International Illiquidity*

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Abstract

Using a parsimonious international asset pricing model in which frictions dislocate security prices from the levels implied by their risk, we derive predictions regarding the effect of illiquidity on the cross-section of international stock returns. Empirically, we first construct daily proxies for illiquidity for six different countries, which exhibit a strong common component but also idiosyncratic variation. With these measures, we document the following findings: First, higher global illiquidity implies a lower slope and higher intercept of the international security market line. Second, alphas and Sharpe ratios are increasing in local illiquidity. Third, betting-against-beta (BAB) strategies in high illiquidity countries outperform those in low illiquidity countries and fourth, accounting for illiquidity improves on the performance of BAB strategies.

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The recent financial crisis has dramatically illustrated how, in times of distress, market frictions can impede the orderly trading activity of arbitrageurs, and have significant effects on asset prices.[1] These phenomena are even more prominent when looking at asset prices in the international context where specialized investors, such as brokers, hedge funds, and investment banks, are responsible for a large fraction of active cross-country investments.

In this paper, we study both theoretically and empirically the effect of frictions, such as funding constraints or barriers that prevent smooth cross-border movement of capital, on asset prices across different countries. We broadly refer to the effect of these frictions as illiquidity. Our contribution to the existing literature is twofold. First, we construct novel daily measures of illiquidity for six developed countries. We find that in addition to a common global component, country-level illiquidity exhibits significant idiosyncratic variation. With these measures at hand, we can not only study how illiquidity affects asset prices locally (i.e. within a given country) but also relative (i.e. globally) across different countries. Second, we look at illiquidity through the lens of a parsimonious international CAPM augmented by capital constraints. Using our proxies we find strong empirical support for the role of both global and local illiquidity for asset prices internationally. Higher global illiquidity affects the international risk-return trade-off by lowering the slope and increasing the intercept of the international security market line. Stocks in countries with higher country-specific illiquidity earn higher alphas and Sharpe ratios. As a result, accounting for the cross-country differences in illiquidity can improve on the performance of betting-against-beta (BAB) type strategies.

We start by building an international CAPM with illiquidity. In our model investors have to fund a fraction of their position in each asset with their own capital. When this constraint binds for at least some investors, the equilibrium expected excess return on any security depends not only on its risk (beta), but also on an additional illiquidity component that is proportional to the capital required to maintain the position in this asset. We focus on the differences in capital requirements at the country level. Note that these are largely unrelated to the betas of individual securities. More precisely, we

[1] See, for example, Brunnermeier and Pedersen (2009), Gârleanu and Pedersen (2011), and He and Krishnamurthy (2012, 2013).

assume that capital requirements can differ across countries and investors: it might be more difficult to fund positions in some markets relative to others, some investors or some countries may face barriers to foreign investment.[2] We show that all these factors would affect the cross-section of international asset returns. Note that the intuition behind our results is valid beyond the particular setting: taxes on investments or liquidity shocks as in Vayanos and Wang (2012) would impose a cost on investors' portfolio holdings identical to the shadow penalty of the funding constraint.

In order to test the predictions of the model we construct country-specific measures for 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. Similarly, using daily bond data for the US, Germany, UK, Canada, Japan, and Switzerland, we construct country-specific illiquidity 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 our illiquidity measure for each country.[3] The basic tenet behind the measure is that large deviations among yields for similar maturities cannot be justified by their respective risk. Larger deviations in a given country should indicate that investors face tighter constraints, either on their ability to fund their positions or to move capital across borders, which make it more difficult for them to take advantage of the mispricing. Government bond markets are particularly well suited to assess the tightness of these constraints as they are among the most liquid markets and represent safe havens during crisis periods, hence, price deviations contain a very strong signal about the overall liquidity in these markets (see, e.g., Krishnamurthy and Vissing-Jorgensen (2012)).

The key advantage of our approach is that it circumvents issues other illiquidity and market stress 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

[2] Cross-border flows may be more costly in terms of capital because such investments require a higher degree of intermediation (see e.g., Hau and Rey (2006) and Gabaix and Maggiori (2013)).

[3] Recently, Musto, Nini, and Schwarz (2014) study the direction of these deviations by linking them to security specific characteristics. They conclude that deviations are mainly driven by security-level liquidity.

(VIX), are not useful for international comparisons (TED spread), or are only available at very low frequency (broker-dealers' leverage).[4] The illiquidity proxies we calculate are available daily, for a history of more than 20 years.

We find that the overall correlation of the six country-specific funding proxies is positive and high: Unconditional pairwise correlations range between 19% (US and Japan) and 74% (Germany and Japan). Moreover, we find that this high unconditional correlation is primarily driven by three crisis episodes – the Asian crisis, the dotcom bubble, and the recent financial crisis – but is much lower outside those periods. More important for testing the implications of our model is the dispersion of illiquidity across countries. While we find no large permanent differences in illiquidity among the countries, illiquidity can become significantly dispersed when some countries experience idiosyncratic illiquidity episodes. Overall, we find distinct periods of heightened country-specific illiquidity which can be traced back to specific political or economic events in a given country but are not shared globally. 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 US measure remains largely unaffected.

Having constructed illiquidity proxies and documented several key facts about them, we turn to assessing its implications for asset prices. Our theory predicts that higher average illiquidity across countries implies a higher intercept and a lower slope of the average international security market line. This happens because constrained investors value securities with higher exposure to the global market factor, similar to Frazzini and Pedersen (2013). We find strong support for this prediction of the model in international stock returns data: 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 our theoretical prediction,

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

global illiquidity carries a positive sign for the intercept regression and a negative sign for the slope regression.

Our theory also predicts that the cross-country differences in illiquidity imply a difference in alpha. More precisely, holding the beta of a security constant, its alpha increases in local illiquidity. We verify this pattern in the cross-section of illiquidity and beta sorted portfolios of international stocks. For example, for high beta stocks, the alpha increases from 0.40% 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.

We proceed to test this implication further by looking at self-financing market-neutral portfolios that are constructed to take advantage of the illiquidity alpha. According to our model betting-against-beta (BAB) strategies should perform significantly better in more illiquid countries. We test this by comparing the performance of two portfolios, one implementing the BAB strategy in countries that have high illiquidity in a given period, the other doing the same for low illiquidity countries. In line with the theoretical prediction we find that the former significantly outperforms the latter. The high minus low illiquidity BAB strategy produces a monthly excess return of 0.742% with an associated t-statistic of 4.48.

Our model provides us with an alternative way to test if conditioning on illiquidity yields alpha. It implies that a trading strategy that is long high illiquidity-to-beta-ratio stocks and short low illiquidity-to-beta-ratio stocks globally (BAIL) should outperform the global BAB strategy. Indeed, we find BAIL to perform better than BAB and more so in times when constraints are more dispersed.

As a last empirical exercise, we ask whether our measures capture the same aspect of illiquidity as indicators such as bid-ask spreads, trading volume, or the Amihud (2002) illiquidity measure, and whether they can be useful beyond standard market illiquidity measures to explain stock returns. These measures are generally argued to aggregate many types of market imperfections, including adverse selection costs and inventory costs. In contrast, our measures are largely free of these concerns, and capture how capital constraints dislocate prices relative to the level implied by their risk. To this end, we orthogonalize our illiquidity proxies with respect to the Amihud (2002) market illiquidity measure extracted from stock returns. Using these measures, we find our theoretical predictions still confirmed in the data.

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, and show empirically that deviations of the Law of One Price can arise between assets with the same cash flows but different margins.[5] Frazzini and Pedersen (2013) model an economy where investors face agent-specific margin constraints. Those who cannot lever up invest in more risky assets which causes their returns to decline. The authors test a betting-against-beta strategy in bond, stock, and credit markets and find strong evidence supporting their predictions. In this paper we combine the elements of the models above to build an international CAPM where securities have a different beta with respect to the global market factor and margin requirements differ across countries and investors. We asses the role of these frictions at the country-level by testing the model prediction using our novel illiquidity measures. We find strong support that both global and country-level illiquidity play an important role for asset prices.

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. 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

[5] 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).

(negative). These findings could potentially complement ours as margin constraints are more prone to bind in times of high disagreement.[6]

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 market 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 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. Bouwman, Sojli, and Tham (2013) study the predictive power of an average stock market Amihud (2002) illiquidity measure for bond excess returns and show that it is also correlated with proxies of funding risk. Lee (2013) constructs a funding proxy measured as the difference of rolling correlations of stock market returns with large and small stocks' asset liquidity and finds that it predicts GDP growth and aggregate stock market returns. Goyenko and Sarkissian (2014) study how an illiquidity proxy from off-the-run T-Bills predicts international stock returns. Fontaine and Garcia (2012) construct a funding liquidity proxy from the different prices of on- and off-the-run bonds and study its predictive power for bond

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

excess returns. Pasquariello (2014) constructs a market dislocation index from three different no arbitrage violations and studies its effect on international stock returns and foreign exchange. Stock and currency portfolios which correlate negatively with market dislocation earn higher returns than portfolios which correlate positively suggesting a negative price of risk.

Related to funding and leverage risk, Adrian, Etula, and Muir (2014) 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 Section 1 we build a margin-augmented international CAPM and derive its predictions. In Section 2, we describe the data and the construction of the funding proxies. Section 3 presents our empirical results. Finally, Section 4 concludes. All proofs are deferred to the Appendix. Additional results are available in an Online Appendix.

1 Model

In this section we build a parsimonous international asset pricing model that will guide our empirical analysis.

1.1 Model

We consider an overlapping-generations world economy with K countries. In each country $k = 1, ..., K$ there exist S_k risky assets; security $s = 1, ..., S_k$ is in total supply $\theta_t^{k,s} > 0$, pays a real dividend $D_t^{k,s}$ in the unique consumption good in period t, and its ex-dividend price is denoted by $P_t^{k,s}$. There also exists a global riskless asset, with the risk-free rate given exogenously and normalized to zero. We assume that purchasing power parity holds and all prices are expressed in US dollars (see, e.g., Bekaert, Harvey, and Lundblad (2007)).

