquidity to beta sorted portfolios and then study the properties of our betting-against-international-illiquidity trading strategy. Finally, we examine the predictive power of the global funding proxy for our trading strategy.

3.1 Sorted Portfolios

We first inspect how returns vary in the cross-section of illiquidity and beta-sorted stocks. Proposition 2 says that holding beta constant, the alpha should increase in the local illiquidity and decrease in global illiquidity, moreover, when holding margins constant, a higher beta means lower alpha. Table 3 reports the results using our international stock data set. We consider three beta and two illiquidity sorted portfolios and report their average excess returns, alphas, market betas, volatilities, and Sharpe ratios. Consistent with the findings in Frazzini and Pedersen (2013), we find that alphas decline from the low beta to the high beta portfolio: Holding illiquidity constant, we find that for low (high) illiquidity stocks, the alpha decreases from 0.527 to 0.395 (0.547 to 0.522), similarly, Sharpe ratios drop from 0.49 to 0.28 (0.50 to 0.37). On the other hand, keeping betas constant, we find that alphas increase from the low illiquidity stocks to high illiquidity stocks. For example, the alpha for low beta stocks increases from 0.527% per month to 0.547%, for medium beta it increases from 0.471% to 0.540% and for high beta stock it increases from 0.395% to 0.522%.

[Insert Table 3 and Figure 5 here.]

The last two columns report summary statistics of the BAIL strategy. The strategies produce high excess returns: The BAIL strategy has an average excess return of 0.827%

per month (t-statistic of 3.53). The associated (annualized) Sharpe ratio is 0.73 and a significant positive alpha of 0.791% per month. Overall, we conclude that the BAIL strategy is highly profitable and produces significant positive excess returns.

3.2 *BAIL versus BAB*

Proposition 4 says that returns to the BAIL strategy should be higher on average than for the BAB strategy. We test this prediction by comparing the returns to the BAB strategy which are presented in the last column of Table 3. In line with our empirical prediction, we find that on average, the BAB strategy performs worse than the BAIL strategy: The average excess return is 0.741% per month which is 11% lower than that of the BAIL strategy. Also in terms of alpha, the strategy performs worse than BAIL: The monthly alpha is 0.731% or 8% lower. In terms of Sharpe ratio both trading strategies perform the same: The annualized Sharpe ratio of the BAB strategy is 0.73. We note that the BAIL strategy has a slightly higher volatility than the BAB strategy. This becomes evident also in Figure 6 where we plot the cumulative returns of the BAB and BAIL strategy for the past 10 years. Both strategies almost move in lock-step until after the Lehman default in the summer of 2008 where BAIL performs much better than BAB. Had we invested 1\$ in January 2003 in BAIL and kept it for 10 years, we would have earned \$5.7 compared to \$3.9 in BAB.⁷ Economically the better performance after 2008 can be traced back to our theoretical predictions: In a world where liquidity risk matters, higher illiquidity generates higher returns. Hence a strategy that is long illiquid stocks should perform particularly well after funding crises.

[Insert Figure 6 here.]

3.3 *Predictive Power of Global Funding Risk*

Finally, we can study the time-series property of the funding proxy. Proposition 5 argues that higher margin constraints imply lower expected returns on both the BAIL and BAB

⁷For the period January 1990 to December 2012, a \$1 investment would have led to \$8 for BAIL and \$6.5 for BAB.

trading strategies. To test this prediction in the data, we regress r_{t+1}^{BAIL} and r_{t+1}^{BAB} onto lagged values of global funding risk:

$$r_{t+1}^{\text{BAIL/BAB}} = \beta \text{ Funding Proxy}_t + \epsilon_{t+1}.$$

The results are reported in Table 4. Our measure of global funding risk is a highly significant predictor of future returns on the BAIL strategy and it also carries the predicted negative sign. Any one standard deviation shock in global funding implies a 0.7% ($0.179 \times 3.9\%$) decrease in the BAIL strategy and similarly a 0.56% decrease in the BAB strategy. As a robustness check, we also include other proxies of funding risk like the TED spread, the VIX, or the US funding proxy (see e.g., Hu, Pan, and Wang (2013)). We note that none of these additional funding proxies load significantly on either the BAIL or the BAB strategy. The VIX and US funding proxy even carry a wrong (positive) sign. This finding is in line with Chen and Lu (2013).

[Insert Table 4 here.]

4 Conclusion

This paper investigates the effect of funding constraints on asset returns across different countries, both theoretically and empirically. We consider a world economy where agents are subject to agent- and country-specific margin constraints, and derive an international funding-liquidity-adjusted CAPM, where expected excess returns do not only depend on the global market risk of assets but on local and global liquidity measures representing how tight funding constraints are, too. In particular, the model has implications for (i) the global and local liquidity effect on asset prices in the time series, and (ii) for the pricing of global and local liquidity risk in the cross-section of international assets.

