Funding Liquidity CAPM: International Evidence*

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Abstract

In this paper we construct daily funding liquidity proxies for six different countries and decompose them into one global and six country-specific indices that exhibit significant independent variation. Using a stylized international asset pricing model in which investors face margin constraints, we derive predictions regarding the effect of funding constraints on the cross-section of international stock returns that are strongly supported by the data: (i) Higher global illiquidity implies a lower slope and higher intercept of the security market line. (ii) Stocks with higher local illiquidity and lower beta earn higher alphas and Sharpe ratios. (iii) Betting-against-beta (BAB) strategies in high illiquidity countries outperform those in low illiquidity countries. Finally, (iv) a beta-adjusted-international-illiquidity (BAIL) strategy that is long high illiquidity-to-beta stocks and short low illiquidity-to-beta stocks earns significant positive risk-adjusted returns and outperforms a simple betting-against-beta strategy.

Keywords: Margin, CAPM, Funding Risk, Liquidity

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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. These institutional investors are responsible for most cross-country investments and when their funding constraints tighten, as for example during the last financial crisis, it may lead to (il)liquidity comovements across the world which affects prices.

We construct daily measures of funding liquidity for six different countries, and combine them to obtain a global funding liquidity measure. We find that the time variation in local illiquidity indices exhibits a large degree of commonality, but there is also significant cross-sectional dispersion with frequent changes in the illiquidity ranking of countries.[1] To assess the asset pricing implication of global and local liquidity we build a stylized international asset pricing model consistent with the above facts. In the model international investors face margin constraints, and assets' margin requirements have a country-specific component. As a result, observed country liquidity levels are functions of global funding-constraint tightness and local margin requirements. Expected excess returns depend not only on global market risk of assets, but also on global and local liquidity. Consistent with the theoretical predictions of the model, we find that (i) the intercept of the security market line (SML) is positively correlated with global illiquidity while the slope of the SML is negatively related, (ii) stocks with higher local illiquidity and lower beta earn higher alphas and Sharpe ratios, (iii) betting-against-beta (BAB) strategies perform significantly better in more illiquid countries, and (iv) a market-neutral trading strategy that is long high illiquidity-to-beta-ratio stocks and short low illiquidity-to-beta-ratio stocks earns significant positive risk-adjusted returns.

We start by constructing country-specific measures for funding illiquidity. We follow the approach of Hu, Pan, and Wang (2013) who calculate price deviations in the U.S. Treasury market compared to a smooth frictionless yield curve. The basic tenet behind the measure is that larger deviations among yields for similar maturities should indicate less capital of arbitrageurs who would eliminate relative mispricings. Bond markets are

[1] Similar to Bekaert, Harvey, and Lundblad (2007), we find significant cross-sectional dispersion both in our local illiquidity measures and in their pricing effects, which indicates that even these developed countries are not fully integrated.

particularly useful to study funding constraints for several reasons. First, many types of investors actively trade in these markets not only for investment but also funding needs. Second, the variation in prices of government bonds can usually be explained by a few factors which keeps the information content easily tractable. Third, government bond markets are among the most liquid markets and represent safe havens during crisis periods, hence, price deviations contain a very strong signal about the overall funding liquidity in these markets (see, e.g., Krishnamurthy and Vissing-Jorgensen (2012)). Moreover, a major advantage of our approach is that it circumvents issues other funding proxies like option-implied volatility (VIX), the TED spread, or broker-dealers' leverage or asset growth have: they either suffer from a very short time-series (VIX), are not useful for international comparisons (TED spread), or are only available at very low frequency (broker-dealers' leverage).[2] The funding proxies we calculate are available daily, for a history of more than 20 years.

Using daily bond data for the 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 create a measure of global funding liquidity from the six local ones. The overall correlation of the six country-specific funding proxies is quite high, especially during crisis periods like 2008 where the conditional correlation was around 80%. 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 (Black Wednesday) while at the same time the corresponding US measure remains relatively calm.

Next we examine the asset pricing implications of the illiquidity factors. To better understand the role funding illiquidity plays in an international setting, we present a

[2] To construct international TED spreads, we would need to use LIBOR rates denoted in different currencies, which are extremely highly correlated.

simple overlapping-generations asset pricing model with funding constraints. Agents are subject to margin constraints that impose limits on their use of leverage; margins vary across both investors and countries, thereby imposing a form of mild segmentation. As a result, we derive an international funding-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 illiquidity measure for asset j, which combines margins on this asset and the Lagrange multpliers that represent how constrained investors are, 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 asset, which commands an additional premium and drives up expected returns. On the other hand, a higher global illiquidity, which is simply the average of the asset-specific illiquidity terms, decreases the expected excess return of asset j, because it increases the required return on the world portfolio. Since information on asset-level margins is not available, we use the empirical funding constraint measure of a country, derived in the first part of the paper, to proxy for the illiquidity of all assets from this country, and use the global funding constraint measure for global illiquidity in our empirical analysis.

The model has three sets of testable prediction. As a first test, we study the security market line (SML) in the data conditional on global illiquidity. Theory predicts that the slope of the SML is negatively related to global illiquidity, while the intercept is positively correlated. Indeed, we find this prediction confirmed: During periods of low illiquidity, the intercept is around 0.191% per month with an associated slope of 0.171%. In periods of high illiquidity, the intercept goes up to 0.510% and the slope becomes 0.008%. We then run regressions from conditional estimates of the intercept and slope of the SML onto global market excess returns and the global illiquidity proxy. We find that in line with the prediction, global illiquidity carries a positive sign for the intercept regression and a negative sign for the slope regression.

We then ask how funding risk affects international asset returns. As a first way to illustrate the cross-sectional asset pricing implications, we consider portfolios sorted on local illiquidity and beta. Our model implies that assets which have high local illiquidity and low beta should earn higher expected returns than stocks with low local 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 local illiquidity. For example, for high beta stocks, the alpha increases from 0.39% per month to 0.52% per month from the low to the high illiquidity stocks. Similarly, the annualized Sharpe ratio jumps from 0.28 to 0.37. Holding illiquidity constant, lower beta stocks earn higher alpha and Sharpe ratios than higher beta stocks. A second prediction from our model is that higher global illiquidity lowers the alpha for local illiquidity and beta sorted stocks. To test this, we calculate average alphas for high and low global illiquidity states. We find that alphas uniformly drop for higher states of global illiquidity. 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 (beta-adjusted-international-illiquidity). 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). The alpha remains statistically significant if we add other variables such as the global Fama and French or momentum factors. Moreover, we also show that BAIL 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.

By construction, the two strategies BAB and BAIL are highly correlated (their unconditional correlation is 78%), it is hence interesting to explore in more depth whether sorting according to illiquidity adds any additional return beyond sorting on stocks' beta. To this end, we first construct for each country a BAB strategy and then sort at the end of each month into two different bins depending on the level of illiquidity. We find a highly significant spread between the high and low illiquidity BAB strategies: The high minus low illiquidity BAB strategy produces a monthly excess return of 0.742% with an associated t-statistic of 4.48. The associated (monthly) alpha is 0.75% (t-statistic of

4.09) and an (annualized) Sharpe ratio of 0.94. These numbers are more attractive than just running a simple BAB strategy using international stocks.

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), among others. 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.[3] Frazzini and 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 asset- 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. Whereas 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 like firm size, stock volatility, the Amihud illiquidity proxy, institutional investors' holdings, and analyst coverage; then construct betting-against-beta strategies within the different margin groups.

[3] In a similar vein, Chabakauri (2013) and Rytchkov (2014) study theoretically how a tightening of margin constraints affects prices in equilibrium. Both authors find that binding margin constraints reduce 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).

Several papers study determinants of the slope of the security market line. For example, Huang, Lou, and Polk (2014) examine how the trading activity of arbitrageurs can generate booms and busts in beta arbitrage and how arbitrage activity changes the slope of the SML. Different from us, these authors exclusively focus on assets with low limits to arbitrage, meaning large and very liquid stocks. Jylhä (2013) studies how margin requirements for U.S. stocks as set by the Federal Reserve between 1934 and 1974 affected the security market line. In line with our theoretical and empirical findings, he confirms the flattening of the securities market line as funding constraints became more binding. Hong and Sraer (2012) posit a model with disagreeing investors subject to short-sell constraints. They find that in times of low (high) disagreement, the slope of the security market line is upward sloping (negative). These findings could potentially complement ours as margin constraints are more prone to bind in times of high disagreement.[4]

We also speak to the literature that studies liquidity risk in an international context. Common to these papers is that they usually proxy illiquidity measures from the stock market directly. For example, 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. 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), Bekaert, Harvey, and Lundblad (2007) and Lee (2011) study how liquidity risk is priced in the cross-section of different stock returns. In particular, the latter shows that the pricing of liquidity risk varies across different countries. Different from these papers, we study funding risk proxies from the fixed income market and how it affects stock returns. Related to funding risk, Fontaine, Garcia, and Gungor (2013) construct illiquidity sorted portfolios of stocks using the Amihud (2002) illiquidity measure and study whether these

[4] For example, Geanakoplos (2003) or Simsek (2013) present models where belief disagreement also increases margins.

portfolios have any significant exposure to the funding liquidity proxy in Fontaine and Garcia (2012). Different from their paper, we sort an international set of stocks based on their country-level funding risk.