We assume overlapping generations of international investors, one representative for each country, indexed by $i = 1, ..., K$. Each generation lives for two periods. In each period t, young agents invest to maximize mean-variance preferences over next period wealth, then consume and exit in period $t + 1$:

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

where $x_{i,t}$ is the vector of risky holdings, D_t and P_t are the vectors of dividends and prices of all risky securities, Ω_t is the conditional variance-covariance matrix of $D_{t+1} + P_{t+1}$, and γ_i denotes agent i's risk aversion. Investor i, born with wealth $W_{i,t} \geq 0$, can invest in all assets of the world economy, but her portfolio holdings in risky securities have to satisfy the following constraint:

$$\sum_{k,s} m_{i,t}^{k} \left| x_{i,t}^{k,s} \right| P_t^{k,s} \leq W_{i,t}. \tag{2}$$

Except for the constraint (2), our assumptions are standard in the international asset pricing literature. For instance, assuming away (2) leads to the standard international CAPM. The constraint implies that investing in (or shorting) country-k securities requires investor i to commit the amount of her capital equal to the multiple $m_{i,t}^{k}$ of the position size, similar to the margin constraints of Black (1972), Brunnermeier and Pedersen (2009), Gârleanu and Pedersen (2011) and Frazzini and Pedersen (2013). We think about this capital constraint as a stylized way to model market frictions that impose a cost on investors' positions and as a result dislocate security prices from the levels implied by the risk-return tradeoff. Capital constraints have received a lot of attention in the recent literature (see e.g., Gromb and Vayanos (2002), and He and Krishnamurthy (2012, 2013)), which motivates our modelling choice. However, we would obtain equivalent implications if we assumed endowment shocks that proxy for illiquidity (following Vayanos and Wang (2012)) or investment taxes (following Stulz (1981)) instead. Note as well that our setting also allows for partial market segmentation, which can be an important friction in the context of international investments. It can be captured by making cross-border flows more costly in terms of capital, for instance because such investments require a higher degree of intermediation (see e.g., Hau and Rey (2006) or Gabaix and Maggiori (2013)).[7]

The first-order condition of (1) subject to (2), after rearranging, gives the optimal demand

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

where $\psi_{i,t}$ is the Lagrange multiplier associated with (2), $\mathbf{sgn}\left(x_{i,t}\right)$ is a diagonal matrix that collects the signs of the asset holdings of investor i, $sgn\left(x_{i,t}^{k,s}\right)$, and $\mathbf{m}_{i,t}$ is a diagonal matrix that collects the $m_{i,t}^k$ terms. Equation (3) illustrates how capital constraints distort the optimal demands of investors. Compared to the standard frictionless tradeoff between higher expected payoff and risk, investors decrease their demand, and they particularly do so in assets that can contribute the most to the relaxation of the constraint.

Combining (3) and the market-clearing condition $\sum_i x_{i,t}^{k,s} = \theta_t^{k,s}$ for all k and s, we obtain equilibrium security prices:

$$P_t^{k,s} = \frac{\mathbb{E}_t\left[D_{t+1}^{k,s} + P_{t+1}^{k,s}\right] - \gamma \mathbf{1}^{k,s}\Omega_t\theta_t}{1 + \sum_i \frac{\gamma}{\gamma_i}\psi_{i,t}m_{i,t}^k sgn\left(x_{i,t}^{k,s}\right)}, \tag{4}$$

where γ is defined as aggregate risk aversion, $\frac{1}{\gamma} = \sum_i \frac{1}{\gamma_i}$, and $\mathbf{1}^{k,s}$ is a vector with 1 in the row of country k's security s and zeros elsewhere.

To close our model, we make a technical assumption that for each investor i $\gamma\theta + \Omega^{-1}\left(\sum_j \frac{\gamma}{\gamma_j}\psi_{j,t}\mathbf{m}_{j,t} - \psi_{i,t}\mathbf{m}_{i,t}\right)P_t > 0$ holds. Absent the capital constraint (2), the equilibrium positions of investors would be proportional to the supply θ, i.e., all investors

[7] Fully integrated markets correspond to the special case where capital requirement $m_{i,t}^k$ can be decomposed as $m_{i,t}^k = m_{i,t}m_t^k$ and therefore $\phi_t^k = m_t^k\sum_i \frac{\gamma}{\gamma_i}\psi_{i,t}m_{i,t}$. In this case only the average tightness of funding constraints across international investors matters, and security excess returns are affected proportionately to the difficult to borrow against them. In contrast, in the general case the degree to which a country's financial market is integrated with others, and the tightness of funding constraints for investors that face more or less barriers matter for security excess returns.

would go long in all risky assets. Our assumption, which is satisfied if θ is sufficiently large and the variation in how binding individual constraints are is not very large, implies that in equilibrium constrained investors reduce their asset holdings but do not start shorting any assets, i.e., $sgn\left(x_{i,t}^{k,s}\right) = 1$ for all i, k and s. Under this assumption, and after some algebra, (4) yields the following result:

Theorem 1. *The equilibrium expected excess return of security s from country k is*

$$\mathbb{E}_t\left[r_{t+1}^{k,s}\right] = \beta_t^{k,s}\lambda_t + \phi_t^k - \beta_t^{k,s}\phi_t^G, \tag{5}$$

with

$$\phi_t^k = \sum_i \frac{\gamma}{\gamma_i}\psi_{i,t}m_{i,t}^k \text{ and } \phi_t^G = \sum_k \phi_t^k \frac{\sum_s \theta_t^{k,s}P_t^{k,s}}{\sum_{k,s}\theta_t^{k,s}P_t^{k,s}}, \tag{6}$$

where $\beta_t^{k,s} = \frac{Cov_t\left(r_{t+1}^{k,s}, r_{t+1}^G\right)}{Var_t\left(r_{t+1}^G\right)}$ is the beta of security s from country k with respect to the global market portfolio, and $\lambda_t = \mathbb{E}_t\left[r_{t+1}^G\right]$ is the expected excess return of the global market portfolio.

From (5) the expected excess return on country-k security depends on the usual CAPM term, and an additional component that reflects the compensation for the capital that investors have to commit in order to invest in this security.[8] Note that there are no a priori reasons why the cost imposed by funding or other frictions on individual securities is proportional to their respective betas $\beta_t^{k,s}$. This is more so in our framework because we consider the variation in capital requirements $m_{i,t}^k$ (and therefore in ϕ_t^k) driven by country-level factors. As a result, market frictions have an effect on the cross-section of security returns.

Finally, a simple rearrangement of (5) allows us to reinterpret Theorem 1 in terms of a security market line:

[8]The term ϕ_t^G appears in (5) because excess returns on the global market portfolio are themselves in part driven by the compensation for the constraint.

Corollary 1. *There is an 'average' global security market line (SML), but securities can be 'off the line' due to the country-level term* ϕ_t^k*:*

$$\mathbb{E}_t\left[r_{t+1}^{k,s}\right] = \underbrace{\phi_t^G}_{average\ intercept} + \beta_t^{k,s}\underbrace{\left(\mathbb{E}_t\left[r_{t+1}^G\right] - \phi_t^G\right)}_{slope\ of\ SML} + \underbrace{\left(\phi_t^k - \phi_t^G\right)}_{country\ effect}.^{9} \tag{7}$$

1.2 Predictions

Based on Theorem 1 we express four testable propositions that will allows us to test the effect of market frictions on asset prices. In the empirical section we will identify the terms ϕ_t^k with our novel measures of country-level illiquidity and market stress. For simplicity we will refer to them as illiquidity.

Proposition 1. *The slope of the average global SML is decreasing in global illiquidity, while the intercept of the average SML is increasing in global illiquidity.*

Proposition 1 follows directly from (7). It sums up the effect of limited capital and market frictions on global risk-return trade-off.

Proposition 2. *Holding illiquidity constant, a higher beta means lower alpha. Holding beta constant, the alpha increases in the local illiquidity and decreases in the global illiquidity measure.*

From (5), a security's alpha with respect to the global market is $\phi_t^k - \beta_t^{k,s}\phi_t^G$. It arises because constrained investors pay a premium for high beta stocks that allow them to get a higher exposure to the global market factor relative to the size of their position. In our setting this is equivalent to increasing their exposure per unit of capital in order to offset the difficulty to use assets from certain countries as collateral, or bypass intermediation barriers to international investments. The same intuition would apply if the friction that penalized portfolio holdings was a tax or a liquidity shock.

[9] 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.

Next, we derive two propositions regarding the self-financing market-neutral portfolios constructed to insulate and take advantage of this alpha. We can think about the performance of these strategies as the extra return that can be obtained in the market by an investor who does not face funding constraints and is small enough not to affect prices.

Proposition 3. *Everything else being equal, the expected return of a self-financing market-neutral portfolio that is long in low beta securities and short in high beta securities (betting against beta, BAB) in country k is positive and increasing in country-specific illiquidity.*

Proposition 3 states that the BAB portfolio, proposed by Frazzini and Pedersen (2013) to exploit the fact that the slope of the SML is smaller than what the frictionless CAPM predicts, performs better in countries where investing is more difficult to fund.

Proposition 4. *The expected return of a self-financing market-neutral portfolio that is long in high illiquidity-to-beta ratio securities and in high illiquidity-to-beta ratio securities (betting against illiquidity, BAIL) is positive and higher than the expected return on a similar long-short trading strategy that ignores sorting on illiquidity.*

Proposition 4 states that taking into account the difference in country-level illiquidity could improve on the performance of the global BAB portfolio.

2 Data

We now turn to an empirical study of how country-level and global illiquidity affects asset prices. The key assumption of our theory is that international investors are capital constrained when forming their optimal portfolio. Capital constraints are a stylized way of modeling market frictions which are notoriously difficult to measure. Because constraints impede orderly trading activity of arbitrageurs, prices can be dislocated relative to a standard risk-return tradeoff. In the following, we construct a measure of illiquidity or market dislocation from the government bond market. International government bond markets present an excellent laboratory for studying times of illiquidity or market distress, as they are generally liquid and are considered as safe havens. Moreover, government bonds represent a main source of collateral for financing other positions. Hence, any general market distress will be manifested in the bond market. Our empirical approach closely follows Hu, Pan, and Wang (2013) who construct an illiquidity measure from price deviations from a smoothed yield curve. Recently, Musto, Nini, and Schwarz (2014) explore the drivers of these price deviations and find that security-level illiquidity is the major source of relative mispricing.