The empirical evidence presented is supportive of the liquidity-adjusted CAPM in that liquidity risk is priced both in the time-series and cross-section. We first construct daily country-specific funding proxies from pricing deviations on government bonds. While the overall correlation between the country-specific measures is quite high, the

measures display distinct idiosyncratic behavior especially during political or economic events. Using the country-level funding proxies, we construct a global funding risk proxy as a GDP-weighted average. Using both the global and country-level funding proxies and a large panel of international stock data, we then test the empirical predictions of our model.

We first sort stocks according to their illiquidity to beta ratio. Our model predicts that holding the beta level of stocks constant, stocks with high illiquidity should earn higher returns than stocks with low illiquidity. The data confirms our predictions: Both alphas and Sharpe ratios are monotonically increasing with the illiquidity level. We then construct a self-financing trading strategy (BAIL) that is long high illiquidity to beta stocks and short low illiquidity to beta stocks. BAIL produces significant abnormal returns and an attractive (annualized) Sharpe ratio of 0.73. Moreover, this strategy outperforms a standard betting-against-beta strategy. Another prediction claims that tighter margins lead to lower returns on BAIL. To test this, we run predictive regressions from BAIL returns onto the global funding proxy and find that global funding is not only a highly significant predictor but also has the expected negative sign. Other standard measures of funding risk such as the TED spread or the VIX have no predictive power.

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Appendix A Proofs and derivations

Proof of Propositions 1 and 2. Rearranging (3) yields

$$E_t \left[r_{t+1}^j \right] = E_t \left[\frac{D_{t+1}^j + P_{t+1}^j - P_t^j}{P_t^j} \right] = r^f + \sum_i \frac{\gamma}{\gamma_i} \psi_{i,t} m_{i,t}^j + \gamma \frac{1}{P_t^j} 1_j^T \Omega_t \theta_t, \quad (\text{A-1})$$

where 1_j is a $J \times 1$ vector with a 1 in row j and zeros everywhere else. The second term on the RHS of this equation is m_t^j by definition. Also, with the definition of Ω_t and r_{t+1}^G we can rewrite the third term:

$$\frac{1}{P_t^j} 1_j^T \Omega_t \theta_t = \frac{1}{P_t^j} \text{Cov}_t \left(D_{t+1}^j + P_{t+1}^j, \theta_t^\top (D_{t+1} + P_{t+1}) \right) = \text{Cov}_t \left(r_{t+1}^j, r_{t+1}^G \right) \theta_t^\top P_t,$$

so (A-1) simplifies to

$$E_t \left[r_{t+1}^j \right] = r^f + m_t^j + \gamma \text{Cov}_t \left(r_{t+1}^j, r_{t+1}^G \right) \theta_t^\top P_t. \quad (\text{A-2})$$

Aggregating (A-2) across all stocks with market portfolio weights $w_t^j = \frac{\theta_t^j P_t^j}{\theta_t^\top P_t}$ that sum up to 1, we obtain

$$E_t \left[r_{t+1}^G \right] = r^f + \sum_j m_t^j \frac{\theta_t^j P_t^j}{\sum_j \theta_t^j P_t^j} + \gamma \text{Var}_t \left(r_{t+1}^G \right) \theta_t^\top P_t.$$

The second term on the RHS is m_t^G by definition, therefore

$$\gamma \text{Var}_t \left(r_{t+1}^G \right) \theta_t^\top P_t = \lambda_t - m_t^G = E_t \left[r_{t+1}^G \right] - r^f - m_t^G.$$

Plugging these into (A-2) and using the definition of β_t^j yields

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

and from here (4) and (6) are straightforward. $\square$

Proof of Proposition 3. From (4) the expected return on the BAIL factor is

$$\begin{aligned} E_t \left[r_{t+1}^{\text{BAIL}} \right] &= \frac{1}{\beta_t^1} \left(E_t \left[r_{t+1}^1 \right] - r^f \right) - \frac{1}{\beta_t^2} \left(E_t \left[r_{t+1}^2 \right] - r^f \right) \\ &= \left(\lambda_t + \frac{m_t^1}{\beta_t^1} - m_t^G \right) - \left(\lambda_t + \frac{m_t^2}{\beta_t^2} - m_t^G \right) = \frac{m_t^1}{\beta_t^1} - \frac{m_t^2}{\beta_t^2}. \end{aligned} \quad (\text{A-3})$$

