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ABSTRACT

Given the cross-sectional and temporal variation in their liquidity, emerging equity markets provide an ideal setting to examine the impact of liquidity on expected returns. Our main liquidity measure is a transformation of the proportion of zero daily firm returns, averaged over the month. We find that our liquidity measures significantly predict future returns, whereas alternative measures such as turnover do not. Consistent with liquidity being a priced factor, unexpected liquidity shocks are positively correlated with contemporaneous return shocks and negatively correlated with shocks to the dividend yield. We consider a simple asset pricing model with liquidity and the market portfolio as risk factors and transaction costs that are proportional to liquidity. The model differentiates between integrated and segmented countries and periods. Our results suggest that local market liquidity is an important driver of expected returns in emerging markets, and that the liberalization process has not eliminated its impact.

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1 Introduction

It is generally acknowledged that liquidity is important for asset pricing. Illiquid assets and assets with high transaction costs trade at low prices relative to their expected cash flows, that is, average liquidity is priced, see, for example, Amihud and Mendelson (1986), Brennan and Subrahmanyam (1996), Datar, Naik and Radcliffe (1998), and Chordia, Roll and Anshuman (2001). Liquidity also predicts future returns and liquidity shocks are positively correlated with return shocks (see Chordia, Roll and Subrahmanyam (2002), Jones (2002), and Amihud (2002)). Furthermore, if liquidity varies systematically (see Chordia, Roll, and Subrahmanyam (2000) and Huberman and Halka (1993)), securities with returns positively correlated with market liquidity should have high expected returns (see Pastor and Stambaugh (2002) and Sadka (2005) for recent empirical work). Acharya and Pedersen (2002) develop a stylized model that leads to three different risk premia associated with changes in liquidity and find these risk premia to be highly significant in U.S. data.[1]

Surprisingly, the growing body of research on liquidity primarily focuses on the United States, arguably the most liquid market in the world. In contrast, our research focuses on markets where liquidity effects may be particularly strong, namely emerging markets. In a 1992 survey by Chuhan, poor liquidity was mentioned as one of the main reasons that prevented foreign institutional investors from investing in emerging markets. If the liquidity premium is an important feature of these data, the focus on emerging markets should yield particularly powerful tests and useful independent evidence.

In addition, many emerging markets underwent a structural break during our sample that likely affected liquidity, namely equity market liberalization.[2] These liberalizations give foreign investors the opportunity to invest in domestic equity securities and domestic investors

[1]There is a vast theoretical literature on liquidity which starts with Kyle (1985), Glosten and Milgrom (1985), Easley and O'Hara (1987) and Admati and Pfleiderer (1988). Models linking liquidity to expected returns and other variates include Amihud and Mendelson (1986), Constantinides (1986), Grossman and Miller (1988), Heaton and Lucas (1996), Vayanos (1998), Lo, Mamaysky and Wang (2001), Holmstrom and Tirole (2002), Eisfeldt (2002), Huang (2003), and O'Hara (2003).

[2]Bekaert, Harvey, and Lumsdaine (2001) show that many macroeconomic and financial time-series show evidence of a break around such liberalizations.

the right to transact in foreign equity securities. This provides an additional verification of the importance of liquidity for expected returns, since, all else equal (including the price of liquidity risk), the importance of liquidity for expected returns should decline post liberalization. This is important, since when focusing on the U.S. alone, the finding of expected return variation due to liquidity can always be ascribed to an omitted variable correlated with a liquidity proxy. After all, there are a priori reasons to suspect relatively small liquidity effects in the U.S. The U.S. market is vast in the number of traded securities and it has a very diversified ownership structure, combining long-horizon investors (less subject to liquidity risk) with short-term investors. Hence, we may observe clientele effects in portfolio choice that mitigate the pricing of liquidity. Such diversity in securities and ownership is lacking in emerging markets, potentially strengthening liquidity effects. Moreover, as an important side-benefit, we can test whether improved liquidity contributes to the decline in the cost of capital post-liberalization that is documented by, for example, Bekaert and Harvey (2000).

There are some serious obstacles to our analysis. First, the data in emerging markets are of relatively poor quality, and detailed transaction data (bid-ask spreads, for example) are not widely available. For example, Domowitz, Glen, and Madhavan (2001) explore trading costs and liquidity in an international context for many countries, but they are forced to focus on trade level data, provided by Elkins/McSherry Inc., over a two year period. Similarly, Jain (2002) explores the relation between equity market trading design and liquidity across various countries, but uses a hand collected time-series of bid-ask spreads spanning only several months. Second, from the perspective of traditional asset pricing empirics, we have relatively short time-series samples making pure time-series country-by-country tests less useful, especially given the volatility of emerging market returns.

To overcome the first problem, we use liquidity measures that rely on the incidence of observed zero daily returns in these markets. Lesmond, Ogden and Trzcinka (1999) argue that if the value of an information signal is insufficient to outweigh the costs associated with transacting, then market participants will elect not to trade, resulting in an observed zero return. The advantage of this measure is that it requires only a *time-series* of daily equity returns. Given the paucity of time-series data on preferred measures such as bid-ask spreads or bona-fide order flow (following Kyle (1985)), this measure is an attractive empirical alternative. To overcome the second problem, we impose cross-country restrictions on the parameter space when examining the dynamics of expected returns and liquidity.

Our analysis is organized into three sections. The second section of the paper introduces and analyzes our two measures of (il)liquidity. The first measure is simply the proportion of zero daily returns. We demonstrate that this measure is highly correlated with more traditional measures of transaction costs for emerging equity markets for the limited periods when overlapping data are available. Lesmond (2005) provides a detailed analysis of emerging equity market trading costs, and confirms the usefulness of this measure. We also provide a case study of how the measure compares to more standard liquidity measures using U.S. data. Our second measure attempts to incorporate potential price impact by using the length of the non-trading (or zero return) interval.

Section 3 characterizes the dynamics of returns and liquidity using various vector autoregressions (VARs). We devote special attention to the hypothesis developed and tested in Amihud (2002) for U.S. data: if liquidity is priced and persistent, liquidity should predict future returns and unexpected liquidity shocks should co-move contemporaneously with unexpected returns. We also contrast global and local components of predictability (see Bekaert (1995) and Harvey (1995) for earlier work).

Section 4 outlines a simple pricing model that we use to interpret the liquidity effects on expected returns. As in Acharya and Pedersen (2005), the model accounts for both liquidity effects though transaction costs and for potential covariation of returns with systematic liquidity. We show that in such a model, local liquidity variables may affect expected returns even under full market integration. We provide an exploratory empirical analysis using country portfolios and the VAR estimates to describe the dynamics of expected returns.

The concluding section summarizes our results and draws lessons for future research.

2 Liquidity Measures for Emerging Markets

2.1 *Data and summary statistics*

Our empirical evidence focuses on 19 emerging equity markets. Table 1 reports summary statistics for all data. From Standard and Poor's Emerging Markets Database (EMDB), we collect monthly returns (U.S. dollar), in excess of the one-month Treasury bill return, and dividend yields for the S&P/IFC Global Equity Market Indices.[3]

Before introducing our preferred measures of liquidity, we construct a measure of equity market turnover (TO) from the same data set: the equity value traded for each month, divided by that month's equity market capitalization. Amihud and Mendelson (1986) show that turnover is negatively related to illiquidity costs. Zimbabwe exhibits the lowest level of average equity market turnover at 0.9% per month, whereas Taiwan exhibits the highest level at 20.9% per month.

Given the paucity of realized transaction cost data for emerging equity markets, our main liquidity measure exploits the effect transactions costs may have on daily returns. Following Lesmond, Ogden and Trzcinka (1999) and Lesmond (2005), we construct the proportion of zero daily returns (ZR) observed over the relevant month for each equity market. We obtain daily returns data in local currency at the firm level from the Datastream research files starting from the late 1980's. For each country, we observe daily returns (using closing prices) for a large collection of firms. The total number of firms available from the Datastream research files accounts for about 90%, on average, of the number of domestically listed firms reported by the World Bank's World Development Indicators. We also present the average number of firms across the sample and the total used at the end of the sample. The difference between the two reflects both increased Datastream coverage and actual equity issuance in these countries. For each country, we calculate the proportion of zero daily returns across all firms, and average this proportion over the month.[4]

As can be seen, zeros are fairly persistent. Some of these equity markets exhibit a very large number of zero daily returns; Colombia, for example, has a 74% incidence of zero daily returns, on average, across domestically listed firms, and the smallest incidence of zero daily returns is 11%, on average, in Taiwan. Given data limitations associated with the firm-level daily returns, we focus on a sample that covers January 1993 to December 2003.

[3]As a robustness check, we also measure returns in local currency, and the results (not reported) are broadly similar.

[4]We also construct capitalization-weighted liquidity measures for each country. Moreover, we computed the zero measure using the Standard and Poor's EMDB daily data over the period from 1996-2003 for which they are available. We find these alternative zero measures to be highly correlated with our.

The zeros measure ignores price impact. Imagine a situation in which a stock trades every other day versus a stock that does not trade for the first 15 days of the month and then trades every day until the end of the month. For both stocks, the zero measures indicate a value of 0.5 for the month. However, the potential price impact after the lengthy non-trading interval in the second case appears to present a much worse instance of illiquidity. Our alternative measure of liquidity attempts to take price impact into account.[5]

Using N stocks in country i, each indexed by j, we create a daily price impact measure as follows:

$$\mathrm{PI}_{i,t} = \frac{\sum_{j=1}^{N} w_j \delta_{j,t} |r_{j,t,\tau}|}{\sum_{j=1}^{N} w_j |r_{j,t,\tau}|}, \tag{1}$$

where w_j represents the weighting of the stocks in the index. We use $w_i = \frac{1}{N}$, representing an equally-weighted measure, but we also compute a capitalization-weighted price impact measure as a robustness check.

$$\delta_{j,t} = \begin{cases} 1, & \text{if } r_{j,t} \text{ or } r_{j,t-1} = 0 \\ 0, & \text{otherwise} \end{cases}. \tag{2}$$

Hence, $\delta_{j,t}$ indicates no trade days (as proxied by zero return days) and the first day after a no trade interval when the price impact is felt. Also,

$$r_{j,t,\tau} = \begin{cases} r_{j,t}, & \text{if } r_{j,t-1} \neq 0 \\ \prod_{k=0}^{\tau-1}(1 + r_{i,t-k}) - 1, & \text{if } r_{j,t-1} = 0 \end{cases}. \tag{3}$$

Here τ represents the number of days the stock has not been trading and $r_{j,t,\tau}$ is an estimate of the return that would have occurred if the stock had traded. Because market-wide factors may dominate return behavior more than idiosyncratic factors in emerging markets, we use the value-weighted market return, $r_{i,t}$, as our proxy for the unobserved return. Note that when a stock does not trade for a lengthy interval, $r_{j,t,\tau}$ may become quite large and $\mathrm{PI}_{i,t}$ may move to 1.0.

Our (il)liquidity measure is then $\mathrm{PI}_{i,t}$ averaged across all days in a particular month for each country. Table 1 illustrates that the salient features of the data are very similar for the $\mathrm{PI}_{\mathrm{i,t}}$ measure and the proportion of zero returns. The least liquid country is now Brazil instead of Colombia. From these two measures, we create two liquidity proxies, $\ell n(1 - ZR)$ and $\ell n(1 - PI)$.

[5]We are grateful to Marco Pagano for comments that inspired the development of this measure.

2.2 *Do zeros measure illiquidity?*

Liquidity and transactions costs are notoriously difficult to measure [see O'Hara (2003), Stoll (2000), and Hodrick and Moulton (2003) for discussions]. The availability of detailed microstructure data in the U.S. market allows for the construction of sharper measures of liquidity. For example, Chordia, Roll and Subrahmanyam (2000, 2002, 2004) calculate daily measures of absolute and proportional bid-ask spreads, quoted share and dollar depth for 1988-1998. Unfortunately, such data are not generally available for emerging markets. Hence, we must rely on an indirect measure. Even for studies focusing on the U.S., indirect measures, starting with the seminal work of Roll (1984)[6], have been and remain popular.

There are a number of other possible liquidity measures. For example, Amihud (2002) examines the average ratio of the daily absolute return to the dollar trading volume on that day. This ratio delivers the absolute (percentage) price change per dollar of daily volume. This is interpreted as the daily price impact of order flow. Pastor and Stambaugh (2002), construct a firm specific liquidity measure by regressing a firm's return minus the market return on the lagged firm return and the lagged signed dollar volume of trading using daily data. The greater the price reversal on the next day, the more negative the coefficient on signed dollar volume and the more illiquid is the stock. The regression is repeated every month for every firm. Each month, the coefficient on the signed volume is averaged to provide a market wide liquidity measure. The measure is adjusted for the time-trend in market capitalization. Their final liquidity measure is the innovation from a regression of changes in the market-wide liquidity measure on lagged changes and the lagged level. While these two measures are straightforward to apply, we do not have dollar volume data on a daily basis in emerging markets. Moreover, volume data are very challenging, and are plagued by trends and outliers – problems that are likely exacerbated in our emerging market data. Finally, both measures require positive volume during the sampling interval, which might be problematic for some emerging markets where non-trading problems are particularly acute.

Nevertheless, it is important to be aware of the limitations of our zeros and price impact measures. First, information-less trades (such as a trade by an index fund) should not

[6] See Ghysels and Cherkoaui (2003) for an application to an emerging market.

give rise to price changes in liquid markets. The market reaction to such a trade may also depend on the particular trading mechanism in place. Whereas trading mechanisms vary substantially across emerging markets, we do not think that noise trades dominate the behavior of our measure. The fact that the zero measure correlates negatively with turnover is indirect evidence supportive of this view. The cross-sectional correlation between the *average* levels of turnover and the *average* incidence of zero daily returns (presented in Table 1) across our sample countries is -0.44, indicating that the zeros measure is potentially reflecting relative *levels* of liquidity across the equity markets in our study. Table 2 presents correlations of these two liquidity measures *across time* within each country. On average, the correlation between the proportion of zero daily returns and equity market turnover within a country is -0.36. Similar numbers are presented for the price impact measure. If positive volume zero returns do occur, we can still interpret zeros as a measure of the lack of informed trading (see Lesmond, Ogden and Trzcinka (1999) for further discussion).

Second, another concern is that there is a zero return (no trading) because of a lack of news. Empirically, shocks or news generate persistent volatility patterns. In addition, higher volatility is likely associated with a higher compensation for providing liquidity, see for instance Vayanos (2004). However, Table 2 indicates that there is no consistent pattern in the correlation between estimates of conditional volatility and the liquidity measure.[7] The correlation is more often positive than negative, though economically small in most cases. On average, the correlation is effectively zero. Perhaps this is not so surprising, as alternative theories (see for example Pagano (1989)) predict a positive relation between volatility and market thinness or illiquidity.