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 describe the data and the construction of the funding proxies. Section 2 presents a model of the margin-augmented CAPM that includes both local and global illiquidity. Section 3 studies the pricing of local and global funding risk in the cross-section of different assets, and finally, we conclude in Section 4. All proofs are deferred to the Appendix.

1 Local and Global Illiquidity Measures

First, we describe the data and the methodology to construct the local and global illiquidity measures. We then show that the illiquidity measures are elevated and rather highly correlated (up to 80%) during crisis periods. Nevertheless, country- or region-specific events seem to be reflected in spikes in the respective local illiquidity measures that are not shared globally.

1.1 Data

We collect our raw data on government bonds and stock return data from Datastream. The frequency is daily, running from 1 January 1990 to 31 December 2012, leaving us with 6001 observations in the time-series.

The bond data spans 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 for our sample period for all available maturities. Furthermore, we 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.[5] 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 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

[5] Duffee (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.

construct the illiquidity measure. Japan and the US are the most active markets, while the average number of bonds in Switzerland and the UK is lower. 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 was a response to the banking crisis in the years 2000.

[Insert Table 1 here.]

As alternative proxies for illiquidity or funding constraints we also consider the TED spread and the volatility index VIX. The TED spread is defined as the difference between the three-month Eurodollar LIBOR rate and the three-month U.S. Treasury bill rate. The VIX is obtained from CBOE, the LIBOR and Treasury bill rates are from Datastream.

1.2 Country-specific and Global Illiquidity Proxies

To construct country-specific illiquidity measures, we follow Hu, Pan, and Wang (2013) who employ the Svensson (1994) method to fit the term structure of interest rates.[6]

The Svensson (1994) model assumes that the instantaneous forward rate f is given by:

$$f_m = \beta_0 + \beta_1 \exp\left(\frac{-m}{\tau_1}\right) + \beta_2 \frac{m}{\tau_1} \exp\left(\frac{-m}{\tau_1}\right) + \beta_3 \frac{m}{\tau_2} \exp\left(\frac{-m}{\tau_2}\right),$$

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:

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

[6] We also use the Nelson and Siegel (1987) and a cubic spline method. All three approaches lead to qualitatively very similar results. We chose the Svensson (1994) method over the other two as it is the most widely used and also the most flexible.

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:[7]

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

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. We verify that our yield curve estimates are reasonable by comparing our term structures with the estimates published by central banks or the international yield curves used in Wright (2011) and Pegoraro, Siegel, and Tiozzo 'Pezzoli' (2013).[8]

The funding illiquidity measure is then defined as the root mean square error between the market yields and the model-implied yields, i.e.

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

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 illiquidity 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.

[7] Note 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.

[8] We thank Fulvio Pegoraro and Luca Tiozzo 'Pezzoli' for sharing their codes.

In a next step, we calculate a global illiquidity proxy, henceforth denoted illiq_t^G, by taking a GDP-weighted average of country-level illiquidity 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 illiquidity 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 illiquidity 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 which is undesirable for interpretation purposes. For these reasons, we prefer to take an average.

1.3 International Illiquidity Proxies Properties

The time-series of all country-specific illiquidity measures together with the global measure, normalized to have zero mean and unit volatility, 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 1990s, especially around the Asian crisis of 1996–1997. It displays further spikes again around the dot-com bubble burst in 2001 and again during the most recent financial crisis.

[Insert Figures 1 2 and 3 here.]

The German illiquidity proxy is especially volatile after 1992 and during the most recent financial crisis. The heightened level of the illiquidity 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 illiquidity proxies of the UK and Switzerland where we see large jumps during the year 1992. Interestingly, these stark movements are completely absent in the US funding illiquidity proxy which displays only moderate movements until 1997 (Asian crisis), except around the first Gulf War in 1991. Further evidence can be found in Figure 2 where we plot the model-implied yields together with the data for Black Wednesday (16 September 1992) both for Germany and the US. As we can see, the observed yields are far off the fitted curve in German (upper right panel), while the observed yields in the US nicely track the model-implied ones. Finally, 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 4 and 5 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 for the U.S. 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 illiquidity 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) for equity and Karnaukh, Ranaldo, and Söderlind (2014) for FX markets). We observe a similar pattern for the country-specific illiquidity measures. Figure 3 plots the average conditional correlation among the different illiquidity proxies.[9] We note that the average correlation peaks during periods of distress such as the dotcom

[9]Conditional correlations are calculated using a rolling window of three years using daily data.

bubble burst or the most recent financial crisis where the correlation reaches almost 80%.

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

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

where Illiq_t^i is the illiquidity proxy of country i and Illiq_t^G is the global illiquidity 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 illiquidity measures with R^2 ranging between 39% and 66%.

Figure 4 depicts the time-series of the global illiquidity proxy. We note that the global measure summarizes the properties of country-level 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 illiquidity proxies. Figure 5 plots the first difference of the global illiquidity proxy together with first differences in the TED spread, another common proxy of funding constraints (see, e.g., Gârleanu and Pedersen (2011)). 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 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 Model

In this section we present a simple asset pricing model with funding constraints. We think about agents as 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.

We apply this model to an international setting by assuming that margin requirements have a country-specific component both for assets and investors. The former may result from the difference in the perceived risk of securities of certain countries, or from regulatory requirements that apply to agents wanting to invest in a certain country. The latter can be the outcome due to 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.

Our model relates the effect of country-specific margin requirements to our measures of local funding liquidity from Section 1. For lack of empirical evidence, we remain agnostic about other dimensions in which margin requirements could vary across assets or investors, and will assume that the effect of any additional cross-sectional variation can be averaged out in the cross-country level analysis.

The model is built in the spirit of Frazzini and Pedersen (2013). We consider an overlapping-generations world economy with I agents, $i = 1, ..., I$, born in each period t with wealth $W_{i,t} \geq 0$. Agents 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. Risky security $j = 1, ..., J$ is in total supply θ_t^j and pays a real dividend D_t^j in the unique consumption good in period t, and its ex-dividend price is denoted by P_t^j. Because exchange rate risks are irrelevant to our argument, we use a framework in which exchange rates do not appear at all. In particular, we abstract from exchange-rate risk by assuming that covered interest rate parity holds and hence measure all prices in dollars (see Bekaert, Harvey, and Lundblad (2007)). The $(J + 1)$th asset is a riskless one, with the risk-free rate r^f, given exogenously, is the same for all investors.

At each time period t, young agents choose a portfolio of holdings $x_{i,t} = \left(x_{i,t}^1, ..., x_{i,t}^J\right)^\top$ 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

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

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 free to invest in all assets of the world economy, but when doing so they are subject to margin constraints. In particular, we assume that agent i has to post a proportional margin of $m^j_{i,t}$ when spending $x^j_{i,t} P^j_t$ on asset j, i.e.

$$\sum_j m^j_{i,t} x^j_{i,t} P^j_t \leq W_{i,t}. \tag{1}$$

This constraint depends on both the agent i and the security j, i.e. combines both investor-specific and asset-specific components. Holding asset j fixed, the differences in margins capture the cross-sectional differences across agents: if agent i faces a lower margin on asset j then agent i', $m^j_{i,t} < m^j_{i',t}$, she can take a larger position in the same asset with the same dollar wealth. On the other hand, keeping i fixed, the differences in $m^j_{i,t}$ capture the cross-sectional differences across assets: if agent i faces a lower margin on asset j compared to asset j', $m^j_{i,t} < m^{j'}_{i,t}$, she can take a larger position in asset j with the same amount of capital. As a special case, our model produces complete or mild segmentations, and various other kinds of barriers for international invesments proposed previously, e.g., Black (1974), Stulz (1981), and Errunza and Losq (1985), and hence it can be interpreted as a generalization of these settings.[10] Finally, setting all margins to zero means (1) never binds, and investors are unconstrained; this would reproduce the standard CAPM.[11] Assuming a country-specific nature to our margins means that if assets j and j' are from the same country, then the proportional margins are the same on them: $m^j_{i,t} = m^{j'}_{i,t}$. For notational simplicity, we keep using $m^j_{i,t}$ instead of introducing one more level

[10]More recent work on equity market integration include Albuquerque and Wang (2008), Bekaert, Harvey, and Lundblad (2007), and Bekaert, Harvey, Lundblad, and Siegel (2011). In particular the latter two extend Acharya and Pedersen (2005) to an international setting, where the local liquidity risk factor is important. In their model, the authors impose an exogenous transaction cost to study the relation between this cost and liquidity risk and how it affects equity premia.