As a last empirical exercise, we ask whether our measures capture the same aspect of illiquidity as indicators such as bid-ask spreads, trading volume, or the Amihud (2002) illiquidity measure, and whether they can be useful beyond standard market illiquidity measures to explain stock returns. These measures are generally argued to aggregate many types of market imperfections, including adverse selection costs and inventory costs (see e.g., Amihud and Mendelson (1980), Glosten and Milgrom (1985), and Kyle (1985)), thus their variation can hardly be purely attributed to changes in capital constraints. In contrast, our measures are likely to be free from many of these frictions. First, the illiquidity measures are calculated from closing mid prices and are hence not affected by bid-ask spreads. Second, they are calculated not from stock returns but bond yields. The latter are known to be explained by three factors only (level, slope, and curvature). Hence, adverse selection or inventory cost are unlikely to cause idiosyncratic deviations from a smooth yield curve.

2.1 Bond Data

We collect 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 6,001 observations in the time-series.

The bond data spans six different countries: Canada, Germany, Japan, the United Kingdom, the United States, and Switzerland.[10] We obtain a daily cross-section of end-

[10]The country choice is driven by two main considerations: First, data availability and second, credit risk considerations. For example, while there is enough data available on some Eurozone countries, these sovereign bonds feature quite a large credit risk component, especially after 2008 (see e.g., Pelizzon, Subrahmanyam, Tomio, and Uno (2014).

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.[11] 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 U.S. 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 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

[11] 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.

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.]

2.2 Stock Data

In order to assess the asset pricing implications of our proxies of illiquidity, 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.

We follow Frazzini and Pedersen (2013) to construct ex-ante betas for our dataset of international stocks 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):

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

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

2.3 Other Illiquidity Proxies

As alternative proxies for illiquidity or capital 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.

We also compare our proxies to Amihud (2002) market liquidity. We construct country-level Amihud illiquidity measures using our international stock data set. In line with the literature, we add a constant to the Amihud measure and take logs to reduce the impact of outliers. The measure is defined as:

$$\mathrm{Illiq}_{i,d} = \log\left(1 + \sum_d \frac{|r_{i,d}|}{P_{i,d}\mathrm{vol}_{i,d}}\right),$$

where $|r_{i,d}|$ is the absolute return of stock i on day d, $P_{i,d}$ is the price in local currency, $\mathrm{vol}_{i,d}$ is the trading volume in monetary units of local currency of stock i on day d, obtained by multiplying the number of shares traded by the closing price. Similar to Karolyi, Lee, and van Dijk (2012), we calculate $\mathrm{Illiq}_{i,t}$ for each stock based on daily data over a non-overlapping three-month rolling window. We first restrict the sample to stocks from major exchanges except for Japan where we use data from two exchanges (Osaka and Tokyo). We require that a stock has at least 10 valid daily observations (return and volume) during the three months. We delete stock days where the trading volume is below 100 USD and remove extreme observations manually. We use data from 1990 onwards except for Germany where we use data after 1999 because the daily trading volume are not available for most German stocks before that date.

2.4 Country-Level 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.[12]

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:

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

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.

[12] 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.

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:[13]

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

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).[14]

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

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

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 the 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.

3 Empirical Results

In this section we document the key time series and cross-sectional properties of our illiquidity measures and then use them to assess the effect of illiquidity on asset prices by testing the predictions of our international CAPM.

[13] 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.

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

3.1 Properties of Illiquidity

The time-series of all country-specific illiquidity measures, normalized to have zero mean and unit volatility, are plotted in Figure 1. In Panel A of Table 2, we report summary statistics. Overall, the average pricing errors are quite small, ranging from 2.8 basis points (bp) for the U.S. to 6.2 bp for Switzerland. The larger pricing errors also come with an overall larger volatility which ranges from 4.5 bp (Switzerland) to 1.37 bp (US).

[Insert Table 2 and Figure 1 here.]

Figure 2 depicts the time-series of our global illiquidity proxy, henceforth denoted illiq_t^G, calculated by taking a market capitalization weighted average of country-level illiquidity proxies in line with our theoretical model presented before.[15]

[Insert Figure 2 here.]

We think of the country-specific and global illiquidity measures as empirical proxies for ϕ_t^k and ϕ_t^G: Namely, investors' failure to correct larger mispricings of safe government bonds reflects tighter constraints on their ability to fund all their positions in a given country or globally. Recall that our stylized framework allows both for a time-series co-movement (through the shadow cost of margin constraints for the representative investor ψ_t) and cross-sectional dispersion (through the margin m_t^j required when borrowing against country j securities) in country-specific illiquidity.

The time-series variation in country-level illiquidity exhibits significant commonality. Pairwise correlations between illiquidity proxies reported in Panel B Table 2 are all

[15] 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 the average.

positive and range between 20% (US and Japan) and 74% (Germany and Japan). 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. Unsurprisingly, we find that all country-level measures co-move positively with the global illiquidity factor and that the latter explains a significant proportion of the variation in the country-level illiquidity with R^2 ranging between 39% and 66%. We note that the high unconditional correlation between country-level illiquidity is driven by a few crisis episodes. Figure 3 plots the average conditional correlation among the different illiquidity proxies.[16] 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%, but is significantly lower otherwise. This is perhaps not surprising, given that 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 also note an upward trend in the conditional correlation which could point towards more market integration.

[Insert Figure 3 here.]

More important for testing the implications of our model is the dispersion of illiquidity across countries. As can be seen from Table 2 the levels of country-level illiquidity are relatively close on average. In other words, there are no large permanent differences in illiquidity between the countries we consider. This is perhaps not surprising given that we include only developed financial markets in our analysis. However, illiquidity can become significantly dispersed when some countries experience idiosyncratic illiquidity episodes. Figure 4 reports the cross-sectional standard deviation of illiquidity measures.

[Insert Figure 4 here.]

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

Overall illiquidity exhibits significant country-specific variation: country- or region-specific events seem to be reflected in spikes in the respective local illiquidity measures that are not shared globally. 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. 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 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 5 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 Figure 5 here.]

Finally, we note that the global illiquidity 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. Another noteworthy observation is that there seems to be a downward trend which intuitively points towards the fact that over time more arbitrage capital has become available and hence, constraints are less binding.

3.2 Global Illiquidity and the Security Market Line

Using our illiquidity measures, we can now test the model predictions. Proposition 1 states that the slope of the average SML should depend negatively on the tightness of global margin constraints, while the intercept is positively related to it. 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 illiquidity risk. To this end, we consider Fama and MacBeth (1973) regressions where we regress excess returns on the basis assets on a constant and the portfolios' trailing-window post-ranking beta:

$$\mathrm{rx}_t^j = \alpha_t + \phi_t \times \beta_t^j + \epsilon_t^j,$$

where rx_t^j is the excess return of the j-th β-sorted portfolio and β_t^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:

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

where r_t^G, r_t^S and r_t^B 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 include 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 illiquidity 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 Local Illiquidity and Alpha

We now inspect how returns vary in the cross-section of illiquidity and beta-sorted stocks. Propositions 2 states that holding local illiquidity constant, a higher beta means lower alpha; holding beta constant, the alpha increases in the local illiquidity. Table 4 reports 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]

Proposition 3 builds on Propositions 2 and states that, everything else being equal, a BAB strategy should perform better in countries with higher local illiquidity. In order to test this proposition we 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 5.

[Insert Table 5 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.

Proposition 4 provides us with an alternative way to test the importance of country-level illiquidity. It states that a portfolio that is globally long high illiquidity-to-beta-ratio stocks and short sells low illiquidity-to-beta-ratio stocks (BAIL) should on average outperform the global betting-against-beta (BAB) portfolio. In order to test Proposition 4 we start by constructing the ratio between illiq_t^i and the estimated beta, $\hat{\beta}_t^i$ for each stock and then rank them in ascending order.[17] The ranked securities are assigned into two different bins: high illiquidity-to-beta stocks and low illiquidity-to-beta stocks. We long the former and short the latter. 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.

The summary statistics for the BAB and BAIL portfolios are presented in Table 4. In line with our 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, again the strategy performs worse then BAIL: the monthly alpha is 0.731%, or 8% lower.

[Insert Table 6 here.]

While the difference in excess returns and alpha of the BAB and BAIL portfolios over our whole sample has the sign predicted by the theory, it is not very large and results in similar Sharpe ratios. To gauge in more detail the differences of the two trading strategies over time, we plot in Figure 7 cumulative returns of the BAB and BAIL strategies for the past 10 years.[18] 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.[19] 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. 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 hit certain countries less than others.

[17]Note that with our illiquidity measures we are able to capture only one dimension along which the margins on stocks can differ, namely the country-level effect. We are agnostic about the other dimensions (e.g. industry) that could improve the sorting on illiquidity and thereby enhance the performance of the BAIL portfolio, and simply assume that the effect of any additional cross-sectional variation is averaged out at the country level.

[18]Time-series before 2003 look similar.

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

[Insert Figure 7 here.]

3.4 Comparison with Market Illiquidity

Of particular interest is the comparison of our results to the ones obtained using country-level stock market illiquidity computed following the methodology in Amihud (2002). For example, Brunnermeier and Pedersen (2009) argue that market and funding liquidity (which could arise due to capital constraints) should be tightly connected. It is therefore important to show that our results do not simply capture stock market liquidity effects that have been show to be important for asset prices (see e.g., Acharya and Pedersen (2005), Spiegel and Wang (2005), Avramov, Chordia, and Goyal (2006), Karolyi, Lee, and van Dijk (2012) among others).[20]

First, we note that the unconditional correlation between country-level Amihud and our illiquidity measures is positive and ranges between 10% (Germany) and 43% (US). In large part the correlation is driven by the 2008 period.[21] As a next step, we want to understand whether there is any variation in our illiquidity proxies which is not captured by the stock market illiquidity measure. To this end, we regress for each country our illiquidity measure onto the Amihud measure and take the residual to be our new illiquidity measure. We then repeat the same exercise as in section 3.3 and check whether there is any cross-sectional variation in returns when sorting on beta and the new illiquidity measure.