As an alternative, we also construct a measure of within-month volatility as in French, Schwert, and Stambaugh (1987). First, we sum the squared returns *at the firm level* within the month, and then average this sum across firms for that month. Table 2 presents correlations between the incidence of zeros and the within-month volatility across time for each

[7]We obtain estimates of the conditional volatility by maximum likelihood for both symmetric GARCH(1,1) and asymmetric threshold GARCH(1,1) models of the measured monthly equity returns for each market. The threshold GARCH model is developed by Zakoian (1994) and Glosten, Jagannathan, and Runkle (1993).

country. On average, the average correlations between the proportion of zero daily returns and the price impact measures with within-month volatility are -0.06 and -0.04, still suggesting that the two liquidity measures are capturing unique aspects of liquidity not entirely driven by the presence or absence of news in a particular period. Nevertheless, given the somewhat larger correlations between the incidence of zeros and both turnover and volatility, we also consider (but do not report) an alternative measure of liquidity that reflects the "residuals" from country-by-country projections of the proportion of zero returns on both turnover and within-month volatility. While these regressions yield R-squares typically between 0.25 and 0.40, the general predictability and asset pricing implications of using the "residual" rather than the liquidity level (as presented in the subsequent sections) are unaffected.

Third, it is possible that our zeros measure artificially reflect other characteristics of the stock market. For example, markets with many small stocks may automatically show a higher level of non-trading compared to markets with larger stocks. Since these small stocks only represent a minor part of the market, the zeros measure may not reflect market-wide transactions costs. This concern is mitigated by the fact that Table 1 reveals a negative relation between the number of companies used in the computation and the average proportion of daily zero returns, with the cross-sectional correlation being -0.52. A larger number of firms covered by Datastream seems to be associated with a lower incidence of zero returns.

Perhaps the most compelling diagnostic is to explore the relationship between the returns-based measure of transaction costs and more standard measures. To this end, Table 2 also presents correlations with available bid-ask spreads. Bid-ask spread data for domestic firms are obtained from the mid to late 1990's for a few countries from the Datastream research files. We find that the proportion of daily zero returns measure is highly correlated, 60% on average, with the mean bid-ask spread across all countries and time-periods for which bid-ask spreads are available. Datastream supplied bid-ask spread data availability are limited; however, Lesmond (2005) also documents that the proportion of zero daily returns is highly correlated with hand-collected bid-ask spreads for a broader collection of emerging equity markets. The correlation between equity market turnover and the bid-ask spread is only about -0.20, on average, but there are some countries (Korea, Malaysia, and Mexico) for which the negative correlation is more pronounced. Taken together, this suggests that the proportion of zero daily returns appears to be picking up a component of liquidity and transaction costs that turnover does not.

Finally, recent research by Lowengrub and Melvin (2002), Karolyi (2005), and Levine and Schmukler (2005) suggests that the trading activity of cross-listed securities may migrate to foreign markets. Firms trading across markets will have price series reported in Datastream in each of the markets in which the asset trades. Because we obtain local market prices, our liquidity measure does not reflect activity in the foreign listed market. If a cross-listed stock trades abroad but not locally, our zeros measure is biased upward. As a robustness check, we recalculate the zeros and price impact measures excluding any firms that are also listed in the U.S. by means of an ADR according to Datastream. The resulting measures are very highly correlated with our original measures, with the correlation exceeding 0.99 in almost every case.

2.3 *A case study using U.S. Data*

For the United States, we explore the relationship between our first measure, the proportion of zero daily returns, and three other measures of transaction costs/liquidity common in the literature. Hasbrouck (2004, 2005) constructs a Bayesian estimate of effective trading costs from daily data using a Gibbs-sampler version of the Roll model.[8] This method yields a posterior distribution for the Roll-implied trading costs from the first-order autocorrelation in returns. For U.S. equity data, Hasbrouck (2005) shows that the correlations between the Gibbs estimate and estimates of trading costs based upon high frequency Trade and Quote (TAQ) data are typically above 0.90 for individual securities in overlapping samples. Hasbrouck (2005) argues that Hasbrouck's (2004) effective cost and Amihud's (2002) price impact measures are, among standard transaction costs estimates based on daily data, most closely correlated with their high-frequency counterparts from TAQ data.

Figure 1a compares the effective cost and price impact measures for the aggregate NYSE and AMEX markets with the incidence of zero daily returns in these markets at the annual

[8] Also see Harris (1990) for an analysis of the Roll estimator.

frequency from 1962-2001. The correlation between the proportion of zero daily returns and Hasbrouck's effective costs and Amihud's price impact are 0.42 and 0.40, respectively. While the major cycles nicely coincide during most of the sample, there is some divergence in the last 5-years. There are a sharp declines in the incidence of zero returns which coincides with the NYSE's move to 1/16th in 1997 and decimalization in 2000, but which are absent from the effective costs and price impact measures. For comparison, we also plot the equally-weighted proportional bid-ask spreads on DJIA stocks from Jones (2001) in Fig. 1a. Interestingly, unlike the other measures of transaction costs, the proportional spread data do exhibit the sharp declines in the late 1990's in accordance with the reduced incidence of zero daily returns. The overall correlation between bid-ask spreads and the proportion of zeros is 30%. Taken together, this evidence suggests that the proportion of zero daily returns for the United States is, at the very least, associated with time-series variation in other measures of transaction costs used in this literature.

Our use of zeros in emerging markets is predicated on the assumption that zero returns proxy for no volume zero returns in these relatively illiquid markets. For the U.S., we can actually construct a no-volume zeros measure. Figure 1b compares the same measures with zero returns observed on pure zero volume days. In this case, the correlation between the proportion of zero daily returns on zero volume days and Hasbrouck's effective costs and Amihud's price impact are much higher at 0.81 and 0.91, respectively. This distinction may be important as zero returns in emerging markets are more likely associated with non-trading than in the U.S. where a significant number of trades are processed with no associated price movement.

We also compare the incidence of zero returns with the reversal measure suggested by Pastor and Stambaugh (2002) (PS). For the PS measure, we consider two alternative constructions. The first conducts firm-level regressions on daily data over each month, averages the reversal coefficients across all firms, and then averages within the year. The second method conducts the firm-level regression on daily data over each year, and averages the reversal coefficient across all firms. Interestingly, these two measures show little correlation with one another and only the first method leads to correlations with Hasbrouck's (2005) effective costs, the Amihud (2002) price impact measure and bid-ask spreads that have the right sign. The Pastor-Stambaugh measure, which measures liquidity, is positively correlated with the proportion of zero daily returns for both methods. Consequently, our measure does not capture aspects of liquidity reflected in the reversal measure.[9]

3 Liquidity and Expected Asset Returns: A VAR Analysis

Amihud (2002) finds evidence that expected excess returns in the U.S. reflect compensation for expected market illiquidity. As illiquidity is persistent, this implies that measures of liquidity should predict returns with a negative sign. Similarly, unexpected market liquidity should be contemporaneously positively correlated with stock returns because a shock to liquidity raises expected liquidity, which in turn lowers expected returns, and hence prices. Amihud finds evidence of this effect in U.S. data as well. In this section, we formulate various simple VAR systems that allow us to test these hypotheses for emerging markets. We are careful to distinguish between local and global liquidity, and allow for time-varying degrees of integration in the model specification. In the next section, we formulate a formal pricing model that differentiates between two main channels through which liquidity can affect expected returns, the transaction cost channel and liquidity as a systematic risk factor channel. The resulting model for expected returns is very similar to the model Acharya and Pedersen (2005) obtain using a simple overlapping generation's economy with time-varying liquidation costs. Acharya and Pedersen show that under mild conditions the Amihud pricing hypotheses are maintained in this model. We will use the expected returns identified by the VARs in this section to test the pricing implications of the model.

3.1 *VAR benchmark specification*

For our benchmark specification, we define the liquidity measure $\mathrm{L}_{i,t} = \ln(1 - ZR_{i,t})$, with $ZR_{i,t}$ the equally weighted zero return measure for country i in month t. Below, we consider other specifications using alternative liquidity measures. Also, define $r_{i,t}$, the value-weighted

[9] We thank Lubos Pastor for making the average of the monthly PS measure available, Charles Jones for the bid-ask spread data and Joel Hasbrouck for providing both the Amihud price impact, the Hasbrouck Gibbs sampled, and the annual PS measures (the second PS measure).

excess return on country index i (measured in dollars). We assume that returns, the liquidity measure, and potentially other instruments follow a (restricted) vector autoregressive system. For the benchmark specification, the VAR variables, $x_{i,t}$, consist of $[r_{i,t}, \text{Ł}_{i,t}]$. However, we also consider other VAR specifications including $[r_{i,t}, \text{Ł}_{i,t}, dy_{i,t}]$ and $[r_{i,t}, \text{Ł}_{i,t}, TURN_{i,t}]$. For country i, the base VAR(1) model is as follows:

$$\begin{aligned} \mathbf{x}_{i,t} &= \mu_{i,t-1} + (\mathbf{A}_0 + Lib_{i,t-1}\mathbf{A}_1)(\mathbf{x}_{i,t-1} - \mu_{i,t-1}) \\ &\quad +(\mathbf{B}_0 + Lib_{i,t-1}\mathbf{B}_1)(\mathbf{x}_{w,t-1} - \mu_{w,t-1}) + \mathbf{\Sigma}_{i,t-1}^{1/2}\epsilon_{i,t}. \end{aligned} \tag{4}$$

The first special feature of the VAR is the presence of the interaction variable $Lib_{i,t}$. We define $Lib_{i,t}$ as the proportion of local market capitalization not subject to foreign ownership restrictions, which was proposed as a time-varying measure of market integration by Bekaert (1995), Edison and Warnock (2003) and De Roon and De Jong (2005). Equity market liberalization takes place when a country first provides foreign investors access to the domestic equity market. $Lib_{i,t}$ is a continuous measure of equity market "openness" designed to reflect the gradual nature of the increasing foreign "investability" of these markets. The measure is based on the ratio of the market capitalization of the constituent firms comprising the S&P-IFC Investable Index to those that comprise the S&P-IFC Global Index for each country. The Global Index, subject to some exclusion restrictions, is designed to represent the overall market portfolio for each country, whereas the Investable index is designed to better represent a portfolio of domestic equities that are available to foreign investors. Hence, a ratio of one means that all of the stocks are available to foreign investors (an extreme example of full integration), whereas a ratio of zero is an extreme example of full market segmentation. Generally, the investability measure is somewhere between 0 and 1. The variable allows us to make the VAR dynamics dependent on the state of market integration in a particularly parsimonious manner.

The constant term is modeled as $\mu_{i,t} = (\alpha_{0,i}+\alpha_1 * Lib_{i,t})$ and $\alpha_{0,i}$ denotes a country-specific fixed effect for each variable; α_1 denotes a vector of cross-sectionally restricted liberalization coefficients for each variable. Essentially, we assume that country specific factors may lead to unmodeled differences in expected returns and liquidity (for example, due to the effects of differing market structures), but capture the change upon liberalization with the function

$\alpha_1 Lib_{i,t}$. Analogously, the VAR conditional variance-covariance matrix for country i is $\mathbf{\Sigma}_{i,t}$, where the Cholesky decomposition of the variance-covariance matrix, $\mathbf{\Sigma}_{i,t}^{\frac{1}{2}}$, is $\mathbf{\Sigma}_0 + Lib_{i,t}\mathbf{\Sigma}_1$. Both $\mathbf{\Sigma}_0$ and $\mathbf{\Sigma}_1$ are lower triangular matrices and are restricted to be identical across countries and time. We estimate the Cholesky decomposition to ensure that the variance-covariance matrix is always positive semi-definite. Finally, given the small time-series nature of our data sample, $\mathbf{A_0}$, $\mathbf{A_1}$, $\mathbf{B_0}$, and $\mathbf{B_1}$, the predictability matrices, are also restricted to be identical across countries. Note that we allow both local and global variables to affect expected returns and expected liquidity, and that, logically, we expect this dependence to vary with the degree to which the local market is integrated in global capital markets.

Additionally, we specify the VAR dynamics for the U.S. market (as a proxy for global factors):

$$\mathbf{x}_{w,t} = \mu_w + \mathbf{A}_w(\mathbf{x}_{w,t-1} - \mu_w) + \mathbf{\Sigma}_w^{1/2}\epsilon_{w,t}. \tag{5}$$

We collect the relevant VAR innovations, $\epsilon_{i,t}$, from (4) for each country as follows:

$$\epsilon_t = \begin{bmatrix} \epsilon_{w,t} \\ \epsilon_{1,t} \\ \vdots \\ \epsilon_{N,t} \end{bmatrix}, \tag{6}$$

where N denotes the number of countries in our sample. Let $\mathbf{\Omega}_t$ denote the conditional variance-covariance matrix for the entire cross-section as follows:

$$\mathbf{\Omega}_t = \begin{bmatrix} \mathbf{\Sigma}_w & \beta_{1,t} \cdot diag(\mathbf{\Sigma}_w) & \cdots & \beta_{N,t} \cdot diag(\mathbf{\Sigma}_w) \\ \beta_{1,t} \cdot diag(\mathbf{\Sigma}_w) & \mathbf{\Sigma}_{1,t} & \cdots & \beta_{1,t} \cdot diag(\mathbf{\Sigma}_w) \cdot \beta'_{N,t} \\ \vdots & & & \\ \beta_{N,t} \cdot diag(\mathbf{\Sigma}_w) & \beta_{N,t} \cdot diag(\mathbf{\Sigma}_w) \cdot \beta'_{1,t} & \cdots & \mathbf{\Sigma}_{N,t} \end{bmatrix}. \tag{7}$$

Here, $diag(\cdot)$ takes the U.S. variance-covariance matrix, but zeros out the off-diagonal elements. Accordingly, $\beta_{i,t} = \beta_0 + Lib_{i,t}\beta_1$ represents a matrix of betas – covariances of the country specific shocks with the U.S. shocks divided by the variances of the U.S. shocks. The matrices, β_0 and β_1, are full matrices assumed identical across countries, while the overall betas do vary with the liberalization regime. The rationale for this covariance matrix is a factor structure where global factors affect both the mean and the conditional variance of the emerging market variable dynamics. If two emerging markets are both exposed to global factors they must also show cross-correlations, but we restrict these covariances to come from the factor structure. From a panel data perspective, this means that we accommodate complete within-country and across-country SUR effects with parameter restrictions.