[11]Similarly to our model, but not in an international setting, Black (1972) assumes a no-borrowing constraint on agents, $m^j_{i,t} = 1$ for all i and j, while Frazzini and Pedersen (2013) consider agent-specific margins, $m^j_{i,t} = m_{i,t}$ 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. $m^j_{a,t} = 0$ and $m^j_{b,t} \geq 0$.

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

$$\sum_i x_{i,t}^j = \theta_t^j. \tag{2}$$

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

$$x_{i,t} = \frac{1}{\gamma_i}\Omega_t^{-1}\left[\mathbb{E}_t\left[D_{t+1} + P_{t+1}\right] - \left(1 + r^f\right)P_t - \psi_{i,t}M_{i,t}\right], \tag{3}$$

where $\psi_{i,t}$ is the Lagrange multiplier associated with the margin constraint of agent i, and $M_{i,t} = \left(m_{i,t}^1 P_t^1, ..., m_{i,t}^J P_t^J\right)^\top$ is a vector of dollar margins.

Combining (2) and (3), we obtain equilibrium security prices:

$$P_t^j = \frac{\mathbb{E}_t\left[D_{t+1}^j + P_{t+1}^j\right] - \gamma \mathbf{1}_j^\top \Omega_t \theta_t}{1 + r^f + \sum_i \frac{\gamma}{\gamma_i}\psi_{i,t} m_{i,t}^j}, \tag{4}$$

where γ is defined as aggregate risk aversion, $\frac{1}{\gamma} = \sum_i \frac{1}{\gamma_i}$, and $\mathbf{1}_j$ is a vector with 1 in row j and zeros elsewhere. 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

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

(4) implies the following funding-liquidity-augmented CAPM:

Theorem 1. *The equilibrium excess return of security j is*

$$\mathbb{E}_t\left[r_{t+1}^j\right] - r^f = \beta_t^j \lambda_t + m_t^j - \beta_t^j m_t^G, \tag{5}$$

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

$$m_t^j = \sum_i \frac{\gamma}{\gamma_i}\psi_{i,t} m_{i,t}^j \text{ and } m_t^G = \sum_j m_t^j \frac{\theta_t^j P_t^j}{\sum_j \theta_t^j P_t^j}. \tag{6}$$

Equation (5) implies that the expected excess return on asset j depends on the usual CAPM term, and two additional liquidity components. The first one, m_t^j, is the weighted average of investors' Lagrange multipliers and the margins they face on asset j, i.e., it represents how constrained investors of asset j are, and hence we think about it as the funding illiquidity of asset j. The second additional component, m_t^G, represents the weighted average of asset-level funding illiquidities, and we refer to it as global funding illiquidity. The term $m_t^j - \beta_t^j m_t^G$ measures the funding illiquidity of asset j relative to illiquidity across all assets. Higher m_t^j implies that more capital has to be committed to maintain the position in this security, and this increases the required return to induce agents to hold the asset. Global illiquidity m_t^G appears in this expression because excess returns on the global market portfolio are themselves in part driven by illiquidity.

Since m_t^j and m_t^G depend on the constraint tightness $\psi_{i,t}$ of all agents, there is a natural correlation between the time series of global and local illiquidity measures. This is in line with the observation that local and global liquidity measures are correlated with each other, and especially so in crisis times when they are high, i.e., when the constraints of investors are more binding and Lagrange multipliers are large. 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. In the special case when margins are investor-specific, i.e., $m_{i,t}^j$ is the same for all js holding i fixed, we get $m_t^G = m_t^j$ for all j, and the liquidity terms together simplify to $\left(1 - \beta_t^j\right) m_t^G$; 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.

Based on Theorem 1 we express four sets of testable implications. We obtain the first two by simply rearranging (5).

Proposition 1. *There is an 'average' security market line, but securities can be 'off the line' due to the local illiquidity term* m_t^j*:*

$$\mathbb{E}_t\left[r_{t+1}^j\right] = \underbrace{r^f + m_t^G}_{\text{average intercept}} + \beta_t^j \underbrace{\left(\mathbb{E}_t\left[r_{t+1}^G\right] - r^f - m_t^G\right)}_{\text{slope of SML}} + \underbrace{m_t^j - m_t^G}_{\text{difference induced by illiquidity}}. \tag{7}$$

Proposition 1 implies that the slope of the average security market line is given by $\left(\mathbb{E}_t\left[r_{t+1}^G\right] - r^f - m_t^G\right)$; lower than the hypothetical unconstrained SML. Moreover, tighter portfolio constraints, and hence higher global illiquidity m_t^G, flatten the security market line. The intercept of the average SML is $r^f + m_t^G$, increasing in global illiquidity. However, assets do not line up on this security market line, if local illiquidity is different from the global, i.e. $m_t^j - m_t^G \neq 0$.[12]

Proposition 2. *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.*

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_H—this portfolio has a return of $r_{t+1}^H = w_H^\top r_{t+1}$, a beta of $\beta_t^H = w_H^\top \beta_t$, and an average margin $m_t^H = w_H^\top m_t$, where r_{t+1}, β_t, and m_t are the vectors of all security returns in the next period, betas, and margins, respectively. Similarly, consider a second portfolio consisting of securities with low illiquidity-to-beta ratios with weights w_L, to obtain a return $r_{t+1}^L = w_L^\top r_{t+1}$, a beta $\beta_t^L = w_L^\top \beta_t$, and average margin $m_t^L = w_L^\top m_t$. Applying leverage $1/\beta_t^H$ to the first portfolio and going long in it (i.e.

[12]This is a result similar to Stulz (1981) who considers an international setting with domestic and foreign investors facing different holding taxes, and shows that there exist three different parallel SMLs for (i) domestic assets, and foreign assets held (ii) long and (iii) short by domestic investors, whereas foreign risky assets not traded by domestic investors lie between the long and short SMLs.

levering up if $\beta_t^H < 1$ and down vice versa), and applying a leverage $1/\beta_t^L$ to the second portfolio and going short, we obtain a factor given by

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

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 (5) 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*

$$\mathbb{E}_t\left[r_{t+1}^{BAIL}\right] = \frac{m_t^H}{\beta_t^H} - \frac{m_t^L}{\beta_t^L} > 0. \tag{8}$$

Proposition 3 shows 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. BAB goes long in low-beta assets (denoted LB) and short in high-beta assets (HB), with appropriately (de)levering: $r_{t+1}^{\text{BAB}} = 1/\beta_t^{LB}\left(r_{t+1}^{LB} - r^f\right) - 1/\beta_t^{HB}\left(r_{t+1}^{HB} - r^f\right)$.

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

$$\mathbb{E}_t\left[r_{t+1}^{BAIL}\right] \geq \mathbb{E}_t\left[r_{t+1}^{BAB}\right]. \tag{9}$$

We provide empirical evidence for Propositions 1-4 in the next section, using the local and global illiquidity measures of Section 1 as proxies for m_t^j and m_t^G.

3 Empirical Analysis

In this section, we first describe the additional data needed to test our model using a panel dataset of international stock returns. Then we present three empirical predictions based on the propositions of Section 2. The first prediction says that the slope of the security market line should be a function of global illiquidity. The second prediction is about how alphas vary with illiquidity and beta, and forms the basis of our beta-adjusted-international-illiquidity (BAIL) trading strategy that goes long stocks with high illiquidity-to-beta ratio while going short stocks with low illiquidity-to-beta ratio. The prediction says that such a portfolio should earn excess returns. The final prediction says that the BAIL strategy should result in higher returns than the betting-against-beta strategy of Frazzini and Pedersen (2013). In our international data set we find empirical support for all three predictions.

3.1 Stock Data and Equity Betas

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 that 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 calculated versus the U.S. Treasury bill rate and the proxy for the global market is the MSCI world index. Panel B of Table 1 reports summary statistics.

From Andrea Frazzini's webpage, we download global size, value, and momentum returns. The data construction is described in Asness and Frazzini (2013).

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):

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

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

3.2 Security Market Line

The first prediction follows directly from Proposition 1 and describes the security market line as a function of global illiquidity.