The results are reported in Table 7. In line with Proposition 2, we find that alphas decline from the low-beta to the high-beta portfolio and that alphas increase from low illiquidity to high illiquidity stocks: For example, holding illiquidity constant, we find that for low (high) illiquidity stocks, the alpha decreases from 0.772% to 0.510% (1.033% to 0.874%), and similarly, Sharpe ratios drop from 0.41 to 0.34 (0.87 to 0.50). On the other hand, keeping betas constant, we find that alphas increase from the low illiquidity

[20] Other possible measures include the Pástor and Stambaugh (2003) Gamma, the Zero measure by Lesmond, Ogden, and Trzcinka (1999) and the Hasbrouck (2004) Gibbs measure. Goyenko, Holden, and Trzcinka (2009) and Fong, Holden, and Trzcinka (2011) run horse races among different liquidity proxies and recommend the Amihud measure as a good proxy of illiquidity.

[21] To save space, we plot figures of other illiquidity measures in the Online Appendix.

stocks to high illiquidity stocks. For example, the alpha for low beta stocks increases from 0.772% per month to 1.033%, for medium beta it increases from 0.731% to 0.951% and for high beta stock it increases from 0.510% to 0.874%.[22] The last column presents the BAIL strategy returns. The alpha is 0.783% per month and statistically significant (t-statistic of 2.22) at the same time, the annualized Sharpe ratio is 0.59.

[Insert Table 7 here.]

3.5 Comparison with Other Illiquidity Measures

In the Online Appendix, we also compare our illiquidity proxies to other common measures of capital constraints. For example, there is an intimate link between funding liquidity and market volatility, and the causality of the relationship can possibly go in either direction.[23] Brunnermeier and Pedersen (2009) among others suggest the VIX index as a proxy for funding liquidity itself. In Section OA-2 of the Online Appendix, we compare our illiquidity proxies with country-level VIX for the longest time-series available.[24] We note that overall the correlation between the time-series is quite high ranging from 49% (Japan) to 66% (Germany and Switzerland).

In addition, we also test for Granger causality between our illiquidity, Amihud (2002) market illiquidity, and volatility in each country. The results yield that we find only limited evidence for causality linkages between our illiquidity and Amihud market illiquidity, which is perhaps not surprising given the relatively low correlation between them. We

[22] While these differences are even larger than in the non orthogonalized results presented in Table 4 note that the data sample is also shorter because of limited availability of volume data to calculate the Amihud (2002) measure.

[23] Hedegaard (2014) finds a large effect from margins onto volatility in the commodity market. Hardouvelis (1990) and Hardouvelis and Peristiani (1992), on the other hand, argue that more stringent margins lead to lower stock market volatility in the US and in Japan, respectively. While from a policy perspective it is interesting to study how margins affect volatility, the relationship can also go the opposite direction. For options and futures, margin requirements are set based on volatility itself. For example, the Chicago Mercantile Exchange (CME) uses the so called SPAN (Standard Portfolio Analysis of Risk) method that calculates the maximum likely loss that could be suffered by a portfolio. The method consists of 16 different scenarios which are comprised of different market prices and volatility.For more information see `http://www.cmegroup.com/clearing/files/span-methodology.pdf`. Similarly, on the London Stock Exchange, the initial margin is calculated based on the maximum loss according to volatility and investors' leverage.

[24] We did not find any data on a Canadian VIX.

find stronger support for volatility causing both stock market and our illiquidity, as well as a reverse causality link.

Finally, in Section OA-3 of the Online Appendix, we compare our global proxy with a range of other illiquidity measures that are not available for countries other than the US. The unconditional correlation ranges between 4% (Fontaine and Garcia (2012) measure) and 65% (Goyenko, Subrahmanyam, and Ukhov (2011) proxy).

4 Conclusion

This paper investigates the effect of capital constraints on asset returns across different countries. We construct daily country-specific illiquidity proxies from pricing deviations on government bonds. While the overall correlation between the country-specific measures is high, the measures display distinct idiosyncratic behavior especially during country-specific political or economic events. The average level of illiquidity and the difference in illiquidity across countries have an important effect on asset prices. In line with the prediction of a parsimonious international CAPM with constraints, higher global illiquidity affects the international risk-return trade-off by lowering the slope and increasing the intercept of the average international security market line. In the same way, the differences in local illiquidity are associated with significant differences in alpha: trading strategies that condition on illiquidity yield attractive returns with highly significant alpha and Sharpe ratios.

Our country-specific illiquidity proxies can be used in several related avenues. Idiosyncratic variation in the cross-section of illiquidity could be applied to test market segmentation. Further, it is possible to study whether innovations in global and local illiquidity are priced risk factors when explaining the cross-section of international stock returns. We leave these tasks for future research.

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Appendix A Proofs and derivations

Proof of Theorem 1. Combining (1) and (2), the Lagrangian of investor i is given by

$$\max_{x_{i,t}} x_{i,t}^{\top}\left(\mathbb{E}_t\left[D_{t+1}+P_{t+1}\right]-P_t\right)-\frac{\gamma_i}{2}x_{i,t}^{\top}\Omega_t x_{i,t}-\psi_{i,t}\left(\sum_{k,s} m_{i,t}^k\left|x_{i,t}^{k,s}\right|P_t^{k,s}-W_{i,t}\right), \tag{A-1}$$

where $\psi_{i,t}$ is the Lagrange multiplier associated with (2). Equation (A-1) yields the first-order condition, and rearranging gives (3). Substituting (3) into the market-clearing condition $\sum_i x_{i,t}^{k,s}=\theta_t^{k,s}$ we obtain (4), or in vector form:

$$P_t=\left(\mathbf{1}+\sum_i \frac{\gamma}{\gamma_i}\psi_{i,t}\mathbf{sgn}\left(x_{i,t}\right)\mathbf{m}_{i,t}\right)^{-1}\left[\mathbb{E}_t\left[D_{t+1}+P_{t+1}\right]-\gamma\Omega_t\theta_t\right], \tag{A-2}$$

where $\mathbf{1}$ is the identity matrix. Substituting it back into (3) and rearranging, we obtain the equilibrium holdings

$$x_{i,t}=\frac{1}{\gamma_i}\left(\gamma\theta_t+\Omega_t^{-1}\left[\sum_j \frac{\gamma}{\gamma_j}\psi_{j,t}\mathbf{sgn}\left(x_{j,t}\right)\mathbf{m}_{j,t}-\psi_{i,t}\mathbf{sgn}\left(x_{i,t}\right)\mathbf{m}_{i,t}\right]P_t\right),$$

and from here, if the technical condition is satisfied, we obtain

$$x_{i,t}=\frac{1}{\gamma_i}\left(\gamma\theta_t+\Omega_t^{-1}\left[\sum_j \frac{\gamma}{\gamma_j}\psi_{j,t}\mathbf{m}_{j,t}-\psi_{i,t}\mathbf{m}_{i,t}\right]P_t\right)>0$$

and

$$P_t^{k,s}=\frac{\mathbb{E}_t\left[D_{t+1}^{k,s}+P_{t+1}^{k,s}\right]-\gamma\mathbf{1}^{k,s}\Omega_t\theta_t}{1+\sum_i\frac{\gamma}{\gamma_i}\psi_{i,t}m_{i,t}^k}.$$

Denote the net return on security s by $r_{t+1}^{k,s}$ and the net return on the global market portfolio by r_{t+1}^G, that is

$$r_{t+1}^{k,s}=\frac{D_{t+1}^{k,s}+P_{t+1}^{k,s}-P_t^{k,s}}{P_t^{k,s}} \text{ and } r_{t+1}^G=\sum_{k,s} r_{t+1}^{k,s}\frac{\theta_t^{k,s}P_t^{k,s}}{\theta_t^{\top}P_t}.$$

Then, expected returns are

$$\mathbb{E}_t\left[r_{t+1}^{k,s}\right]=\sum_i\frac{\gamma}{\gamma_i}\psi_{i,t}m_{i,t}^k+\frac{1}{P_t^{k,s}}\gamma\mathbf{1}^{k,s}\Omega_t\theta_t=\phi_t^k+\frac{1}{P_t^{k,s}}\gamma\mathbf{1}^{k,s}\Omega_t\theta_t, \tag{A-3}$$

and aggregating across all securities with weights $\theta_t^{k,s}P_t^{k,s}/\theta_t^{\top}P_t$, we obtain the expected global market return

$$\mathbb{E}_t\left[r_{t+1}^G\right]=\sum_{k,s}\phi_t^k\frac{\theta_t^{k,s}P_t^{k,s}}{\theta_t^{\top}P_t}+\frac{1}{\theta_t^{\top}P_t}\gamma\theta_t^{\top}\Omega_t\theta_t=\phi_t^G+\frac{1}{\theta_t^{\top}P_t}\gamma\theta_t^{\top}\Omega_t\theta_t. \tag{A-4}$$

On the other hand

$$Cov_t\left(r^{k,s}_{t+1}, r^G_{t+1}\right) = \frac{1}{P^{k,s}_t}\frac{1}{\theta^\top_t P_t} Cov_t\left(D^{k,s}_{t+1} + P^{k,s}_{t+1}, \theta^T_t\left(D_{t+1} + P_{t+1}\right)\right) = \frac{1}{P^{k,s}_t}\frac{1}{\theta^\top_t P_t}\mathbf{1}^{k,s}\Omega_t\theta_t \tag{A-5}$$

and

$$Var_t\left(r^G_{t+1}\right) = \frac{1}{\left(\theta^T_t P_t\right)^2} Var_t\left(\theta^T_t\left(D_{t+1} + P_{t+1}\right)\right) = \frac{1}{\left(\theta^T_t P_t\right)^2}\theta^T_t\Omega_t\theta_t, \tag{A-6}$$

thus security betas are given by

$$\beta^{k,s}_t = \frac{Cov_t\left(r^{k,s}_{t+1}, r^G_{t+1}\right)}{Var_t\left(r^G_{t+1}\right)} = \frac{\theta^T_t P_t}{P^{k,s}_t}\frac{\mathbf{1}^{k,s}\Omega_t\theta_t}{\theta^T_t\Omega_t\theta_t}. \tag{A-7}$$