3.2 *Estimation*

The parameters to be estimated are the country-specific fixed effects, $\alpha_{0,i}$; the liberalization effect, α_1; the cross-sectionally restricted matrices $\mathbf{A}_0$, $\mathbf{A}_1$, $\mathbf{B}_0$, and $\mathbf{B}_1$; the components of the Cholesky decomposition of the VAR innovation variance-covariance matrix, $\mathbf{\Sigma}_0$ and $\mathbf{\Sigma}_1$; the parameters of the U.S. market process; and the beta matrices. The log likelihood function for a the full panel can be expressed as follows:

$$L = \sum_{t=1}^{T} l_t = -\frac{k \cdot (N+1)}{2} \ln(2\pi) - \sum_{t=1}^{T} (\frac{1}{2} \ln |\mathbf{\Omega}_{t-1}| - \frac{1}{2} \epsilon_t' \mathbf{\Omega}_{t-1}^{-1} \epsilon_t) \tag{8}$$

where k is the number of endogenous variables, and $k \cdot (N+1)$ is the number of individual equations. For a base specification of 2 variables, this involves 39 parameters. We estimate the parameters describing the VAR process using a quasi-maximum likelihood (QMLE) methodology, reporting robust standard errors as in Bollerslev and Wooldridge (1992).

There is a large literature on statistical inference problems with respect to establishing return predictability (see Stambaugh (1999) and Hodrick (1992)). The results in that literature are not directly applicable to our framework because we have a panel set-up. Nevertheless, the amount of time series information is limited and we must recognize that the asymptotic distribution of t-tests may poorly approximate the true finite sample distribution. We therefore conduct a Monte Carlo experiment to examine the small sample properties of the pooled time-series cross-sectional VAR estimator. We focus on the bivariate VAR, including returns and liquidity.

Let the simulated series be denoted as $\tilde{\mathbf{x}}_{i,t} = [r_{i,t}, \text{Ł}_{i,t}]$. The base VAR(1) model we simulate is as follows:

$$\begin{aligned} \tilde{\mathbf{x}}_{w,t} &= \mu_w + \mathbf{A}_w(\tilde{\mathbf{x}}_{w,t-1} - \mu_w) + \mathbf{\Sigma}_w^{1/2} \tilde{\epsilon}_{w,t}. \\ \tilde{\mathbf{x}}_{i,t} &= \mu_{i,t-1} + (\mathbf{A}_0 + Lib_{i,t-1}\mathbf{A}_1)(\tilde{\mathbf{x}}_{i,t-1} - \mu_{i,t-1}) \end{aligned}$$

$$+(\mathbf{B}_0 + Lib_{i,t-1}\mathbf{B}_1)(\tilde{\mathbf{x}}_{w,t-1} - \mu_{w,t-1}) + \mathbf{\Sigma}_{i,t-1}^{1/2}\tilde{\epsilon}_{i,t}. \tag{9}$$

where $\tilde{\epsilon}_{w,t}$ and $\tilde{\epsilon}_{i,t}$ are drawn from the standard normal distribution, $Lib_{i,t}$ represents the observed liberalization indicators, and the first row of $\mathbf{A}_0$, $\mathbf{A}_1$, $\mathbf{B}_0$, $\mathbf{B}_1$, and $\mathbf{A}_w$ is constrained to be a row of zeros, so that under the null, lagged endogenous variables *do not* predict returns for emerging markets or the U.S. (and that is true across liberalization regime). The innovation covariance matrix is as in (7) with the correlations across emerging markets zeroed out. However, the innovations of all variables are allowed to be correlated within countries as in the observed data. The panel effects across emerging markets greatly complicate the estimation of the model and turn out to be of second order importance. Therefore, the Monte Carlo (and some other systems we will estimate) focus on a system where the cross-country correlation among emerging markets is set to zero. For each replication (with the identical number of time-series observations as we have in the observed data), we estimate the unconstrained VAR(1) for returns and liquidity using the pooled MLE methodology presented in (8). We also consider a simulation under the alternative of return predictability, where the simulated data are drawn in exact accordance with our parameter estimates obtained below.

The appendix table presents some relevant percentiles of the empirical distribution for the coefficient describing the predictive nature of liquidity for future returns, one of the key parameters of interest if liquidity is priced. Under the null of no predictability, the mean coefficient is -0.0092, and the t-statistic is -0.42, indicating some negative estimation bias for the observed liquidity effect. This is quite common in univariate time-series contexts when the innovations between the two variables are correlated and the predictive variable displays significant persistence. The distribution of the t-statistic is similarly biased, meaning that for a two-sided test at the 5% level, the critical value is -2.45. Under the alternative hypothesis of return predictability, this bias remains with the mean coefficient estimate at -0.062, while the data generating process used the data estimate of -0.053. However, one can easily detect predictability under the alternative that it is valid, as the right-hand tail of this distribution is generally well below zero. More precisely, the power of a test of the null hypothesis of liquidity not predicting future returns is 0.73 for a 5% and 0.81 for a 10% two-sided test (using the Monte Carlo critical values). We use the Monte Carlo evidence for all subsequent tests.

3.3 *Specification tests*

In Table 3, we present some simple specification tests on the residuals from the bivariate VAR. We report the first-order autocorrelation coefficient for each country's residuals. We find that the simple bivariate VAR model suffices to generate white noise return residuals. We also present asymptotic p-values, country by country, for a Wald test that the first three autocorrelations are jointly zero. For only two countries do we find the first-order autocorrelation coefficient of the return residuals to be above 0.2 (Colombia and Malaysia) and, using the asymptotic test, we only reject the null of no serial correlation for one country (Colombia). With Monte Carlo based critical values, the test continues to reject for Columbia. The model is less successful with respect to liquidity. There are five countries with residual autocorrelation coefficients over 0.2 in absolute value, with the autocorrelation coefficient close to -0.4 for Indonesia. We also conduct a joint Wald test where the null hypothesis is that all of the first three autocorrelations across countries are jointly zero (with $18 \times 3 = 54$ restrictions); the test is not rejected for the return residuals, but is strongly rejected for the liquidity residuals. While the joint test is significant at the 5% level under the Monte Carlo critical value, there are only three countries for which the test rejects the null of no serial correlation at the 5% level using the Monte Carlo distribution. Use of the asymptotic distribution would have resulted in rejections for eight countries. Hence, the standard asymptotic tests over-reject and paint too negative a picture of the VAR's ability to capture return-liquidity dynamics. Nevertheless, the predominance of negative autocorrelations suggests that the estimated and cross-sectionally constrained autocorrelation coefficient for local liquidity is somewhat too high for these countries. The specification tests results are robust to the inclusion of additional instruments, such as market turnover or the dividend yield.

3.4 *Empirical results*

3.4.1 Bivariate VAR, benchmark

In Table 4, we present estimation results for the bivariate VAR(1), which includes excess returns and market liquidity, as specified in equations (4)-(7). First, we display the VAR dynamics in the form of the own-country effects, A_0 and A_1, as well as the predictability effects associated with lagged U.S. variables, B_0 and B_1, where the A_1 and B_1 matrices measure the liberalization effects.

We start the discussion by investigating the predictive power of local variables for returns. Excess returns display positive autocorrelation, on average across the countries, consistent with Harvey (1995); however, the coefficient is not statistically significant. Return autocorrelation does not seem to be affected by the liberalization regime. The return coefficient on lagged local liquidity (in segmented markets) is statistically significant, -0.053 (with a standard error of 0.020); however, the coefficient becomes less negative in integrated markets, though the change is not significant. Hence, we confirm Amihud's (2002) results for segmented markets, but not for integrated markets.

An interesting possibility is that liquidity spuriously predicts returns because it is a non-trading measure. When there is significant non-trading, information only slowly gets impounded in prices which may lead to autocorrelated returns. In periods of very high illiquidity (low liquidity), news will take longer to affect returns, and this might be what the regression picks up. If this is the main mechanism driving our negative return-liquidity coefficients, the true autocorrelation coefficient should be higher than the 0.0524 feedback coefficient we measure here, as we now partially control for non-trading. To investigate this, we also run the VAR with the liquidity variable zeroed out, we find the average autocorrelation coefficient to be lower (0.049) – not higher. As a result, it seems unlikely that non-trading is the reason we observe return predictability.

We also present several Wald tests on return predictability, split up over local versus global instruments. For the tests with local factors, the null hypothesis is that the first row of $\mathbf{A}_0 = 0$ under segmentation and $\mathbf{A}_0 + \mathbf{A}_1 = 0$ under integration. For segmented countries, the test rejects the null of no predictability with a p-value of 0.03; however for integrated countries, the test fails to reject (p-value of 0.15). For the tests on return predictability using global factors, the null hypothesis is that the first row of $\mathbf{B}_0 = 0$ under segmentation and $\mathbf{B}_0 + \mathbf{B}_1 = 0$ under integration. Both tests fail to reject the null hypotheses, with p-values of 0.51 and 0.78, respectively. Under the Monte Carlo distribution, the null hypothesis of no predictability for segmented countries is also rejected, while all other tests fail to reject under the Monte Carlo distribution. Taken together, this evidence suggests that local variables play the dominant role in emerging market return predictability. We also investigate the effects of change in financial openness on return predictability testing the null hypotheses that $\mathbf{A}_1 = 0$ or $\mathbf{B}_1 = 0$. Both hypotheses are not rejected with an asymptotic p-values of 0.62 and 0.49, respectively.

Turning to the liquidity equations, we see that the liquidity variable displays significant autocorrelation, with an estimated coefficient on lagged liquidity of 0.91. Acharya and Pedersen (2005), working with a liquidity measure proposed by Amihud (2002), find a persistence level of 0.94 for U.S. data. Lagged returns significantly affect future liquidity for segmented markets; the estimated coefficients is positive and statistically significant. High returns in one month predict improved subsequent market liquidity. Griffin, Nardari and Stulz (2004) examine the relationship between past returns and future trading activity in 45 countries, measured by turnover, and also find a positive effect. Interestingly, a detailed analysis of their results reveals that the effect is less strong for some more developed markets and nonexistent for the U.S. (at least over the full sample). We also find that liberalization reduces the coefficient. For the U.S., we find the effect to be borderline significant. Griffin et al. speculate that a costly stock market participation story is behind the results, but it would appear difficult to explain our findings with such a story. While the empirical standard deviations computed from the Monte Carlo are slightly larger than the asymptotic standard errors for these parameter estimates, the conclusions are qualitatively unchanged. We return to these findings when we add turnover to the VAR.

Next, we examine how U.S. returns and liquidity affect local variables. A 1% increase in U.S. market returns predicts a 22 basis point increase in local returns in segmented markets; however, the coefficient is not significant. Such a cross-serial correlation would be consistent with a market where securities trade infrequently and world or U.S. news is slowly affecting prices. If liquidity improves upon liberalization, the effect may diminish; however, the importance of global factors should also increase upon liberalization. We find that the coefficient slightly decreases upon liberalization, but the change in coefficients is insignificant. U.S. market returns do affect liquidity positively and significantly, but the effect is dramatically reduced upon liberalization. Overall, we find the relationship between returns and future liquidity to be much weaker, economically at least, for liberalized markets. Global liquidity also affects local returns negatively but the effect is insignificant and disappears alltogether for liberalized countries.

It is also of interest to investigate how liberalization affects the unconditional means of returns and liquidity. The critical parameters are the coefficients on $Lib_{i,t-1}$, α_1, reported in Table 4. Both coefficients have unexpected signs. If liberalizations reduce the cost of capital, we would expect a negative coefficient in the return equation, but we find a positive coefficient. Bekaert and Harvey (2000) discuss extensively the difficulty in finding a liberalization effect using return measures in emerging markets. However, the coefficient is not significant. Similarly, if liberalizations improve liquidity, we would expect a positive liquidity coefficient, but the coefficient is negative. Again, the coefficient is not significantly different from zero. A joint Wald test for $\alpha_1 = 0$ is not rejected with a p-value of 0.58. Taken together, the role for the liberalization state in the mean effects governing the VAR dynamics appears limited.

We also present evidence on the U.S. market VAR dynamics. U.S. market returns do not display economically or statistically significant autocorrelation. Further, while the return predictability coefficient on lagged liquidity is nearly identical to the pooled coefficient for segmented emerging markets, it is not statistically significantly different from zero. Lagged U.S. market returns do significantly predict future U.S. market liquidity, as discussed before. Finally, U.S. market liquidity is very persistent, with an autocorrelation coefficient near 1; this reflects the sharp declines in illiquidity (and bid-ask spreads) over the last 15 years. A Wald test of the null hypothesis that the U.S. dynamics are equivalent to the VAR dynamics of a fully integrated emerging market, $\mathbf{A}_w = \mathbf{A}_0 + \mathbf{A}_1$, is rejected with a p-value less than 0.01

Next, we explore the contemporaneous relationships between our variables. Table 4 displays the two pieces, $\mathbf{\Sigma}_0$ and $\mathbf{\Sigma}_1$, that make up the Cholesky decomposition of the VAR innovation variance-covariance matrix. Each matrix is lower triangular. Of main interest is the off-diagonal component that describes the average *within country* contemporaneous relationship between innovations in excess returns and liquidity, c_{21}. The coefficient is positive and highly statistically significant for segmented markets (the off-diagonal element for $\mathbf{\Sigma}_0$). It is not significantly affected by the liberalization state (the off-diagonal element for

$\mathbf{\Sigma}_1$). Consequently, shocks to liquidity are positively correlated with return shocks, which in conjunction with the significantly negative lagged liquidity coefficient, is consistent with the Amihud hypothesis that liquidity is priced. In both cases, this is more pronounced in markets with lower levels of foreign investability. While the liberalization effects are not significant, the standard deviation of both the excess returns and the liquidity variable falls sharply and in a statistically significant manner following equity market liberalization. A simple Wald test of the null hypothesis that $\mathbf{\Sigma}_1 = 0$ is sharply rejected with a p-value of less than 0.01. For the U.S. market equations, we find c_{21} to be significantly negative. Note that the asymptotic standard errors used here are very close to the empirical standard deviations computed from the Monte Carlo, so that the evidence regarding c_{21} is robust to finite sample inference.

Finally, we present evidence on the contemporaneous covariances between local and U.S. shocks. In segmented markets, the beta reflecting the covariance between U.S. and local returns is positive and not significant; however, as the degree of investability increases, the betas become highly significant, and exceeds one. The majority of the other beta coefficients are not statistically significant with two exceptions. Local liquidity surprisingly has a positive beta with respect to U.S. returns, but the coefficient is only marginally significant and goes to zero post liberalization. Also, the beta of local returns with respect to U.S. liquidity switches from positive to negative upon liberalization. While the change is statistically significant, the resulting beta for a fully liberalized economy is not. A Wald test of the null hypothesis that U.S. covariances do not vary with the liberalization state, β_1=0, is rejected with a p-value less than 0.01, but this is driven by the strong positive local return beta with respect to the U.S.