Suppose portfolio 1 puts positive weights in assets $j \in \mathcal{J}_1 \subset \{1, 2, \dots, J\}$ and zero in the rest, and denote the asset with the lowest m_t^j / β_t^j ratio of those in $\mathcal{J}_1$ by j_1 . The m/β ratio of portfolio 1 then satisfies

$$\frac{m_t^1}{\beta_t^1} = \frac{w_1^T m_t}{w_1^T \beta_t} = \frac{\sum_{j \in \mathcal{J}_1} w_j m_t^j}{\sum_{j \in \mathcal{J}_1} w_j \beta_t^j} = \frac{\sum_{j \in \mathcal{J}_1} w_j \beta_t^j \frac{m_t^j}{\beta_t^j}}{\sum_{j \in \mathcal{J}_1} w_j \beta_t^j} \geq \frac{\sum_{j \in \mathcal{J}_1} w_j \beta_t^j \frac{m_t^{j_1}}{\beta_t^{j_1}}}{\sum_{j \in \mathcal{J}_1} w_j \beta_t^j} = \frac{m_t^{j_1}}{\beta_t^{j_1}} \frac{\sum_{j \in \mathcal{J}_1} w_j \beta_t^j}{\sum_{j \in \mathcal{J}_1} w_j \beta_t^j} = \frac{m_t^{j_1}}{\beta_t^{j_1}}.$$

Similarly, suppose portfolio 2 puts positive weights in assets $j \in \mathcal{J}_2 \subset \{1, 2, \dots, J\}$ and zero in the rest, and denote the asset with the highest m_t^j/β_t^j ratio of those in $\mathcal{J}_2$ by j_2 . The m/β ratio of portfolio 2 then satisfies

$$\frac{m_t^2}{\beta_t^2} = \frac{w_2^T m_t}{w_2^T \beta_t} = \frac{\sum_{j \in \mathcal{J}_2} w_j m_t^j}{\sum_{j \in \mathcal{J}_2} w_j \beta_t^j} = \frac{\sum_{j \in \mathcal{J}_2} w_j \beta_t^j \frac{m_t^j}{\beta_t^j}}{\sum_{j \in \mathcal{J}_2} w_j \beta_t^j} \leq \frac{\sum_{j \in \mathcal{J}_2} w_j \beta_t^j \frac{m_t^{j_2}}{\beta_t^{j_2}}}{\sum_{j \in \mathcal{J}_2} w_j \beta_t^j} = \frac{m_t^{j_2}}{\beta_t^{j_2}} \frac{\sum_{j \in \mathcal{J}_2} w_j \beta_t^j}{\sum_{j \in \mathcal{J}_2} w_j \beta_t^j} = \frac{m_t^{j_2}}{\beta_t^{j_2}}.$$

Therefore, if portfolio 1 consists of assets with the highest m_t^j/β_t^j and portfolio 2 consist of assets with the lowest m_t^j/β_t^j of all stocks possible, we have

$$E_t [r_{t+1}^{\text{BAIL}}] = \frac{m_t^1}{\beta_t^1} - \frac{m_t^2}{\beta_t^2} \geq \frac{m_t^{j_1}}{\beta_t^{j_1}} - \frac{m_t^{j_2}}{\beta_t^{j_2}} > 0,$$

which confirms Proposition 3. □

Proof of Proposition 4. Analogously to (A-3), if the BAB factor goes long in portfolio 1* and short in portfolio 2* with appropriately (de)levering them, its expected return is

$$E_t [r_{t+1}^{\text{BAB}}] = \frac{m_t^{1*}}{\beta_t^{1*}} - \frac{m_t^{2*}}{\beta_t^{2*}}.$$

As BAIL goes long in the portfolio with assets with the highest m/β and short in assets with the lowest m/β , whereas BAB goes long in assets with the highest $1/\beta$ and short in assets with the lowest $1/\beta$, we have

$$\frac{m_t^1}{\beta_t^1} \geq \frac{m_t^{1*}}{\beta_t^{1*}} \text{ and } \frac{m_t^2}{\beta_t^2} \leq \frac{m_t^{2*}}{\beta_t^{2*}},$$

and (8) is straightforward from here. □

Appendix B Tables

Table 1
Data Summary Statistics

This table reports summary statistics of the stocks (Panel A) and bonds (Panel B) used for six different countries: US, Germany, United Kingdom, Canada, Japan, and Switzerland. Panel A shows country-level summary statistics, monthly mean and volatility, for the stocks used in our sample. Panel B reports the average number of bonds used each day to calculate the term structure (ts) and the funding proxy (fund). To estimate the term structure, we use bonds of maturities ranging from 3 months to 10 years. To calculate the funding measure, we eliminate bonds of maturities less than one year. The data runs from January 1990 to December 2012.