Combining (A-3), (A-4) and (A-7), we obtain (5). □

Proof of Propositions 3 and 4. Suppose an investor creates a market-neutral portfolio by going long a security or a portfolio with beta β^L_t and illiquidity ϕ^L_t, and going short a security or portfolio with beta β^S_t and illiquidity ϕ^S_t, and applying leverages of $1/\beta^L$ and $1/\beta^S$ to the two legs, respectively. From (5), the expected return on this long-short portfolio is:

$$E_t\left[r^{\text{L-S}}_{t+1}\right] = \frac{1}{\beta^L_t}E_t\left[r^L_{t+1}\right] - \frac{1}{\beta^S_t}E_t\left[r^S_{t+1}\right] = \left(\lambda_t + \frac{\phi^L_t}{\beta^L_t} - \phi^G_t\right) - \left(\lambda_t + \frac{\phi^S_t}{\beta^S_t} - \phi^G_t\right) = \frac{\phi^L_t}{\beta^L_t} - \frac{\phi^S_t}{\beta^S_t}. \tag{A-8}$$

It is easy to see that if both legs are constructed from assets of the same country k, and the long part consists of low-beta securities while the portfolio goes short in high-beta securities, we obtain a BAB portfolio of country k with expected return

$$E_t\left[r^{k,\text{BAB}}_{t+1}\right] = \phi^k_t\left(\frac{1}{\beta^L_t} - \frac{1}{\beta^S_t}\right) > 0.$$

Keeping the term in the parentheses constant, the return of the country-k BAB portfolio is increasing in ϕ^k_t, which confirms Proposition 3. In the meantime, a global BAB portfolio that goes long in low-beta assets and short in high-beta assets maximizes $1/\beta^L_t - 1/\beta^S_t$, but by ignoring illiquidity, might not maximize the right-hand side of (A-8). It can therefore be dominated by a BAIL strategy that goes long assets with the highest ϕ^L_t/β^L_t possible and goes short in assets with the lowest ϕ^S_t/β^S_t possible. This confirms Proposition 4. □

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 illiquidity proxy (illiq). To estimate the term structure, we use bonds of maturities ranging from 3 months to 10 years. To calculate the illiquidity 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	10,891	2,385	1,149	2,951	945	3,105	356
Average Number of Traded Stocks	3,973	1,082	323	560	309	1,567	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
Excess Return 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	illiq	ts	illiq	ts	illiq	ts	illiq	ts	illiq	ts	illiq
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.

Panel A: Summary Statistics

	US	GE	UK	CA	JP	SW
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

	US	GE	UK	CA	JP	SW
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:

$$\begin{aligned}\alpha_t &= a_1 + b_1 r_t^G + c_1 r_t^S + d_1 r_t^B + e_1 \mathrm{Illiq}_{t-1}^G + u_{1,t},\\ \phi_t &= a_2 + b_2 r_t^G + c_2 r_t^S + d_2 r_t^B + e_2 \mathrm{Illiq}_{t-1}^G + u_{2,t},\end{aligned}$$

where r_t^G, 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
Illiquidity and Beta Sorted Portfolios

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 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. 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	
	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
t-stat	(2.40)	(1.87)	(1.28)	(2.41)	(2.10)	(1.75)
CAPM Alpha	0.527	0.471	0.395	0.547	0.540	0.522
t-stat	(2.80)	(2.08)	(1.24)	(3.06)	(2.83)	(2.10)
Beta (ex ante)	0.56	1.02	1.51	0.63	1.01	1.54
Beta (realized)	0.61	0.85	1.23	0.77	0.99	1.16
Volatility (annualized)	14.8	17.8	24.2	15.6	18.5	22.2
Sharpe Ratio (annualized)	0.49	0.39	0.28	0.50	0.44	0.37

Table 5
High versus Low Illiquidity BABs

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

Table 6
BAIL versus BAB

This table reports estimated excess returns and alphas for the BAIL and BAB trading strategies. 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). Alphas are in monthly percent and t-statistics are adjusted according to Newey and West (1987). Data runs from January 1990 to December 2012.

	BAB	BAIL
Excess Returns	0.741	0.827
t-stat	(3.51)	(3.53)
CAPM alpha	0.731	0.791
t-stat	(2.48)	(3.53)
Volatility (annualized)	12.1	13.5
Sharpe Ratio (annualized)	0.73	0.73

Table 7
Illiquidity and Beta Sorted Portfolios Orthogonalized

This table reports portfolio returns of illiquidity-to-beta sorted portfolios where illiquidity measures have been orthogonalized with respect to the Amihud (2002) market illiquidity measure. 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. 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. Using these orthogonalized illiquidity measures, we build a BAIL strategy that is long the high illiquidity to beta stocks and short the low illiquidity to beta stocks.

	Low Illiq			High Illiq			
	low β	mid β	high β	low β	mid β	high β	BAIL
Excess Return	0.521	0.745	0.794	0.887	0.963	1.056	0.783
t-stat	(1.53)	(1.69)	(1.27)	(3.26)	(2.51)	(1.85)	(2.21)
CAPM Alpha	0.772	0.731	0.510	1.033	0.951	0.874	0.783
t-stat	(2.29)	(2.36)	(1.80)	(3.52)	(4.32)	(5.06)	(2.22)
Beta (ex-ante)	0.53	0.87	1.41	0.56	0.88	1.39	0
Beta (realized)	0.51	0.85	1.44	0.57	0.86	1.33	0.14
Volatility (annualized)	15.3	19.6	28.0	12.1	17.2	25.5	15.8
Sharpe Ratio (annualized)	0.41	0.45	0.34	0.87	0.67	0.50	0.59

Appendix C Figures

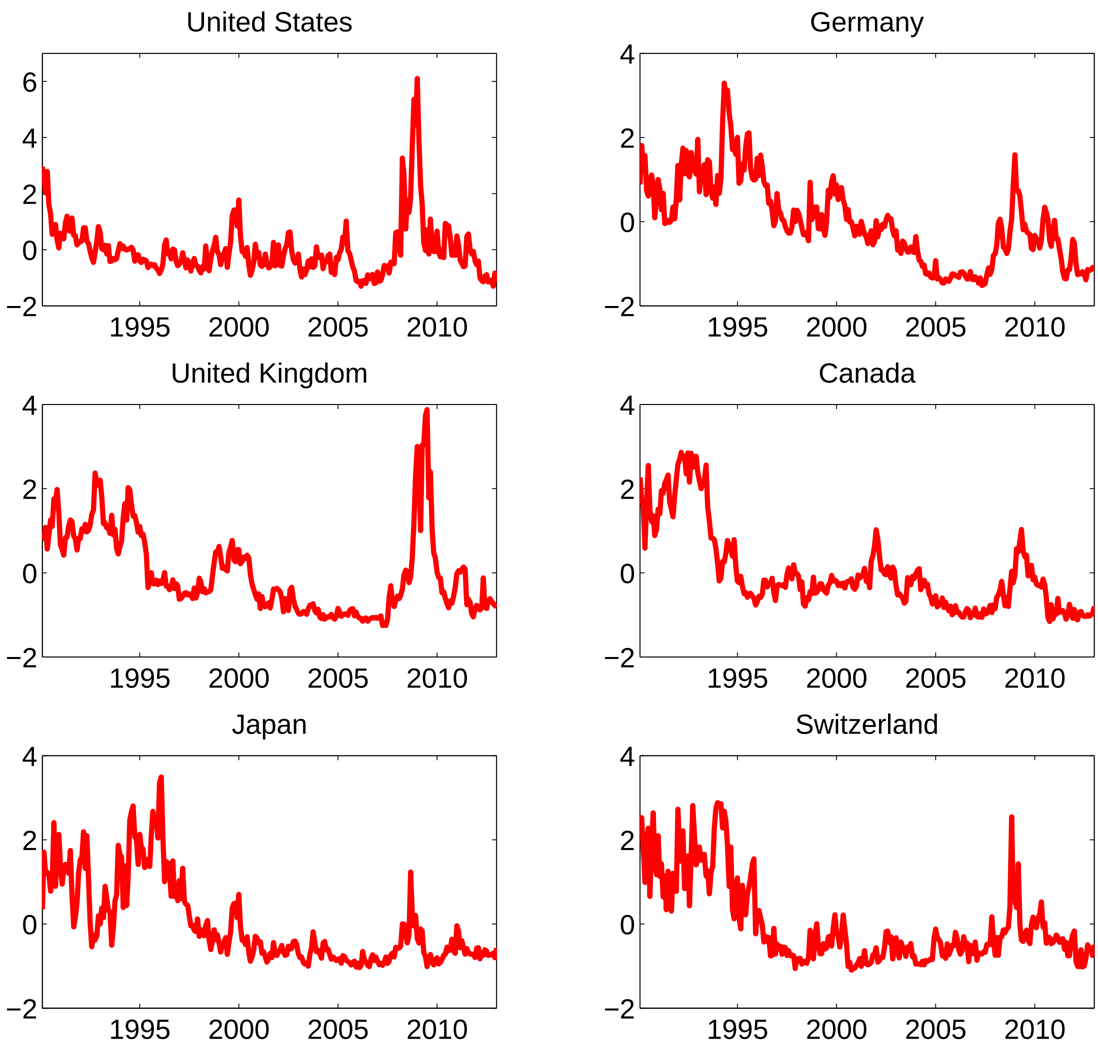

Figure 1. Illiquidity Measures All Countries

This figure plots country-level illiquidity proxies for six different countries: United States, Germany, United Kingdom, Canada, Japan, and Switzerland. The time-series are normalized to have zero mean and unit volatility. Data is monthly and runs from January 1990 to December 2012.