In sum, the bivariate VAR of local returns and equally-weighted liquidity suggests that the degree of equity market liquidity predicts future excess returns and that shocks to returns and liquidity are positively correlated. These effects are strongest for markets with lower levels of foreign investor access. Moreover, local sources of predictability are stronger than global sources.

3.4.2 Alternative VAR specifications

In this section, we consider two alternative VAR specifications that either facilitate the dividend yield or equity market turnover as additional endogenous variables. Table 5 presents several key parameters of interest from these additional specifications for comparison with the bivariate VAR presented in Table 4 (full results are available upon request). The benchmark bivariate case is labeled Case A, where as the additional cases with the dividend yield or turnover are labeled Case B or C, respectively.

It is interesting to consider dividend yields from at least two perspectives. First, suppose dividend growth rates are stochastic but are not very predictable. In this case, variation in the dividend yield will primarily reflect variation in discount rates. Consequently, if liquidity is priced and persistent, it will generate time-variation in dividend yields. In particular, because improved liquidity lowers expected returns, we expect the innovations in liquidity and dividend yields to be negatively correlated. In addition, dividend yields may therefore help capture the predictive power of liquidity, so their inclusion in the VAR may decrease the magnitude of the coefficient on Ł in the return regression. Second, the dividend yield may capture other predictable components in returns. While dividend yields have long been viewed as particularly strong predictors of equity returns, some recent work (e.g. Ang and Bekaert (2004), Engstrom (2003), and Goyal and Welch (2003)) demonstrates that this predictive power may not be statistically robust. Investigating the relative predictive power of the dividend yield and liquidity measures for emerging markets, which show little correlation with established markets, is therefore interesting in its own right.

Turning to the table (Case B), dividend yields do not significantly predict returns, regardless of the liberalization regime consistent with the recent mixed evidence. Further, the U.S. dividend yield does not significantly predict future returns either. Still, the inclusion of these additional variables does increase the parameter associated with the predictability of returns from lagged liquidity, so that it is no longer statistically significant. As mentioned, this could be completely consistent with an important role for liquidity in pricing. If dividend yields and liquidity are negatively correlated, the trivariate coefficient on liquidity should be smaller than the bivariate coefficient reported here. The contemporaneous covariance between liquidity and dividend yield shocks reported in the table is indeed negative and highly significant for segmented countries, but the estimate becomes less negative as investability rises. Note that this represents the correlation purged of return effects because of the Cholesky decomposition formulation Conversely, because dividend yield variation partially reflects variation in liquidity, the univariate coefficient on the dividend yield is higher (0.0933) and is significantly different from zero. As is true in the trivariate VAR, investability substantially undermines the predictive power of the dividend yield but increases the coefficient on the U.S. dividend yield. However, these interaction effects are not significant. Finally, in the trivariate system, liquidity also negatively and significantly predicts future dividend yields (but only in segmented markets).

As in the bivariate case, we also present several Wald tests on return predictability. Recall, the null hypotheses are that the first row of $\mathbf{A}_0 = 0$ under segmentation and $\mathbf{A}_0 + \mathbf{A}_1 = 0$ under integration, when local instruments are considered. As in the bivariate case, the first test rejects the null of no predictability with a p-value of 0.02, even though none of the individual estimates are significant. This suggests a degree of colinearity between liquidity and dividend yields, consistent with priced liquidity. The null hypothesis of no return predictability from local factors under integration is not rejected at the 5% level, though it is at the 10% level. The tests fail to reject the null hypothesis of no return predictability using global factors under either segmentation or integration.

Given that equity market turnover is a natural candidate for local market trading activity, we also consider a specification which includes turnover. In Case C in Table 5, lagged local or U.S. equity market turnover do not significantly predict future excess returns and their inclusion does not drive out the predictive power of the liquidity measure. The predictability of future returns by lagged local market liquidity is actually more pronounced in Case C for segmented markets, although the coefficient increases significantly for countries with greater degrees of investability. This evidence is consistent with the idea that the proportion of zero daily returns is picking up a feature of market liquidity and transaction costs not related to equity market turnover and is more important for expected returns. Finally, there also appears to be a positive contemporaneous relation between returns and turnover shocks for segmented countries which is relatively unaffected by the liberalization state.

We also investigate whether past returns predict future turnover as suggested by Griffin, Nardari, and Stulz (2004). The estimated coefficient is positive and significant, but it is reduced considerably for higher levels of investability. In contrast, the coefficient on past local returns in the liquidity equation is 0.111 with a t-statistic of 3.865, quite similar to the bivariate estimate. It is not affected by the inclusion of turnover. The Wald tests on return predictability continue to exhibit significant predictive power for local factors under market segmentation. However, there is also marginal predictive power for local factors under market integration and the integration state significantly affects predictability.

3.4.3 VARs with alternative liquidity measures

Table 6 investigates the robustness of our results across liquidity measures. We report results for bivariate VARs including returns and three different liquidity measures: one based on value-weighted zero returns, the equally-weighted price impact based measure, and the value-weighted price impact measure. In the discussion, we only focus on the salient features of the dynamics.

First, the coefficient on past liquidity in the return equation is consistently negative. The predictability is much stronger for the value-weighted measure based on zeros, but it is weaker for the price impact measure. In fact, the coefficient is no longer significant for the equal-weighted price impact measure, but the in value-weighted case, it is significant at the 5% level even when the Monte Carlo critical values are used. Consistent with the benchmark case, the coefficients are much smaller for liberalized countries. One of the main hypotheses underlying the article is thus confirmed: variation in the degree of market integration affects the predictive power of liquidity in the expected direction, but the change in the coefficient is only statistically significant for the value-weighted zero return measure. For the U.S., we find consistently negative, but insignificant coefficients.

Second, equally-weighted liquidity measures are significantly more persistent than value-weighted measures, with the differences being smaller for liberalized markets. Third, the predictive power of returns for future liquidity for segmented markets is restricted to the equally-weighted zeros based measure, but the coefficient is consistently positive. Interestingly, for liberalized markets, the coefficient becomes more positive for all alternative measures.

Fourth, we also report the effect of liberalization on the unconditional averages in Table 6. For returns, the effects are not robust across measures. We observe a significant increase for the value-weighted zero return measure, and insignificant coefficients with opposite signs for the price impact measures. However, if we investigate trivariate VARs with dividend yields, the dividend yield consistently decreases but the effect is mostly not significant. For liquidity, the value-weighted measures show significant improvements in liquidity post-liberalization whereas the equally weighted measures show insignificant negative coefficients.

Fifth, we always observe a positive correlation between return and liquidity shocks, but it is not significantly different from zero in the case of the equally-weighted price impact measure. For the U.S. VAR dynamics, the negative return-liquidity correlation seems robust to the measure even though it is not always significantly different from zero.

Sixth, in terms of the beta exposures, there is one result that is very robust across the different measures. The return beta with respect to the U.S. market return is around 0.35 to 0.4 for segmented countries and rises with about 0.85-0.90 for a fully liberalized country.

4 Liquidity and Expected Asset Returns: A Simple Pricing Model

4.1 *Transactions costs and liquidity*

In this section, we set out a simple model that considers two channels through which liquidity may affect expected returns: as a transaction cost and as a systematic risk factor. We contrast the implications of liquidity pricing under international market integration and segmentation.

Assuming exogenously determined but proportional transaction costs as in Jones (2002), poor liquidity or high transaction costs drive a wedge between the gross returns that we measure in the data and the actually obtained returns ("net returns"), that is:

$$\exp(r_{t+1}^{\text{net}}) = \frac{\exp(r_{t+1}^{\text{gross}})}{TC_{t+1}}, \tag{10}$$

where $TC_{t+1} \geq 1$ presents a transaction cost measure (if $TC = 1$, there are no transaction costs), and r_{t+1}^{net} and r_{t+1}^{gross} are continuously compounded returns.

We postulate that the log of the transaction cost measure is proportional to the liquidity measure, Ł, that is:

$$\ell n(TC_{t+1}) = v\text{Ł}_{t+1} \quad (v < 0), \tag{11}$$

(10) and (11) hold for each market, i, and for the U.S., w. Recall that our liquidity measure, Ł, is defined as $\ell n(1 - ZR)$, so that a greater incidence of zero returns is associated with a reduction in market liquidity. In general, the coefficient v will be market specific, v_i. Note that we implicitly assume that everybody has the same one-year or one-month horizon in which they trade once. Of course, in reality, the trading frequency is endogenous. It is likely that an asset with high transaction costs will be traded less frequently and held longer.[10] The total transaction cost associated with an asset could be measured as the turnover in a given year times the transaction cost, including fixed costs and the bid-ask spread (see Jones (2002)). Unfortunately, we cannot measure transaction costs that precisely since we do not have complete bid-ask spread data. Further, while these explicit costs of transacting in equity markets are important, they do not reflect the implicit costs associated with trading, such as the price impact. These additional costs may be particularly important in emerging equity markets. However, a zero daily return may reflect the presence of all transaction costs market participants face.

While the transaction cost channel suffices to induce predictable variation in gross expected returns, a rapidly growing literature asserts liquidity is priced. For liquidity to be priced at the aggregate level, there must be a systematic component to liquidity variation, and overall, stocks must perform poorly when liquidity dries up. In this case, the expected equity premium is negatively linked to liquidity, and shocks to liquidity change expected returns and hence prices. It is informative to explore a simple pricing model where the transactions cost effect and "liquidity risk" interact. In particular, the pricing model should apply to *net* returns but we only observe *gross* returns. Hence, the pricing relations become quite complex even under simple assumptions. We start with a model imposing the assumption of global market integration and then consider the case of perfectly segmented markets.

[10] See Amihud and Mendelson (1986) for an interesting analysis of the resulting potential clientele effects. Also, see Huang (2003).

4.2 *Pricing under global market integration*

We ignore currency effects, measuring all returns in dollars and assuming a dollar risk-free rate. We assume that there are two risk factors affecting the world pricing kernel: net U.S. market returns ($r^{\text{net}}_{w,t+1}$) and U.S. liquidity ($Ł_{w,t+1}$). We assume that the log pricing kernel under market integration is given by:

$$m^I_{t+1} = \ell n(M^I_{t+1}) = -\gamma_w r^{\text{net}}_{w,t+1} - \gamma_{Ł,w} Ł_{w,t+1}, \tag{12}$$

where γ_w is the world price of market risk and $\gamma_{Ł,w}$ is the world price of liquidity risk. It follows for all returns, $r^{net}_{i,t+1}$,

$$E_t[exp(r^{net}_{i,t+1})M^I_{t+1}] = 1, \tag{13}$$

holds under global market integration.

Let r^f_t be the continuously-compounded risk free interest rate. Assume that all continuously-compounded returns and $Ł_{w,t+1}$ are jointly normally distributed. Then,

$$r^f_t = -E_t[m_{t+1}] - \frac{1}{2}\text{Var}_t[m_{t+1}]. \tag{14}$$

Hence,

$$E_t[r^{\text{net}}_{i,t+1}] = r^f_t - \frac{1}{2}\text{Var}_t[r^{\text{net}}_{i,t+1}] + \gamma_w \text{Cov}_t[r^{\text{net}}_{i,t+1}, r^{\text{net}}_{w,t+1}] + \gamma_{Ł,w}\text{Cov}_t[r^{\text{net}}_{i,t+1}, Ł^{\text{net}}_{w,t+1}]. \tag{15}$$

Equation (15) follows from the main pricing equation (13) and the normal distributional assumption, after substituting in (14). Markets that do well when the world market performs well or liquidity is high, require high expected net returns.

To express the model in terms of gross observed returns, we need to solve for the variances and covariances in terms of moments for gross returns in equation (15):

$$\begin{aligned}
\text{Var}_t[r^{\text{net}}_{i,t+1}] &= \text{Var}_t[r^{\text{gross}}_{t+1} - v_i Ł_{i,t+1}] && (16)\\
&= \text{Var}_t[r^{\text{gross}}_{i,t+1}] + v_i^2 \text{Var}_t[Ł_{i,t+1}] - 2v_i \text{Cov}_t[r^{\text{gross}}_{i,t+1}, Ł_{i,t+1}], \\
\text{Cov}_t[r^{\text{net}}_{i,t+1}, r^{\text{net}}_{w,t+1}] &= \text{Cov}_t[r^{\text{gross}}_{i,t+1} - v_i Ł_{i,t+1}, r^{\text{gross}}_{w,t+1} - v_w Ł_{w,t+1}] && (17)\\
&= \text{Cov}_t[r^{\text{gross}}_{i,t+1}, r^{\text{gross}}_{w,t+1}] + v_i v_w \text{Cov}_t[Ł_{i,t+1}, Ł_{w,t+1}] \\
&\quad -v_i \text{Cov}_t[Ł_{i,t+1}, r^{\text{gross}}_{w,t+1}] - v_w \text{Cov}_t[r^{\text{gross}}_{i,t+1}, Ł_{w,t+1}],
\end{aligned}$$

and

$$\mathrm{Cov}_t[r^{\mathrm{net}}_{i,t+1}, Ł_{w,t+1}] = \mathrm{Cov}_t[r^{\mathrm{gross}}_{i,t+1}, Ł_{w,t+1}] - v_i \mathrm{Cov}_t[Ł_{i,t+1}, Ł_{w,t+1}]. \tag{18}$$

Combining (10), (11), (15)-(17), we obtain,

$$\begin{aligned} E_t[r^{\mathrm{gross}}_{i,t+1}] - r^f_t \;=\;& \gamma_w \mathrm{Cov}_t[r^{\mathrm{gross}}_{i,t+1}, r^{\mathrm{gross}}_{w,t+1}] \leftarrow \text{ [world market risk]} \\ & +(\gamma_{Ł,w} - \gamma_w v_w)\mathrm{Cov}_t[r^{\mathrm{gross}}_{i,t+1}, Ł_{w,t+1}] \leftarrow \text{ [world liquidity risk]} \\ & +v_i E_t[Ł_{i,t+1}] + v_i \mathrm{Cov}_t[Ł_{i,t+1}, r^{\mathrm{gross}}_{i,t+1}] \leftarrow \text{ [local liquidity risk]} \\ & -v_i \gamma_w \mathrm{Cov}_t[Ł_{i,t+1}, r^{\mathrm{gross}}_{w,t+1}] \leftarrow \text{ [cross liquidity-return effect]} \\ & +(\gamma_w v_i v_w - \gamma_{Ł,w} v_i)\mathrm{Cov}_t[Ł_{i,t+1}, Ł_{w,t+1}] \leftarrow \text{ [liquidity covariation effect]} \\ & -\frac{1}{2}\mathrm{Var}_t[r^{\mathrm{gross}}_{i,t+1}] - \frac{1}{2}v_i^2 \mathrm{Var}_t[Ł_{i,t+1}] \leftarrow \text{ [Jensen's inequality terms]} \end{aligned} \tag{19}$$

The simple pricing relation in (15) for net returns with two risks and a Jensen's inequality term turns into a pricing equation with eight terms.