Panel A: Stocks Summary Statistics							
	All	US	GE	UK	CA	JP	SW
Number of Stocks Considered	10891	2385	1149	2951	945	3105	356
Average Number of Traded Stocks	3973	1082	323	560	309	1567	132
Mean Return (monthly percentage)	0.67	1.18	0.55	0.70	1.22	0.13	0.82
Return Volatility (annualized)	17.0	16.9	17.5	19.7	22.5	25.2	17.7
Mean Excess Return	0.39	0.91	0.28	0.43	0.95	-0.15	0.54
ExcessReturn Volatility	17.1	16.9	17.6	19.8	22.6	25.4	17.8

Panel B: Bonds Summary Statistics												
	US		GE		UK		CA		JP		SW	
	ts	fund	ts	fund	ts	fund	ts	fund	ts	fund	ts	fund
1990-2000	124	99	151	130	16	13	44	35	100	92	31	27
2001-2007	77	61	52	42	12	9	20	16	155	133	15	10
2008-2013	146	122	39	32	17	13	27	21	164	138	12	9
ALL	115	93	105	90	17	13	37	30	127	111	23	19

Table 2
Summary Statistics Funding Proxies

Panel A reports summary statistics (mean, standard deviation, maximum and minimum) for six different country specific funding proxies in basis points. The countries are the United States (us), Germany (ge), United Kingdom (uk), Canada (ca), Japan (jp), and Switzerland (sw). Panel B reports the unconditional correlation between the country-specific funding measures. Panel C reports the estimated coefficients with the associated t-statistic and R^2 from the following regression

$$\text{fund}_t^i = \beta_0 + \beta_1^i \text{fund}_t^G + \epsilon_t^i,$$

where fund_t^i is the funding proxy of country i and fund_t^G is the global funding proxy. t-statistics are calculated using Newey and West (1987). Data is weekly and runs from January 1990 to October 2013.

	us	ge	uk	ca	jp	sw
Panel A: Summary Statistics						
mean	2.8187	4.1686	5.2110	4.9072	3.1202	6.2104
stdev	1.3745	2.2466	3.3190	3.2859	2.3174	4.5334
max	11.2033	11.5660	18.0775	14.3064	11.2129	19.2864
min	1.0278	0.7561	1.0510	1.1027	0.7185	1.2254
Panel B: Cross Correlation						
	us	ge	uk	ca	jp	sw
us	100.00%					
ge	32.38%	100.00%				
uk	49.09%	68.14%	100.00%			
ca	32.12%	57.91%	66.44%	100.00%		
jp	19.46%	74.37%	43.85%	41.92%	100.00%	
sw	38.15%	68.43%	66.53%	67.43%	61.04%	100.00%
Panel C: Loading on Global Funding Proxy						
β_0	0.625 (1.60)	0.091 (0.21)	-0.526 (-1.48)	0.303 (0.41)	-0.797 (-1.49)	-1.412 (-1.86)
β_1	3.802 (4.45)	7.067 (7.79)	9.943 (12.02)	7.980 (4.68)	6.789 (5.72)	13.211 (8.08)
Adj. R^2	51.46%	66.64%	60.41%	39.58%	57.75%	57.15%

Table 3
Portfolio Returns

This table reports portfolio returns of illiquidity-to-beta sorted portfolios: At the beginning of each calendar month, we sort stocks in ascending order on the basis of their ratio between the country-level illiquidity and the estimated beta at the end of the previous month. The ranked stocks are then assigned to four different bins: Low illiquidity. The rightmost column reports summary statistics of our BAIL strategy. To construct this trading strategy, we sort stocks into two different bins: High and low illiquidity-to-beta ratio and rebalance every calendar month. Both portfolios are rescaled to have a beta of one at portfolio formation. The BAIL strategy is a self-financing portfolio that is long in high illiquidity-to-beta ratio stocks and shorts low illiquidity-to-beta ratio stocks. BAB is a self-financing portfolio that is long in low beta stocks and short in high beta stocks (see Frazzini and Pedersen (2013)). CAPM Alpha is the intercept in a regression of monthly excess returns onto the global market excess return. Returns and alphas are in monthly percent, t-statistics are shown below the coefficient estimates, and 5% statistical significance is indicated in bold. Beta (ex ante) is the average estimated beta at portfolio formation. Beta (realized) is the realized loading on the market portfolio. Volatilities and Sharpe ratios are annualized.