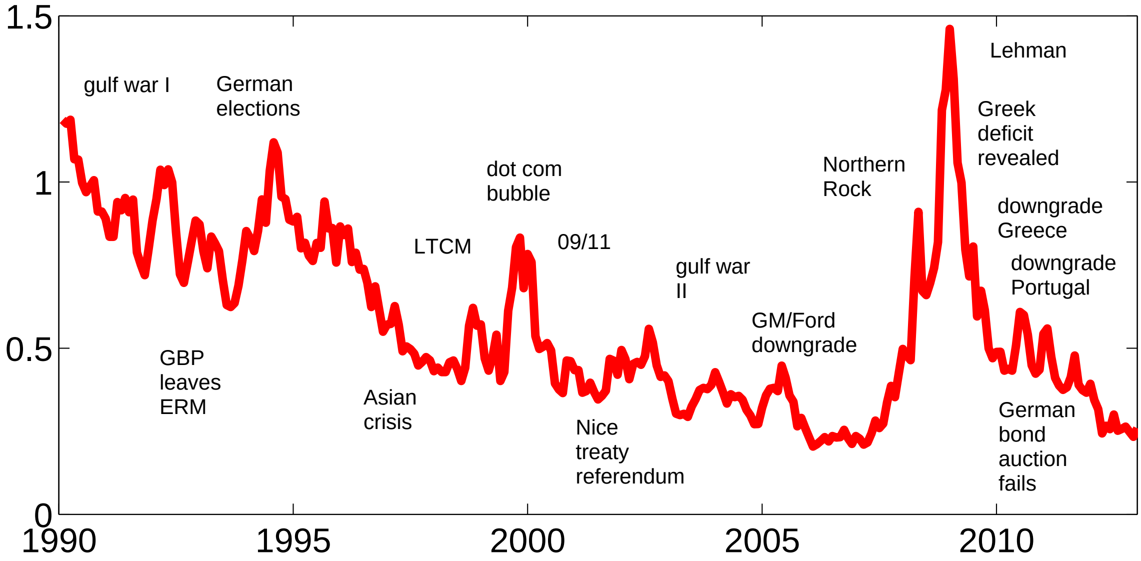

Figure 2. Global Funding Illiquidity

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.

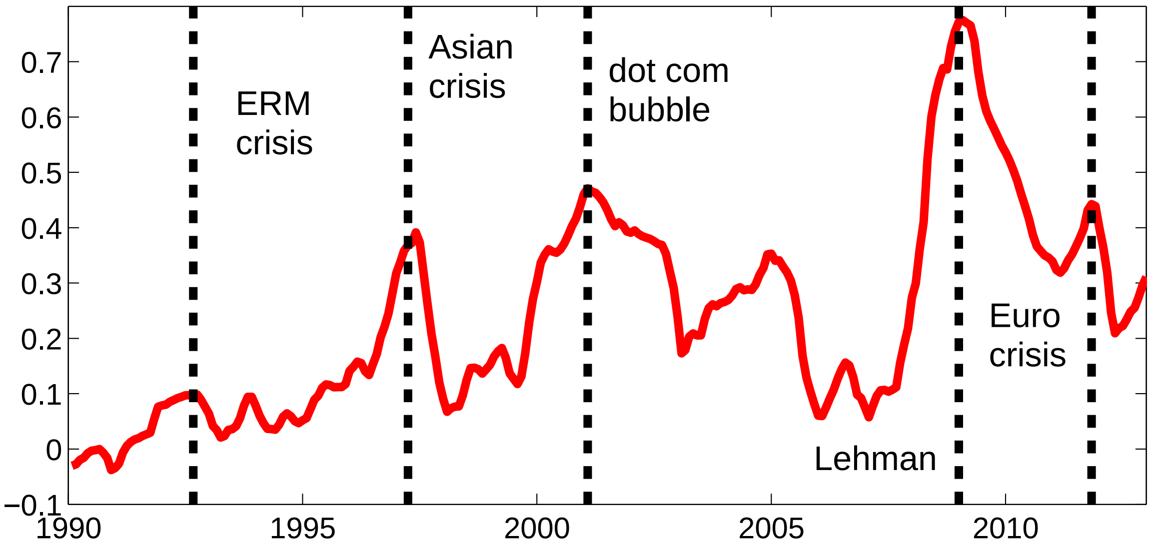

Figure 3. Average Conditional Correlation of Country-Specific Illiquidity Measures

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.

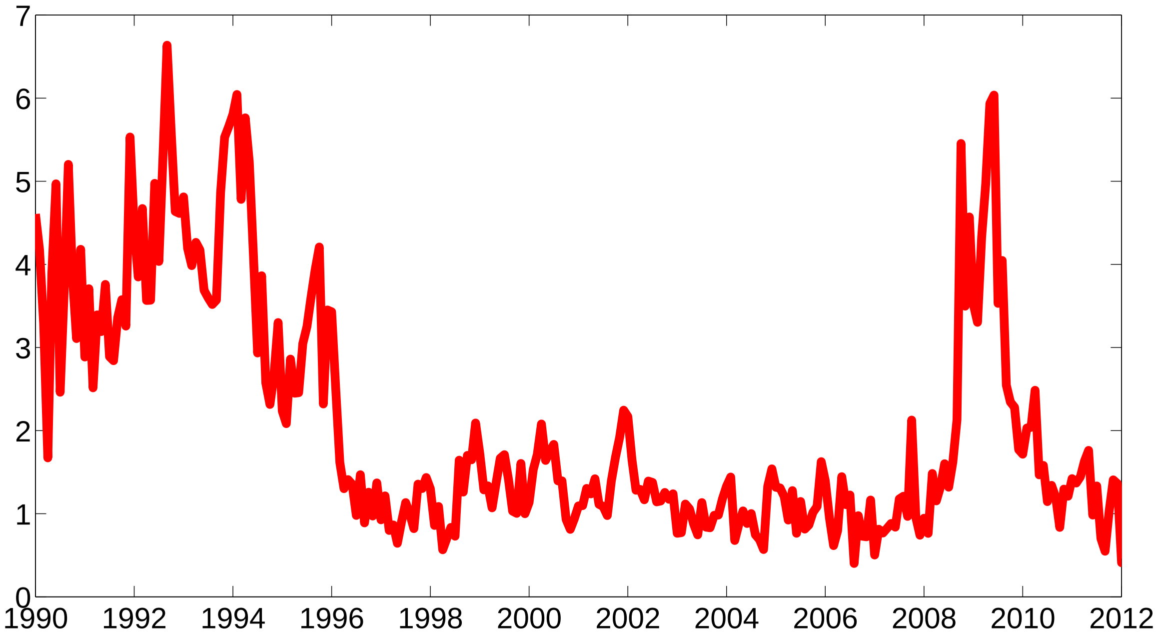

Figure 4. Cross-Sectional Standard Deviation of Country-Specific Illiquidity Measures

This figure present the cross-sectional standard deviation of country-specific illiquidity measures (Germany, Canada, United Kingdom, US, Japan, and Switzerland). The standard deviations are calculated monthly, the data runs from January 1990 to December 2012.