The first term in equation (19) reflects world market risk; the second term reflects world liquidity risk but the price of world liquidity risk is $\gamma_{Ł,w} - \gamma_w v_w$, not $\gamma_{Ł,w}$. Assuming positive prices of risk, and with v_w likely negative, this exposure is larger than reflected in the world price of liquidity risk. The extra terms arise because correlation between gross returns and world liquidity contributes to the correlation between net U.S. and local returns. It is useful to immediately contrast this term with the third line: $v_i \left[E_t[Ł_{i,t+1}] + \mathrm{Cov}_t[Ł_{i,t+1}, r^{\mathrm{gross}}_{i,t+1}]\right]$. These terms reflect pure local liquidity risks. The first component simply captures the assumption that illiquid securities must have higher expected returns because of transactions costs; the second that this expected return must be even higher when that market is subject to local liquidity risk. The latter seems counter intuitive as it lowers the expected return for securities with positive liquidity risk. However, in a world of full integration, local liquidity risks are not likely to influence net returns, that is, $\mathrm{Cov}_t[Ł_{i,t+1}, r^{\mathrm{net}}_{i,t+1}] = 0$ is a fair assumption. If this is the case, we obtain $\mathrm{Cov}_t[Ł_{i,t+1}, r^{\mathrm{gross}}_{i,t+1}] = -v_i \mathrm{Var}_t[Ł_{i,t+1}]$, indicating that the local liquidity term mitigates the transactions cost effect.

The fourth line shows that a positive covariation between local liquidity and the market return implies a higher expected return. This term also arises in the Acharya and Pedersen (2005) model, and they offer an extensive economic motivation for why investors may accept a lower return on a security that is liquid in a down market. The fifth line shows that the expected return increases with the covariance between local market liquidity and world market liquidity. This essentially is the commonality-in-liquidity effect referred to by Chordia, Roll, and Subramanyam (2001), Hasbrouck and Seppi (2000), and Huberman and Halka (1999). The term also arises in the Acharya and Pedersen (2005) framework. In the context of our global pricing framework, applied to emerging markets, both the cross-liquidity return and liquidity covariance effects may be expected to be small. It is not likely that, for emerging markets, local liquidity covaries much with U.S. returns or U.S. liquidity. The final line represents the Jensen's inequality terms. What is most striking about the pricing framework developed here is that even under global market integration, local factors enter the asset pricing equation.

4.3 *Pricing under market segmentation*

Under segmentation, the price of local liquidity and the local equity return enter the pricing kernel:

$$m^S_{t+1} = \ell n(M^S_{t+1}) = -\gamma_i r^{\text{net}}_{i,t+1} - \gamma_{\text{Ł},i} Ł_{i,t+1} \tag{20}$$

Under joint normality,

$$E_t[r^{\text{net}}_{i,t+1}] = r^f_t - \frac{1}{2}\text{Var}_t[r^{\text{net}}_{i,t+1}] + \gamma_i \text{Var}_t[r^{\text{net}}_{i,t+1}] + \gamma_{\text{Ł},i}\text{Cov}_t[r^{\text{net}}_{i,t+1}, Ł^{\text{net}}_{i,t+1}]. \tag{21}$$

Notice that r^f_t is a domestic interest rate and the model would normally apply to local excess returns. However, the use of local excess returns in emerging markets is hampered by the presence of extreme returns and interest rates in the data. Therefore, we follow most of the literature and formulate the model in U.S. dollars. If uncovered interest rate parity holds or exchange rate shocks are uncorrelated with the kernel formulated in equation (20), our expected excess return expressions are identical for local currency or dollar returns. Again, we must transform net into gross returns. We use:

$$\text{Cov}_t[r^{\text{net}}_{i,t+1}, Ł_{i,t+1}] = \text{Cov}_t[r^{\text{gross}}_{i,t+1}, Ł_{i,t+1}] - v_i \text{Var}_t[Ł_{i,t+1}] \tag{22}$$

and the expression for $\text{Var}_t[r^{\text{net}}_{i,t+1}]$ in Equation (16):

$$E_t[r^{\text{gross}}_{i,t+1}] - r^f_t \quad = \quad (\gamma_i - \frac{1}{2})\text{Var}_t[r^{\text{gross}}_{i,t+1}] \tag{23}$$

$$[\gamma_{\text{Ł},i} - (\gamma_i - \frac{1}{2})2v_i]\text{Cov}_t[r^{\text{gross}}_{i,t+1}, \text{Ł}_{i,t+1}]$$
$$v_i E_t[\text{Ł}_{i,t+1}] + v_i[v_i(\gamma_i - \frac{1}{2}) - \gamma_{\text{Ł},i}]\text{Var}_t[\text{Ł}_{i,t+1}]$$

While the same risks are present in the integrated model as well, now they have different coefficients. Assume, $\gamma_i > \frac{1}{2}$ and $\gamma_{\text{Ł},i} > 0$. The variance of liquidity then features a positive coefficient even when the Jensen's inequality is accounted for. Whereas the covariance between local returns and local liquidity surprisingly receives a negative coefficient in the integrated model, it has the expected positive coefficient here as it represents a genuine liquidity risk. However, the price of risk is not $\gamma_{\text{Ł},i}$, but potentially larger due to the relation between transaction costs and liquidity variation. Again, the expression for expected returns contains a transactions cost term, $v_i E_t[\text{Ł}_{i,t+1}]$, a term in the variance of liquidity representing the Jensen's inequality effect, and covariation terms that arise from the correlation between transaction costs and aggregate risks. These terms simplify because we use aggregate country portfolios. The indirect transaction costs term features a positive coefficient under the assumptions above and counter-balances the direct transactions costs effect.

4.4 *Model estimation*

Before the models in equations (10)-(23) become estimatible, we must make a few auxiliary assumptions. First, the models feature a number of country-specific parameters which give rise to a rather large parameter space. We resolve this by making country-specific parameters a function of the liberalization state, for example, the transactions costs parameter is:

$$v_i = v_0 + v_1 Lib_{i,t} \tag{24}$$

v_i only depends on two common parameters which distinguish transaction cost effects across liberalized and non-liberalized markets. Consistent with this assumption, we let $\gamma_i = \gamma_S$ and $\gamma_{\text{Ł},i} = \gamma_{\text{Ł},S}$. We formulate an encompassing model that is still parsimonious. Define $\theta^j_{i,t}$ as a parameter function for the j^{th} priced risk in country i that could in principle depend on the liberalization intensity measured at time t:

$$\theta^j_{i,t} = \theta^j_0 + \theta^j_1 Lib_{i,t} \tag{25}$$

Our models are nested in the following model:

$$
\begin{aligned}
E_t[r^{\text{gross}}_{i,t+1}] - r^f_t \;=\;& v_i E_t[\text{Ł}_{i,t+1}] + \theta^1_{i,t}\text{Var}_t[r^{gross}_{i,t+1}] \\
& +\theta^2_{i,t}\text{Var}_t[\text{Ł}_{i,t+1}] + \theta^3_{i,t}\text{Cov}_t[\text{Ł}_{i,t+1}, r^{gross}_{i,t+1}] \\
& +\theta^4_{i,t}\text{Cov}_t[\text{Ł}_{i,t+1}, r^{gross}_{w,t+1}] + \theta^5_{i,t}\text{Cov}_t[\text{Ł}_{i,t+1}, \text{Ł}_{w,t+1}] \\
& +\theta^6_{i,t}\text{Cov}_t[r^{gross}_{i,t+1}, \text{Ł}_{w,t+1}] + \theta^7_{i,t}\text{Cov}_t[r^{gross}_{i,t+1}, r^{gross}_{w,t+1}]. \qquad (26)
\end{aligned}
$$

Such a formulation does not impose the theoretical restrictions implied by the model derived in Section 3. We investigate three restricted models, which are summarized in the following table.

	Mixed model	Full integration	Full segmentation
v_i	$v_0 + v_1 Lib_{i,t}$	v_1	v_0
$\theta^1_{i,t}$	$(-\frac{1}{2})Lib_{i,t} + (\gamma_i - \frac{1}{2})(1 - Lib_{i,t})$	$-\frac{1}{2}$	$\gamma_S - \frac{1}{2}$
$\theta^2_{i,t}$	$(-\frac{1}{2})v_i^2 Lib_{i,t} + v_i[(\gamma_S - \frac{1}{2})v_i - \gamma_{\text{Ł},S}](1 - Lib_{i,t})$	$-\frac{1}{2}v_i^2$	$v_i[v_i(\gamma_S - \frac{1}{2}) - \gamma_{\text{Ł},S}]$
$\theta^3_{i,t}$	$v_i Lib_{i,t} + [\gamma_{\text{Ł},S} - (\gamma_S - \frac{1}{2})2v_i](1 - Lib_{i,t})$	v_i	$\gamma_{\text{Ł},S} - (\gamma_S - \frac{1}{2})2v_i$
$\theta^4_{i,t}$	$-v_i\gamma_w Lib_{i,t}$	$-v_i\gamma_w$	0
$\theta^5_{i,t}$	$(\gamma_w v_w - \gamma_{\text{Ł},w})v_i Lib_{i,t}$	$(\gamma_w v_w - \gamma_{\text{Ł},w})v_i$	0
$\theta^6_{i,t}$	$(\gamma_{\text{Ł},w} - \gamma_w v_w)Lib_{i,t}$	$(\gamma_{\text{Ł},w} - \gamma_w v_w)$	0
$\theta^7_{i,t}$	$\gamma_w Lib_{i,t}$	γ_w	0

The fully segmented model has only three parameters, the fully integrated model has four parameters and the mixed model has seven parameters. The mixed model reduces to one of the extreme models when the liberalization intensity indicator is either 0 or 1. Consequently, these are very parsimonious models. Of course, the underlying assumptions are extreme: no temporal or cross-sectional variation in the prices of risk. We also investigate the relative role of the transaction cost channel versus the systematic liquidity risk exposure through which liquidity can affect expected returns. To focus on the first, we set $\gamma_{\text{Ł},w} = \gamma_{\text{Ł},S} = 0$; to focus on the latter, we set $v_w = v_i = 0$.

Our second set of auxiliary assumptions concern the dynamics of expected returns and conditional second moments. Our model essentially constrains the relation between the two but to test the model restrictions, we must exogenously specify either volatility or expected return dynamics. We choose to follow the pricing framework of Campbell (1987) and Harvey

(1989, 1991) in which expected returns are assumed to be exact linear functions of a set of instruments. Denote the residuals from these projections as

$$\mathbf{u}_t = [\mathbf{u}_{i,t}, u_{w,t}, \mathbf{u}_{\text{Ł}_i,t}, u_{\text{Ł}_w,t}] \text{ for } i = 1, \ldots, N. \tag{27}$$

We make the assumption that

$$E[\mathbf{u}_t | \mathbf{I}_{t-1}] = 0. \tag{28}$$

This is a strong assumption, as it requires returns and the liquidity measure (zero returns) to exhaust the information set (see Harvey (1991) for further discussion).

The model can be estimated in two steps. First, our previously estimated vector autoregressive systems determine the $\mathbf{u}_t$. Second, we estimate the following pricing moments using panel GMM:

$$\begin{aligned}
e_{w,t} &= r_{w,t} - r_{f,t-1} - v_w \text{Ł}_{w,t} - \gamma_w u_{w,t}^2 - \gamma_{\text{Ł},w} u_{w,t} u_{\text{Ł}_w,t} \\
e_{i,t} &= r_{i,t} - r_{f,t-1} - v_i \text{Ł}_{i,t} - \theta_{i,t-1}^1 u_{i,t}^2 - \theta_{i,t-1}^2 u_{\text{Ł}_i,t}^2 - \theta_{i,t-1}^3 u_{\text{Ł}_i,t} u_{i,t} \\
&\quad - \theta_{i,t-1}^4 u_{\text{Ł}_i,t} u_{w,t} - \theta_{i,t-1}^5 u_{\text{Ł}_i,t} u_{\text{Ł}_w,t} - \theta_{i,t-1}^6 u_{i,t} u_{\text{Ł}_w,t} - \theta_{i,t-1}^7 u_{i,t} u_{w,t}.
\end{aligned}$$

The orthogonality conditions to estimate this system can be summarized as follows:

$$\mathbf{g}_t = \begin{bmatrix} e_{w,t} \otimes \mathbf{x}_{w,t-1} \\ e_{i,t} \otimes (\mathbf{x}_{i,t-1}, Lib_{i,t-1}) \end{bmatrix}. \tag{29}$$

In our empirical work, we primarily focus on the benchmark case, $\mathbf{x}_{i,t} = [r_{i,t}, \text{Ł}_{i,t}]$, corresponding to the bivariate VAR. We also consider several robustness checks. For the emerging markets, the system has 72 orthogonality conditions, where our least parsimonious model has only 16 parameters (the U.S. system has 3 additional conditions). We report the standard test of over-identifying restrictions. We also consider a comparison across models by evaluating the Hansen and Jagannathan (1991) distance metric, which measures the (squared) distance that the implied pricing kernel is from the region of acceptable pricing kernels. This amounts to a simple re-weighting of the moment conditions by the inverse of the inner product of the raw returns with the lagged instrument set. In contrast to the optimal GMM weighting matrix which is model specific, this weighting scheme is constant across all models, and facilitates an interesting means of model comparison (see Jagannathan and Wang (1996)).

4.5 *Empirical results*

Our bivariate VAR, described above, using returns and equal-weighted zero returns as our measure of liquidity acts as the first stage that defines *unexpected* return and liquidity shocks for each country. We decided to pre-estimate the U.S. parameters using a longer sample from 1962-2003 from CRSP. This ensures that the world parameters are identical across models.[11]

Table 7 presents the results for several pricing models, detailed above. First, in Panel A, we present evidence on the three basic theoretical models associated with either a fully integrated case, a fully segmented case, or a mixed variant. In this case, we consider some alternatives as robustness checks. In Panel B, we present evidence on the unrestricted case where the coefficients associated with various covariances are left unrestricted. To begin, it is important to note that all models we consider are rejected with p-values below 0.01 based upon the tests of over-identifying restrictions. While the J-test is known to over-reject the null hypothesis in small samples, these statistics are quite large suggesting that asset pricing in the emerging market context is very challenging. For this reason, we focus instead on the economic information that can be extracted from these cases.