	low β	Low Illiq mid β	high β	low β	High Illiq mid β	high β	BAIL	BAB
Excess Return	0.609	0.587	0.561	0.651	0.674	0.678	0.827	0.741
<i>t-stat</i>	2.40	1.87	1.28	2.41	2.10	1.75	3.53	3.51
CAPM Alpha	0.527	0.471	0.395	0.547	0.540	0.522	0.791	0.731
<i>t-stat</i>	2.80	2.08	1.24	3.06	2.83	2.10	3.53	2.48
Beta (ex ante)	0.56	1.02	1.51	0.63	1.01	1.54	0.00	0.00
Beta (realized)	0.61	0.85	1.23	0.77	0.99	1.16	0.26	0.07
Volatility (annualized)	14.8	17.8	24.2	15.6	18.5	22.2	13.5	12.1
Sharpe Ratio (annualized)	0.49	0.39	0.28	0.50	0.44	0.37	0.73	0.73

Table 4
Predictive Regressions Market Returns

This table reports estimated coefficients and associated t-statistics for predictive regressions from the BAIL and BAB trading strategies (see Table 3) onto different proxies of global funding risk:

$$r_{t+1}^{\text{BAIL/BAB}} = \beta \text{ Funding Proxy}_t + \epsilon_{t+1}.$$

All variables are standardized, meaning de-meanded and divided by their standard deviation. t-statistics are calculated using Newey and West (1987). Data runs from January 1990 to December 2012.

		BAIL				BAB			
Global Funding	-0.179					-0.159			
<i>t-stat</i>	(-2.84)					(-2.38)			
TED-Spread		-0.089				-0.066			
<i>t-stat</i>		(-1.37)				(-0.80)			
VIX		0.066				-0.016			
<i>t-stat</i>		(1.18)				(-0.23)			
US Funding		0.062				0.064			
<i>t-stat</i>		(1.08)				(1.01)			
Adj. R^2	3.22%	0.79%	0.44%	0.38%	2.54%	0.43%	0.00%	0.41%	