Prediction 1. *In months of low global illiquidity, the intercept of the average security market line is lower than in months of high illiquidity. At the same time, low illiquidity months imply a higher slope than high illiquidity months.*

In other words, Prediction 1 says that the slope of the average security market line (SML) should depend negatively on margin constraints while the intercept is positively related. As a first illustration, we follow the procedure in Cohen, Polk, and Vuolteenaho (2005) and divide our monthly data sample into quintiles according to the level of global illiquidity. We then examine the pricing of beta-sorted portfolios in these quintiles and estimate the empirical SML. Figure 6 depicts the average intercept and slope of the

SML for different levels of global illiquidity ranging from low illiquidity (bin 1) to high illiquidity (bin 5).

[Insert Figure 6 here.]

We note that in line with our prediction, the slope coefficient is decreasing with global illiquidity and the intercept is increasing. For example, for low illiquidity states the average intercept is 0.191% with a slope of 0.171% whereas for high illiquidity, the intercept increases to 0.51% and the slope decreases to 0.008%.

We now want to study in more detail how the intercept and the slope are affected by global funding risk. To this end, we consider again Fama and MacBeth (1973) regressions:

$$r^j_{t+1} = \alpha_t + \phi_t \times \beta^j + \epsilon^j_{t+1}$$

where r^j_{t+1} is the excess return of the j-th β-sorted portfolio and β^j is the post-ranking beta of portfolio j. This gives us the time-series of the intercept α_t and the slope ϕ_t of the SML for each quintile of global illiquidity. In the second stage, we now estimate the following two regressions:

$$\begin{aligned} \alpha_t &= a_1 + b_1 r^M_t + c_1 r^S_t + d_1 r^B_t + e_1 \text{Illiq}^G_t + u_{1,t}, \\ \phi_t &= a_2 + b_2 r^M_t + c_2 r^S_t + d_2 r^B_t + e_2 \text{Illiq}^G_t + u_{2,t}, \end{aligned}$$

where r^M_t, r^S_t and r^B_t is the excess return on the global market, size and book-to-market portfolio. While the global size and book-to-market portfolio are not accounted for in our theory, we control for these variables as it is well-know that these factors have an effect on the shape of the SML as well (see e.g., Hong and Sraer (2012)). The estimated coefficients are presented in Table 3.

[Insert Table 3 here.]

In line with our theoretical predictions, we find that global illiquidity has a positive (negative) effect on the intercept (slope) of the SML. When we just have global market excess returns and global illiquidity, the coefficient on the intercept regression has a value of 0.008 with an associated t-statistic of 1.83 and the coefficient for the slope regression is -0.013 with an associated t-statistic of 1.87. Adding other factors like the global size or book-to-market variables does not alter the results: The estimated coefficient for the intercept is 0.009 with a t-statistic of 2.04 and for the slope regression with find that the coefficient is -0.009 with a t-statistic of -1.70.

3.3 Portfolios Sorted According to Beta and Illiquidity

We now inspect how returns vary in the cross-section of illiquidity and beta-sorted stocks. Propositions 2 and 3 lead to the formulation of the following prediction:

Prediction 2. *Holding margins constant, a higher beta means lower alpha. Holding beta constant, the alpha increases in the local illiquidity and decreases in global illiquidity. Stocks with a higher country-specific illiquidity to beta ratio earn higher returns on average than stocks with low illiquidity to beta ratios.*

Table 4 and Figure 7 (upper two panels) report the results using our international stock data set. We consider three beta- and two illiquidity-sorted portfolios and document 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%), and 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 4 and Figure 7 here.]

To test the impact of global illiquidity on the alpha of the six local illiquidity and beta sorted portfolios, we calculate conditional CAPM alphas using rolling regressions with a window size of 60 months.[13] We then calculate average alphas for low and high global illiquidity regimes, where low and high global illiquidity are defined as times in the lowest and highest quartile, respectively. The theoretical prediction from the model says that a higher global illiquidity should lower the CAPM alpha. In Figure 7 (lower two panels) we plot the average alpha for the six test portfolios. We note that except for the low local illiquidity, low beta sorted portfolio, alphas uniformly decrease for high global illiquidity states for low local illiquidity (left lower panel) and high local illiquidity (right lower panel). We note that alphas uniformly drop from low to high global illiquidity states except for the low beta, low local illiquidity sorted portfolios. However, the average alpha for high global illiquidity is 0.433% per month compared to 0.535% per month for low illiquidity states. The difference between the alphas becomes larger for higher local illiquidity states, for example, in states of high global illiquidity, the high local illiquidity-high beta sorted portfolio yields an average alpha of 0.448% (per month) compared to 0.622% in states of low global illiquidity.

Given the sorted portfolios, and to further test Propositions 3 and 4, we now construct a portfolio that is long high illiquidity-to-beta-ratio stocks and short sells low illiquidity-to-beta-ratio stocks. We call this portfolio the beta-adjusted-international-illiquidity or BAIL portfolio. For each stock we start by constructing the ratio between illiq_t^i and the estimated beta, $\hat{\beta}_t^i$, before ranking 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 weigh 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:

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

The second to last column of Table 4 reports summary statistics of the BAIL strategy. The strategy produces high excess returns with an attractive Sharpe ratio: BAIL has

[13] Using different window size does not alter our results.

an average excess return of 0.827% per month (t-statistic of 3.53), a significant positive alpha of 0.791% per month, and the associated (annualized) Sharpe ratio is 0.73. Overall, we conclude that the BAIL strategy is highly profitable and produces significant positive excess returns.

3.4 BAIL versus BAB

Finally, Proposition 4 compares the return of the beta-adjusted-international-illiquidity strategy with a betting-against-beta strategy, leading to the following prediction:

Prediction 3. *A self-financing zero-beta trading strategy that goes long high illiquidity-to-beta stocks and shorts low illiquidity-to-beta stocks generates higher returns on average than a self-financing strategy long in low-beta and short in high-beta stocks.*

Thus, Prediction 3 says that returns to the BAIL strategy should be higher on average than for the BAB strategy. We test this by comparing the BAIL to the BAB factor. The summary statistics of the BAB factor are presented in the last column of Table 4. 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, 11% lower than that of the BAIL strategy. In terms of alpha, the strategy performs worse then BAIL: the monthly alpha is 0.731%, or 8% lower. In terms of Sharpe ratios, the two trading strategies perform similarly, with annualized Sharpe ratios of 0.73. We note that the BAIL strategy has a slightly higher volatility than the BAB strategy. This becomes evident also in Figure 8 where we plot the cumulative returns of the BAB and BAIL strategies for the past 10 years. The two strategies move almost in lock-step until after the Lehman default late 2008, whereas BAIL performs much better than BAB after that. 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.[14] Economically the better performance after 2008 can be traced back to our theoretical predictions: In a world where liquidity risk matters and affects countries to different extent, it generates higher difference in returns.

[14]For the period January 1990 to December 2012, a \$1 investment would have lead to \$8 for BAIL and \$6.5 for BAB.

Hence, a strategy that goes long high illiquidity assets and short low-illiquidity assets and thus exploits this difference should perform particularly well after funding crises that hits certain countries less than others.

[Insert Figure 8 and Table 5 here.]

Both BAIL and BAB are (de)levered in a way to have zero-beta, hence, in the following, we want to check whether they remain significant once we control for other factors known to predict equity trading strategies. Table 5 reports estimated alphas if we regress the strategy returns onto factors other than the market. In particular, we include the global size, book-to-market and momentum portfolios from Asness and Frazzini (2013). The alphas remain positive and significant even if we add four factors to the regression. This holds for both the BAB and BAIL portfolio. Interestingly, we note that global momentum lowers the t-statistic on the BAIL strategy from 2.92 (3 factor model) to 2.09. This finding relates to Asness, Moskowitz, and Pedersen (2013), who report that global momentum return premia can be partially explained by global funding risk.

Comparing BAIL to BAB is difficult as by construction the two trading strategies are very highly correlated. Another powerful way to inspect whether illiquidity is priced in stocks conditional on stocks' beta is to first construct a BAB strategy within each country, and then sort each month the country-level BAB strategies into high and low illiquidity bins. The summary statistics of the two trading strategies are reported in Table 6.

[Insert Table 6 here.]

The high-illiquidity BAB portfolio produces significantly higher excess returns than a corresponding low-illiquidity BAB portfolio: The average monthly return on the former is 0.989% (t-statistic of 5.12) whereas the latter has an average return of 0.247% (1.46). The alpha of the high illiquidity portfolio is 1.01% and the annualized Sharpe ratio is 1.08. If we would construct a high illiquidity minus low illiquidity portfolio, we would have earned a monthly alpha of 0.75% with a t-statistic of 4.09, and an annualized Sharpe ratio of 0.94. Overall we conclude that conditioning on illiquidity yields very attractive returns with highly significant alpha.