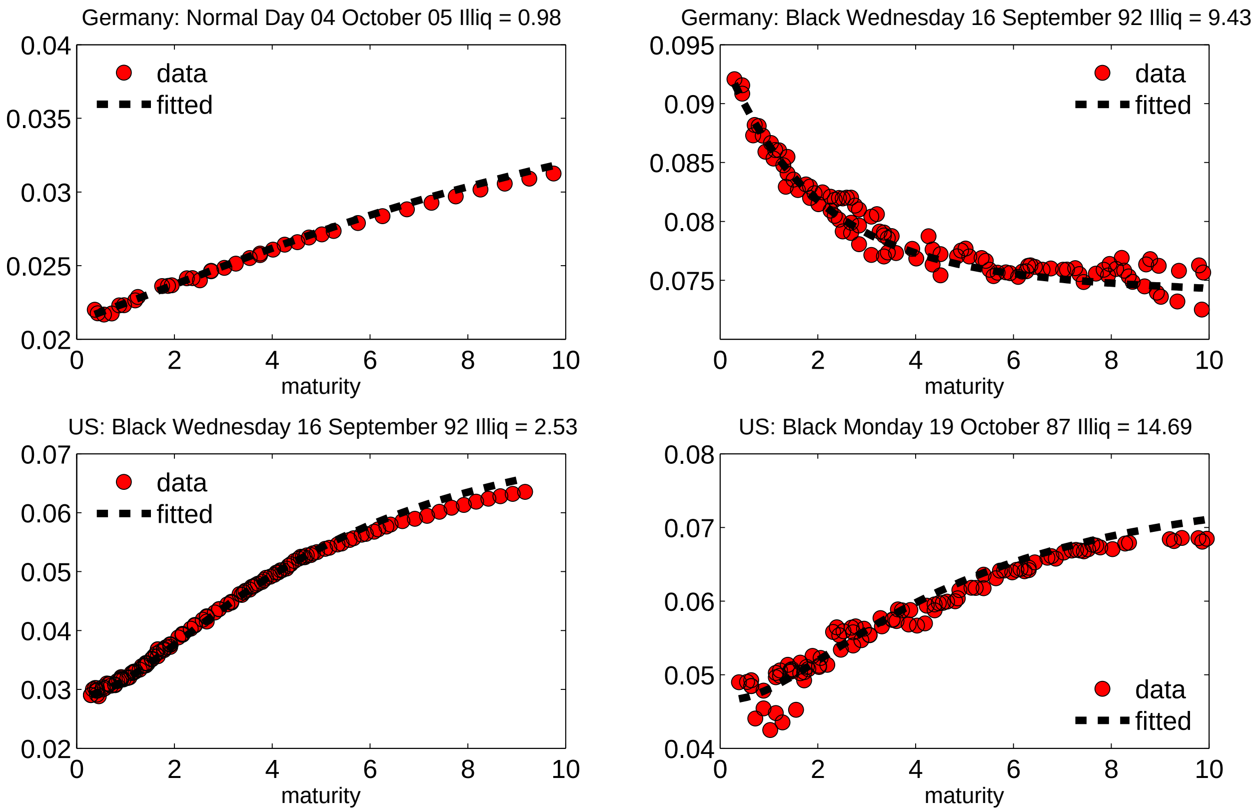

Figure 5. International Term Structures Different Days

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

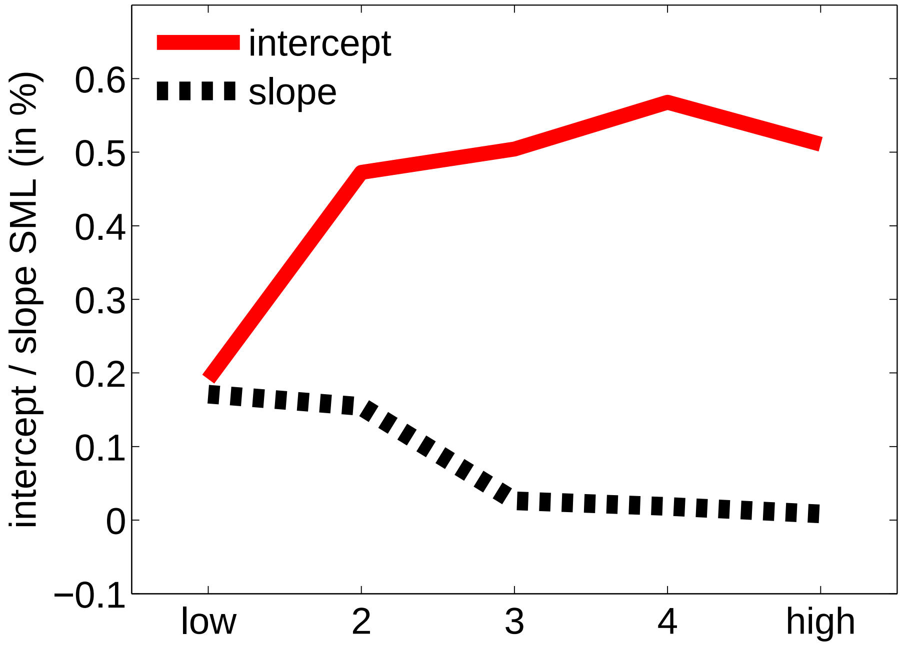

Figure 6. Intercept and Slope Security Market Line

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.

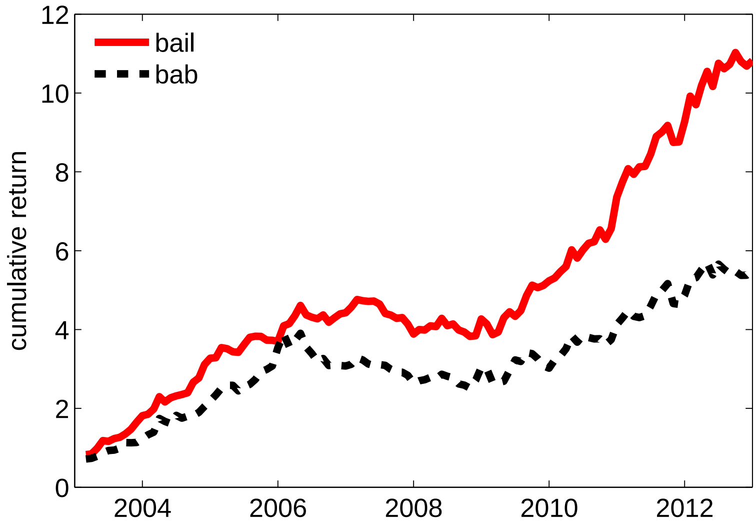

Figure 7. BAIL versus BAB cumulative returns

This figure plots the cumulative return of BAIL and BAB. Data is monthly and starts in 2003 and ends in 2012.

Online Appendix to "International Illiquidity"

This online appendix contains three sections. We first study how our country-level illiquidity proxies are related to country-level illiquidity measures using the methodology in Amihud (2002). We then study how the country-level illiquidity proxies are related to measures of country-level VIX. In the last section, we compare our global illiquidity proxies to other common proxies of illiquidity extracted from bond and stock markets.

Appendix OA-1 Comparison with Amihud (2002) Illiquidity Measures

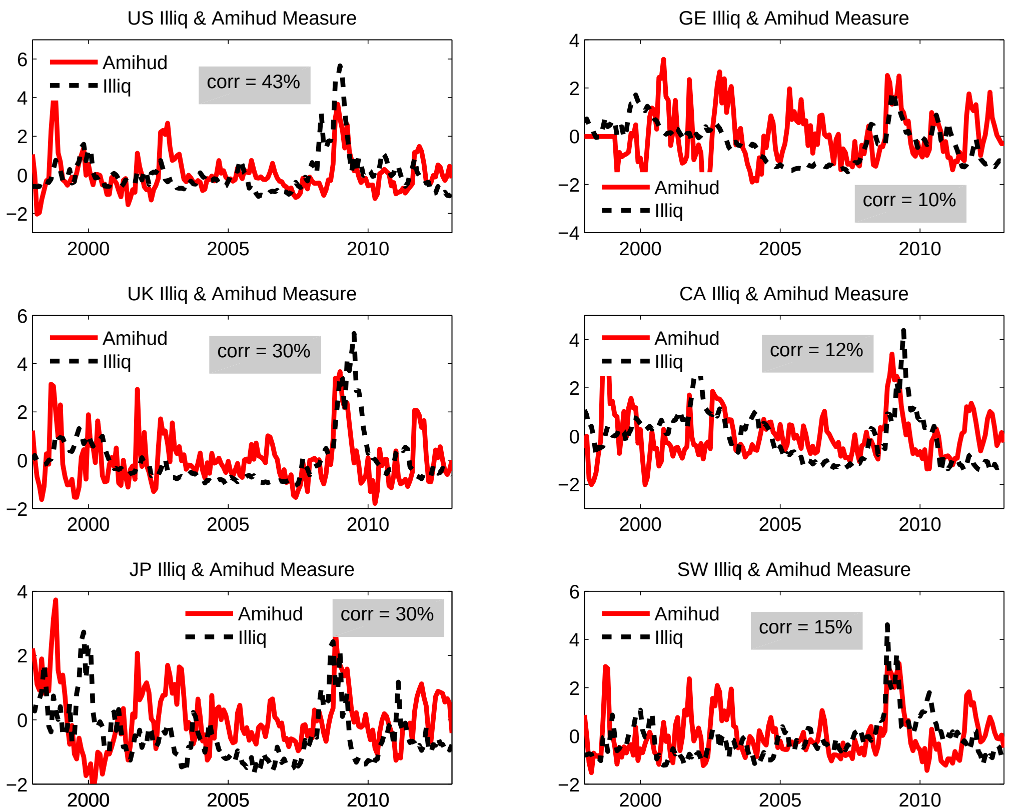

Figure OA-1. Illiquidity Proxies and Amihud Measure

This figure plots our illiquidity proxies together with country-level Amihud (2002) illiquidity measures.

Value-weighted averages of the Amihud illiquidity measures are plotted in Figure OA-1 together with our illiquidity proxies. We note that overall correlations between the two measures vary a lot. For example, correlations range from as little as 10% for Germany to 43% for the US. We also note that the correlations seem to be come stronger after 2008, when the two measures co-move more.

Appendix OA-2 Comparison with Country-Level VIX

There is an intimate link between margins and market volatility. Per a Congressional mandate, margins on stocks have been controlled by the Federal Reserve since 1934. The objective of this regulation includes curbing excessive leverage and reducing the stock price volatility. However, empirical evidence on the relationship between margins and stock market volatility is often ambiguous. On the one hand, Schwert (1989) and Hsieh and Miller (1990) find no effect from margin requirements as set by the Federal Reserve on prices but find that market volatility tends to increase together with margins. More recently, Hedegaard (2014) finds a large effect from margins onto volatility in the commodity market. Hardouvelis (1990) and Hardouvelis and Peristiani (1992), on the other hand, argue that more stringent margins lead to lower stock market volatility in the US and in Japan, respectively.

While from a policy perspective it is interesting to study how margins affect volatility, the relationship can also go the opposite direction. For options and futures, margin requirements are set based on volatility itself. For example, the Chicago Mercantile Exchange (CME) uses the so called SPAN (Standard Portfolio Analysis of Risk) method that calculates the maximum likely loss that could be suffered by a portfolio. The method consists of 16 different scenarios which are comprised of different market prices and volatility.* Similarly, on the London Stock Exchange, the initial margin is calculated based on the maximum loss according to volatility and investors' leverage.

One natural question that arises is obviously whether and how the illiquidity measures relate to proxies of conditional market volatility. In the following, we study the relationship between country-level VIX proxies and our illiquidity measures. The reason why we look at the VIX rather than say conditional volatility measures using country-level returns, is because the VIX is often used as a proxy for funding illiquidity itself (see e.g., Brunnermeier and Pedersen (2009)).

Figure OA-2 plots the illiquidity proxies together with country-level VIX for the longest time-series available.† We note that overall the correlation between the time-series is quite high ranging from 49% (Japan) to 66% (Germany and Switzerland).

Appendix OA-2.1 Causality

In the following, we study in more detail the relationship between stock volatility, Amihud and our illiquidity measure. A priori, the causality between the three variables could go either way. For example, a crash in market prices could impose greater constraint on traders' resources (i.e. funding liquidity) and consequently traders are less able to provide liquidity to the market. As funding liquidity declines, so does market liquidity. This however generates a liquidity spiral: reduced market liquidity pushes prices down and worsens the funding problem which again reduces market liquidity and increases market volatility as market conditions deteriorate. We look at this relationship by performing Granger causality tests using a vector autoregression (VAR) framework. Table OA-1 reports the results.

- **Illiquidity ⇒ Volatility and Amihud:** We find that for the US and Switzerland, we reject the null that illiquidity does not Granger cause volatility and for the US and Japan we reject the null that Illiquidity does not cause the Amihud illiquidity.

*For more information see `http://www.cmegroup.com/clearing/files/span-methodology.pdf`.
†We did not find any data on a Canadian VIX.