Appendix C Figures

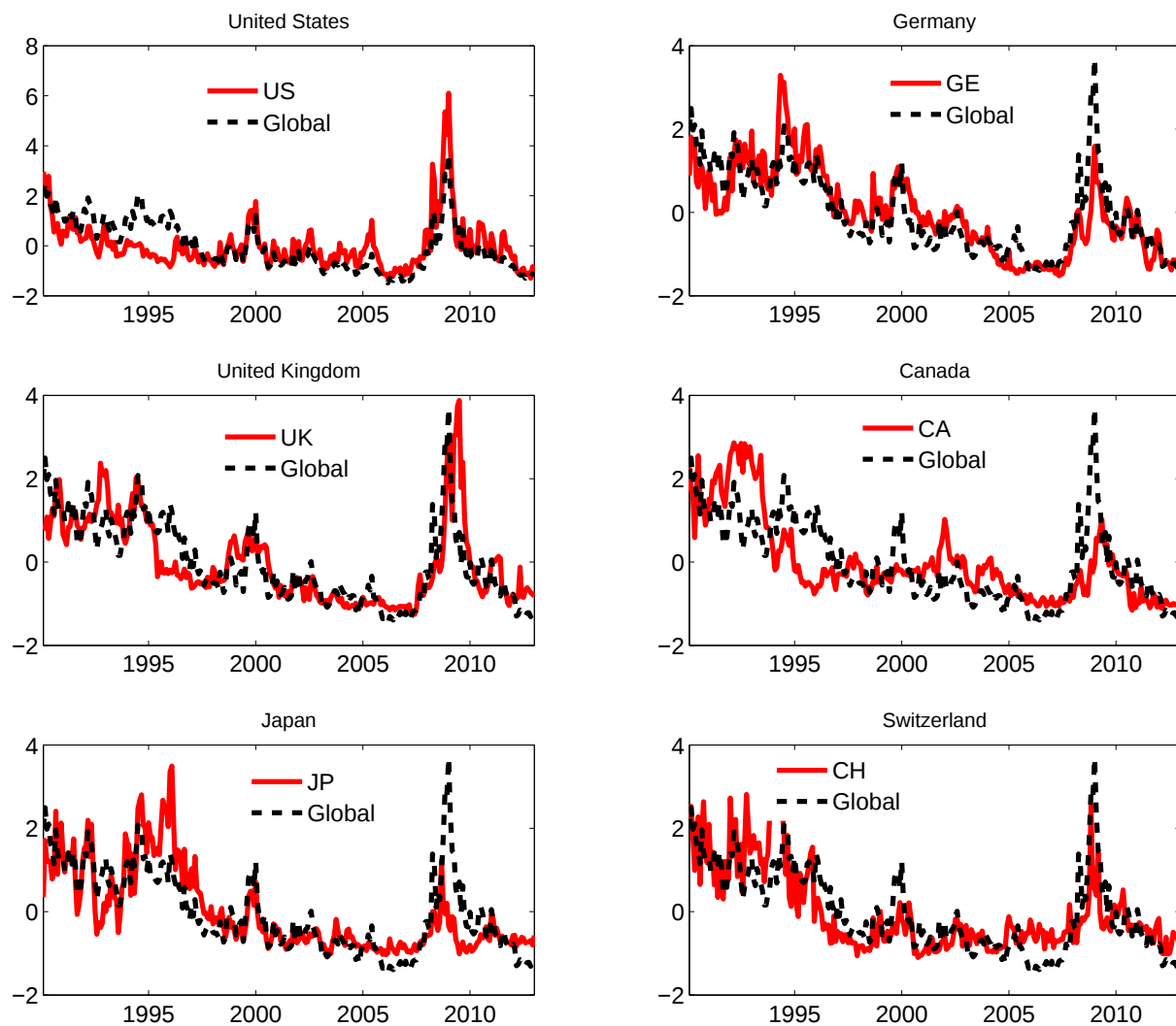


Figure 1. Funding Measures All Countries

These figures plots funding liquidity proxies for six different countries: United States, Germany, United Kingdom, Canada, Japan, and Switzerland. The global funding liquidity proxy is defined as the average from the six proxies where each country-specific funding measure. We weight each country-specific funding measure by its GDP (in USD). Data is monthly and runs from January 1990 to December 2012.

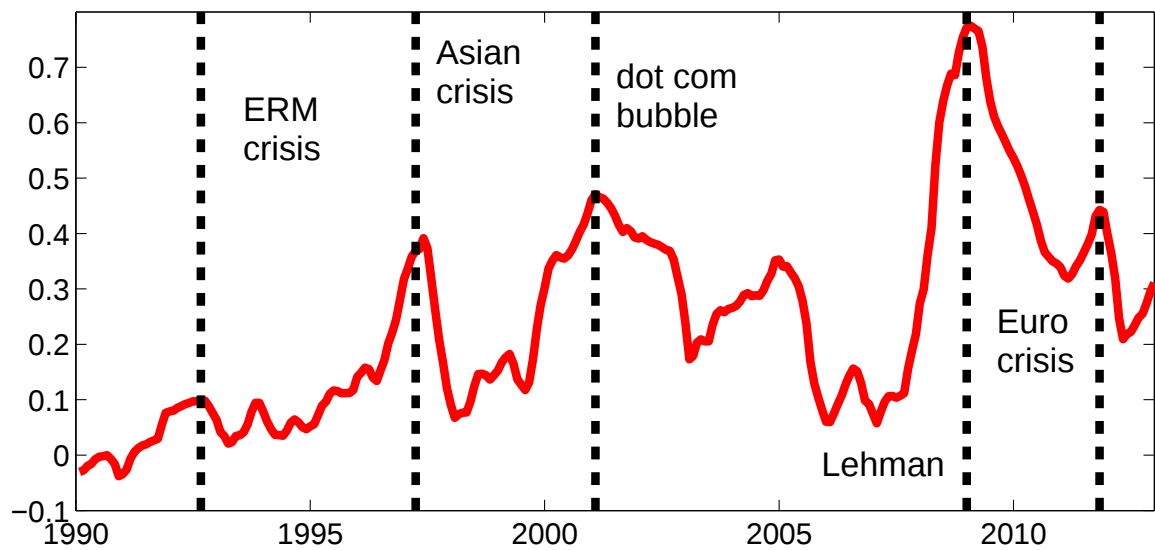


Figure 2. Average Conditional Correlation of Country-Specific Funding Measures

This figure presents the conditional average correlation among all six country-specific funding proxies (Germany, Canada, United Kingdom, US, Japan, and Switzerland). Conditional correlations are calculated using a rolling window of three years using daily data. Data is sampled monthly and runs from January 1990 to December 2012.