4 Conclusion

This paper investigates the effect of funding constraints on asset returns across different countries. 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.

Next we consider a model of the 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.

Finally, we provide empirical evidence that is supportive of the liquidity-adjusted CAPM in that liquidity risk is priced both in the time-series and cross-section. We first examine the slope and intercept of the security market line. According to our model, higher illiquidity should imply a higher intercept and a lower slope. This prediction is verified in the data: When we sort stocks into months of high and low illiquidity, we find that the intercept of the SML goes up while the slope decreases. We then 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 illiqudity. 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, and outperforms a standard betting-against-beta strategy. Finally, BAB strategies in countries with high illiquidity significantly outperform BAB in low illiquidity countries.

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Appendix A Proofs and derivations

Proof of Theorem 1 and Proposition 1. Rearranging (4) yields

$$E_t\left[r^j_{t+1}\right] = E_t\left[\frac{D^j_{t+1}+P^j_{t+1}-P^j_t}{P^j_t}\right] = r^f + \sum_i \frac{\gamma}{\gamma_i}\psi_{i,t}m^j_{i,t} + \gamma\frac{1}{P^j_t}1^T_j\Omega_t\theta_t, \tag{A-1}$$

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^j_t by definition. Also, with the definition of Ω_t and r^G_{t+1} we can rewrite the third term:

$$\frac{1}{P^j_t}1^T_j\Omega_t\theta_t = \frac{1}{P^j_t}Cov_t\left(D^j_{t+1}+P^j_{t+1}, \theta^\top_t\left(D_{t+1}+P_{t+1}\right)\right) = Cov_t\left(r^j_{t+1}, r^G_{t+1}\right)\theta^\top_t P_t,$$

so (A-1) simplifies to

$$E_t\left[r^j_{t+1}\right] = r^f + m^j_t + \gamma Cov_t\left(r^j_{t+1}, r^G_{t+1}\right)\theta^\top_t P_t. \tag{A-2}$$

Aggregating (A-2) across all stocks with market portfolio weights $w^j_t = \frac{\theta^j_t P^j_t}{\theta^\top_t P_t}$ that sum up to 1, we obtain

$$E_t\left[r^G_{t+1}\right] = r^f + \sum_j m^j_t\frac{\theta^j_t P^j_t}{\sum_j \theta^j_t P^j_t} + \gamma Var_t\left(r^G_{t+1}\right)\theta^\top_t P_t.$$

The second term on the RHS is m^G_t by definition, therefore

$$\gamma Var_t\left(r^G_{t+1}\right)\theta^\top_t P_t = \lambda_t - m^G_t = E_t\left[r^G_{t+1}\right] - r^f - m^G_t.$$

Plugging these into (A-2) and using the definition of β^j_t yields

$$E_t\left[r^j_{t+1}\right] = r^f + m^j_t + \beta^j_t\left(\lambda_t - m^G_t\right) = r^f + m^j_t + \beta^j_t\left(E_t\left[r^G_{t+1}\right] - r^f - m^G_t\right),$$

and from here (5) and (7) are straightforward. □

Proof of Proposition 3. From (5) the expected return on the BAIL factor is

$$\begin{aligned} E_t\left[r^{\text{BAIL}}_{t+1}\right] &= \frac{1}{\beta^H_t}\left(E_t\left[r^H_{t+1}\right]-r^f\right) - \frac{1}{\beta^L_t}\left(E_t\left[r^L_{t+1}\right]-r^f\right) \\ &= \left(\lambda_t + \frac{m^H_t}{\beta^H_t} - m^G_t\right) - \left(\lambda_t + \frac{m^L_t}{\beta^L_t} - m^G_t\right) = \frac{m^H_t}{\beta^H_t} - \frac{m^L_t}{\beta^L_t}. \end{aligned} \tag{A-3}$$

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

$$\frac{m^H_t}{\beta^H_t} = \frac{w^T_H m_t}{w^T_H\beta_t} = \frac{\sum_{j\in\mathcal{J}_H}w_j m^j_t}{\sum_{j\in\mathcal{J}_H}w_j\beta^j_t} = \frac{\sum_{j\in\mathcal{J}_H}w_j\beta^j_t\frac{m^j_t}{\beta^j_t}}{\sum_{j\in\mathcal{J}_H}w_j\beta^j_t} \geq \frac{\sum_{j\in\mathcal{J}_H}w_j\beta^j_t\frac{m^{jH}_t}{\beta^{jH}_t}}{\sum_{j\in\mathcal{J}_H}w_j\beta^j_t} = \frac{m^{jH}_t}{\beta^{jH}_t}\frac{\sum_{j\in\mathcal{J}_H}w_j\beta^j_t}{\sum_{j\in\mathcal{J}_H}w_j\beta^j_t} = \frac{m^{jH}_t}{\beta^{jH}_t}.$$

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

$$\frac{m_t^L}{\beta_t^L} = \frac{w_L^T m_t}{w_L^T \beta_t} = \frac{\sum_{j \in \mathcal{J}_L} w_j m_t^j}{\sum_{j \in \mathcal{J}_L} w_j \beta_t^j} = \frac{\sum_{j \in \mathcal{J}_L} w_j \beta_t^j \frac{m_t^j}{\beta_t^j}}{\sum_{j \in \mathcal{J}_L} w_j \beta_t^j} \leq \frac{\sum_{j \in \mathcal{J}_L} w_j \beta_t^j \frac{m_t^{jL}}{\beta_t^{jL}}}{\sum_{j \in \mathcal{J}_L} w_j \beta_t^j} = \frac{m_t^{jL}}{\beta_t^{jL}} \frac{\sum_{j \in \mathcal{J}_L} w_j \beta_t^j}{\sum_{j \in \mathcal{J}_L} w_j \beta_t^j} = \frac{m_t^{jL}}{\beta_t^{jL}}.$$

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

$$E_t\left[r_{t+1}^{\text{BAIL}}\right] = \frac{m_t^H}{\beta_t^H} - \frac{m_t^L}{\beta_t^L} \geq \frac{m_t^{jH}}{\beta_t^{jH}} - \frac{m_t^{jL}}{\beta_t^{jL}} > 0,$$

which confirms Proposition 3. □

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

$$E_t\left[r_{t+1}^{\text{BAB}}\right] = \frac{m_t^{LB}}{\beta_t^{LB}} - \frac{m_t^{HB}}{\beta_t^{HB}}.$$

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 $1/\beta$ (i.e., lowest β) and short in assets with the lowest $1/\beta$, we have

$$\frac{m_t^H}{\beta_t^H} \geq \frac{m_t^{LB}}{\beta_t^{LB}} \text{ and } \frac{m_t^L}{\beta_t^L} \leq \frac{m_t^{HB}}{\beta_t^{HB}},$$

and (9) 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 pencentage)	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 Illiquidity Proxies

Panel A reports summary statistics (mean, standard deviation, maximum and minimum) for six different country specific illiquidity 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 illiquidity measures. Panel C reports the estimated coefficients with the associated t-statistic and R^2 from the following regression

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

where illiq_t^i is the illiquidity proxy of country i and illiq_t^G is the global illiquidity 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 Illiquidity Proxy						
β_0	0.625	0.091	-0.526	0.303	-0.797	-1.412
	(1.60)	(0.21)	(-1.48)	(0.41)	(-1.49)	(-1.86)
β_1	3.802	7.067	9.943	7.980	6.789	13.211
	(4.45)	(7.79)	(12.02)	(4.68)	(5.72)	(8.08)
Adj. R^2	51.46%	66.64%	60.41%	39.58%	57.75%	57.15%

Table 3
Regression Intercept and Slope of SML

This table reports OLS regression coefficient of the intercept and slope of the SML on global market, size, and book-to-market portfolio returns and global illiquidity:

$$\alpha_t = a_1 + b_1 r_t^M + c_1 r_t^S + d_1 r_t^B + e_1 \text{Illiq}_t^G + u_{1,t},$$
$$\phi_t = a_2 + b_2 r_t^M + c_2 r_t^S + d_2 r_t^B + e_2 \text{Illiq}_t^G + u_{2,t},$$

where r_t^M, r_t^S and r_t^B is the excess return on the global market (mrkt), size (sml) and book-to-market (hml) portfolio. The intercept (α_t) and slope (ϕ_t) are estimated using the Fama and MacBeth (1973) methodology. t-statistics reported in parentheses are adjusted according to Newey and West (1987). Data is monthly and runs from January 1990 to December 2012.