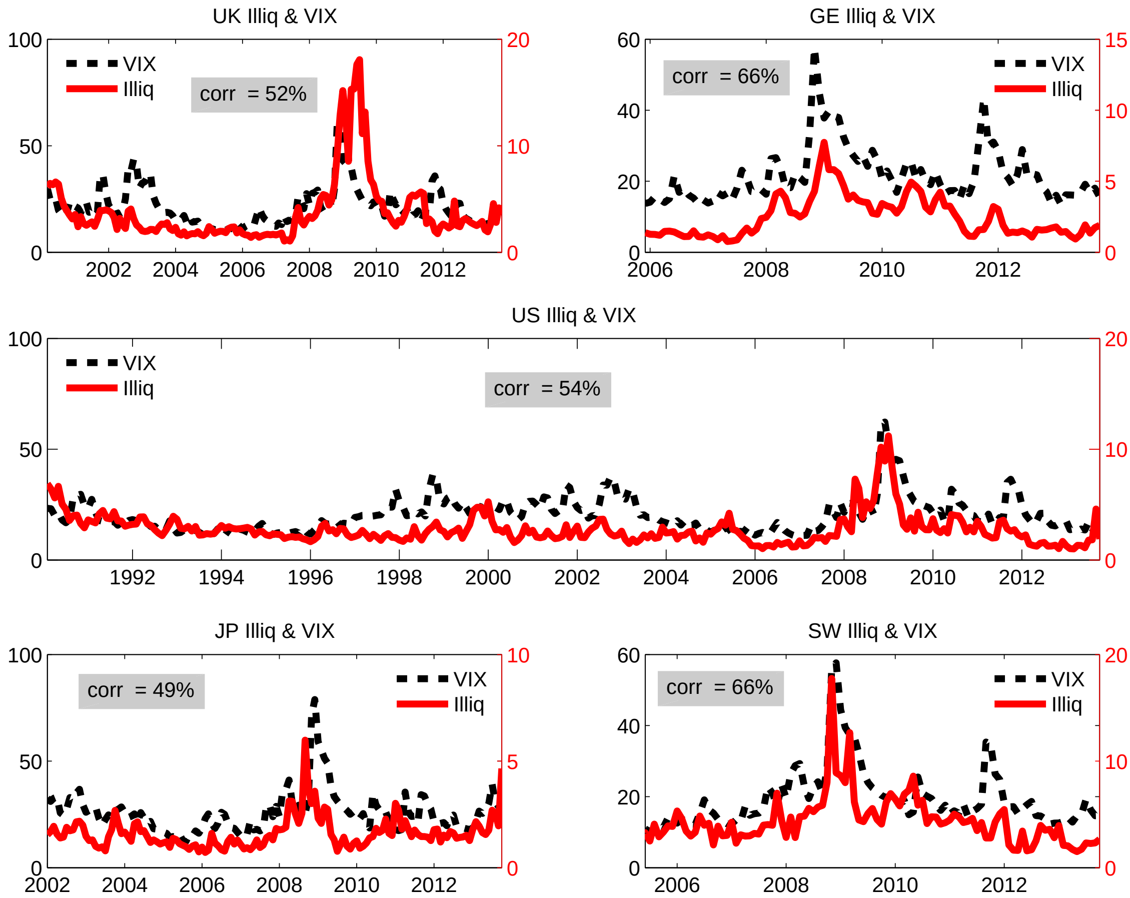

Figure OA-2. Illiquidity Proxies and Country-Level VIX

This figure plots monthly country-level VIX together with the illiquidity proxies. Data is monthly and starts in January 1990 (US), February 1992 (GE), February 2000 (UK), February 2001 (JP), May 2005 (SW) and ends in December 2012.

- **Volatility $\Rightarrow$ Illiquidity and Amihud:** We reject the null of no Granger causality between volatility and illiquidity (Amihud) for US, Germany and United Kingdom (US and United Kingdom).
- **Amihud $\Rightarrow$ Illiquidity and Volatility:** We reject the null of no Granger causality from the Amihud illiquidity proxy onto our illiquidity proxy (volatility) for the UK only (US, Germany and UK).

Appendix OA-3 Comparison Funding Proxies Others

In the following, we compare different proxies of illiquidity used in the literature with our global illiquidity measure.

Table OA-1
Granger Causality Test

This table shows Granger causality tests between illiquidity, the Amihud measure and the country-level VIX. We test whether the row variable does not Granger cause the column variable. We report the χ^2 and p-value (in parentheses) for each pair. The optimal lag length is chosen according to the Schwartz criterion.

		US				GE	
	Illiq	VIX	Amihud		Illiq	VIX	Amihud
Illiq		4.27	3.84	Illiq		0.06	0.018
		(0.02)	(0.02)			(0.94)	(0.98)
VIX	3.84		7.69	VIX	2.79		0.52
	(0.02)		(0.00)		(0.06)		(0.59)
Amihud	1.73	3.50		Amihud	0.29	4.16	
	(0.18)	(0.03)			(0.74)	(0.01)	
		CA				UK	
	Illiq	VIX	Amihud		Illiq	VIX	Amihud
Illiq			0.52	Illiq		0.11	0.89
			(0.60)			(0.89)	(0.40)
VIX				VIX	7.22		2.61
					(0.00)		(0.08)
Amihud	1.95			Amihud	8.26	3.66	
	(0.14)				(0.00)	(0.02)	
		JP				SW	
	Illiq	VIX	Amihud		Illiq	VIX	Amihud
Illiq		0.61	2.76	Illiq		3.86	1.94
		(0.55)	(0.06)			(0.02)	(0.15)
VIX	0.05		0.19	VIX	1.66		1.15
	(0.95)		(0.83)		(0.20)		(0.32)
Amihud	0.07	0.35		Amihud	1.02	1.02	
	(0.93)	(0.71)			(0.36)	(0.36)	

- Goyenko, Subrahmanyam, and Ukhov (2011), Goyenko (2013), and Goyenko and Sarkissian (2014) calculate the illiquidity of off-the-run T-Bills with maturities between 6 and 12 months. Illiquidity is the average spread between ask and bid prices scaled by the mid-point. The monthly average spread is then computed for each security and then equal weighted across different assets for each month.

- Based on theory in Vayanos (2004), Fontaine and Garcia (2012) extract a latent liquidity premium from estimating a term structure model from a panel of pairs of US Treasury securities where each pair has similar cash flows but different ages. The intuition is that older bonds are less liquid.

- The US VIX is often used as a proxy of funding illiquidity (see e.g., Brunnermeier and Pedersen (2009)). We also look at Treasury implied volatility (TIV) constructed in Mueller, Vedolin, and Choi (2013). The TIV is akin to the VIX and represents a model-free implied volatility measure from one-month options written on 30-year Treasury futures.

- The TED spread is the difference between the three-month Eurodollar deposit yield (LIBOR) and three-month US T-Bills.

- The global Amihud illiquidity proxy is constructed in a similar way as our global illiquidity proxy by weighting each country specific Amihud illiquidity proxy by its GDP and then aggregate it to the global measure.

The different time-series are plotted in Figure OA-3. We note that all proxies tend to increase during crisis periods such as the 2008 financial crisis. The unconditional correlation between the different proxies and our global can be as big as 65% (Goyenko, Subrahmanyam, and Ukhov (2011) proxy) and as low as 4% (Fontaine and Garcia (2012) measure).

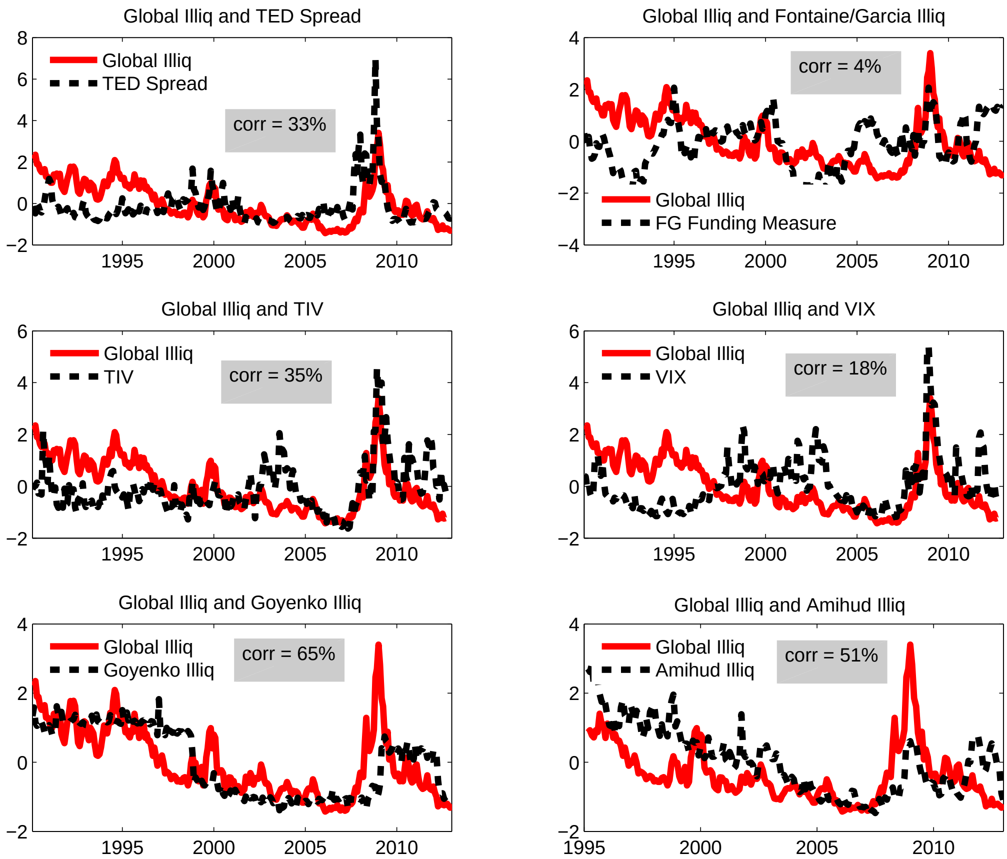

Figure OA-3. Global Illiquidity Proxy and Other Funding Measures

This figure plots monthly global illiquidity together with different proxies of illiquidity such as the TED spread (upper left panel), the Fontaine and Garcia funding measure (upper right panel), Treasury implied volatility (middle left panel), US VIX (middle right panel), the Goyenko, Subrahmanyam, and Ukhov (2011) illiquidity proxy (lower left panel) and a global Amihud illiquidity proxy (lower right panel). All variables are normalized, i.e. they are de-meaned and have a standard deviation of one.