To begin, we present the fully integrated case, for which we estimate three parameters, v_1 – the gross to net return adjustment, γ_w – the price of world market risk, and $\gamma_{\mathrm{L},w}$ – the price of world market liquidity risk. In all cases, we constrain the various local prices of risk to be identical across countries. The gross to net adjustment parameter is negative and significant. Evaluated at the average zero, this term represents about 20 basis points per month, a reasonable estimate. The pre-estimated prices of world market and world liquidity risk are positive and statistically significant, though the latter is only borderline significant. It is important to note that the standard errors reported in the table ignore the sampling error associated with the first stage VAR that generate the return and liquidity shocks that enter this analysis, and hence likely underestimate the true standard error. Further, of the models under consideration, the fully integrated model has one of the largest HJ-distances, suggesting that this model does a *relatively* poor job of explaining emerging markets returns.

Next, we consider the case of full segmentation. This model involves the estimation of

[11]The v_w estimate proved unrealistically large, so we set it to zero. The resulting model fits the data as well the model with non-zero v_w and has positive prices of risk.

three parameters as well: v_0 – the gross to net return adjustment, γ_s – the price of local market risk, and $\gamma_{\text{L},S}$ – the price of local market liquidity risk. The sign of the gross to net return parameter is positive and significant, which is not the direction expected, suggesting higher levels of liquidity are associated with a higher gross to net adjustment. Second, the local price of market risk is not significant; however, the price of local liquidity risk is positive and significant, almost four standard errors from zero. Of the main models considered, the fully segmented model is associated with the lowest HJ-distance metric. These estimates suggest a 45 and 85 basis point per month compensation for local market and liquidity risk, respectively.

As the markets under exploration in this study are neither fully segmented nor integrated, we also consider the mixed model where risk compensation varies over the liberalization process. This model requires the estimation of six parameters, aggregating the two extreme versions above. In this case, the gross to net adjustment parameter is positive and significant for fully segmented markets, but moves to zero for markets displaying greater foreign investor access. The pre-estimated prices of world market and liquidity risk are necessarily identical to the fully integrated case. The price of local market risk is not significant; however, the price of local liquidity risk has the right sign and is highly significant. The HJ-distance associated with the mixed model is not as small as the full segmentation model. For segmented markets, these estimates suggest a -31 and 106 basis point per month compensation for local market and liquidity risk, respectively. For integrated markets, these estimates suggest a -4 and 27 basis point per month compensation for global market and liquidity risk, respectively. Across the three models considered, the only robust result seems to be that the price of local liquidity risk is an important driver of expected returns.

As an additional check, we consider three alternative specifications. In the first and second, we consider alternatives where we shut down either the gross to net return transaction costs adjustments, v_i, or the prices of risks associated with local and global systematic liquidity, $\gamma_{\text{L},S}$ and $\gamma_{\text{L},w}$ respectively. The removal of a transaction costs effect still yields a positive and significant price of local liquidity risk. However, this model has a larger HJ distance. The removal of all systematic liquidity pricing does not have a large effect on the price of world market risk, but it does yield a negative estimate for v_0. This model actually yields the lowest HJ distance.

Finally, we also estimate the general mixed model, but we replace the equally weighted zero return liquidity measure with its value-weighted counterpart. The pre-estimated U.S. pricing evidence is very similar to the equal-weighted liquidity case. Here, the gross-to-net return transaction cost adjustment is not significant, but the price of local liquidity risk is strongly significant, reinforcing the notion that local liquidity risk is important in the determination of expected returns for emerging markets.

Finally, Panel B considers two unrestricted models that facilitate a separate coefficient for each of the various conditional variances and covariances presented free of any theoretical restrictions. In the first, case we assume that there is no sensitivity to the liberalization regime, whereas the second case allows the parameters to vary across liberalization state. These models involves the estimation of eight and sixteen parameters, respectively. In the first case, only four of the parameters in this model are statistically significant. Both the prices of world market, θ_6, and world liquidity risk, θ_7, are negative and significant, but in an unexpected direction. The price of risk associated with commonality in liquidity, θ_5, is positive and significant. The price of local market liquidity risk, θ_3, is positive and highly significant, consistent with the theoretically restricted models. The HJ-distance associated with this model is relatively large in comparison to the theoretical models that facilitate local risks. In the second case, only four of the parameters are statistically significant: the two associated with the price of local liquidity, $\theta_{3,0}$ and $\theta_{3,1}$, and the two associated with the price of world market risk, $\theta_{7,0}$ and $\theta_{7,1}$. The price of local liquidity is positive, but significantly reduced with greater degrees of liberalization (but still positive). The price of world market risk is negative under segmentation, but significantly increased with liberalization, and positive for integrated markets. The HJ distance associated with this model is also quite large.

Taken together, it is very clear that the various channels for risk compensation are extremely difficult to estimate with precision.[12] However, the evidence on the price of local

[12]We also considered the shocks associated with the alternative VARs presented in Table 5 that include either dividend yields or turnover; the pricing evidence (not reported) across these alternatives is very similar with a significant role for local liquidity risks in all cases. However, when we use the price impact measure,

market risk is fairly robust across the cases considered here, strongly suggesting that local market liquidity is an important driver of expected returns in emerging markets, and that the liberalization process has not eliminated its impact. Models with an important role for local liquidity risks and allowing segmentation do not only out-perform on the HJ distance measure criterion, but also generate by far the highest cross-sectional correlation between average returns over the sample with the expected returns generated by the various models. The best models here are the market segmentation (panel A) and unrestricted (with no role for liberalization) (panel B) models, for which the correlations between expected and average returns are 0.51 and 0.61, respectively.

5 Conclusions

There is a growing consensus that systematic variation in liquidity matters for expected returns. We examine this issue for a set of markets where liquidity ought to be particularly important – emerging markets. We start by proposing a measure of liquidity and transaction costs, first analyzed by Lesmond (2005) and Lesmond, Ogden and Trzcinka (1999): the proportion of daily zero firm returns averaged over the month. The measure is easy to compute and, as expected, is indeed positively correlated with bid-ask spreads (where available) and negatively correlated with equity market turnover. We find that the zero measure captures an aspect of liquidity that is not present in turnover. In all of our analysis, turnover has an insignificant impact on returns in the presence of the zero measure. We also show that the zero measure significantly predicts returns in emerging markets, and unexpected liquidity shocks are positively correlated with returns and negatively correlated with dividend yields.

Finally, if liquidity is priced, a model with market and liquidity risk may be a good description of expected returns. For emerging markets, there is the added complication that the market may be segmented or integrated. Many of the markets that we examine underwent a liberalization process and liberalization may affect the dynamic relation between returns and liquidity. We consider several models that allow for local or world market and liquidity risks depending on whether a country is integrated or segmented. We also separate

local liquidity risk is less important.

the transaction cost and systematic risk effects of liquidity variation on expected returns, leading to a model where local factors matter even under the hypothesis of global market integration. Whereas our analysis is exploratory in nature, we find a very clear evidence that local liquidity risk is important.

In future work, we intend to apply our asset pricing framework to developed markets. While we expect less cross-country variation in liquidity in these markets, the richer data will allow us to build more intricate measures of liquidity and construct powerful tests of whether liquidity is globally and locally priced.

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Table 1

Summary statistics

Sample: 1987:01 2003:12

	Argentina	Brazil	Chile	Colombia	Greece	India	Indonesia	Korea	Malaysia	Mexico	Pakistan	Philippines	Portugal	Taiwan	Thailand	Turkey	Venezuela	Zimbabwe	Average
Monthly Return (US$)																			
Mean	0.031	0.023	0.018	0.015	0.018	0.010	0.005	0.011	0.009	0.021	0.014	0.008	0.014	0.016	0.014	0.030	0.016	0.026	0.017
Standard deviation	0.211	0.168	0.078	0.088	0.115	0.091	0.139	0.121	0.100	0.118	0.103	0.104	0.101	0.134	0.123	0.199	0.140	0.167	0.128
Autocorrelation	-0.066	-0.011	0.212	0.397	0.082	0.107	0.195	0.023	0.103	0.270	0.034	0.263	0.250	0.058	0.091	0.101	0.045	0.174	0.129
Observations	204	204	204	204	204	204	168	204	204	204	204	204	204	204	204	204	204	204	202
Return (Local Currency)																			
Mean	0.098	0.133	0.023	0.028	0.022	0.017	0.010	0.011	0.010	0.032	0.019	0.012	0.014	0.016	0.015	0.067	0.038	0.047	0.034
Standard Deviation	0.362	0.232	0.071	0.088	0.115	0.094	0.107	0.104	0.090	0.110	0.100	0.096	0.099	0.130	0.116	0.195	0.127	0.144	0.132
Autocorrelation	0.241	0.227	0.214	0.389	0.109	0.107	0.111	0.074	0.077	0.289	0.026	0.203	0.272	0.046	0.029	0.061	0.119	0.122	0.151
Observations	204	204	204	204	204	204	168	204	204	204	204	204	204	204	204	204	204	204	202
Dividend yield																			
Mean	0.0022	0.0032	0.0038	0.0037	0.0033	0.0015	0.0014	0.0013	0.0019	0.0016	0.0047	0.0010	0.0021	0.0007	0.0022	0.0029	0.0030	0.0039	0.0025
Standard deviation	0.0016	0.0026	0.0019	0.0017	0.0018	0.0006	0.0009	0.0006	0.0007	0.0006	0.0028	0.0005	0.0008	0.0003	0.0013	0.0019	0.0031	0.0023	0.0014
Autocorrelation	0.828	0.871	0.969	0.977	0.897	0.933	0.957	0.776	0.924	0.907	0.953	0.948	0.913	0.898	0.856	0.855	0.978	0.948	0.910
Observations	204	204	204	204	204	204	168	204	204	204	204	204	204	204	204	194	204	204	201
Turnover (Value Traded/MCAP) (TO)																			
Mean	0.035	0.050	0.010	0.007	0.033	0.094	0.049	0.141	0.028	0.038	0.278	0.024	0.032	0.209	0.074	0.113	0.017	0.009	0.069
Standard deviation	0.021	0.025	0.006	0.004	0.034	0.099	0.027	0.108	0.018	0.017	0.448	0.014	0.024	0.090	0.057	0.114	0.017	0.008	0.063
Autocorrelation	0.739	0.816	0.423	0.474	0.788	0.844	0.710	0.877	0.725	0.649	0.920	0.668	0.798	0.641	0.685	0.842	0.674	0.553	0.712
Observations	204	204	204	204	204	204	169	204	204	204	204	204	204	204	204	204	204	204	202
Proportion of daily (local currency) zero returns in that month (ZR)																			
Mean	0.426	0.692	0.692	0.740	0.343	0.336	0.640	0.180	0.307	0.600	0.600	0.633	0.601	0.112	0.543	0.267	0.443	0.576	0.485
Standard deviation	0.190	0.072	0.068	0.090	0.196	0.062	0.073	0.076	0.085	0.058	0.097	0.122	0.077	0.029	0.066	0.116	0.269	0.120	0.104
Autocorrelation	0.968	0.935	0.849	0.838	0.984	0.700	0.811	0.892	0.799	0.859	0.881	0.899	0.830	0.491	0.819	0.927	0.962	0.889	0.852
Observations	186	168	174	144	192	168	165	204	204	189	138	196	192	196	204	192	168	132	178
Price pressure of non-trading (PI)																			
Mean	0.557	0.833	0.809	0.830	0.411	0.435	0.726	0.246	0.362	0.709	0.732	0.697	0.679	0.157	0.614	0.339	0.546	0.653	0.574
Standard deviation	0.229	0.063	0.063	0.085	0.257	0.145	0.082	0.110	0.107	0.091	0.138	0.127	0.084	0.046	0.077	0.118	0.286	0.139	0.125
Autocorrelation	0.949	0.740	0.641	0.586	0.975	0.625	0.743	0.857	0.780	0.800	0.794	0.794	0.614	0.424	0.576	0.877	0.930	0.895	0.756
Observations	192	168	174	144	192	168	165	194	202	192	149	196	169	196	202	192	168	132	178
Ave. number of firms	43	307	162	35	239	713	183	666	470	92	167	135	159	257	379	180	26	30	236
Total number of firms	83	572	227	53	380	892	308	1612	815	163	240	217	271	562	401	295	53	89	402

The monthly returns (U.S.$) and dividend yields are from the S&P/IFC. Equity market turnover for each month is the equity value traded for that month, divided by that month's equity market capitalization from Standard and Poor's. Finally, the proportion of zero daily (local currency) returns and price impact of non-trading observed over the month for each equity market use daily returns data at the firm level which are obtained from the Datastream research files starting from the late 1980's. For each country, we observe daily returns (using closing prices) for a large collection of firms listed on a domestic exchange. For each country, we calculate the proportion of zero daily returns and price impact across all firms, and average these figures over the month.

Table 2
Correlations of percentage of zero daily returns with alternative measures of liquidity

	Bid-ask spread	Turnover (TO)	Price Impact (PI)	Bid-ask spread and turnover (TO)	GARCH conditional volatility	TARCH conditional volatility	Within month volatility
Argentina		-0.24	0.95		-0.43	-0.31	-0.23
Brazil	0.12	-0.22	0.42	0.06	0.65	0.74	-0.09
Chile		-0.04	0.64		-0.01	-0.29	0.07
Colombia		-0.04	0.68		-0.30	-0.32	0.09
Greece		-0.55	0.97		0.38	0.13	-0.09
India		-0.57	0.69		0.08	-0.29	0.10
Indonesia	0.72	-0.31	0.79	-0.05	-0.20	-0.13	0.06
Korea	0.77	-0.54	0.96	-0.25	0.14	0.15	-0.23
Malaysia	0.51	-0.41	0.81	-0.54	-0.21	-0.19	-0.10
Mexico	0.60	-0.28	0.48	-0.09	-0.12	-0.12	-0.11
Pakistan		-0.41	0.87		0.22	0.12	-0.02
Philippines	0.88	-0.38	0.82	-0.33	-0.23	-0.09	-0.08
Portugal	0.42	-0.33	0.25	-0.19	-0.37	-0.39	-0.01
Taiwan		-0.48	0.76		-0.38	-0.36	-0.60
Thailand	0.79	-0.12	0.60	-0.59	0.40	0.43	-0.07
Turkey	0.56	-0.51	0.91	0.19	0.09	0.43	-0.05
Venezuela		-0.56	0.97		-0.03	0.00	-0.01
Zimbabwe		-0.27	0.88		-0.18	-0.18	0.19
Cross-sectional average		-0.44	0.99				
Time-series average	0.60	-0.35	0.74	-0.20	-0.03	-0.04	-0.07

For each country, we calculate the proportion of zero daily returns (ZR) and price impact of non-trading (PI) across all firms, and average this proportion over the month. Bid-ask spreads at the firm level are obtained from the Datastream research files (where available) for the countries shown here. Equity market turnover (TO) is the value traded for that month divided by that month's equity market capitalization. Estimates of conditional volatility are obtained for each country by maximum likelihood estimation of a symmetric GARCH(1,1) and an asymmetric threshold GARCH(1,1) (TARCH). Following French, Schwert, and Stambaugh (1987), within-month volatility is constructed by first summing the squared returns for each firm within the month, and then averaging across firms for that month.