	a	mrkt	smb	hml	illiq	Adj. R^2
Intercept	-0.004	0.208			0.008	13.72%
t-stat	(-1.34)	(5.43)			(1.83)	
Slope	0.010	0.651			-0.013	51.41%
t-stat	(2.12)	(12.89)			(-1.87)	
Intercept	-0.004	0.198	0.220	0.065	0.009	17.48%
t-stat	(-1.38)	(5.63)	(2.72)	(1.36)	(2.04)	
Slope	0.010	0.629	0.502	0.149	-0.009	59.81%
t-stat	(2.85)	(13.70)	(4.64)	(1.92)	(-1.70)	

Table 4
Portfolio Returns

The is 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 country-level illiquidity and the estimated beta at the end of the previous month. The ranked stocks are then assigned to six different bins: Low/High illiquidity, and low/mid/high beta. The two rightmost columns report summary statistics of the BAIL and BAB strategies. To construct BAIL, 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 stocks and shorts low illiquidity-to-beta stocks. Similarly, 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 Illiq			High Illiq		BAIL	BAB
	low β	mid β	high β	low β	mid β	high β		
Excess Return	0.609	0.587	0.561	0.651	0.674	0.678	0.827	0.741
t-stat	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
t-stat	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 5
Alphas BAIL versus BAB

This table reports estimated alphas for the BAIL and BAB trading strategy. BAIL is a self-financing portfolio that is long the high illiquidity to beta stocks and short the low illiquidity to beta stocks. BAB is long the low-beta portfolio and short the high-beta portfolio. The alphas are calculated from regressions of monthly excess returns onto the market (CAPM), the global Fama and French (1993) mimicking portfolios (3 factor model), and the global Carhart (1997) momentum factor (4 factor model). Alphas are in monthly percent and t-statistics are adjusted according to Newey and West (1987). Data runs from January 1990 to December 2012.

	CAPM	3-factor	4-factor
BAIL	0.791	0.591	0.443
t-stat	(3.53)	(2.92)	(2.09)
BAB	0.731	0.603	0.470
t-stat	(2.48)	(3.02)	(2.25)

Table 6
International BAB and Illiquidity

This table reports estimated excess returns and alphas of a trading strategy that each month constructs a betting-against-beta strategy in each country and then sorts according to their liquidity level into two bins (low and high). HML is the high-illiquidity minus the low-illiquidity portfolio. Alphas are in monthly percent and t-statistics are adjusted according to Newey and West (1987). Data runs from January 1990 to December 2012.

	low	high	HML
Excess return	0.247	0.989	0.742
t-stat	1.46	5.12	4.48
CAPM alpha	0.38	1.01	0.75
t-stat	1.76	4.11	4.09
Volatility (annualized)	9.58	10.98	9.37
Sharpe Ratio (annualized)	0.31	1.08	0.94