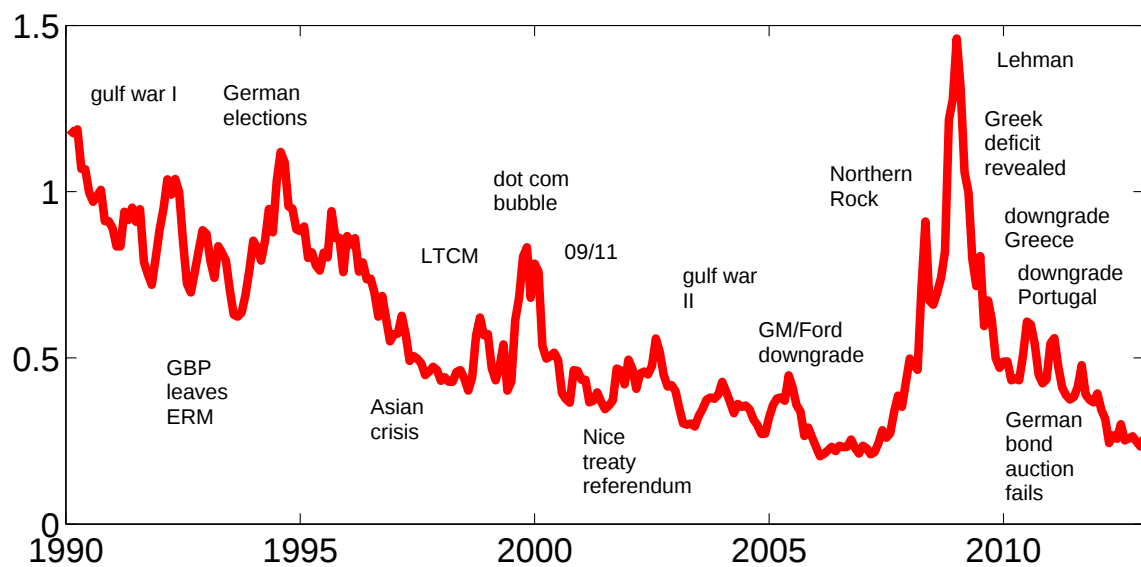


Figure 3. Global Funding Liquidity

This figure presents global funding liquidity (in basis points). Global funding liquidity is calculated as the GDP-weighted average from the six country-specific funding liquidity proxies (Germany, Canada, United Kingdom, US, Japan, and Switzerland). Data is monthly and runs from January 1990 to December 2012.

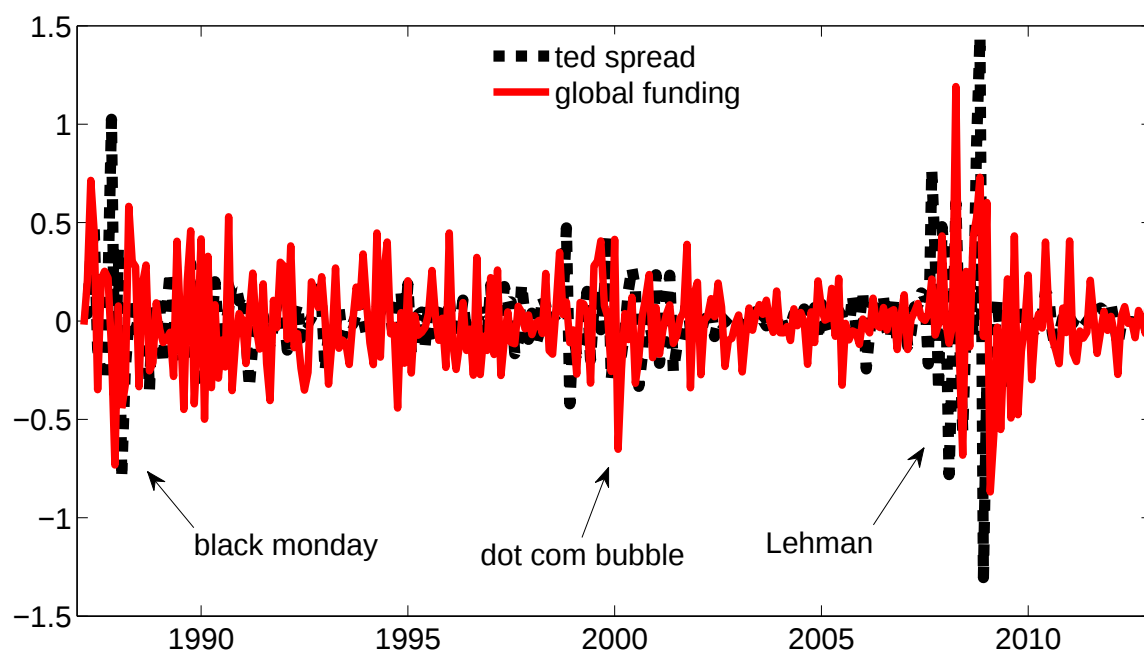


Figure 4. First Differences in Global Funding Liquidity and TED Spread

This figure plots first differences in the global funding liquidity proxy and the TED spread. The sample period is from February 1987 to December 2012.