Table 3

Specification tests of the bivariate VAR system

	Returns		Liquidity	
	First-order autocorrelation	Wald Test: first three autocorrelations = 0 asymptotic p-value	First-order autocorrelation	Wald Test: first three autocorrelations = 0 asymptotic p-value
Argentina	-0.007	0.903	-0.017	0.096
Brazil	-0.030	0.621	-0.103	0.067
Chile	0.042	0.804	-0.227	<0.001*
Colombia	0.279	0.015*	-0.239	0.045
Greece	-0.095	0.586	0.138	0.821
India	0.036	0.043	-0.382	<0.001*
Indonesia	0.162	0.084	0.021	0.086
Korea	0.052	0.854	0.016	0.041
Malaysia	0.048	0.030	-0.096	0.192
Mexico	0.084	0.800	-0.173	0.039
Pakistan	-0.043	0.761	-0.146	0.046
Philippines	0.129	0.441	-0.135	0.461
Portugal	0.007	0.793	-0.059	0.730
Taiwan	-0.055	0.390	-0.330	<0.001*
Thailand	0.025	0.160	-0.247	0.046
Turkey	-0.073	0.451	-0.191	0.188
Venezuela	-0.161	0.260	-0.056	0.916
Zimbabwe	-0.066	0.710	-0.140	0.261
Joint test (all countries)		0.937		<0.001*
United States	0.003	0.847	-0.031	0.640

This table presents several specification tests based upon on the residuals from the benchmark bivariate VAR for returns and liquidity. We report the first-order autocorrelation coefficient for each country's return and liquidity residuals. We also present asymptotic p-values, country-by-country, for a Wald test that the first three autocorrelations are jointly zero. Finally, we also conduct a joint Wald test where the null hypothesis is that all of the first three autocorrelations across countries are jointly zero (with 18x3=54 restrictions); asymptotic p-values are reported. A * indicates the test statistic exceeds the Monte Carlo critical value for significance at the 5% level. We also report similar evidence for the U.S.

Table 4

Vector autoregression of returns and liquidity

1993-2003

VAR dynamics:

$\mathbf{A_0}$		Estimate	Standard Error	$\mathbf{A_1}$		Estimate	Standard Error
R_t	R_{t-1}	0.0524	*0.0419*	R_t	R_{t-1}	-0.0104	*0.0542*
	$\mathcal{L}_{t-1}$ (ZR)	-0.0531	*0.0200*		$\mathcal{L}_{t-1}$ (ZR)	0.0316	*0.0254*
$\mathcal{L}_t$ (ZR)	R_{t-1}	0.1144	*0.0287*	$\mathcal{L}_t$ (ZR)	R_{t-1}	-0.0463	*0.0402*
	$\mathcal{L}_{t-1}$ (ZR)	0.9085	*0.0141*		$\mathcal{L}_{t-1}$ (ZR)	-0.0042	*0.0187*
$\mathbf{B_0}$				$\mathbf{B_1}$			
R_t	$R_{w,t-1}$	0.2172	*0.1659*	R_t	$R_{w,t-1}$	-0.0150	*0.2064*
	$\mathcal{L}_{w,t-1}$ (ZR)	-0.0535	*0.0834*		$\mathcal{L}_{w,t-1}$ (ZR)	0.0441	*0.1135*
$\mathcal{L}_t$ (ZR)	$R_{w,t-1}$	0.2865	*0.1309*	$\mathcal{L}_t$ (ZR)	$R_{w,t-1}$	-0.1857	*0.1669*
	$\mathcal{L}_{w,t-1}$ (ZR)	0.0220	*0.0588*		$\mathcal{L}_{w,t-1}$ (ZR)	-0.1046	*0.0803*
R_t	Lib_{t-1}	0.0170	*0.0382*				
$\mathcal{L}_t$ (ZR)	Lib_{t-1}	-0.0270	*0.0271*				

U.S. VAR dynamics:

$\mathbf{A_w}$				$\mathbf{\Sigma_w}$			
$R_{w,t}$	$R_{w,t-1}$	0.0092	*0.1001*		c_{11} (Return)	0.0389	*0.0024*
	$\mathcal{L}_{w,t-1}$ (ZR)	-0.0501	*0.0381*		c_{21} (Return and $\mathcal{L}$)	-0.0024	*0.0011*
$\mathcal{L}_{w,t}$ (ZR)	$R_{w,t-1}$	0.0672	*0.0328*		c_{22} ($\mathcal{L}$)	0.0144	*0.0009*
	$\mathcal{L}_{w,t-1}$ (ZR)	0.9986	*0.0144*				

Cholesky decomposition of variance-covariance matrix:

$\mathbf{\Sigma_0}$	c_{11} (Return)	0.1568	*0.0043*	$\mathbf{\Sigma_1}$	c_{11} (Return)	-0.0525	*0.0051*
	c_{21} (Return and $\mathcal{L}$)	0.0277	*0.0043*		c_{21} (Return and $\mathcal{L}$)	-0.0041	*0.0056*
	c_{22} ($\mathcal{L}$)	0.0995	*0.0034*		c_{22} ($\mathcal{L}$)	-0.0141	*0.0045*

Exposures to world shocks:

β_0				β_1			
R_t	$R_{w,t}$	0.3101	*0.1822*	R_t	$R_{w,t}$	0.9111	*0.2180*
$\mathcal{L}_t$ (ZR)	$R_{w,t}$	0.1199	*0.0531*	$\mathcal{L}_t$ (ZR)	$R_{w,t}$	-0.1031	*0.0691*
R_t	$\mathcal{L}_{w,t}$ (ZR)	0.1676	*0.3452*	R_t	$\mathcal{L}_{w,t}$ (ZR)	-0.9232	*0.4401*
$\mathcal{L}_t$ (ZR)	$\mathcal{L}_{w,t}$ (ZR)	0.1319	*0.3476*	$\mathcal{L}_t$ (ZR)	$\mathcal{L}_{w,t}$ (ZR)	0.1217	*0.4504*

Local return predictability	Wald Test	p-value	Global return predictability	Wald Test	p-value
Segmented	7.13	0.03*	Segmented	1.36	0.51
Integrated	3.73	0.15	Integrated	0.49	0.78
Change in predictability	2.64	0.62	Change in predictability	3.41	0.49

This table presents bivariate VAR maximum likelihood estimates, including excess returns and $\mathcal{L}$. We include the lagged U.S. return, lagged U.S. liquidity, and lagged Liberalization Intensity indicator as additional exogenous variables, as well as fixed effects (not reported). We parameterize the Cholesky decomposition of the VAR innovation covariance as $\Sigma_0 + Lib_{it}\Sigma_1$, where c_{ij} denotes the ***i,j*** th element of these two lower triangular matrices. We present Bollerslev and Wooldridge (1992) robust standard errors. In Nov 2001, S&P/IFC removed Colombia, Pakistan, Venezuela, and Zimbabwe from the Investability classification, forcing our investability measure to zero; we retain these values for our measure, but our evidence is similar over the earlier period that excludes this later period.

Finally, we present several Wald tests on return predictability. For the first tests on return predictability from local factors, the null hypothesis is that the first row of A_0=0 under segmentation and A_0+A_1=0 under integration. For the tests on return predictability from global factors, the null hypothesis is that the first row of B_0=0 under segmentation and B_0+B_1=0 under integration. For the tests on the overall changes in predictability in each case, the null hypotheses are that A_1=0 or B_1=0. The test statistics have X^2 distributions under the null with 2 degrees of freedom. For the predictability tests, a * indicates the test statistic exceeds the Monte Carlo critical value for significance at the 5% level.

Table 5

Alternative VAR specifications for returns, liquidity, turnover, and dividend yields

1993-2003

Dependent variable: R_t	**Case A**	**Case B**	**Case C**
A_0			
$\mathcal{L}_{t-1}$(ZR)	-0.0531	-0.0224	-0.0731
	0.0200	*0.0250*	*0.0267*
DY_{t-1} or TO_{t-1}		0.0758	0.0116
		0.0462	*0.0078*

Dependent variable: R_t	**Case A**	**Case B**	**Case C**
A_1			
$\mathcal{L}_{t-1}$(ZR)	0.0316	-0.0036	0.0519
	0.0254	*0.0328*	*0.0338*
DY_{t-1} or TO_{t-1}		-0.0576	-0.0084
		0.0602	*0.0098*

Dependent variable: R_t	**Case A**	**Case B**	**Case C**
B_0			
$R_{w,t-1}$	0.2172	0.2367	0.2431
	0.1659	*0.1907*	*0.1997*
$\mathcal{L}_{w,t-1}$(ZR)	-0.0535	0.0695	-0.1702
	0.0834	*0.1401*	*0.1467*
$DY_{w,t-1}$ or $TO_{w,t-1}$		0.3906	0.0213
		0.2994	*0.0413*

Dependent variable: R_t	**Case A**	**Case B**	**Case C**
B_1			
$R_{w,t-1}$	-0.0150	-0.0454	-0.0360
	0.2064	*0.2408*	*0.2481*
$\mathcal{L}_{w,t-1}$(ZR)	0.0441	0.0440	0.2201
	0.1135	*0.1733*	*0.1814*
$DY_{w,t-1}$ or $TO_{w,t-1}$		0.0880	-0.0436
		0.3677	*0.0501*

Dependent variable: DY_{t-1} or TO_{t-1}	**Case B**	**Case C**
A_0		
R_{t-1}	-0.0182	0.3072
	0.0162	*0.1295*
$\mathcal{L}_{t-1}$(ZR)	-0.0331	0.1268
	0.0096	*0.0798*
DY_{t-1} or TO_{t-1}	0.8851	0.8075
	0.0176	*0.0234*

Dependent variable: DY_{t-1} or TO_{t-1}	**Case B**	**Case C**
A_1		
R_{t-1}	0.0250	-0.2609
	0.0222	*0.1718*
$\mathcal{L}_{t-1}$(ZR)	0.0312	-0.1333
	0.0127	*0.1012*
DY_{t-1} or TO_{t-1}	0.0331	-0.0579
	0.0234	*0.0294*

Cholesky decomposition of variance-covariance matrix

Σ_0	**Case A**	**Case B**	**Case C**
(Return and $\mathcal{L}$)	0.0277	0.0260	0.0264
	0.0043	*0.0042*	*0.0042*
(Return and DY or TO)		-0.0162	0.0824
		0.0024	*0.0191*
($\mathcal{L}$ and dy or TO)		-0.0132	0.0824
		0.0026	*0.0191*

Σ_1	**Case A**	**Case B**	**Case C**
(Return and $\mathcal{L}$)	-0.0041	-0.0015	-0.0019
	0.0056	*0.0053*	*0.0053*
(Return and DY or TO)		-0.0062	-0.0178
		0.0030	*0.0233*
($\mathcal{L}$ and dy or TO)		0.0098	-0.0178
		0.0034	*0.0233*

Local return exposures to world shocks

β_0	**Case A**	**Case B**	**Case C**
$R_{w,t}$	0.3101	-0.2274	-0.2357
	0.1822	*0.1638*	*0.1679*
$\mathcal{L}_{w,t}$	0.1199	0.4421	0.3628
	0.0531	*0.4261*	*0.4305*
$DY_{w,t-1}$ or $TO_{w,t-1}$		3.0170	-0.0391
		2.7940	*0.0466*

β_1	**Case A**	**Case B**	**Case C**
$R_{w,t}$	0.9111	0.7094	0.7209
	0.2180	*0.2061*	*0.2103*
$\mathcal{L}_{w,t}$	-0.1031	-0.6582	-0.5464
	0.0691	*0.5373*	*0.5444*
$DY_{w,t-1}$ or $TO_{w,t-1}$		-4.3340	0.0448
		3.5090	*0.0586*

Local return predictability	Wald Tests					
Segmented	7.13	0.03	10.29	0.02	11.26	0.01
Integrated	3.73	0.15	6.56	0.09	7.63	0.05
Change in predictability	2.64	0.62	12.13	0.21	22.22	0.01

Global return predictability	Wald Tests					
Segmented	1.36	0.51	1.59	0.66	3.51	0.32
Integrated	0.49	0.78	0.49	0.92	3.46	0.33
Change in predictability	3.41	0.49	7.57	0.58	21.01	0.01

This table presents maximum likelihood estimates for three alternative VAR specifications: our benchmark bivariate VAR including excess returns and $\mathcal{L}$; a trivariate VAR including excess returns, $\mathcal{L}$, and dividend yields; as well as a trivariate VAR including excess returns, $\mathcal{L}$, and market turnover. As in Table 4, the Liberalization Intensity indicator is included in all cases as an additional exogenous variable. Due to computation limitations, the trivariate VARs do not incorporate the full cross-country covariances implied by the factor structure; within-country covariances are included. To conserve space, we only present select estimates of interest. We present return predictability coefficients, as well as the predictability coefficients for dividend yields and turnover. We parameterize the Cholesky decomposition of the VAR innovation covariance as $\Sigma_0 + Lib_{it}\Sigma_1$, where c_{ij} denotes the i,j th element of these two lower triangular matrices.

We highlight the contemporaneous relation between returns, L, turnover, and dividend yields (plus dividend yields and turnover with L), which are assumed to differ across liberalization state. We also present Bollerslev and Wooldridge robust standard errors below each estimate in italics. Finally, we present several Wald tests on predictability. For the first tests on return predictability from local factors, the null hypothesis is that the first row of A_0=0 under segmentation and A_0+A_1=0 under integration.

For the tests on return predictability from global factors, the null hypothesis is that the first row of B0=0 under segmentation and B0+B1=0 under integration. For the tests on the overall changes in predictability in each case, the null hypotheses are that A1=0 or B1=0. The test statistics have X^2 distributions under the null with 2 (bivariate) or 3 (trivariate) degrees of freedom.