Appendix C Figures

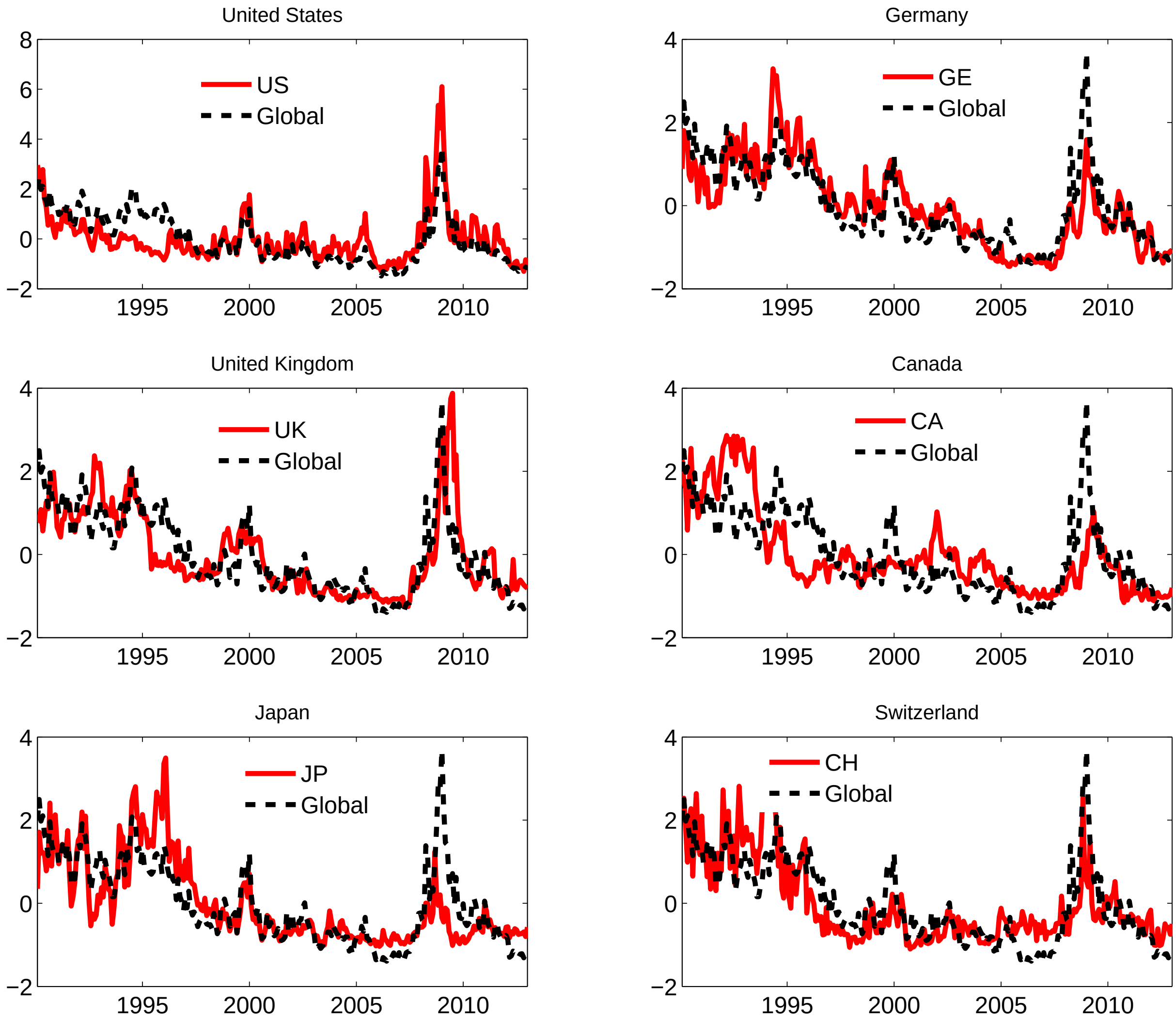

Figure 1. Illiquidity Measures All Countries

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

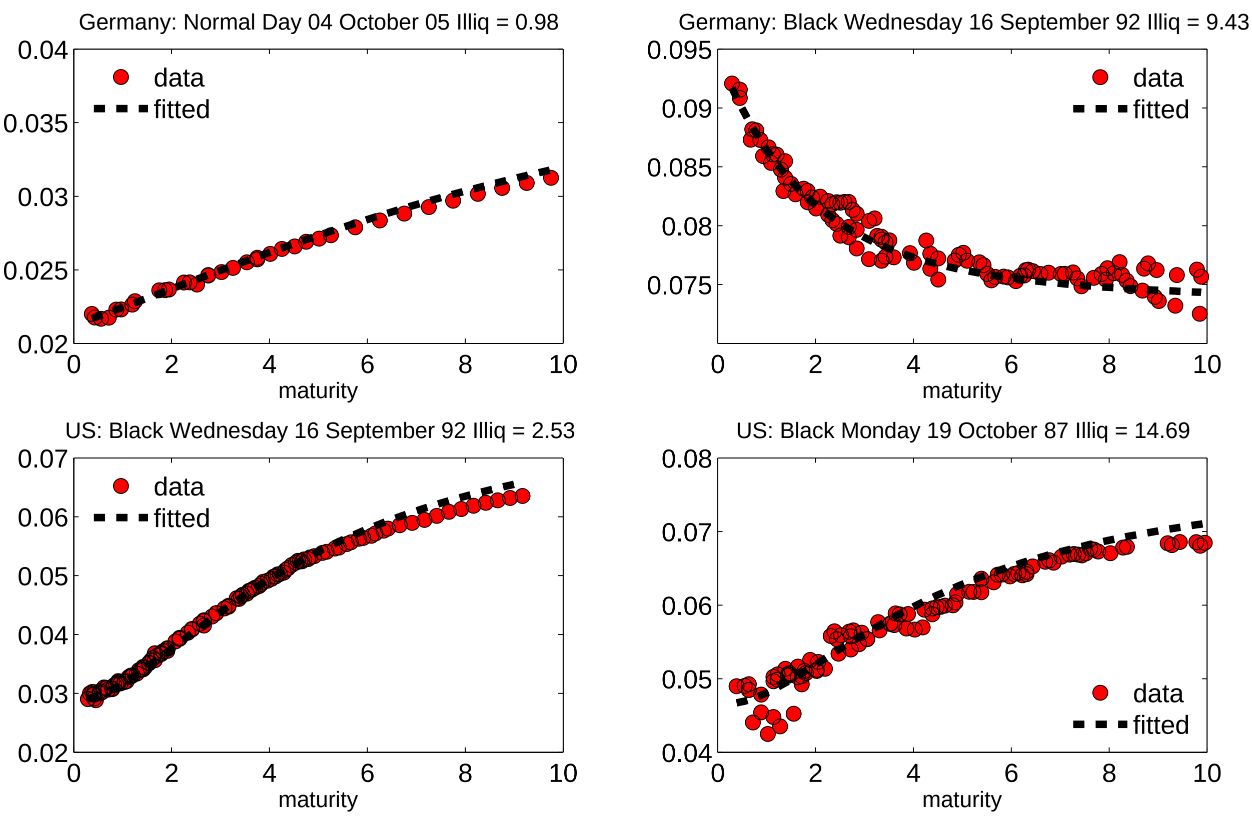

Figure 2. International Term Structures Different Days

This figure presents data and model-implied yields for Germany and the US for three different days.

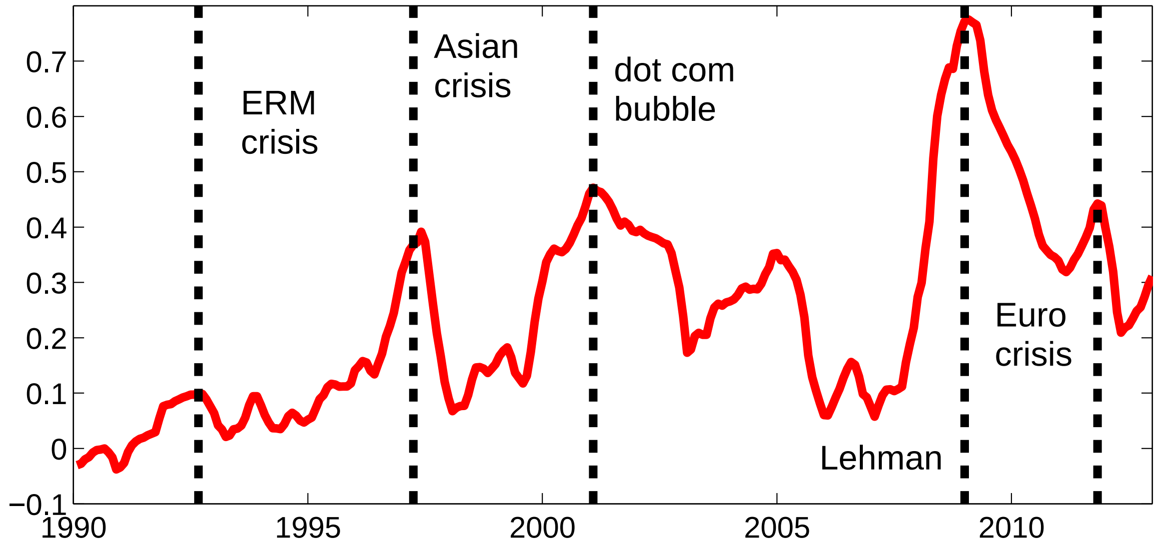

Figure 3. Average Conditional Correlation of Country-Specific Illiquidity Measures

This figure present the conditional average correlation among all six country-specific illiquidity 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.