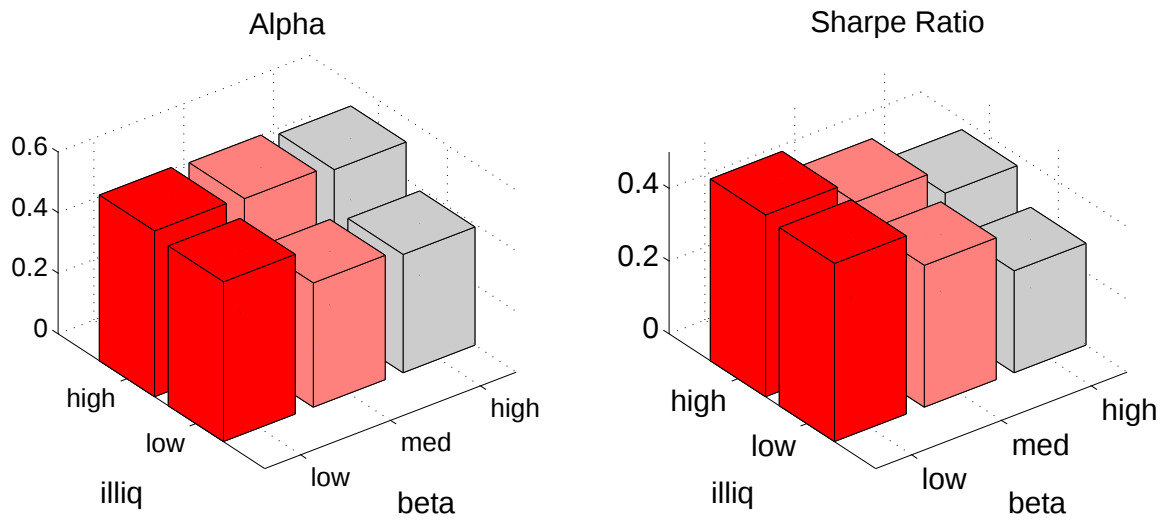


Figure 5. CAPM Alpha and Sharpe Ratio of Illiquidity and beta sorted portfolio

The left panel plots monthly CAPM alphas from beta and illiquidity sorted portfolios. The right panel plots the Sharpe ratio of these portfolios. At the end of each month, we double sort stocks into three beta and two illiquidity portfolios. The sample period is from January 1990 to December 2012.

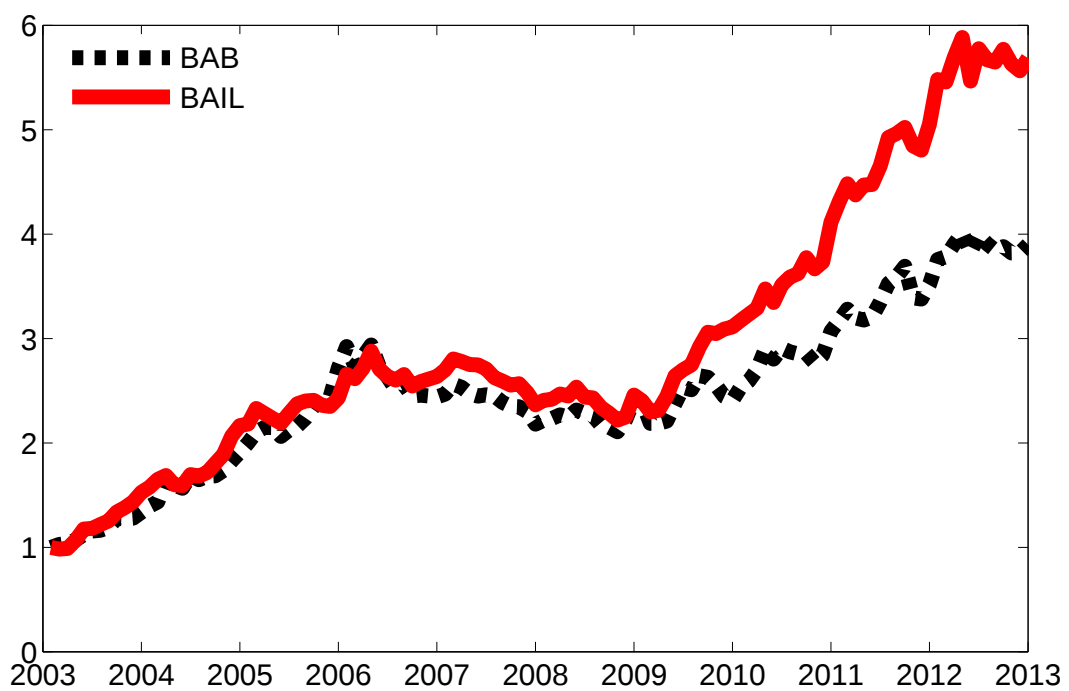


Figure 6. BAIL versus BAB cumulative returns

This figure plots the cumulative return of investing \$1 in 2003 in BAIL and BAB and keeping it for 10 years. The sample period is from January 2003 to December 2012.