Table 6

VARs for returns and alternative liquidity measures

1993-2003

VAR dynamics:		$\mathcal{L}_t$(ZR) Value-Weighted		$\mathcal{L}_t$(PI) Equal-Weighted		$\mathcal{L}_t$(PI) Value-Weighted	
A_0		Estimate	Standard Error	Estimate	Standard Error	Estimate	Standard Error
R_t	R_{t-1}	0.0548	*0.0430*	0.0496	*0.0419*	0.0526	*0.0434*
	$\mathcal{L}_{t-1}$	-0.1321	*0.0302*	-0.0177	*0.0150*	-0.0323	*0.0130*
$\mathcal{L}_t$	R_{t-1}	0.0296	*0.0393*	0.0390	*0.0560*	0.0209	*0.0915*
	$\mathcal{L}_{t-1}$	0.6415	*0.0275*	0.8360	*0.0215*	0.6185	*0.0301*
A_1							
R_t	R_{t-1}	-0.0185	*0.0567*	-0.0074	*0.0541*	-0.0148	*0.0576*
	$\mathcal{L}_{t-1}$	0.1255	*0.0354*	0.0070	*0.0186*	0.0263	*0.0158*
$\mathcal{L}_t$	R_{t-1}	0.0281	*0.0506*	0.1395	*0.0841*	0.1962	*0.1350*
	$\mathcal{L}_{t-1}$	0.2389	*0.0319*	-0.0635	*0.0287*	0.0535	*0.0390*
B_0							
R_t	$R_{w,t-1}$	0.2157	*0.2112*	0.1920	*0.1866*	0.2125	*0.2263*
	$\mathcal{L}_{w,t-1}$	-0.4416	*0.1736*	-0.0095	*0.0377*	-0.0520	*0.0651*
$\mathcal{L}_t$	$R_{w,t-1}$	0.2422	*0.1712*	0.0542	*0.2672*	1.0680	*0.4258*
	$\mathcal{L}_{w,t-1}$	-0.8978	*0.1565*	0.0319	*0.0532*	-0.1320	*0.1472*
B_1							
R_t	$R_{w,t-1}$	-0.0119	*0.3208*	0.0208	*0.2162*	-0.0093	*0.3540*
	$\mathcal{L}_{w,t-1}$	0.4042	*0.2272*	0.0150	*0.0499*	0.0433	*0.0874*
$\mathcal{L}_t$	$R_{w,t-1}$	-0.1588	*0.2090*	0.0850	*0.3588*	-1.3180	*0.5641*
	$\mathcal{L}_{w,t-1}$	0.5369	*0.1965*	-0.0655	*0.0752*	-0.1294	*0.2075*
R_t	Lib_{t-1}	0.0805	*0.0322*	-0.0070	*0.0345*	0.0204	*0.0273*
$\mathcal{L}_t$	Lib_{t-1}	0.1835	*0.0289*	-0.0853	*0.0511*	0.1664	*0.0647*
Cholesky decomposition of variance-covariance matrix:							
Σ_0	$c_{11\ (Return)}$	0.1554	*0.0042*	0.1571	*0.0043*	0.1567	*0.0043*
	$c_{21\ (Return\ and\ \mathcal{L})}$	0.0331	*0.0059*	0.0013	*0.0086*	0.0415	*0.0138*
	$c_{22\ (\mathcal{L})}$	0.1404	*0.0044*	0.1963	*0.0072*	0.3180	*0.0105*
Σ_1	$c_{11\ (Return)}$	-0.0511	*0.0051*	-0.0527	*0.0051*	-0.0524	*0.0051*
	$c_{21\ (Return\ and\ \mathcal{L})}$	-0.0251	*0.0072*	0.0271	*0.0117*	-0.0286	*0.0186*
	$c_{22\ (\mathcal{L})}$	-0.0498	*0.0054*	0.0107	*0.0098*	0.0082	*0.0140*
U.S. VAR dynamics:							
A_w							
$R_{w,t}$	$R_{w,t-1}$	0.0085	*0.1048*	0.0059	*0.0832*	0.0072	*0.1067*
	$\mathcal{L}_{w,t-1}$	-0.0974	*0.0713*	-0.0228	*0.0177*	-0.0405	*0.0303*
$\mathcal{L}_{w,t}$	$R_{w,t-1}$	0.0226	*0.0192*	0.2780	*0.0875*	0.1021	*0.0584*
	$\mathcal{L}_{w,t-1}$	0.9876	*0.0155*	0.9936	*0.0178*	0.9784	*0.0201*
Σ_w	$c_{11\ (Return)}$	0.0396	*0.0025*	0.0392	*0.0024*	0.0395	*0.0024*
	$c_{21\ (Return\ and\ \mathcal{L})}$	-0.0013	*0.0008*	-0.0124	*0.0030*	-0.0048	*0.0020*
	$c_{22\ (\mathcal{L})}$	0.0084	*0.0005*	0.0369	*0.0023*	0.0255	*0.0016*
Exposures to world shocks:							
β_0							
R_t	$R_{w,t}$	0.3430	*0.1829*	0.3792	*0.1864*	0.3745	*0.1809*
$\mathcal{L}_t$	$R_{w,t}$	0.0785	*0.0626*	0.0244	*0.1065*	0.2457	*0.1597*
R_t	$\mathcal{L}_{w,t}$	-0.6951	*0.7131*	-0.1964	*0.1470*	-0.3766	*0.2247*
$\mathcal{L}_t$	$\mathcal{L}_{w,t}$	-0.4985	*0.6998*	0.1255	*0.1287*	-0.2033	*0.5554*
β_1							
R_t	$R_{w,t}$	0.9112	*0.2224*	0.8521	*0.2257*	0.8869	*0.2169*
$\mathcal{L}_t$	$R_{w,t}$	-0.0656	*0.0801*	0.0890	*0.1465*	-0.2197	*0.2047*
R_t	$\mathcal{L}_{w,t}$	-0.3017	*1.1110*	-0.2421	*0.1945*	0.0106	*0.2853*
$\mathcal{L}_t$	$\mathcal{L}_{w,t}$	0.9078	*0.8964*	0.0004	*0.1087*	0.3593	*0.7890*

This table presents bivariate VAR maximum likelihood estimates, including excess returns and $\mathcal{L}$. In contrast to the benchmark case presented in Table 3, we consider three alternative liquidity measures: value-weighted zero return, equally-weighted price impact, and value-weigthed price impact. We include the lagged U.S. return, lagged U.S. liquidity, and lagged Liberalization Intensity indicator as additional exogenous variables, as well as fixed effects (not reported). We parameterize the Cholesky decomposition of the VAR innovation covariance as $\Sigma_0 + Lib_{it}\Sigma_1$, where c_{ij} denotes the i,j th element of these two lower triangular matrices. We present Bollerslev and Wooldridge (1992) robust standard errors.

Table 7

Liquidity pricing

1993-2003

Panel A: Theoretical models	Full integration	Full segmentation	Mixed	Mixed (no transaction cost adjustment)	Mixed (no systematic liquidity)	Mixed (value-weighted liquidity measure)
v_0		0.0064	0.0217		-0.0044	0.0002
		(0.0024)	(0.0083)		(0.0039)	(0.0053)
v_1	-0.0028		-0.0217		0.0047	0.0030
	(0.0015)		(0.0088)		(0.0043)	(0.0060)
γ_s		0.268	-0.420	-0.957	0.086	-0.373
		(0.215)	(0.600)	(0.630)	(0.232)	(0.429)
$\gamma_{\mathcal{L},s}$		2.660	9.577	5.531		4.518
		(0.675)	(2.348)	(1.723)		(1.611)
γ_w	2.292*		2.292*	2.292*	2.678*	2.848*
	(1.106)		(1.106)	(1.106)	(1.128)	(1.100)
$\gamma_{\mathcal{L},w}$	35.91*		35.91*	35.91*		57.24*
	(18.450)		(18.450)	(18.450)		(41.080)
J-Test	302.8	227.6	182.9	247.9	254.0	217.0
p-value	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
HJ-distance	123.0	94.0	128.2	121.1	87.6	96.7

Panel B: Unrestricted models	Model (no liberalization)	Model (with liberalization) segmented	integrated
v	-0.0089	0.0001	-0.0052
	(0.0092)	(0.0246)	(0.0277)
θ^1	0.362	-0.237	-0.259
	(0.481)	(0.430)	(0.579)
θ^2	-1.877	-1.116	-0.060
	(0.881)	(1.890)	(2.316)
θ^3	4.652	11.850	-9.277
	(1.584)	(3.139)	(4.136)
θ^4	5.894	-0.598	5.644
	(3.943)	(9.087)	(11.000)
θ^5	34.710	15.010	12.630
	(15.820)	(36.710)	(43.730)
θ^6	-40.550	-6.269	-30.060
	(17.440)	(31.380)	(41.640)
θ^7	-9.198	-13.410	17.730
	(4.258)	(5.865)	(8.929)
J-Test	205.9	117.2	
p-value	<0.001	<0.001	
HJ-distance	149.9	183.6	

This table presents evidence on liquidity pricing effects. Panel A contains evidence on our theoretical models: full integration, full segmentation, and mixed. The * indicates that the prices of world market and liquidity risk, γ_w and $\gamma_{\mathcal{L},w}$, are pre-estimated using GMM from the US CRSP data over 1962-2003; for the pre-estimation, we set $v_w = 0$. Taken the US estimates as given, we estimate each model using the investability measure to represent financial integration for the mixed model. We also consider three alternative mixed models that allow both global and local risk sources. In the first and second, we consider alternatives where we shut down either the gross to net return transaction costs adjustments or the prices of risks associated with local and global systematic liquidity, respectively. Finally, we also estimate the general mixed model, but we replace the equally weighted zero return liquidity measure with the value-weighted counterpart. In Panel B, we present estimates for two unrestricted model: one where all prices of risk are constant across liberalization state, and the other where prices of risk vary.

In all cases, we report the standard test of over-identifying restrictions, and we also consider a comparison across models by evaluating the Hansen and Jagannathan (1991) squared-distance metric. Asymptotic standard errors are reported in parantheses.

Appendix Table

Monte Carlo analysis of return predictability

	DGP: no return predictability (null)	
	R_{t+1} on *LIQ* $_t$	
	Coefficien	T-statistic
Median	-0.0109	-0.51
Mean	-0.0110	-0.51
2.5%	-0.0546	-2.37
5.0%	-0.0450	-2.14
95.0%	0.0220	1.04
97.5%	0.0277	1.39

For our sample of 18 emerging markets, plus the U.S., we simulate from the estimated bivariate VAR, including returns and liquidity, except that under the null, returns are not predicted by lagged variables. However, the innovations of all variables are allowed to be correlated as in the observed data within but not across emerging markets. The observed fixed effects are randomized across the sample for each replication. We employ the observed liberalization indicators for each replication. For each replication, we then estimate the unconstrained VAR(1) for returns and liquidity using our pooled MLE methodology. This table presents the mean and three relevant percentiles of the empirical distribution for the coefficients and robust *t*-statistics of excess returns on lagged *LIQ*.

Figure 1a

Comparison of Transaction Costs/Liquidity Measures using U.S. Data

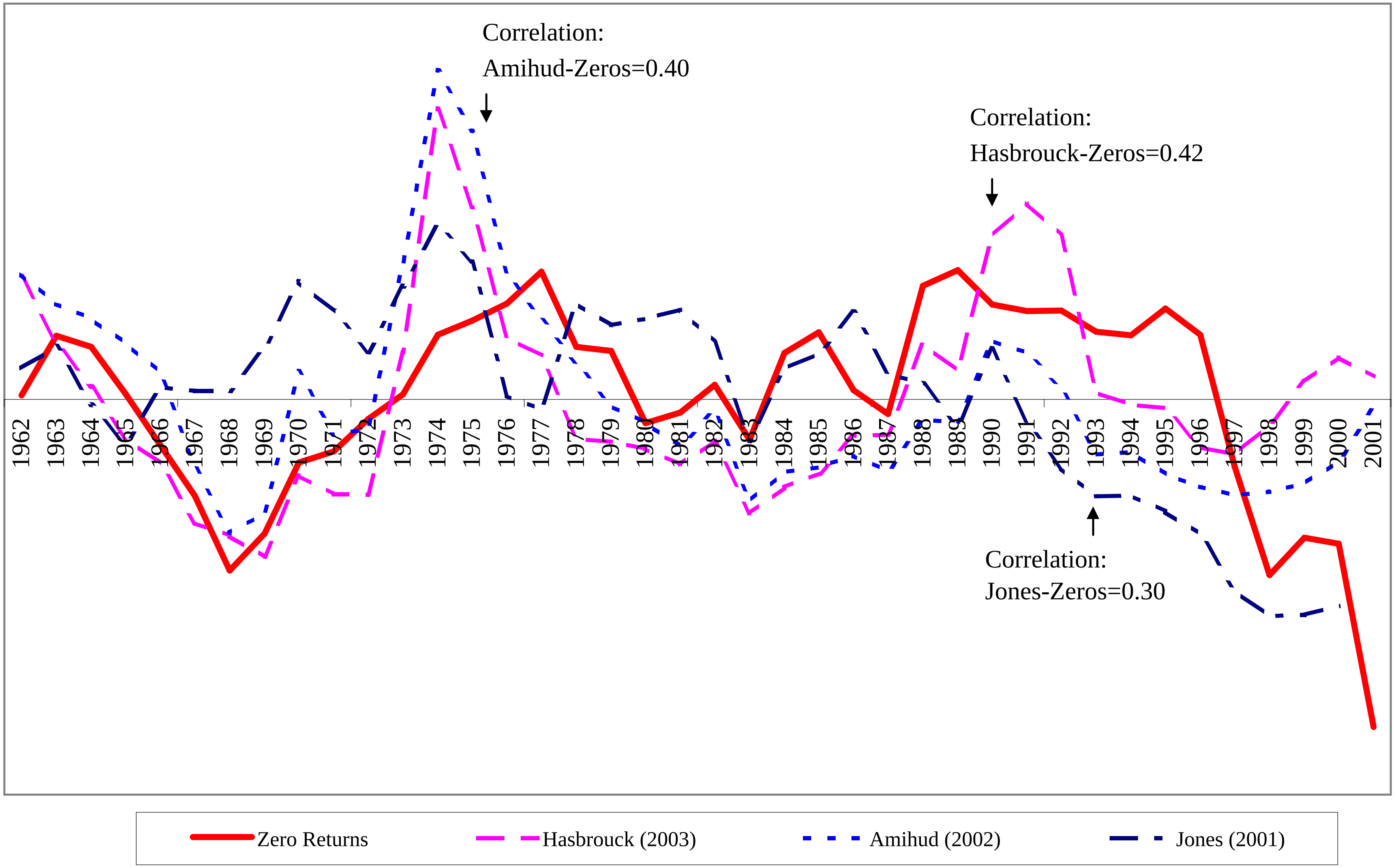

Figure 1b

Comparison of Transaction Costs/Liquidity Measures using U.S. Data: Zero Volume