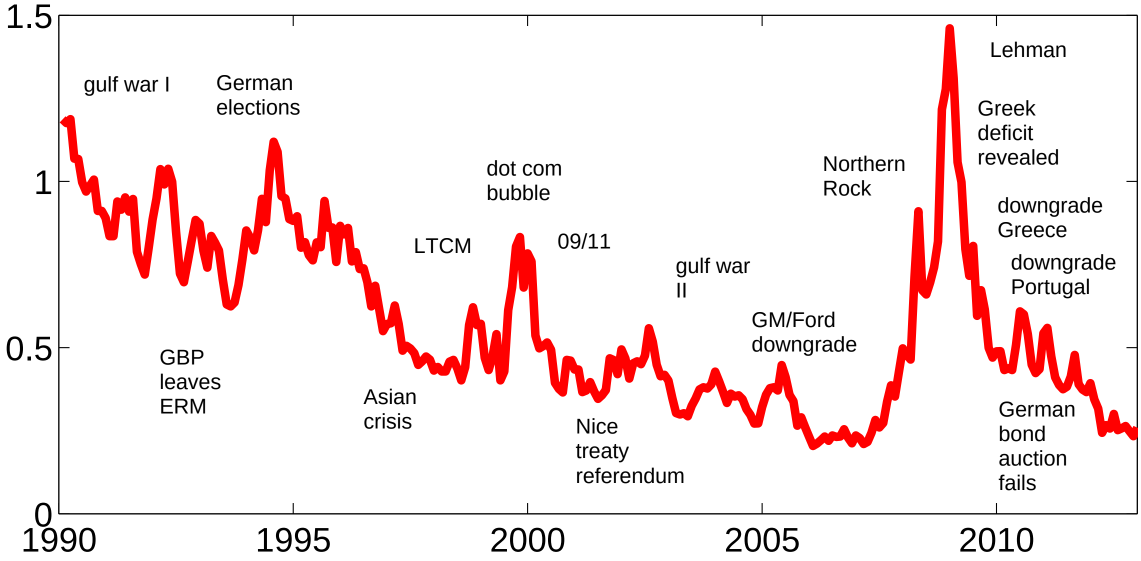

Figure 4. Global Funding Liquidity

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

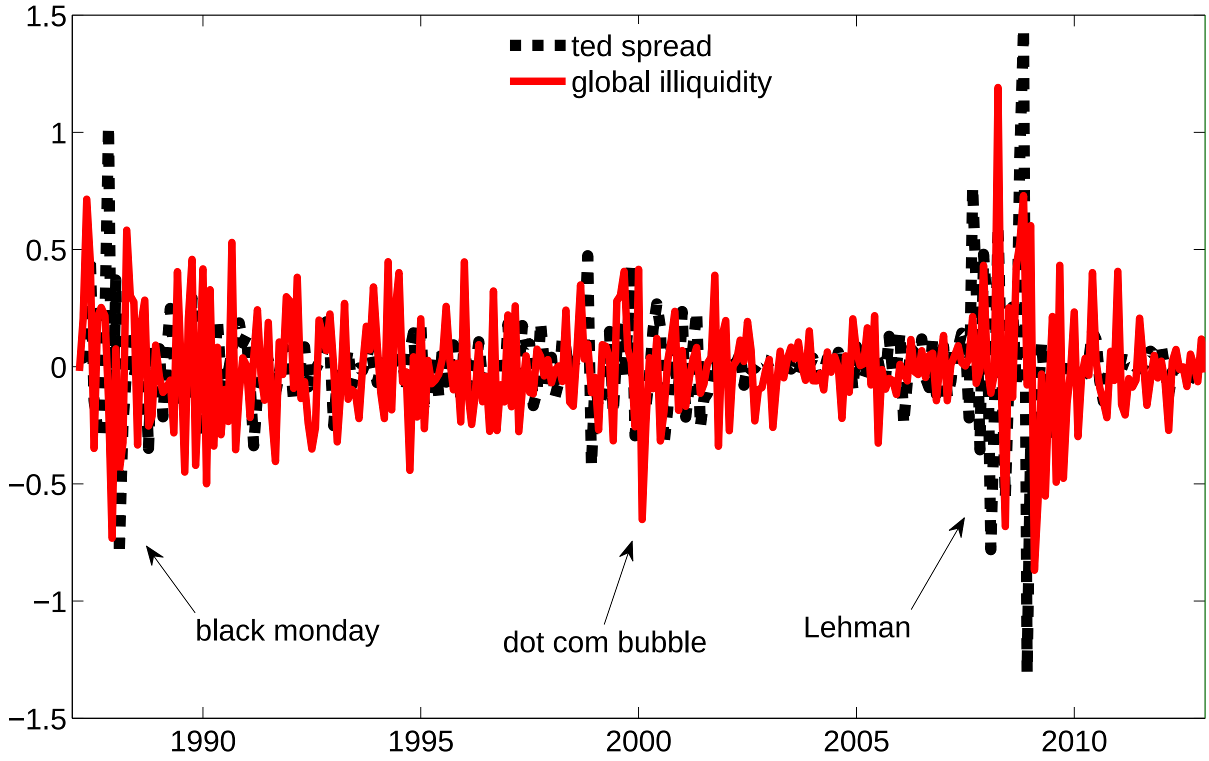

Figure 5. First Differences in Global Illiquidity and TED Spread

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

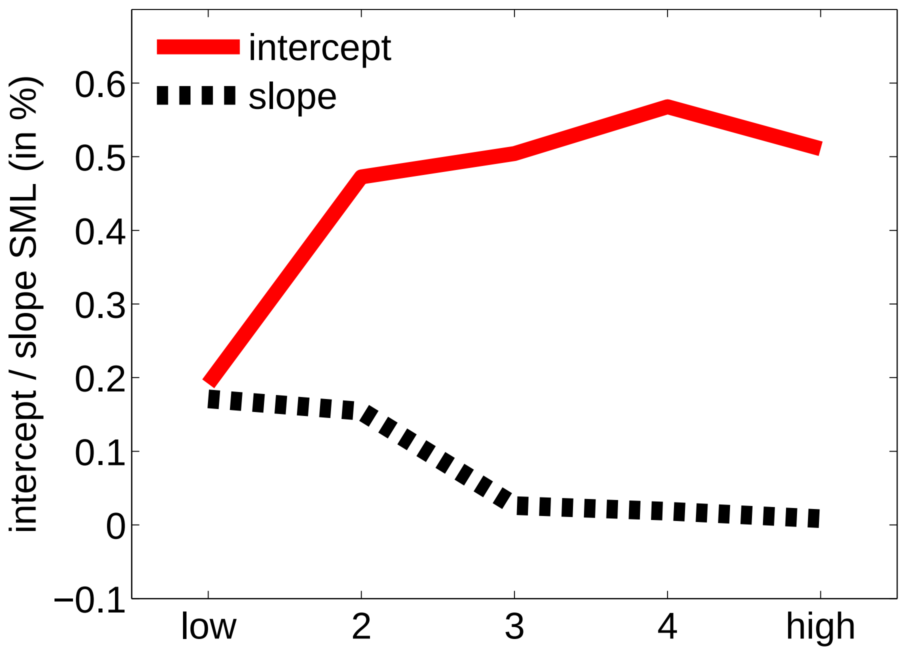

Figure 6. Intercept and Slope Security Market Line

This figure plots the average intercept and slope of the security market line for different global illiquidity quintiles. The full sample period is from January 1990 to December 2012.

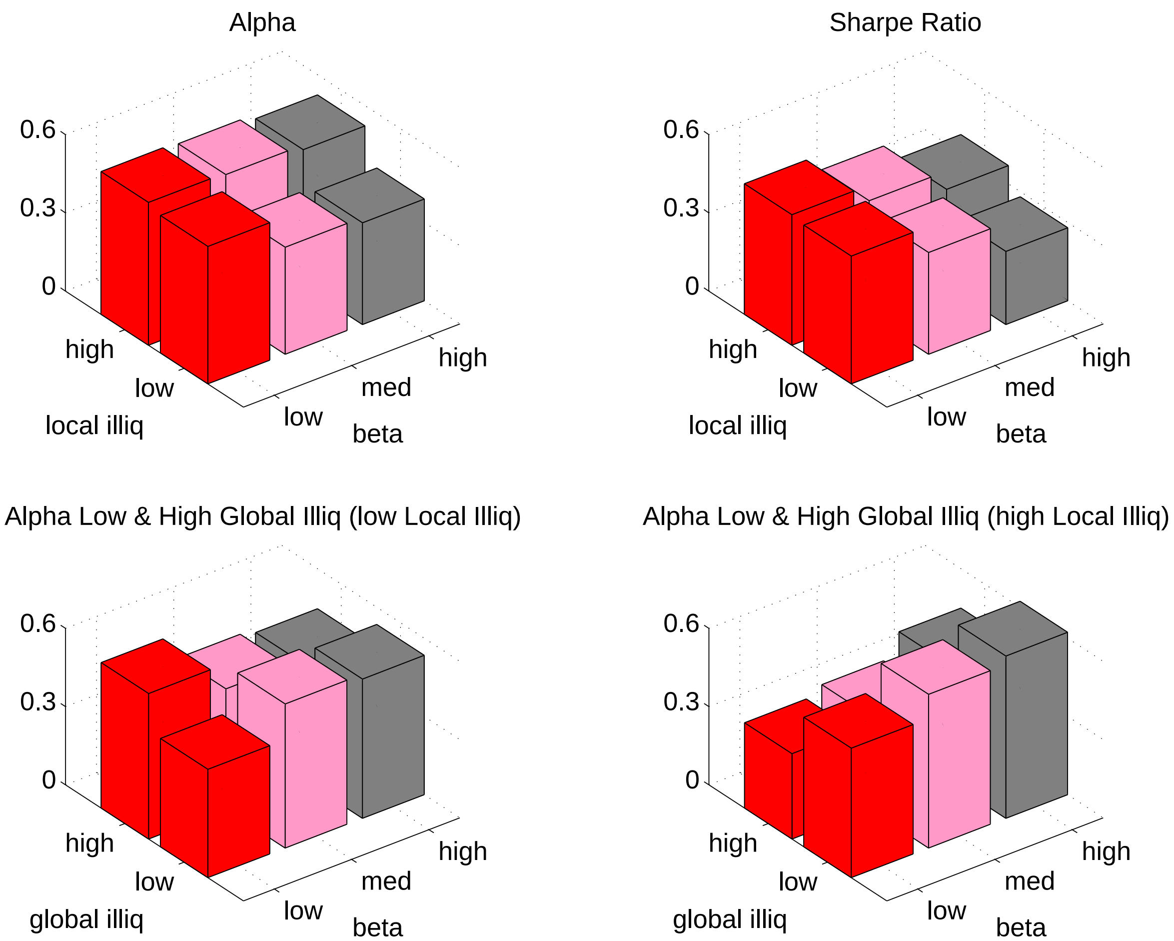

Figure 7. CAPM Alpha and Sharpe Ratio of Illiquidity and beta sorted portfolio

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.

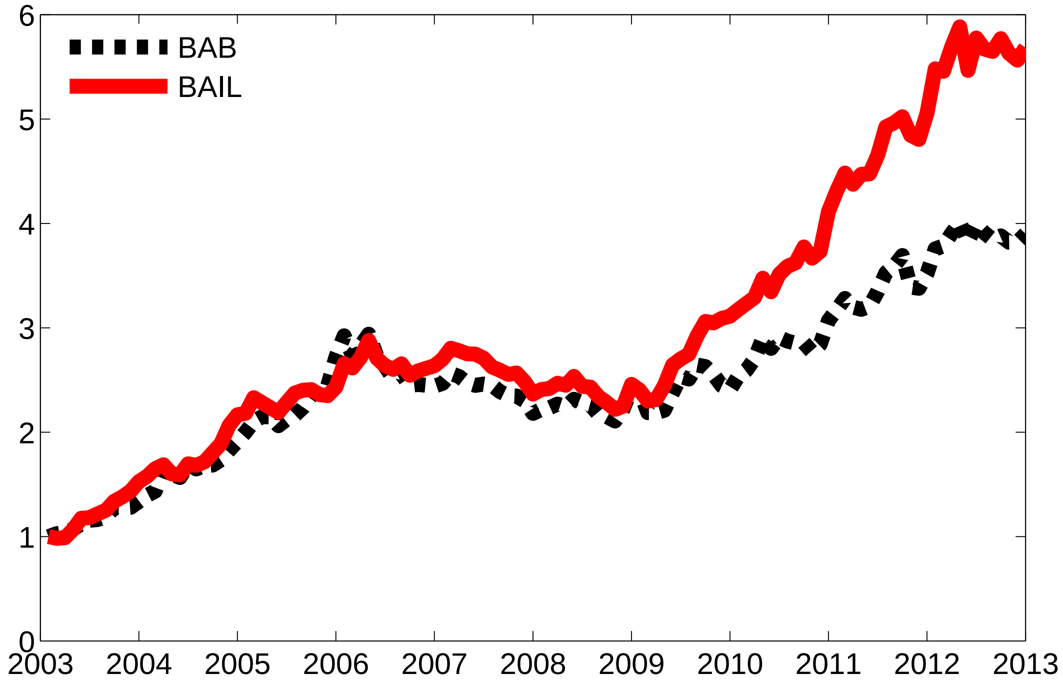

Figure 8. BAIL versus BAB cumulative returns

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.